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Conditional dependence structure and risk spillovers between Bitcoin and fiat currencies

Mobeen Ur Rehman [a,b], Paraskevi Katsiampa [c,*], Rami Zeitun [d], Xuan Vinh Vo [e]

[a] Institute of Business Research, University of Economics Ho Chi Minh City, Viet Nam
[b] South Ural State University, 76, Lenin Prospekt, Chelyabinsk, Russian Federation
[c] Sheffield University Management School, The University of Sheffield, Conduit road, Sheffield S10 1FL, UK
[d] Finance and Economics, Qatar University, P.O. Box: 2713, Doha, Qatar
[e] Institute of Business Research and CFVG, University of Economics Ho Chi Minh City, Viet Nam

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ABSTRACT

This paper investigates the extreme dependence and risk spillovers between Bitcoin and the currencies of the BRICS and G7 economies. We find time-varying dependence between Bitcoin and all currencies. Moreover, when analysing risk spillovers from Bitcoin to currencies, we find that Bitcoin exercises significant power over most currencies, with the South African rand and Brazilian real holding both the highest downside and upside risk before and during the COVID-19 pandemic period, respectively. When considering risk spillovers from currencies towards Bitcoin, the Japanese yen exhibits the highest downside spillovers. Importantly, we find asymmetric spillovers between extreme upward and downward movements.

1. Introduction

Over the last decade, blockchain applications and digital currencies have been under the spotlight. Bitcoin in particular, which popularised blockchain as the technology behind it, has drawn a lot of public attention since its introduction in 2009. This could be attributed not only to its innovative features, simplicity, and growing popularity (Urquhart, 2016) as well as the remarkable profits it could provide its users with in short periods of time (Kristoufek, 2013) but also to the questions raised regarding its nature and purpose (Trimborn and Härdle, 2018). Bitcoin is a digital currency designed to work as a medium of exchange using cryptography to secure the transactions without being subject to any government intervention. However, it is primarily utilised for speculation rather than as an alternative currency or medium of exchange (Baur et al., 2018), and has a place in financial markets and in portfolio management (Dyhrberg, 2016). Moreover, Bitcoin's volatility is significantly higher than the volatility of widely used currencies (Yermack, 2015; Baur and Dimpfl, 2021). Thus, forecasting of its price returns becomes a more challenging task compared to forecasting the returns of mainstream assets, especially during periods of high volatility relative to periods of low volatility (Koutmos, 2019). Yet, besides questions related to Bitcoin's purpose, concerns regarding security and the required regulation of digital currencies have also arisen (Cumming et al., 2019).

* Corresponding author.
E-mail addresses: Rehman@ueh.edu.vn (M.U. Rehman), P.Katsiampa@sheffield.ac.uk (P. Katsiampa), rami.zeitun@qu.edu.qa (R. Zeitun), vinhvx@ueh.edu.vn (X.V. Vo).

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Recently, Bitcoin has received a lot of academic attention as well. Among other research areas, several studies have investigated the relationship between Bitcoin and different assets, showing that Bitcoin is isolated from other markets, although this may have started changing. Nevertheless, the existing literature has mainly focused on financial assets and commodities, such as stocks, bonds, gold, and oil. Previous related studies often excluded fiat currencies from their analyses, although the foreign exchange (FX) market is the largest and most liquid market in the world (Boero et al., 2011), with global trading in FX markets averaging 5.1 trillion US dollars per day in April 2016 (BIS, 2016). Furthermore, while few studies have examined the relationship between Bitcoin and some currencies (e.g., Aharon et al., 2021; Baur et al., 2018; Baumöhl, 2019; Urquhart and Zhang, 2019), little is known about how Bitcoin prices and exchange rates co-move during extreme market conditions. Indeed, research on the extreme dependence between Bitcoin and currencies, i.e. the relationship between Bitcoin and currencies during upturn and downturn market periods, is very limited. This is true despite the fact that distinguishing between periods of high and low price volatility in the Bitcoin market is of high importance, especially for revealing heterogeneity in the explanatory power of market risk factors (Koutmos, 2019). Moreover, to the best of the authors' knowledge, no previous study has thoroughly examined the extreme dependence between cryptocurrencies and currencies of emerging markets. Yet, emerging countries' economies are becoming more and more integrated with other economies (Wen and Cheng, 2018), while the positive impact that financial technology advancements have the potential to make, especially on countries where many people still have no access to traditional financial or banking services, has been commonly discussed.

Nonetheless, given their high volatility, cryptocurrencies could also pose risks to both cryptocurrency users and investors who should diversify (Baumöhl, 2019). Analysing co-movements between different markets is important for risk diversification in portfolio management (Ning, 2010; Sun et al., 2008), and understanding co-movements between Bitcoin and exchange rates, in particular, is therefore of high importance to international investors. However, investors are not interested merely in unconditional correlations. Instead, they are interested in correlations in different states of the market, including times during which, e.g., Bitcoin or a currency is in distress, in which case investors' overall portfolios are likely to drop in value (Borri, 2019), a fact that highlights the importance of investigating extreme dependencies between Bitcoin and currencies. In addition, spillover effects of extreme upward or downward Bitcoin movements on exchange rates and vice versa could have significant implications in terms of risk management, trading, and hedging strategies for international portfolios (Reboredo et al., 2016; Shahzad et al., 2018b).

Consequently, motivated by the importance of studying the dependence structure between Bitcoin and exchange rates in international financial markets, the aim of this paper is to study extreme dependencies and test for risk spillovers between Bitcoin and foreign exchange markets. In particular, given the importance of financial technology to emerging markets and the increasing integration of emerging markets with the rest of the world (Wen and Cheng, 2018), we investigate the extreme dependence between Bitcoin and the currencies of the BRICS and G7 economies during upturn and downturn market periods.

The relevance of the BRICS countries to cryptocurrency price dynamics lies in the high cryptocurrency adoption rate in these countries, the Bitcoin mining landscape as well as the countries' steps towards digital currency implementation. Specifically, in terms of cryptocurrency adoption rate, the percentage of those who own cryptocurrency in 2022 is 29%, 18%, and 10% in India, Brazil, and South Africa, respectively (Laycock, 2022). Moreover, Russia, along with the United States, was estimated to have traded the highest amounts of Bitcoin during 2019–2021 (Statista, 2022a), with approximately 420 million US dollars worth of Russian rubles being used to purchase Bitcoin on an exchange in 2020 (Statista, 2022b). On the other hand, China was the country that remained the largest Bitcoin miner for a long time until late 2021, while Russia was the second largest crypto miner for most of 2020 and remained among the top five largest crypto miners since then (Statista, 2022c).[1] The BRICS countries have also been considering the implementation of blockchain technology in banking systems (Gusarova et al., 2021). In particular, in 2019, China announced it would launch a project to create the digital yuan (Didenko et al., 2020), while Russia announced it could consider the creation of a gold-backed cryptocurrency to facilitate international settlements (Tass, 2019). On the other hand, Brazil has recently announced the approval of a law to regulate the cryptocurrency market (Gusson, 2022). Importantly, though, the BRICS countries have been considering the development of a single payment transaction system among them, which could be implemented in the form of a digital currency, in order to facilitate trade transactions and reduce their reliance on US dollars in settlement (Palmer, 2019).

To achieve our aim, we employ a wide range of static and dynamic multivariate copula specifications. Multivariate copulas have found several applications in economics, finance as well as risk management. This is due to their flexibility, enabling the representation of the joint distribution of variables even when the variables under consideration have different distributions, and the fact that they can isolate the dependence measure from the margins (Boero et al., 2011; Czado et al., 2012; Shahzad et al., 2018b). Furthermore, copulas are more advantageous than the linear correlation coefficient when studying relationships between variables (Shahzad et al., 2018b; Sun et al., 2008), as the latter is only a partial measure of their full dependence structure (Malevergne and Sornette, 2006). We also quantify and test the impact of upward and downward movements of Bitcoin prices on currencies and vice versa. We measure the asymmetric upside and downside risk spillovers between Bitcoin and the foreign exchange markets under consideration by using three different measures of upside and downside risk, namely the Value-at-Risk (VaR), Conditional Value-at-Risk ($CoVaR$), and delta Conditional Value-at-Risk ($\Delta CoVaR$) measures.

Among others, our results reveal temporal variations in the dependence between Bitcoin and the considered fiat currencies, with the dependence increasing after the COVID-19 pandemic outbreak for most FX markets. We further find that Bitcoin has significant influence over most of the fiat currencies considered, with the South African rand and Brazilian real holding both the highest downside and upside risk before and during the COVID-19 pandemic period, respectively, when analysing risk spillovers from Bitcoin to FX

[1] It is also worth mentioning that Bitcoin mining activity has recently increased in several developed countries, including the United States, Canada, and Germany, as well, with most Bitcoin mining having taken place in the United States in 2021 (Statista, 2022c).

markets. On the other hand, when considering risk spillovers from FX markets towards Bitcoin, we find that Bitcoin's sensitivity to fiat currencies increased during the COVID-19 pandemic period and that the Japanese yen exhibits the highest risk spillover effects. Finally, when analysing spillovers from Bitcoin to FX markets and vice versa we find evidence of discrepancies in the spillover effects between extreme upward and downward movements and thus of asymmetric spillovers.

Our contribution is threefold. First, we contribute to the literature on the relationship between cryptocurrencies and fiat currencies (e.g., Aharon et al., 2021; Baumöhl, 2019; Urquhart and Zhang, 2019). In our study, we analyse a wide range of commonly traded currencies over a ten-year period, including the COVID-19 pandemic period. In particular, this is the first study to consider the currencies of all the BRICS countries, among others, when investigating the relationship between cryptocurrencies and fiat currencies. Our focus is on the extreme dependence between Bitcoin and currencies, and our study is the first to investigate the dependence structure between Bitcoin and the BRICS currencies, besides the currencies of the G7 economies. We do so by employing a broad range of time-invariant and time-varying copula functions. Second, this is the first study of risk spillover effects between Bitcoin and FX markets during upturn and downturn market periods. Our risk spillover analysis may further guide investors to consider the association between these markets before formulating portfolios. Third, we discuss the implications of our results for selecting optimal trading strategies during upturn and downturn market periods. Our analysis therefore brings new insights to interdependencies between Bitcoin and fiat currencies during extremely volatile market periods and our results have important implications for investors, as they can benefit from understanding the asymmetric behaviour between Bitcoin and the different foreign exchange markets.

The remainder of the paper is organised as follows: Section 2 reviews relevant literature. Section 3 discusses the methodology. Section 4 presents the data employed in this study. Section 5 discusses the results. Finally, Section 6 concludes.

2. Literature review

2.1. Related literature on the dependence structure between financial markets

In recent years, the analysis of the dependence between international markets during extreme fluctuations has received a lot of attention. Previous studies that have examined the dependence structure during upturn and downturn market periods between foreign exchange markets, in particular, include those of Albulescu et al. (2018), Boero et al. (2011), Dias and Embrechts (2010), Loaiza-Maya et al. (2018), Min and Czado (2014), and Patton (2006), among others. More specifically, while examining for asymmetric exchange rate dependence structure using conditional copulas, Patton (2006) found evidence of the Deutsche mark-US dollar and Japanese yen-US dollar exchange rates being more correlated when they are depreciating against the dollar than when they are appreciating. Similarly, Boero et al. (2011) investigated the bivariate dependence structure for different pairs of exchange rates measured against the US dollar in the pre- and post-Euro periods, using the Deutsche mark to represent the Euro before 1999. Although the authors found that the dependence for the Euro-Swiss franc pair remained unaffected over the whole sample period, the results for the Euro-Japanese yen and Euro-GBP pairs revealed not only discrepancies in the dependence structure in the pre- and post-Euro periods but also asymmetric tail dependence, suggesting different co-movements during appreciations and depreciations against the US dollar. Moreover, Dias and Embrechts (2010) studied the Euro-US dollar and Japanese yen-US dollar pairs by utilising a flexible time-varying copula model and documented significant time-varying correlations, dependent on past return realisations. More recently, Albulescu et al. (2018) studied the bivariate dependence structure between the exchange rates of Euro, GBP, Canadian dollar, and Japanese yen against the US dollar, and found positive dependence between all the exchange rates considered. Furthermore, similar to the study of, e.g., Dias and Embrechts (2010), their results revealed time-varying dependence, which, however, intensified after the recent financial crisis for all the pairs of exchange rates apart from the Japanese yen-GBP and Japanese yen-Canadian dollar pairs. Nevertheless, the authors also found evidence of symmetric tail dependence suggesting no substantial differences between the tail dependence in bull and bear markets, as opposed to earlier studies, such as those of Patton (2006) and Boero et al. (2011), which found asymmetries in the dependence structure of exchange rates.

Several studies have also examined the relationship between currencies and stock markets. For instance, Ranaldo and Söderlind (2010) found that the Swiss franc and Japanese yen appreciate against the US dollar when US stock prices fall. Michelis and Ning (2010) studied the dependence structure between Canadian stock returns and the US dollar-Canadian dollar exchange rate returns and found significant asymmetric static and dynamic tail dependence between the two, with a stronger dependence in the left than in the right tail of their joint distribution. In addition, Reboredo et al. (2016), using copulas, studied downside and upside risk spillover effects from exchange rates to stock prices and vice versa for various emerging economies and identified a positive relationship between stock prices and currencies in emerging economies against the US dollar and Euro as well as bidirectional but asymmetric downside and upside spillovers. The authors also found asymmetric discrepancies in the size of the spillovers when the domestic currencies value against the US dollar and Euro.

Other studies have investigated the extreme dependence between commodity markets - with an emphasis on oil markets - and different currencies. For instance, Reboredo (2012), Wu et al. (2012), Aloui et al. (2013), and Aloui and Aïssa (2016) examined the dependence structure between oil prices and exchange rates employing various copula-based GARCH models. Interestingly, Reboredo (2012) found that oil price-exchange rate dependence is overall weak, in spite of its substantial rise after the onset of the global financial crisis, and that there is no extreme dependence between oil prices and exchange rates. However, Aloui et al. (2013) and Aloui and Aïssa (2016) found evidence of significant and symmetric dependence for the oil-exchange rate pairs considered in their studies, with the recent financial crisis and great recession having a considerable impact on the dependence structure (Aloui and Aïssa, 2016). More recently, Kim and Jung (2018) also examined the relationship between crude oil prices and exchange rates and found further evidence of significant dependence for all of their considered pairs, barring the Mexican peso-Brent pair, and that crude oil price

increases are related to depreciations of major currencies. Moreover, Ji et al. (2019) studied the dynamic dependence between crude oil and the US dollar and Chinese RMB, and found that the dependence between crude oil and the RMB exchange rate is weakly positive with lower tail dependence, whereas the dependence between crude oil and the US dollar is significantly negative with lower-upper and upper-lower tail dependence. The latter study also found a significant risk spillover from crude oil to both the US and Chinese exchange rate markets, with the spillover effect being significantly asymmetric for the Chinese RMB in response to fluctuating oil prices, but with the asymmetry of the spillover not being significant for the US dollar. What is more, Aloui et al. (2013) and Wu et al. (2012) showed that Student-t copulas are more advantageous in terms of capturing the extreme dependence and forecasting performance when studying the dependence structure between crude oil and the US dollar.

Copula functions have found several applications in financial markets as well. For instance, Rodriguez (2007) modelled the dependence between several East Asian and Latin American stock indices with switching-parameter copulas and found evidence of changing dependence during periods of turmoil, with amplified tail dependence and asymmetry in the considered Asian markets but with symmetry and tail independence in Latin American markets. Jondeau and Rockinger (2006), using Gaussian and Student-t copula functions, showed that the conditional dependence between European markets augments more significantly following movements in the same direction than after movements in opposite directions. Furthermore, Shahzad et al. (2018a) modelled the downside and upside spillover effects, systemic, and tail dependence risks of Islamic equity indices and found larger downside spillover effects and systemic risk for the DJ Islamic Financials World and USA Islamic indices, but greater exposure to upside spillover risk effects for Islamic indices from Japan and the DJ World financials. Moreover, in a study of the dependence structure between several international financial markets using a mixed copula model, Hu (2006) found that pairs with lower correlations hold a similar probability to crash together as pairs with higher correlations. Several studies have also investigated the dependence structure between emerging countries' stock markets and other financial markets. Examples of such studies include those of Hammoudeh et al. (2014), Jian et al. (2018), and Wen and Cheng (2018), among others.[2]

2.2. Related literature on cryptocurrencies

Recently there has been an increased interest in studying cryptocurrency markets as well.[3] Previous studies have examined several properties of Bitcoin and other cryptocurrencies. For instance, studies on cryptocurrency price volatility include, e.g., those of Baur and Dimpfl (2018), Katsiampa (2017), and Yaya et al. (2021), all of which employed various models to analyse the volatility dynamics of cryptocurrencies, while Bouri et al. (2019), Jiang et al. (2018), and Phillip et al. (2018) found evidence of long memory in cryptocurrency markets. On the other hand, Osterrieder and Lorenz (2017) found that cryptocurrencies exhibit heavier tail behaviour and are therefore riskier than traditional currencies.

Several studies have also investigated the relationship between Bitcoin and different assets in order to establish whether cryptocurrencies can act as diversifiers, hedge or safe haven against mainstream assets. Examples of such studies include, e.g., those of Baur et al. (2018), Corbet et al. (2018), Giudici and Abu-Hashish (2019), Yermack (2015), and Yousaf and Yarovaya (2021), all of which found consistent results about Bitcoin being weakly correlated with financial assets and commodities, such as stocks, bonds, gold, and oil. Nonetheless, this seems to have started changing (Corbet et al., 2020a; Maghyereh and Abdoh, 2021). Moreover, Baur et al. (2018), Baumöhl (2019), Giudici and Abu-Hashish (2019), Guesmi et al. (2019), Urquhart and Zhang (2019), and Yermack (2015) studied the relationship between Bitcoin and some currencies, finding similar results regarding Bitcoin being isolated from foreign exchange markets as well. Yermack (2015) further argued that it is nearly impossible to hedge Bitcoin's risk and that Bitcoin is a rather useless tool for risk management. However, Guesmi et al. (2019) argued that Bitcoin could offer diversification and hedging benefits for investors, with hedging strategies including gold, oil, emerging stock markets, and Bitcoin significantly reducing a portfolio's risk, in comparison to a portfolio consisting of gold, oil, and stocks from emerging stocks only. On the other hand, Urquhart and Zhang (2019) concluded that Bitcoin can act as an intraday hedge for the Swiss Franc, Euro, and British pound, but acts as a diversifier for the Australian dollar, Canadian dollar, and Japanese yen. The latter study also found that Bitcoin is a safe haven during periods of extreme market turmoil for the Canadian dollar, Swiss Franc, and British pound. Aharon et al. (2021) further found that Bitcoin is independent of the main currencies considered in their study when employing static analysis, thereby suggesting that Bitcoin could provide hedging benefits. Yet, the authors' dynamic analysis indicated that Bitcoin is not isolated from fiat currencies, with its connectedness increasing during crises, thus suggesting that Bitcoin is not a safe-haven, in line with Smales (2019).

Nevertheless, although the dependence structure during upturn and downturn market periods has been extensively studied in the literature for several markets, and despite the fact that the literature on Bitcoin has rapidly emerged, the relationship between cryptocurrencies and other assets or currencies during periods of extreme fluctuations still remains underexplored. To the best of the authors' knowledge, only Baumöhl (2019) has examined dependencies of cryptocurrencies with fiat currencies during extreme market conditions. More specifically, using the quantile cross-spectral approach, Baumöhl (2019) found some significant negative dependence between cryptocurrencies and FX markets from both the short- and long-term perspectives. However, Baumöhl (2019) considered mainly currencies of developed countries. Moreover, no past study has explored risk spillover effects of extreme downward or upward cryptocurrency movements on fiat currencies and vice versa.

In this paper, we thus investigate co-movements between Bitcoin and nine major currencies, including the currencies of all the BRICS countries, during upturn and downturn market periods. We do so by employing various static and dynamic copula functions,

[2] A more comprehensive overview of the literature on applications of copulas to financial time series can be found in Patton (2009).

[3] For a systematic review of literature on cryptocurrencies, see Corbet et al. (2019).

which provide an improved model fit compared to linear correlation coefficients (Shahzad et al., 2018b; Sun et al., 2008) and which allow us to study not only average movements across marginals but also joint extreme upward and downward movements (Reboredo et al., 2016). Importantly, we also study the asymmetric upside and downside risk spillovers between the considered currencies and Bitcoin, by quantifying three risk measures, namely the *VaR*, *CoVaR*, and delta *CoVaR* measures, as discussed in the next section. To the best of our knowledge, this is the first study of the dependence structure between Bitcoin and the BRICS currencies, besides the currencies of developed countries, as well as the first study of risk spillover effects between Bitcoin and FX markets during extreme market conditions.

3. Methodology

3.1. The marginal distribution model

In order to investigate the dependence structure between Bitcoin and FX markets, we first estimate the marginal distribution of each return series using the Autoregressive Moving Average - Generalised Autoregressive Conditional Heteroskedasticity (thereafter ARMA-GARCH) model. The mean equation for the returns of Bitcoin and fiat currencies, r_t, characterised by an ARMA(p, q) model is given as follows

$$r_t = c + \sum_{i=1}^{p} \phi_i r_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}, \tag{1}$$

where p and q represent non-negative integers, ϕ_i and θ_j denote the autoregressive (AR) and moving average (MA) coefficients, and $\varepsilon_t = \sigma_t z_t$, where z_t denotes an *i.i.d.* random variable having zero mean and unit variance and σ_t^2 represents the conditional variance with its dynamics defined by the GARCH model given as

$$\sigma_t^2 = \omega + \sum_{k=1}^{m} \alpha_k \, \varepsilon^2{}_{t-k} + \sum_{l=1}^{n} \beta_l \sigma^2{}_{t-l}, \tag{2}$$

where ω, α_k, and β_l are the conditional variance parameters to be estimated.[4] Following Hansen (1994), we allow for a skewed Student-*t* density distribution for the innovations in order to capture asymmetries and fat tails of the returns' distribution, expressed as

$$f(z_t, v, \mathfrak{y}) = \begin{cases} bc\left(1 + \dfrac{1}{v-2}\left(\dfrac{bz_t + a}{1 - \mathfrak{y}}\right)^2\right)^{-(v+1)/2}, & z_t < -a \Big/ b \\ bc\left(1 + \dfrac{1}{v-2}\left(\dfrac{bz_t + a}{1 + \mathfrak{y}}\right)^2\right)^{-(v+1)/2}, & z_t \geq -a \Big/ b \end{cases} \tag{3}$$

where v represents the degrees of freedom parameter ($2 < v \leq \infty$), η represents the symmetry parameter ($-1 < \eta < 1$), and a, b and c are constants given as $a = 4\eta c\left(\frac{v-2}{v-1}\right)$, $b^2 = 1 + 3\eta - a^2$, and $c = \Gamma\left(\frac{v+1}{2}\right) \Big/ \sqrt{\pi(v-2)}\,\Gamma\left(\frac{v}{2}\right)$. It is worth mentioning that the skewed Student-t distribution encompasses a large set of conventional densities. Specifically, when $\eta = 0$ and v is finite, it converges to the symmetric Student-t distribution, whereas when $\eta = 0$ and $v \to \infty$, it converges to the Gaussian distribution.

3.2. Copula methodology

To examine the dependence structure between Bitcoin and currency returns during upturn and downturn market periods, we employ copulas, as they allow us to study not only average but also extreme (or tail) dependence (Reboredo et al., 2016), and hence the probability that two variables jointly experience extreme upward or downward movements. Indeed, copulas are functions that link univariate distributions to the multivariate distribution of the related variables, while providing a very general way of introducing dependence among series with known marginals. Copula theory is based on the Sklar theorem, according to which a joint distribution $F_{XY}(x, y)$ of two continuous random variables, X and Y, can be expressed in terms of a copula function, C, as follows

$$F_{XY}(x, y) = C\big(F_X(x), F_y(y)\big) = C(u, v), \tag{4}$$

where $u = F_X(x)$ and $v = F_Y(y)$ are the marginal distribution functions of the random variables. This reveals that a copula is a multivariate function with uniform marginals that represents the dependence structure between two random variables and is uniquely determined on $RanF_x \times RanF_y$ when the margins are continuous.[5]

We obtain the joint probability density function of the two variables, X and Y, from the copula density function, $c(u, v) = \frac{\partial^2 C(u,v)}{\partial u \partial v}$, as

[4] We use different combinations of values of the lag order parameters p, q, m, and n ranging from 0 to 2, and the optimal marginal distribution model for each series is selected based on the minimum value of the Akaike Information Criterion (AIC).

[5] For more details about copulas, see Joe (1997) and Nelsen (2007).

follows

$$f_{XY}(x,y) = c(u,v)f_Y(y)f_X(x), \tag{5}$$

where $f_Y(y)$ and $f_X(x)$ represent the marginal densities of the variables Y and X, respectively. Consequently, in order to characterise the joint density of two variables, we need information on the marginal densities as well as on the copula density function. The upper (right) and lower (left) tail dependence is then given as

$$\lambda_U = lim_{u\to 1} Pr\left[X \geq F_X^{-1}(u)\,|Y \geq F_Y^{-1}(u)\right] = lim_{u\to 1}\frac{1-2u+C(u,u)}{1-u} \tag{6}$$

and

$$\lambda_L = lim_{u\to 0} Pr\left[X \leq F_X^{-1}(u)\,|Y \leq F_Y^{-1}(u)\right] = lim_{u\to 0}\frac{C(u,u)}{u}, \tag{7}$$

respectively, where λ_U, $\lambda_L \in [0,1]$, suggesting a non-zero probability of observing an extremely small (large) value for one series alongside an extremely small (large) value for another series.

In our study, we employ a battery of copula specifications with different feature dependencies and static and time-varying parameters. Specifically, we use four bivariate symmetric copulas with tail independence, namely the Normal copula, Student-t copula, Frank copula, and Plackett copula. As for asymmetric copulas, we employ the Gumbel (rotated Gumbel) copula with upper (lower) tail dependence and lower (upper) tail independence, the Clayton (rotated Clayton) copula with lower (upper) tail dependence and upper (lower) tail independence, and the symmetrised Joe-Clayton copula (SJC) with a special case of the symmetric tail dependence.[6] Moreover, similar to Shahzad et al. (2018b), we model the time-varying dependence for all the above copula functions by allowing the copula parameter to vary according to an evolution equation. For Gaussian and Student-t copulas, we specify a linear dependence parameter, ρ_t, which evolves according to an ARMA(1,q)-type process (see, e.g., Patton, 2006) as follows

$$\rho_t = \wedge\left[\Psi_0 + \Psi_1\rho_{t-1} + \Psi_2\frac{1}{q}\sum_{j=1}^{q}\phi^{-1}\left(u_{t-j}\right).\phi^{-1}\left(v_{t-j}\right)\right], \tag{8}$$

where $\wedge(x) = (1-e^{-x})(1+e^{-x})^{-1}$ is the modified logistic transformation required to keep the value of ρ_t in $(-1,1)$. The dependence parameter is thus explained by the constant term Ψ_0, the autoregressive term Ψ_1, and the parameter on the average product of the last q observations of the transformed variables, Ψ_2. For a Student-t copula, the parameter dynamics are given in Eq. (8) by substituting $\phi^{-1}(x)$ by $t_\upsilon^{-1}(x)$. The dynamics of the Gumbel and rotated Gumbel copulas are assumed to follow an ARMA(1,q) process given as.

$$\delta_t = \omega + \beta\delta_{t-1} + \alpha\frac{1}{q}\sum_{j=1}^{q}\mid u_{t-j} - v_{t-j}\mid. \tag{9}$$

It can be noted that the rotated Gumbel copula is better suited if the variables are highly correlated at low values (Albulescu et al., 2018).

Finally, for the SJC copula, the tail dependence parameters are given as follows

$$\lambda_t^U = \Delta\left(\omega_U + \beta_U\rho_{t-1} + \alpha_U\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|\right) \tag{10}$$

and

$$\lambda_t^L = \Delta\left(\omega_L + \beta_L\rho_{t-1} + \alpha_L\frac{1}{q}\sum_{j=1}^{q}|u_{t-j} - v_{t-j}|\right), \tag{11}$$

where $\Delta(x) = (1+e^{-x})^{-1}$ is the logistic transformation used to retain λ_t^U and λ_t^L in (0,1).

3.3. VaR, CoVaR, and Delta CoVaR risk measures

In this study, both downside (long position) and upside (short position) *VaR* and *CoVaR* measures for the Bitcoin and currency returns are quantified using copulas. For a given confidence level $1-\alpha$, the downside (upside) *VaR* measure at time t is given by $Pr(r_t \leq VaR_{\alpha,\,t}) = \alpha$ ($Pr(r_t \geq VaR_{1-\alpha,\,t}) = \alpha$). The downside and upside *VaR* measures can be determined from the marginal models as

$$VaR_{\alpha,t}^{downside} = \mu_t + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t \tag{12}$$

and

[6] A more detailed discussion and presentation of these copulas can be found in, e.g., Albulescu et al. (2018).

$$VaR_{\alpha,t}^{upside} = \mu_t + t_{\upsilon,\eta}^{-1}(1-\alpha)\sigma_t, \tag{13}$$

where μ_t and σ_t denote the conditional mean and standard deviation, respectively, of the return series, computed through the mean and variance equation of the ARMA-GARCH model as shown in Eqs. (1)–(2), and $t_{\upsilon,\eta}^{-1}(\alpha)$ represents the αth quantile of the skewed Student-t distribution as shown in Eq. (3).

As a result of possible dependencies between Bitcoin and FX markets, we study the effect of financial distress in the Bitcoin market, as measured by its *VaR*, on the *VaR* measure of the FX markets and vice versa. We also consider the *CoVaR* measure, as developed by Adrian and Brunnermeier (2011) and Girardi and Ergün (2013).[7] Let r_t^c and r_t^{btc} denote the returns of a currency and Bitcoin, respectively. Then for a confidence level $1-\beta$ and the β-quantile of the conditional distribution of r_t^c, the downside *CoVaR* measure for the returns of the given FX market for an extreme downward Bitcoin price movement is given as

$$Pr\left(r_t^c \le CoVaR_{\beta,t}^{c,downside} | r_t^{btc} \le VaR_{\alpha,t}^{btc,downside}\right) = \beta, \tag{14}$$

whereas the upside *CoVaR* measure for the returns of the given currency for an extreme upward Bitcoin price movement is given as

$$Pr\left(r_t^c \ge CoVaR_{\beta,t}^{c,upside} | r_t^{btc} \ge VaR_{1-\alpha,t}^{btc,upside}\right) = \beta, \tag{15}$$

where $VaR_{\alpha,\,t}^{btc}$ is the α-quantile of the Bitcoin price return distribution and $Pr(r_t^{btc} \le VaR_{\alpha,\,t}^{btc}) = \alpha$ quantifies the potential loss that Bitcoin price returns may experience at a confidence level $1-\alpha$ for a specific time horizon, while $VaR_{1-\alpha,\,t}^{btc}$ measures the potential loss when assuming a short position for a specific time horizon at a confidence level $1-\alpha$. The systemic impact of a given currency on Bitcoin can be measured accordingly by considering the *CoVaR* measure for the Bitcoin market instead of the FX market as shown above. The *CoVaR* measures shown in Eqs. (14) and (15) can be represented in terms of copulas as follows

$$C\left(F_{r_t^c}\left(CoVaR_{\beta,t}^c\right), F_{r_t^{btc}}\left(VaR_{\alpha,t}^{btc}\right)\right) = \alpha\beta \tag{16}$$

and

$$1 - F_{r_t^c}\left(CoVaR_{\beta,t}^c\right) - F_{r_t^{btc}}\left(VaR_{1-\alpha,t}^{btc}\right) + C\left(F_{r_t^c}\left(CoVaR_{\beta,t}^c\right), F_{r_t^{btc}}\left(VaR_{1-\alpha,t}^{btc}\right)\right) = \alpha\beta, \tag{17}$$

where $F_{r_t^c}$ and $F_{r_t^{btc}}$ denote the marginal distributions of the currency and Bitcoin price returns, respectively. Similar to Reboredo and Ugolini (2015), we compute the *CoVaR* measure by following a two-step procedure. In the first step, Eq. (16) or Eq. (17) can be solved in order to obtain the value of $F_{r_t^c}(CoVaR_{\beta,\,t}^c)$, given the significance levels for the *VaR* and *CoVaR* measures, respectively, and for a specific form of copula function. In the second step, we use the distribution function for Bitcoin and currency returns as given by the marginal distribution model in Eqs. (1)–(2) and calculate the *CoVaR* value for the FX market as $F_{r_t^c}^{-1}(F_{r_t^c}(CoVaR_{\beta,\,t}^c))$.

Finally, similar to Adrian and Brunnermeier (2011) and Girardi and Ergün (2013), we compute the systemic risk contribution of a currency, *c*, as the delta *CoVaR* ($\Delta CoVaR$) measure, which is defined as the difference between the *VaR* value of the FX market as a whole conditional on the distressed state of FX market *c* ($R_t^c \le VaR_{\alpha,\,t}^c$) and the *VaR* value of the FX market as a whole conditional on the benchmark state of FX market *c*, considering it as the median of the return distribution of market *c*, or, alternatively, as the *VaR* value for $\alpha = 0.5$. Consequently, the systemic risk contribution of FX market *c* is calculated as

$$\Delta CoVaR_t^{d/c} = \frac{\left(CoVaR_{\beta,t}^{\frac{d}{c}} - CoVaR_{\beta,t}^{\frac{d}{c},\alpha=0.5}\right)}{CoVaR_{\beta,t}^{d/c,\alpha=0.5}}. \tag{18}$$

The importance of $\Delta CoVaR$ lies in the fact that it captures the marginal contribution of systemic risk of FX market *c* to the overall risk. For robustness, similar to Reboredo et al. (2016), we employ the Kolmogorov-Smirnov (KS) bootstrapping test developed by Abadie (2002) to compare the *CoVaR* values and test the asymmetry in risk spillovers. More specifically, the KS test measures the difference between two cumulative quantile functions relying on the empirical distribution function but without taking any underlying distribution function into consideration, and is given as

$$KS_{mn} = \left(\frac{mn}{m+n}\right)^{1/l} sup_x \mid F_m(x) - G_n(x) \mid, \tag{20}$$

where $F_m(x)$ and $G_n(x)$ are the cumulative *CoVaR* and *VaR* distribution functions, respectively, while *m* and *n* denote the two sample sizes. We therefore test the hypothesis of no systemic impact between currency and Bitcoin returns as

$$H_0 : CoVaR_{\beta,t}^C = VaR_{\beta,t}^C.$$

[7] By definition, the *CoVaR* measure for asset *i* is the *VaR* value for asset *i* conditional on asset *j* exhibiting an extreme movement.

4. Data and preliminary analysis

Our dataset consists of daily values for the Euro, Japanese yen, British pound sterling, Canadian dollar, Brazilian real, Chinese yuan, Indian rupee, Russian ruble, and South African rand as well as for Bitcoin against the US dollar from 6th January 2012 to 6th January 2022, covering a ten-year period. The Euro, Japanese yen, British pound sterling, and Canadian dollar in particular are among the top six most traded currencies with the US dollar being the most traded one (BIS, 2019), whereas all the nine currencies considered in this study represent the currencies of the BRICS and G7 economies. Therefore, our study investigates the underlying dependence and risk spillovers between Bitcoin and the G7 and BRICS FX markets to highlight diversification opportunities for international investors. Data for all the currency exchange rates and Bitcoin were sampled from Thomson Reuters DataStream. Returns for all the sampled time series are calculated by taking the first difference of the natural logarithmic prices between two consecutive days.

Fig. 1 presents the time plot of the currencies of the BRICS countries as well as of Bitcoin over the sample period. Fig. S1 (supplementary material) further presents the plots of the currencies of the G7 countries. As shown in these figures, Bitcoin prices have experienced a lot of fluctuations during the sample period. After reaching almost 20,000 US dollars towards the end of 2017, the price of Bitcoin declined sharply in 2018. Bitcoin's price started rising again in 2020 and surpassed the price mark of 63,000 US dollars in April 2021 which however was followed by a sharp decline, resulting in a price drop of over 30,000 US dollars within the next few months. The most recent price surge in Bitcoin was witnessed in the autumn of 2021, which resulted in Bitcoin prices to rise up to 68,000 US dollars and which again plummeted to less than 45,000 US dollars by the beginning of January 2022. The above suggest that Bitcoin's price exhibited increased volatility during the Covid-19 pandemic period. On the other hand, FX markets exhibit less volatile behaviour throughout the sample period.

Table 1 reports descriptive statistics for the currency and Bitcoin returns. It can be noticed that with the exception of the Indian rupee, all other FX markets and Bitcoin have positive average daily returns over the sampled period, with the average daily Bitcoin returns (0.34%) being by far higher than the average returns of the fiat currencies. Similar results are found for the maximum (0.56) and minimum (−0.83) values. The large difference between the maximum and minimum values of Bitcoin returns further coincides with its large standard deviation value (0.066), confirming that Bitcoin returns exhibit the highest volatility. When comparing the fiat currencies considered in this study, the Brazilian real exhibits the highest average daily returns (0.04%), whereas the Russian ruble and Chinese yuan exhibit the highest (0.010) and lowest (0.002) volatility, respectively, as indicated by the standard deviation measure. It can also be noticed that the returns of the Japanese yen, Euro, Canadian dollar, and Indian rupee, along with Bitcoin, are negatively skewed, indicating that these series have a longer left tail, while the opposite result is true for the returns of all other currencies. Moreover, all the sampled series exhibit high kurtosis values and thus have heavy-tailed distributions. It is worth noting, however, that although Bitcoin exhibits higher kurtosis than most fiat currencies, as consistent with Osterrieder and Lorenz (2017), the opposite is true for the Indian rupee, Russian ruble, and British pound. The Jarque-Bera test results further suggest the rejection of the null hypothesis of normality for all return series at the 1% level of significance. In order to test for the stationarity of our return series, we employ the Augmented Dickey Fuller (ADF), Philips Peron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Both the ADF and PP tests reject the null hypothesis of a unit root in all the time series at the 1% significance level, whereas the KPSS test results fail to reject the null hypothesis of stationarity of our time series. Consequently, all the three tests confirm the stationarity of our return series. Furthermore, the Lagrange multiplier test for conditional heteroscedasticity indicates the presence of ARCH effects in all the return series. Finally, the unconditional correlation coefficient between Bitcoin and the different currencies indicates weak correlations between Bitcoin and FX markets, a finding that is consistent with the results of previous studies (e.g., Baur et al., 2018; Baumöhl, 2019; Urquhart and Zhang, 2019; Yermack, 2015), implying that Bitcoin and FX markets are not integrated.

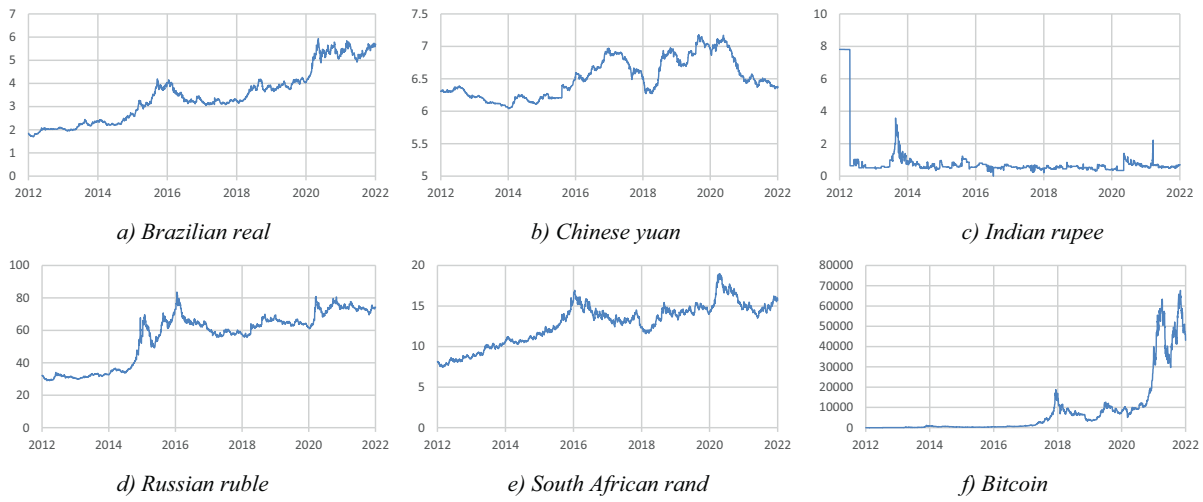

Fig. 1. Time plots of the currencies of the BRICS countries and Bitcoin.

Table 1
Descriptive statistics for the entire sample period (6th January 2012- 6th January 2022).

	Japanese yen	Euro	British pound	Canadian dollar	Brazilian real	Chinese yuan	Indian rupee	Russian ruble	South African rand	Bitcoin
Mean	0.00015	0.00005	0.00005	0.00009	0.00044	0.00000	−0.00093	0.00032	0.00026	0.00337
Maximum	0.03169	0.02259	0.08311	0.02392	0.08356	0.01818	1.38629	0.10936	0.05202	0.56041
Minimum	−0.03433	−0.02601	−0.03225	−0.02870	−0.06069	−0.01439	−1.48871	−0.12864	−0.05994	−0.83423
Std. dev.	0.00523	0.00481	0.00557	0.00459	0.00899	0.00200	0.00551	0.01041	0.00957	0.06633
Skewness	−0.13473	−0.07311	1.19565	−0.06336	0.14858	0.46183	−0.54793	0.68312	0.21810	−0.26519
Kurtosis	7.23655	5.29178	24.26735	5.12282	8.62537	12.48707	40.31831	26.96363	5.31297	23.64723
JB stats.	1958***	573***	49752***	491***	3447***	9869***	151408***	62581***	602***	46338***
ADF	−50.6015***	−51.1606***	−49.2355***	−50.8311***	−48.9375***	−51.8594***	−35.4721***	−52.0022***	−49.9371***	−30.0273***
PP	−50.6007***	−51.1877***	−49.3646***	−50.8325***	−48.9082***	−52.0904***	−66.0683***	−51.9971***	−49.9373***	−62.8500***
KPSS	0.3344	0.0725	0.0823	0.1760	0.0517	0.2137	0.1485	0.1312	0.0966	0.1463
ARCH(20)	10.4713***	9.9299***	6.5591***	8.2521***	6.2073***	6.3953***	12.0996***	56.0696***	6.5080***	36.0301***
Correlation with Bitcoin	0.0184***	−0.0172***	−0.0210***	−0.0248***	0.0019***	−0.0097***	−0.0201***	−0.0085***	0.0038***	–

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

5. Empirical findings

5.1. Marginal distribution model parameter estimates

In this study, we employed the ARMA-GARCH model under the skewed Student-t distribution. Estimation results of our marginal distribution models are presented in Table 2. We observe significant autoregressive behaviour in the Brazilian real, Indian rupee, South African rand, Japanese yen, British pound, and Euro as well as in Bitcoin. As for the conditional variance equation, the estimated ARCH coefficient is significant for Bitcoin and all the considered fiat currencies, suggesting that the previous day's shocks affect the current volatility levels. Similarly, the estimated GARCH coefficient is also significant for all considered series, indicating that shocks in these markets persist, with the highest persistence level observed for Euro. Moreover, the asymmetry parameter estimates suggest that error terms are characterised by a distribution with asymmetries in all cases except for the Euro, Canadian dollar, and Indian rupee. The residual diagnostic test results for testing the appropriateness of our marginal distribution models further show that there are no ARCH effects in the residuals or serial correlation in the squared standardised residuals. We can therefore proceed with using copula models to capture dependencies between the returns of Bitcoin and fiat currencies.

Fig. 2 depicts the plots of the conditional variances of the returns of our sampled series. Although we observe time-varying volatility in all the markets during the sample period, the Chinese yuan exhibits comparatively less volatility clustering. As could have been expected, though, Bitcoin exhibits the highest levels of volatility among all the sampled series and across the entire sample period, supporting the findings of Yermack (2015) and Baur and Dimpfl (2021) that Bitcoin's volatility is significantly higher than the volatility of widely used currencies.

5.2. Copula results

Table 3 presents the estimation results of both time-invariant and time-varying copula dependence structures between the returns of Bitcoin and the different currencies under consideration. The Akaike Information Criterion (AIC) adjusted for small sample bias was employed in order to select the best copula model, while all the fitted copulas were also selected based on minimum AIC values. The results reveal temporal variations in the dependence structure of the sampled fiat currencies with Bitcoin, as we find that all the sampled series exhibit properties of time-varying copula specifications. This result is somewhat consistent with the findings in Urquhart and Zhang (2019) and Majdoub et al. (2021) who found time-varying correlations between Bitcoin and fiat currencies, implying a dynamic relationship between them. More specifically, our results show that the Euro, British pound, Canadian dollar, Brazilian real, Chinese yuan, and South African rand exhibit time-varying zero tail dependence with Bitcoin as given by the time-varying Gaussian copula. This result suggests diversification benefits of portfolios including Bitcoin with the Euro, British pound, Canadian dollar, Brazilian real, Chinese yuan, and South African rand in case of extreme return movements in either direction. It is worth noting that Baumöhl (2019) and Urquhart and Zhang (2019) also found that Bitcoin can act as a diversifier for some currencies. On the other hand, the time-varying rotated Clayton copula appears to be the best fitted model between Bitcoin and the Indian rupee, indicating upper tail dependence and lower tail independence. On the contrary, the time-varying Clayton copula best describes the dependence structure between the Russian ruble and Bitcoin, suggesting lower tail dependence and upper tail independence, and thus increased co-movements during turbulent periods (Albulescu et al., 2018). Similarly, we find lower tail dependence of Bitcoin with the Japanese yen as given by the rotated Gumbel copula framework, suggesting high correlations at low values, and thus low diversification benefits since both tend to move towards the same direction under bearish market conditions. Therefore, these results suggest that the Indian rupee, Russian ruble, and Japanese yen have an asymmetric tail dependence with Bitcoin.[8] Our results thus provide insights into tail dependencies between Bitcoin and FX markets.

Fig. 3 displays the time evolution of the dependence parameter of the best fitted copula specification for Bitcoin with each sampled currency, illustrating the dynamic dependence over the sampled period, similar to the time-varying dependence between fiat currencies previously found in the literature (e.g. Albulescu et al., 2018; Dias and Embrechts, 2010). It is evident that the majority of the FX markets exhibit volatile dependence structure with Bitcoin, as consistent with the copula results discussed above. Furthermore, these deviations in the dependence structure are persistent during the period under examination, which direct us towards the investigation of potential risk spillovers between the considered pairs, as explained in the next sub-section.

5.3. Risk analysis

Next, we extended our analysis by measuring the upside and downside spillover effects by quantifying the upside and downside VaR, $CoVaR$, and $\Delta CoVaR$ risk measures for each Bitcoin-FX market pair. Tables 4 and 5 report the empirical results of the VaR and $CoVaR$ measures from and to Bitcoin, respectively, which have important implications to policy makers and investors in terms of risk spillover effects.

The results of Tables 4 and 5 clearly show that the downside VaR measure of the Bitcoin returns is far greater than the downside VaR measure of FX markets, supporting the speculative nature of Bitcoin trading (Baur et al., 2018) and its substantial price declines. Moreover, we notice from Table 4 that, among all the considered FX markets, the South African rand has the highest in absolute terms

[8] It is worth mentioning that Boero et al. (2011) also found evidence of asymmetric tail dependence when studying the bivariate dependence structure for different pairs of exchange rates measured against the US dollar.

Table 2
Marginal ARMA-GARCH model parameter estimates: Entire sample period (6th January 2012- 6th January 2022).

	Japanese yen	Euro	British pound	Canadian dollar	Brazilian real	Chinese yuan	Indian rupee	Russian ruble	South African rand	Bitcoin
c (Cst)	0.0002**	0.0001	0.0000	0.0001	0.0000	0.0000	0.0000	0.0001	0.0002	0.0024***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0002)	(0.0005)
ϕ_1(AR(1))	−1.0698***	−1.1110*	−0.9927***	−0.4067	−0.4124**	−0.6353	1.5632***	−0.1756	−0.0070	−0.1404***
	(0.3116)	(0.6616)	(0.1995)	(0.3038)	(0.1847)	(0.5343)	(0.0549)	(1.3122)	(0.1283)	(0.0148)
ϕ_2(AR(2))	−0.7354***	−0.1666	−0.0441	0.0814	0.1421	0.1634	−0.7953***	−0.6193	0.9161***	−0.9266***
	(0.1805)	(0.7017)	(0.1935)	(0.2600)	(0.1144)	(0.3464)	(0.1620)	(0.8114)	(0.1380)	(0.0160)
θ_1(MA(1))	1.0926***	1.1350	1.0064***	0.4124	0.2769	0.4342***	−1.4026*	0.2173	0.0091	0.1335***
	(0.3320)	(0.6542)	(0.2153)	(0.2922)	(0.2004)	(0.1001)	(0.8532)	(1.3245)	(0.1295)	(0.0150)
θ_2(MA(2))	0.7203***	0.1810	0.0641	−0.0935	−0.2603**	−0.2023	0.8232***	0.6398	−0.9369***	0.9238***
	(0.2061)	(0.6985)	(0.2085)	(0.2460)	(0.1227)	(0.3255)	(0.1532)	(0.7020)	(0.1376)	(0.0173)
ω (Cst)	0.2799**	0.0771*	0.4719	0.1133*	−0.0030	−0.1043***	0.7693	0.0096	0.8427*	0.2711*
	(0.1320)	(0.0451)	(0.3595)	(0.0612)	(0.0026)	(0.0104)	(0.5983)	(0.0044)	(0.4586)	(0.1581)
α_1(ARCH)	0.0586***	0.0343***	0.0483**	0.0417***	0.3685*	0.0402***	0.1395***	0.0986***	0.0338***	0.2857***
	(0.0120)	(0.0062)	(0.0208)	(0.0070)	(0.2031)	(0.0053)	(0.0391)	(0.0262)	(0.0115)	(0.0868)
β_1(GARCH)	0.9358***	0.9629***	0.9353***	0.9544***	0.8885***	0.3753***	0.8253***	0.8951***	0.9571***	0.8670***
	(0.0128)	(0.0067)	(0.0313)	(0.0076)	(0.0241)	(0.0054)	(0.0563)	(0.0268)	(0.0145)	(0.0186)
Asymmetry	−0.1310***	0.0484	0.3103***	0.0693	46.742***	13.956***	−8.4597	0.6027***	0.2801***	0.1772***
Tail	7.2074***	1.4702***	4.4004***	1.6599***	1.6595***	2315.9***	0.4998***	6.7055***	1.2150***	8.5106***
LL	10,336.5	10,462.65	10,125.85	10,529.32	13,324.54	13,434.34	5623.46	9150.51	8556.299	4629.60
AIC	−7.9168	−8.0135	−6.5986	−8.0646	−10.2066	−7.4422	1.9536	−7.0077	−6.5522	−3.5421
ARCH(20)	0.5233	1.1712	1.0640	1.4202	0.0005	0.0165	0.8632	0.3311	1.2039	0.5371
	[0.9586]	[0.2696]	[0.3816]	[0.1014]	[1.0000]	[0.4231]	[0.5642]	[0.9977]	[0.2402]	[0.9523]
Q(20)	19.0080	16.9889	20.0816	11.4278	0.6543	0.2005	17.6531	22.9237	15.5906	57.4194
	[0.2682]	[0.3863]	[0.2166]	[0.7823]	[0.0000]	[0.23543]	[0.1896]	[0.1158]	[0.4819]	[0.0000]
Q^2(20)	10.4144	24.5798	21.9537	27.0484	0.0095	0.0345	18.6862	6.6546	25.4799	9.6271
	[0.9175]	[0.1369]	[0.2340]	[0.1014]	[0.0000]	[1.0000]	[0.2963]	[0.9927]	[0.1123]	[0.9434]

Notes: Standard errors are in parentheses (). *P*-values are in square brackets []. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

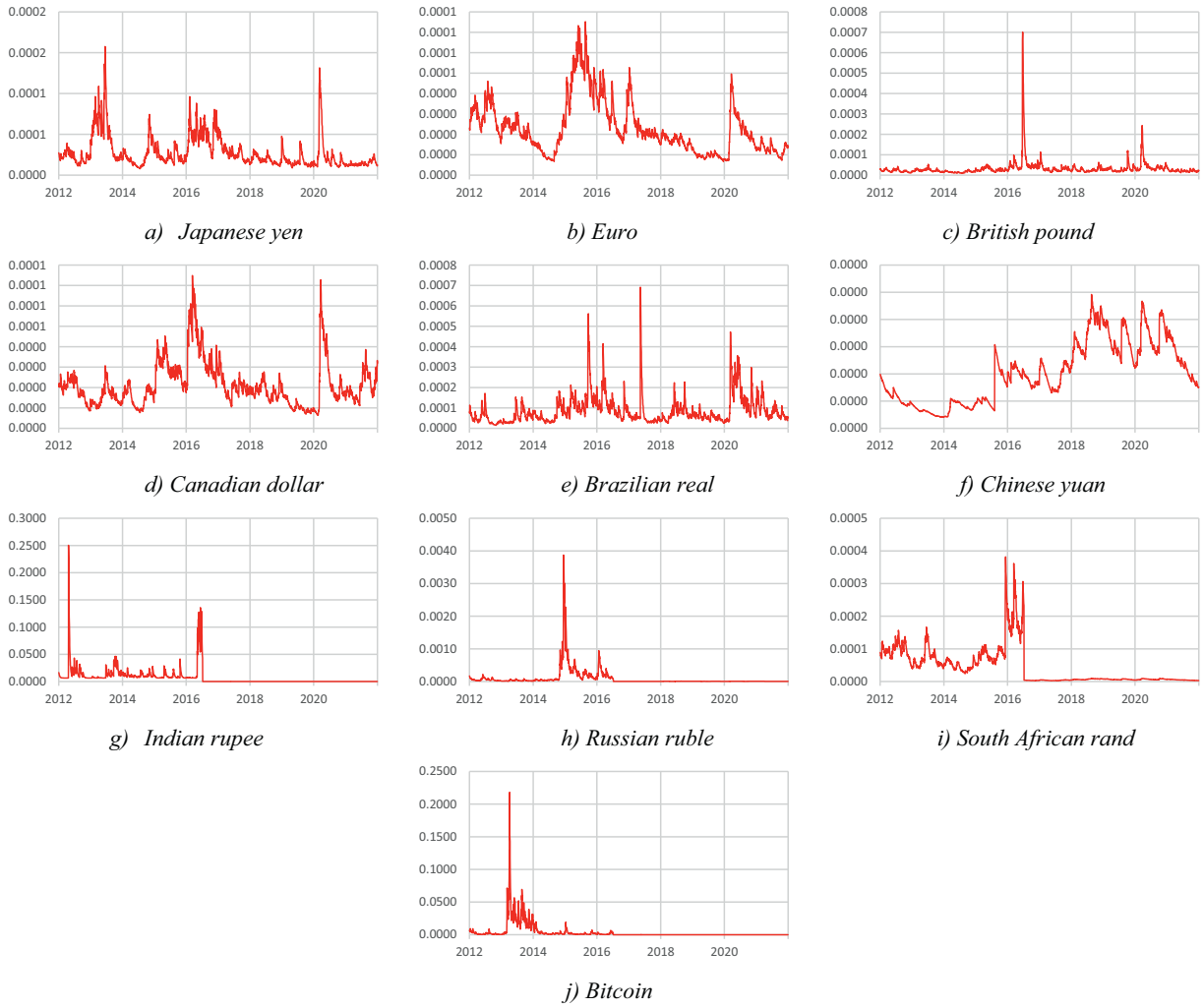

Fig. 2. Conditional volatility of the sampled currencies and Bitcoin: Entire sample period (6th January 2012- 6th January 2022).

downside and upside *VaR* measures, and hence the highest downside and upside risk. The riskiness of the South African rand compared to the other FX markets is further confirmed by its high standard deviation value (see Table 1). Consequently, although Bitcoin appears to be the riskiest series overall, among the FX markets, the South African rand holds the highest downside and upside risk. The above results suggest that investors may experience an extreme downside (upside) risk spillover from Bitcoin to South African rand when holding a long (short) position. On the other hand, the Chinese yuan has the lowest in absolute terms downside and upside *VaR* measures, and hence the lowest downside and upside risk. This result could be attributed to the impact of Chinese regulations on Bitcoin markets. For instance, China prohibited banks from handling Bitcoin transactions in 2013, banned initial coin offerings (ICOs) in 2017, banned cryptocurrency trading in 2019, and restricted cryptocurrency mining in 2021.[9] Borri and Shakhnov (2020) noted unprecedented declines in trading volumes on Chinese cryptocurrency exchanges following the 2017 regulatory measures in particular imposed on the Chinese cryptocurrency market. Yet, such national regulatory actions not only have a significant impact on domestic cryptocurrency markets but may also spill across markets heterogeneously (Auer and Claessens, 2018; Borri and Shakhnov, 2020). Indeed, Auer and Claessens (2018) found a massive shift of Bitcoin trading towards the Japanese yen in response to China signalling the possibility of strict regulation of Bitcoin in January 2017. Similarly, Borri and Shakhnov (2020) documented substantial Bitcoin transaction volume increases in exchange for the Korean won, Japanese yen, and US dollar in 2017.

We also notice from Table 4 that in most cases the downside *CoVaR* measure of the FX markets is greater in absolute terms than or equal to the corresponding downside *VaR* measure. Exceptions to this are the *VaR* values of the Japanese yen and British pound, which are greater in absolute terms than their *CoVaR* measures. As for upside risk spillovers, the upside *VaR* values are higher than the

[9] More information on China's restrictions on cryptocurrency trading can be found in Borri and Shakhnov (2020) and Pilarowski and Yue (2017).

Table 3
Copula results: Entire sample period (6th January 2012- 6th January 2022).

	Japanese yen	Euro	British pound	Canadian dollar	Brazilian real	Chinese yuan	Indian rupee	Russian ruble	South African rand
Panel A: Time-invariant copulas									
1.Gaussian									
B	−0.0059***	−0.0506***	−0.04232***	−0.0542***	−0.01989***	−0.01629***	0.0122***	0.0021***	−0.0168***
	(0.0196)	(0.0195)	(0.01950)	(0.0195)	(0.01957)	(0.01960)	(0.0196)	(0.0196)	(0.0196)
AIC	−0.0893	−6.6805	−4.67607	−7.6646	−1.03123	−0.69165	−0.3880	−0.0111	−0.7358
LL	−0.0450	−3.3406	−2.33842	−3.8327	−0.51600	−0.34621	−0.1944	−0.0059	−0.3683
2.Clayton's									
∂	0.0257***	0.0001	0.00010	0.0001	0.00010	0.00010***	0.0001	0.0104***	0.0001
	(0.0199)	(0.0763)	(0.00510)	(0.0233)	(0.02035)	(8.29350)	(0.0050)	(0.0443)	(0.0200)
AIC	−1.7854	0.0222	0.01560	0.0326	0.00942	0.01552	0.0018	−0.2839	0.0162
LL	−0.8931	0.0107	0.00742	0.0159	0.00432	0.00738	0.0005	−0.1424	0.0077
3.Rotated Clayton									
Δ	0.0001	0.0001	0.00010***	0.0001	0.00010	0.00462***	0.0202***	0.0002	0.0001
	(0.0442)	(0.0220)	(5.22020)	(0.0495)	(0.04440)	(0.04270)	(0.0206)	(0.0204)	(0.0337)
AIC	0.0136	0.0199	0.02247	0.0277	0.00906	−0.05799	−1.0143	0.0067	0.0022
LL	0.0064	0.0096	0.01085	0.0135	0.00415	−0.02938	−0.5076	0.0029	0.0007
4.Plackett									
∏	0.9760***	0.8576***	0.88557***	0.8694***	0.94096***	0.95244***	1.0294***	0.9951***	0.9577***
	(0.0583)	(0.0503)	(0.05120)	(0.0493)	(0.05468)	(0.05520)	(0.0603)	(0.0582)	(0.0561)
AIC	−0.1639	−6.8066	−4.41335	−6.0289	−1.08859	−0.70132	−0.2442	−0.0064	−0.5428
LL	−0.0823	−3.4037	−2.20706	−3.0149	−0.54468	−0.35104	−0.1225	−0.0036	−0.2718
5.Frank									
η	0.0004	0.0001	0.00015***	0.0001	0.00010	0.00024	0.0583***	0.0013	0.0003
	(0.0185)	(0.0739)	(0.00200)	(0.2949)	(0.00561)	(0.06620)	(0.1416)	(0.1563)	(0.5603)
AIC	0.0034	0.0052	0.00639	0.0051	0.00258	0.00417	−0.2456	0.0028	0.0040
LL	0.0013	0.0022	0.00281	0.0022	0.00091	0.00170	−0.1232	0.0010	0.0016
6.Gumbel									
Ø	1.1000***	1.1000***	1.10000***	1.1000***	1.10000***	1.10000***	1.1000***	1.1000***	1.1000***
	(0.0167)	(0.0168)	(0.01710)	(0.0173)	(0.01657)	(0.01620)	(0.0160)	(0.0166)	(0.0163)
AIC	73.1670	98.1433	102.71146	112.2631	81.54031	68.86030	52.1940	73.2179	71.0105
LL	36.5831	49.0713	51.35535	56.1312	40.76977	34.42977	26.0966	36.6086	35.5049
7.Rotated Gumbel									
γ	1.1000***	1.1000***	1.10000***	1.1000***	1.10000***	1.10000***	1.1000***	1.1000***	1.1000***
	(0.0158)	(0.0169)	(0.01670)	(0.0175)	(0.01667)	(0.01680)	(0.0164)	(0.0161)	(0.0169)
AIC	51.7952	102.7622	96.08443	120.1972	86.03475	83.55440	64.0632	59.7683	87.8372
LL	25.8972	51.3807	48.04183	60.0982	43.01699	41.77682	32.0312	29.8838	43.9182
8.Student-t									
θ	−0.0063***	−0.0509***	−0.04256***	−0.0539***	−0.01998***	−0.01655***	0.0121***	0.0018***	−0.0166***
	(0.0197)	(0.0206)	(0.01980)	(0.2416)	(0.01993)	(0.02540)	(0.0199)	(0.0207)	(0.0223)
T	29.5667***	96.5149***	99.99212	99.9914***	99.50246***	99.47272***	99.9563***	99.9995***	99.9894***
	(4.4666)	(26.0969)	(26.60130)	(18.5430)	(62.79337)	(47.98550)	(1.5722)	(15.3987)	(5.7605)
AIC	−2.8306	−6.9590	−4.24192	−4.0920	−0.96230	−0.66471	0.3138	0.6370	−0.2328
LL	−1.4161	−3.4803	−2.12173	−2.0468	−0.48192	−0.33312	0.1561	0.3177	−0.1172
9.Symmetrized JC									
E	0.0000	0.0000	0.00000	0.0000	0.00000	0.00000	0.0000	0.0000	0.0000
	(18.6070)	(1681.9745)	(0.00000)	(812,668.7)	(683,800.4)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
M	0.0000	0.0000	0.00000	0.0000	0.00000	0.00000	0.0000	0.0000	0.0000
	(60954)	(106.2819)	(0.00000)	(2192.7277)	(312.26275)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AIC	2.1989	12.9420	8.55486	11.8406	6.02073	4.600363438	2.0834	3.2884	5.3689

(*continued on next page*)

Table 3 (*continued*)

	Japanese yen	Euro	British pound	Canadian dollar	Brazilian real	Chinese yuan	Indian rupee	Russian ruble	South African rand
LL	1.0987	6.4702	4.27666	5.9195	3.00960	2.299415142	1.0410	1.6435	2.6837
Panel B: Time-varying copulas									
1.Gaussian									
$\grave{\omega}$	−0.0052***	−0.0949***	−0.17855***	−0.13412***	−0.02566***	−0.0004***	0.0368***	0.0028***	−0.0429***
	(0.0271)	(0.0602)	(0.07600)	(0.32595)	(0.03028)	(9.3643)	(0.0538)	(0.0479)	(0.0608)
α	0.1135***	−0.1679***	−0.27782***	−0.05997***	−0.10229***	0.0161***	−0.2013***	−0.1019***	0.1374***
	(0.1209)	(0.1414)	(0.18660)	(0.19740)	(0.10797)	(0.0136)	(0.1998)	(0.1868)	(0.1892)
β	0.6398***	0.3392***	−1.81786***	−0.37436***	0.88475***	1.9678***	−0.2302***	−0.2749***	−0.6943***
	1.1341	(0.8943)	(0.26060)	(5.75176)	(0.95928)	(0.0406)	(2.1421)	(3.9200)	(2.0743)
AIC	−2.0050	**−8.9400**	**−6.90423**	**−7.82195**	**−2.71880**	**−6.3369**	−3.1118	−0.5313	**−1.4699**
LL	−1.0037	−4.4712	−3.45327	−3.91213	−1.36055	−3.1696	−1.5571	−0.2668	−0.7361
2.Clayton's									
Ψ_0	−0.2350***	−0.2830***	0.00011	0.00015	−0.18028***	0.1694***	−0.1015***	−0.0932***	0.0006
	(0.4598)	(0.2703)	(0.20290)	(0.18348)	(0.13179)	(0.1805)	(0.3266)	(0.0461)	(0.0427)
Ψ_1	−1.2821***	−1.3412***	−1.57899***	−1.62597***	−2.00586***	2.2155***	1.9735	−2.9592***	−1.6478***
	(0.0549)	(0.7406)	(0.08270)	(0.97321)	(0.43740)	(0.6378)	(63.7709)	(0.3424)	(0.1042)
Ψ_2	1.3154***	0.9330***	0.00004	0.00000	0.61603***	−0.3913***	0.4384***	0.7468***	−0.0012
	(0.3183)	(0.1535)	(0.13160)	(0.50179)	(0.17931)	(0.3307)	(8.6598)	(0.0505)	(0.0457)
AIC	−3.8847	−1.8178	0.01712	0.03376	−0.16753	−0.1950	−1.7304	**−0.9013**	0.0178
LL	−1.9435	−0.9100	0.00741	0.01573	−0.08491	−0.0986	−0.8663	−0.4518	0.0077
3.Rotated Clayton									
$\grave{\omega}$	−0.5096***	0.0013	0.00028	0.00013	0.00844	0.4218***	0.6435***	0.0002	0.1295
	(0.1925)	(0.0914)	(0.40420)	(0.17197)	(0.50007)	(0.1031)	(0.0827)	(0.1925)	(8.7899)
α	1.0883***	−1.6184***	−1.51072***	−1.58958***	−1.47407***	0.9135***	−0.8921***	−1.7402***	2.9430
	(0.2866)	(0.3600)	(0.30480)	(0.30954)	(7.06799)	(0.1886)	(0.1696)	(0.3325)	(1.8148)
β	1.4494***	−0.0034	−0.00035	0.00009	−0.02329***	−0.9761***	−1.7026***	0.0002	−0.2375
	(0.4588)	(0.1194)	(0.21530)	(0.09147)	(0.14957)	(0.8766)	(0.2278)	(0.4400)	(19.2752)
AIC	−3.5148	0.0215	0.02399	0.02919	0.01062	−2.8373	**−7.5938**	0.0060	−0.4133
LL	−1.7586	0.0096	0.01084	0.01344	0.00416	−1.4198	−3.7981	0.0019	−0.2078
4.Gumbel									
$\grave{\omega}_u$	1.9721***	3.2646***	3.16003***	2.30080***	3.24758	−1.0092***	−0.6622***	1.7520***	3.5907***
	(0.4483)	(0.0642)	(1.67020)	(6.92428)	(488.94471)	(0.5458)	(1.1931)	(6.9466)	(5.5812)
α_u	−1.6396***	−3.2549***	−3.15856***	−2.29958***	−3.23830	1.2794***	0.2154***	−1.7487***	−3.5325***
	(0.5270)	(0.0319)	(1.51060)	(6.88190)	(442.23939)	(0.4290)	(1.2027)	(6.8665)	(5.1134)
β_u	−0.9513***	−0.0139	−0.00009	−0.00259	−0.01917	−0.5952***	1.3052***	−0.0091	−0.1184***
	(0.3675)	(5.2077)	(0.44390)	(0.40501)	(130.98588)	(0.3541)	(0.4009)	(0.6093)	(1.0124)
AIC	−2.8616	−1.2772	−0.40471	−0.01844	−0.52682	−3.9708	−4.3590	−0.0582	−0.1286
LL	−1.4319	−0.6397	−0.20351	−0.01037	−0.26456	−1.9865	−2.1807	−0.0302	−0.0655
5.Rotated Gumbel									
$\grave{\omega}_L$	1.8183***	2.2120***	3.12125***	2.77823***	3.24549***	−1.1566***	2.1643***	2.4825***	3.0212***
	(1.2247)	(0.8778)	(1.95300)	(3.51186)	(2.96821)	(1.4739)	(2.7942)	(4.2530)	(2.2017)
α_L	−1.9355***	−2.0133***	−3.11880***	−2.77698***	−3.23145***	1.3474***	−2.2612***	−2.4444***	−3.0161***
	(1.1377)	(0.9693)	(1.77860)	(3.43182)	(2.69886)	(1.3336)	(2.5528)	(4.1591)	(2.0658)
β_L	0.7835***	−0.6041***	−0.00339	−0.00242	−0.03753**	−0.4461***	0.3872***	0.1670***	−0.0113
	(0.5594)	(0.3411)	(0.48780)	(0.40507)	(0.79222)	(0.4550)	(0.8218)	(0.6038)	(0.4377)
AIC	**−4.3108**	−1.0887	−0.29051	−0.02473	−0.26318	−0.7397	−0.3649	−0.4776	−0.1274
LL	−2.1565	−0.5455	−0.14641	−0.01352	−0.13274	−0.3710	−0.1836	−0.2399	−0.0648
6.Symmetrized JC									

(*continued on next page*)

Table 3 (*continued*)

	Japanese yen	Euro	British pound	Canadian dollar	Brazilian real	Chinese yuan	Indian rupee	Russian ruble	South African rand
$\dot{\omega}_U$	−18.1729***	−16.0795***	−17.97148***	−22.44653***	−17.43965***	−20.1660***	−16.2675***	−17.1410***	−20.4156***
	(1.0000)	(72.6053)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(3.1063)	(1.4189)	(1.0000)
β_U	0.0000	−1.7258***	0.00000	0.00000	0.00000	0.0000	−1.8711	−0.0109	0.0000
	(1.0000)	(24.3021)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(1.0386)	(1.0312)	(1.0000)
α_U	0.0000	−0.0047	0.00000	0.00000	0.00000	0.0000	−0.0069	−0.0005	0.0000
	(1.0000)	(1.0023)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(1.0717)	(1.0001)	(1.0000)
$\dot{\omega}_L$	−16.3259***	−22.5052***	−21.52233***	−18.17616***	−17.50885***	−17.7887***	−16.4155***	−15.9352***	−17.8176***
	(1.0000)	(1.5038)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(91.7833)	(85.0650)	(1.0000)
β_L	0.0000	0.0001	0.00000	0.00000	0.00000	0.0000	−0.2502	−1.2538**	0.0000
	(1.0000)	(1.0000)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(30.4899)	(28.2794)	(1.0000)
α_L	0.0000	0.0000	0.00000	0.00000	0.00000	0.0000	−0.0121	−0.0035	0.0000
	(1.0000)	(1.0000)	(1.00000)	(1.00000)	(1.00000)	(1.0000)	(1.9606)	(1.0031)	(1.0000)
AIC	15.5816	35.5674	33.60273	42.99854	24.73613	21.7203	11.8412	15.5755	23.9697
LL	7.7885	17.7814	16.79907	21.49697	12.36576	10.8578	5.9183	7.7854	11.9825
7.Student-t									
Ψ_0	−0.0111***	−0.0720***	−0.14221***	−0.21540***	−0.09781***	−0.0645***	0.0249***	−0.0033**	−0.0308***
	(0.0489)	(0.1102)	(0.07670)	(0.05055)	(0.08273)	(0.0867)	(0.0539)	(0.0682)	(0.0530)
Ψ_1	0.1222***	−0.0284***	−0.17160***	0.03597***	−0.22289***	−0.1351***	−0.1123***	−0.0459***	0.0722***
	(0.1078)	(0.0688)	(0.09240)	(0.09178)	(0.09965)	(0.1115)	(0.1366)	(0.1116)	(0.0940)
Ψ_2	−0.4085***	0.5926***	−1.11448***	−2.01046***	−1.90836***	−1.9893***	−0.0626	−1.3384***	−0.3312***
	(1.7749)	(2.1050)	(1.19550)	(0.00663)	(0.15703)	(0.0319)	(2.6026)	(1.3537)	(1.8195)
υ	5.0000***	5.0000***	4.99999***	4.99999***	5.00000***	5.0000***	5.0000***	5.0000***	5.0000***
	(0.3717)	(0.4731)	(0.46260)	(0.83633)	(0.46741)	(1.2885)	(0.3868)	(0.3670)	(0.6629)
AIC	42.9180	59.8254	76.29205	119.83873	68.53755	73.3278	75.7469	81.1894	76.5503
LL	21.4575	29.9112	38.14449	59.91783	34.26724	36.6624	37.8719	40.5932	38.2736

Notes: Standard errors are in parentheses (). AIC values are adjusted for small sample bias. Minimum AIC values are highlighted in bold and represent the best fitted copula. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

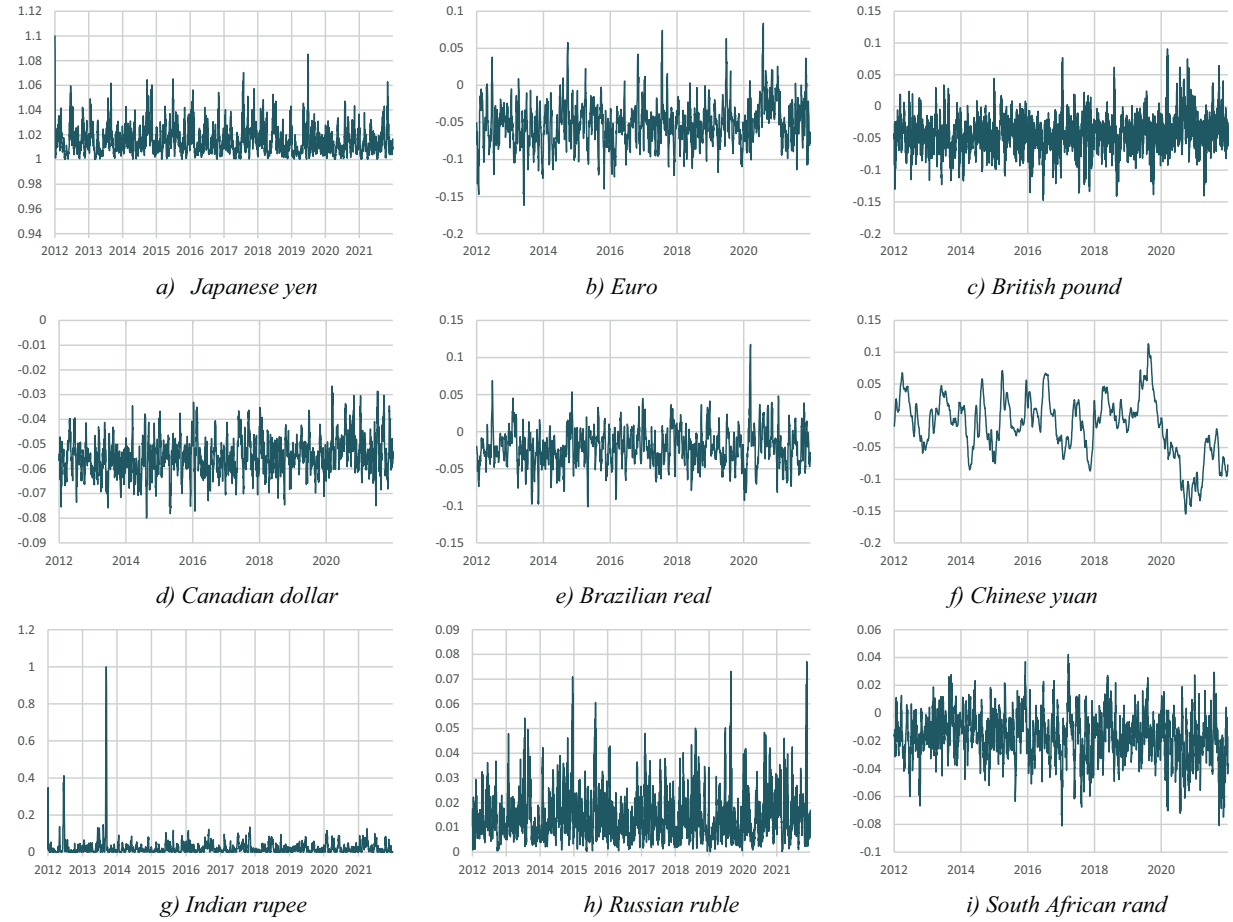

Fig. 3. Time-varying dependence structure (based on the best fitted copula) of Bitcoin with the sampled currencies: Entire sample period (6th January 2012- 6th January 2022).

Table 4
VaR and CoVaR results (from Bitcoin to FX markets): Entire sample period (6th January 2012- 6th January 2022).

	Downside			Upside		
	VaR	CoVaR	H_o:CoVaR = VaR H_1:CoVaR<VaR	VaR	CoVaR	H_o:CoVaR = VaR H_1:CoVaR>VaR
Japanese yen	−0.0099	−0.0098	0.0468	0.0103	0.0081	0.3550
	(0.0033)	(0.0033)	[0.0067]	(0.0033)	(0.0026)	[0.0000]
Euro	−0.0091	−0.0150	0.5880	0.0092	0.0151	0.5910
	(0.0026)	(0.0045)	[0.0000]	(0.0026)	(0.0045)	[0.0000]
British pound	−0.0103	−0.0101	0.0609	0.0103	0.0101	0.0609
	(0.0032)	(0.0031)	[0.0001]	(0.0032)	(0.0031)	[0.0001]
Canadian dollar	−0.0088	−0.0129	0.5910	0.0089	0.0131	0.5940
	(0.0023)	(0.0033)	[0.0000]	(0.0023)	(0.0033)	[0.0000]
Brazilian real	−0.0169	−0.0278	0.5040	0.0175	0.0284	0.5000
	(0.0064)	(0.0109)	[0.0000]	(0.0064)	(0.0109)	[0.0000]
Chinese yuan	−0.0025	−0.0045	0.5620	0.0055	0.0045	0.1560
	(0.0013)	(0.0025)	[0.0000]	(0.0031)	(0.0025)	[0.0000]
Indian rupee	−0.0076	−0.1707	1.0000	0.0078	0.7960	1.0000
	(0.0037)	(0.1109)	[0.0000]	(0.0037)	(8.4173)	[0.0000]
Russian ruble	−0.0171	−0.0175	0.0284	0.0172	0.0168	0.0341
	(0.0115)	(0.0120)	[0.2450]	(0.0115)	(0.0113)	[0.0960]
South African rand	−0.0183	−0.0416	0.9650	0.0185	0.0418	0.9645
	(0.0037)	(0.0086)	[0.0000]	(0.0037)	(0.0086)	[0.0000]

Notes: The above table reports average values of the VaR and CoVaR measures for the sample period. Values in parentheses () present standard errors, whereas values in square brackets [ ] denote the respective *p*-values of the Kolmogorov-Smirnov test.

Table 5
VaR and CoVaR results (from FX markets to Bitcoin): Entire sample period (6th January 2012- 6th January 2022).

	Downside			Upside		
	VaR	CoVaR	H_o:CoVaR = VaR H_1:CoVaR<VaR	VaR	CoVaR	H_o:CoVaR = VaR H_1:CoVaR>VaR
Japanese yen	−0.1483	−0.1583	0.0563	0.1531	0.1475	0.0383
	(0.1224)	(0.1325)	[0.0005]	(0.1223)	(0.1180)	[0.0433]
Euro	−0.1483	−0.1281	0.1230	0.1531	0.1330	0.1200
	(0.1224)	(0.1058)	[0.0000]	(0.1223)	(0.1057)	[0.0000]
British pound	−0.1483	−0.1301	0.1070	0.1531	0.1350	0.1040
	(0.1224)	(0.1078)	[0.0000]	(0.1223)	(0.1077)	[0.0000]
Canadian dollar	−0.1483	−0.1279	0.1220	0.1531	0.1327	0.1220
	(0.1224)	(0.1053)	[0.0000]	(0.1223)	(0.1052)	[0.0000]
Brazilian real	−0.1483	−0.1346	0.0862	0.1531	0.1395	0.0828
	(0.1224)	(0.1099)	[0.0000]	(0.1223)	(0.1098)	[0.0000]
Chinese yuan	−0.0025	−0.1372	1.0000	0.1531	0.1421	0.0778
	(0.0013)	(0.1175)	[0.0000]	(0.1223)	(0.1174)	[0.0000]
Indian rupee	−0.1483	−0.1493	0.0115	0.1531	0.1442	0.0563
	(0.1224)	(0.1302)	[0.9950]	(0.1223)	(0.1150)	[0.0006]
Russian ruble	−0.1460	−0.1460	0.0172	0.1531	0.1450	0.0525
	(0.1211)	(0.1211)	[0.8330]	(0.1223)	(0.1158)	[0.0015]
South African rand	−0.1483	−0.1362	0.0747	0.1531	0.1411	0.0790
	(0.1224)	(0.1134)	[0.0000]	(0.1223)	(0.1133)	[0.0000]

Notes: The above table reports average values of the VaR and CoVaR measures for the sample period. Values in parentheses () present standard errors, whereas values in square brackets [] denote the respective *p*-values of the Kolmogorov-Smirnov test.

corresponding upside *CoVaR* measures in the case of the Japanese yen, British pound, Chinese yuan, and Russian ruble. These results suggest that for both long and short positions, Bitcoin exercises significant power over all the fiat currency returns considered except for the Japanese yen and British pound in either upside or downside market conditions and the Chinese yuan and Russian ruble during extreme upward market movements. The Japanese yen and British pound therefore present good diversification opportunities against Bitcoin's speculative price movements. It is worth noting that Urquhart and Zhang (2019) further found that Bitcoin can act as an intraday diversifier for the Japanese yen but as an intraday hedge for the British pound. Similarly, our results suggest that the Russian ruble and Chinese yuan also provide diversification opportunities against Bitcoin but only during upward price movements. These results are important for investors who consider Bitcoin and fiat currencies in a single portfolio.

With regard to the results of risk spillovers from FX markets towards Bitcoin (Table 5), we notice that, among all the considered FX markets, the Japanese yen has the highest whereas the Canadian dollar and Euro have the smallest in absolute terms downside spillovers towards Bitcoin returns, as indicated by the downside *CoVaR* measure. These results suggest that the Canadian dollar and Euro exhibit the lowest whereas the Japanese yen exhibits the highest risk spillover effects. These findings are of high importance to investors interested in a portfolio consisting of fiat currencies and Bitcoin while holding a long position. In terms of upside risk spillovers, we notice that the upside *VaR* value for each FX market is greater than the corresponding upside *CoVaR* value. Therefore, no FX market is strong enough in terms of risk spillovers to affect the *VaR* value of Bitcoin. This could be attributed to the sharp fluctuations in the daily price of Bitcoin (see also Figs. 1 and 2), resulting from the fact that Bitcoin is primarily used for speculation purposes (Baur et al., 2018). Holding a short position in Bitcoin and the FX markets thus poses no risks if the later experience upward price changes. These results indicate Bitcoin's negligible sensitivity to price changes in other fiat currencies.

Figs. 4 and 5 illustrate the evolution of downside and upside risk spillovers from Bitcoin to fiat currencies and from currencies to Bitcoin, respectively. By looking at the trajectories of the risk spillovers from Bitcoin to FX markets (Fig. 4), it is evident that the downside *CoVaR* measures are higher in absolute terms than the corresponding *VaR* measures for most of the FX markets. In contrast, with regard to the risk spillovers from the FX markets towards Bitcoin (Fig. 5), the downside *VaR* measures are higher than the corresponding *CoVaR* measures in all cases except for the Japanese yen, Indian rupee, and Chinese yuan. These results imply the sensitivity of FX markets to Bitcoin's downside returns and spillover during downside market conditions. We further observe significant changes in the trajectories of the risk spillovers as measured by both upside and downside *CoVaR/ VaR* measures for all of our sampled series. These changing patterns across risk spillovers have important implications for investors with a single portfolio and can be a useful indicator for holding either a short or a long position.

In order to further investigate the risk spillover between Bitcoin and the considered FX markets, we also employed the $\Delta CoVaR$ measure of Adrian and Brunnermeier (2011) and Girardi and Ergün (2013). The results are presented in Table 6, while Figs. 6 and 7 depict the evolution of the risk spillovers between Bitcoin and the FX markets. Looking at the spillovers from Bitcoin to the FX markets in Table 6, we notice that the downside $\Delta CoVaR$ measure is higher than the upside $\Delta CoVaR$ measure for all the FX markets except for the British pound and Indian rupee. As for the spillover effects from the FX markets to Bitcoin, it is evident that the downside $\Delta CoVaR$ is higher than the upside $\Delta CoVaR$ value for the Japanese yen, Chinese yuan, Indian rupee, and Russian ruble. These results indicate the presence of asymmetric spillovers between extreme upward and downward movements. Therefore, our results are important for investors' decision making related to the selection of trading strategies and reveal that different FX markets have different effects in the trading strategies adopted by investors in case of holding either short or long positions in Bitcoin and FX markets simultaneously. Furthermore, the higher downside $\Delta CoVaR$ values compared with the upside $\Delta CoVaR$ values call for careful selection of currencies

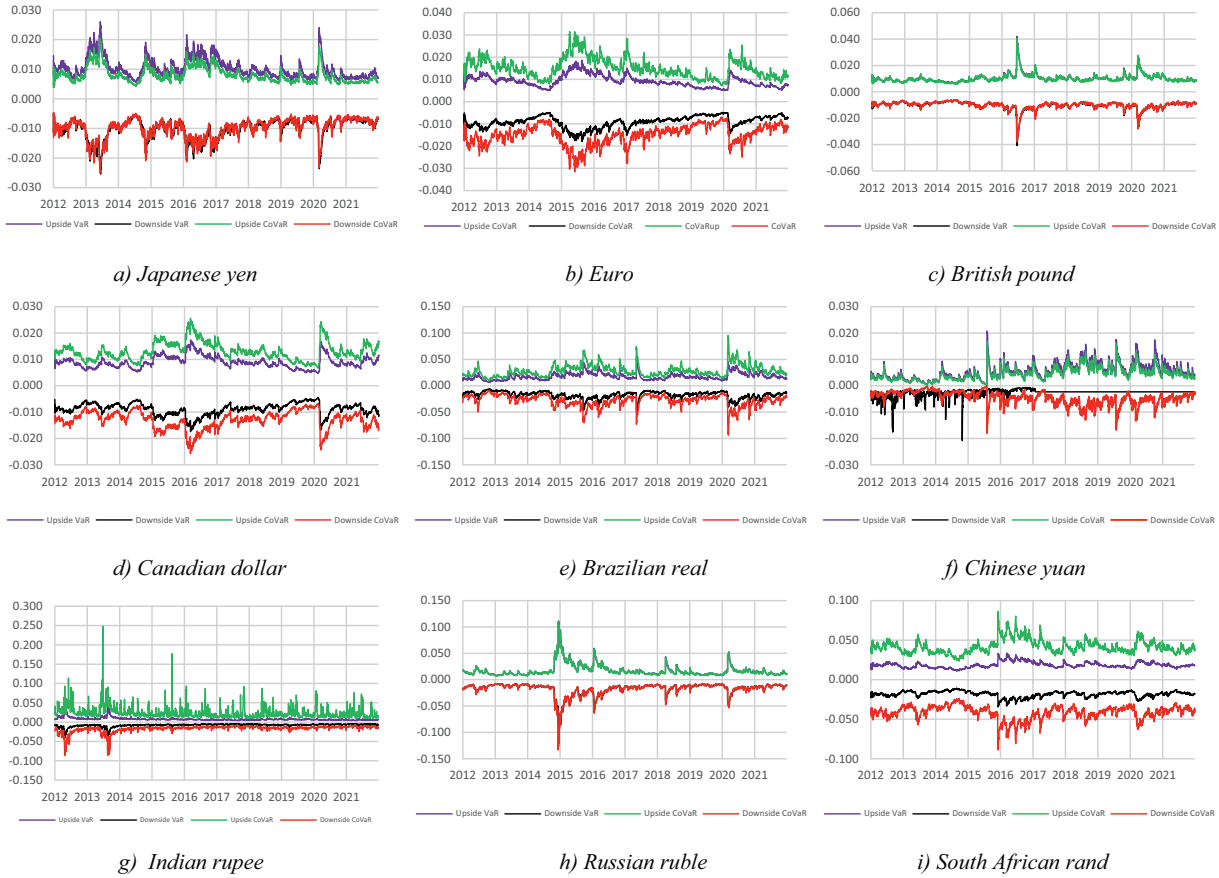

Fig. 4. Upside and downside VaR-CoVaR (from Bitcoin to FX markets): Entire sample period (6th January 2012- 6th January 2022).

included in a portfolio together with Bitcoin when the overall market faces a downward price trend.

Due to the fact that analysing asymmetric risk spillover effects is of high importance for financial decision making, we also tested for asymmetric risk spillovers by checking for significant differences between upside and downside spillovers using the KS statistic. The results of our analysis, which are also shown in Table 6, show that with regard to the risk spillovers from Bitcoin to the FX markets, the downside $\Delta CoVaR$ measure is significantly higher than the upside $\Delta CoVaR$ measure for all the FX markets except for the British pound. As for the risk spillovers from the FX markets to Bitcoin, the test results further provide statistical evidence of the downside $\Delta CoVaR$ being significantly higher than the upside $\Delta CoVaR$ measure in all cases. These results thus confirm the presence of asymmetry between upside and downside spillovers. This finding is consistent with past literature that has found asymmetric downside and upside spillovers between currencies and financial markets (see, e.g., Ji et al., 2019; Reboredo et al., 2016). This result is also somewhat consistent with Bouri et al. (2018) who found asymmetric return spillovers in bull and bear market conditions between Bitcoin and financial assets, including the US dollar index. The presence of asymmetry between upside and downside risk spillovers found in our study calls for careful adjustment of a portfolio comprising Bitcoin and fiat currencies as well as for different investment strategies during downturn and upturn market conditions. Furthermore, in our study the downside risk spillover is found dominant over the upside spillover, a result that indicates increased risk for investors when the overall market does not perform well and calls for careful investment during periods of economic and financial turbulence. Investors can benefit from understanding this asymmetric behaviour between Bitcoin and FX markets, as the difference between the downside $\Delta CoVaR$ and upside $\Delta CoVaR$ measures is crucial for investors while taking long and short positions in bearish and bullish markets.

5.4. Robustness checking

In our study, we further examine potential changes in the dependence structure and risk spillover behaviour between Bitcoin and fiat currencies after the COVID-19 outbreak. Next, we therefore split our sample data into two sub-periods, namely the pre-COVID period from 6th January 2012 to 30th December 2019, and the COVID-19 period starting from 31st December 2019, when the first

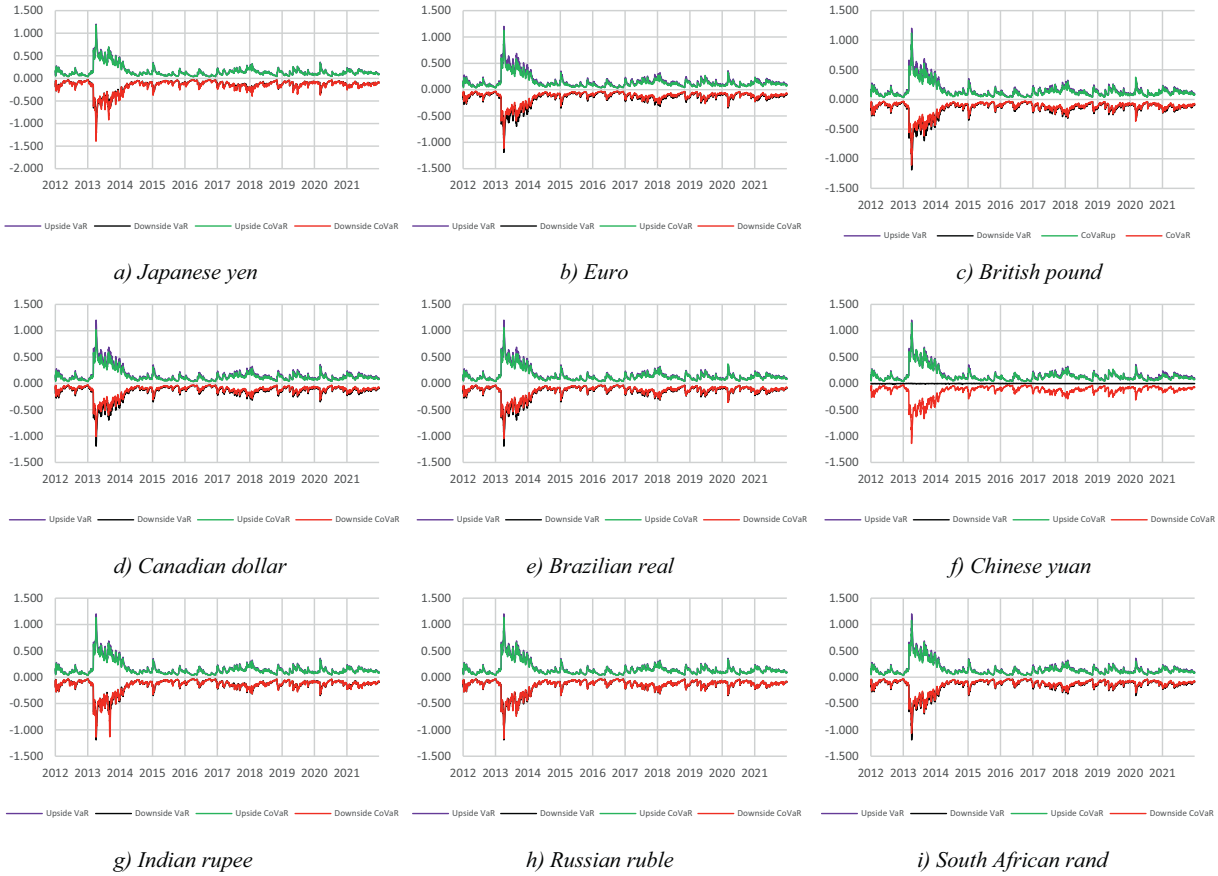

Fig. 5. Upside and downside VaR-CoVaR (from FX markets to Bitcoin): Entire sample period (6th January 2012- 6th January 2022).

Table 6
ΔCoVaR results: Entire sample period (6th January 2012- 6th January 2022).

	From Bitcoin to FX			From FX to Bitcoin		
	Down	Up	H_o:ΔCoVaR (Down) = ΔCoVaR(Up) H_1:ΔCoVaR (Down) > ΔCoVaR(Up)	Down	Up	H_o:ΔCoVaR (Down) = ΔCoVaR(Up) H_1:ΔCoVaR (Down) > ΔCoVaR(Up)
Japanese yen	0.9926	0.7853	0.8670	1.0746	0.9712	0.0481
	(0.1203)	(0.0643)	[0.0000]	(0.2211)	(0.1554)	[0.0000]
Euro	1.6569	1.6438	0.0437	0.8749	0.8797	0.0797
	(0.1883)	(0.1843)	[0.0137]	(0.1688)	(0.1468)	[0.0000]
British pound	0.9831	0.9833	0.0192	0.8868	0.8912	0.0709
	(0.0793)	(0.0814)	[0.7240]	(0.1718)	(0.1496)	[0.0000]
Canadian dollar	1.4760	1.4725	0.0866	0.8706	0.8755	0.1260
	(0.0818)	(0.2717)	[0.0000]	(0.1664)	(0.1403)	[0.0000]
Brazilian real	1.6430	1.6146	0.0843	0.9193	0.9220	0.0537
	(0.1983)	(0.2312)	[0.0000]	(0.1777)	(0.1514)	[0.0010]
Chinese yuan	2.1360	0.8556	0.7030	59.4584	0.9300	1.0000
	(1.4741)	(1.3825)	[0.0000]	(51.7889)	(0.1605)	[0.0000]
Indian rupee	2.2323	3.1255	0.4070	1.0107	0.9505	0.3190
	(0.3062)	(1.7289)	[0.0000]	(0.2087)	(0.1500)	[0.0000]
Russian ruble	1.0231	0.9818	0.2990	0.9936	0.9553	0.3160
	(0.1151)	(0.1046)	[0.0000]	(0.1924)	(0.1509)	[0.0000]
South African rand	2.2816	2.2628	0.0744	0.9253	0.9277	0.0701
	(0.1801)	(0.1830)	[0.0000]	(0.1755)	(0.1467)	[0.0000]

Note: Values in parentheses () present standard errors, whereas values in square brackets [] denote the respective *p*-values of the Kolmogorov-Smirnov test.

COVID-19 case was reported, to 6th January 2022.[10]

5.4.1. Preliminary sub-period analysis

Summary statistics for the return series considered in this study for the two sub-periods are reported in Table S1 (supplementary material). With the exception of the Brazilian real, Russian ruble, and Bitcoin,[11] all other markets witnessed declines in their average daily returns during the COVID-19 period compared to the pre-COVID period, with the average returns of the Chinese yuan, British pound, and Indian rupee becoming negative. Specifically, the average daily returns ranged from −0.65% (Japanese yen) to 6.36% (Chinese yuan) during the pre-COVID period, and from −6.67% (Chinese yuan) to 5.26% (Brazilian real) during the COVID-19 period. The standard deviation, and thus variability, increased for the Canadian dollar, Euro, Brazilian real, South African rand, and Bitcoin during the COVID-19 period, with the Chinese yuan and Canadian dollar constituting the most volatile currencies in the pre-COVID and COVID-19 periods, respectively. Moreover, with the exception of the Canadian dollar, the remaining G7 countries' currency return series as well as the Chinese yuan returns experienced declines in skewness during the COVID-19 period. We also observe an increase in the kurtosis values for the Japanese yen, Euro, Canadian dollar, and Bitcoin in the COVID-19 period, indicating heavier distribution tails after the COVID-19 outbreak, whereas the opposite is true for the British pound and BRICS currency returns.

We further notice that the unconditional correlation coefficient between Bitcoin and the fiat currencies remained practically zero in the pre-COVID period, as consistent with the unconditional correlations found for the entire sample period as well as findings in past studies (e.g., Baur et al., 2018; Baumöhl, 2019; Urquhart and Zhang, 2019; Yermack, 2015). However, Bitcoin's unconditional correlations with all currencies apart from the Indian rupee became negative or more negative during the COVID-19 period. Importantly, with the only exception of the Russian ruble, the unconditional correlations increased in absolute terms.[12] This result is in line with the study of Aharon et al. (2021) which found that in stressful times, including the COVID-19 pandemic period, Bitcoin is not isolated from fiat currencies. Our finding is further consistent with Corbet et al. (2020a) and Maghyereh and Abdoh (2021), who found that Bitcoin has started becoming more correlated with financial assets.

In addition, estimation results of our marginal distribution models for the two sub-periods are presented in Tables S2 and S3. We find again significant autoregressive behaviour in most currencies in the two sub-periods. Furthermore, the estimated ARCH coefficient is found significant for most series, and the estimated GARCH coefficient is found significant for Bitcoin and all the considered fiat currencies, with the highest persistence level being observed again for Euro in both sub-periods.

5.4.2. Copula results for the sub-periods

When splitting the sample into the pre-COVID and COVID-19 sub-periods, we find again temporal variations in the dependence between the sampled fiat currencies and Bitcoin. Specifically, in the pre-COVID period (Table S4) the Euro, British pound, Canadian dollar, and Brazilian real exhibit again zero tail dependence with Bitcoin, as given by the time-varying Gaussian copula. On the other hand, the time-varying Clayton copula is found to be the best fitted model for the dependence of the Japanese yen, Indian rupee, and South African rand with Bitcoin, indicating increased co-movements of these FX markets with Bitcoin during turbulent periods (Albulescu et al., 2018). Finally, the time-varying Gumbel and rotated Gumbel copulas best describe the dependence of Bitcoin with the Chinese yuan and Russian ruble, respectively. These results suggest asymmetric tail dependencies of the Japanese yen and BRICS currencies with Bitcoin during the pre-COVID period, with upper tail dependence for the Chinese yuan but with lower tail dependence for the rest.

As for the COVID-19 period (Table S5), with the only exception of the dependence structure between the South African rand and Bitcoin, which is now found to be best described by the time-invariant Student-t copula, the dependence of all other fiat currencies with Bitcoin is again time-varying. In particular, the dependence of the Euro, British pound, and Canadian dollar with Bitcoin is best described again by the time-varying Gaussian copula, suggesting zero tail dependence. A similar result is now found for the dependence between the Chinese yuan and Bitcoin as well. This result is somewhat in line with Le et al. (2021a) who found that during the COVID-19 crisis Bitcoin is disconnected from other assets, including currencies, in tail-dependency networks. On the other hand, the dependence between the Japanese yen and Bitcoin is now best explained by the time-varying Student-t copula, indicating time-varying symmetric non-zero tail dependence, and thus no difference between the tail dependence in bear and bull markets (Albulescu et al., 2018). Nonetheless, the time-varying rotated Clayton copula best describes the dependence of the Brazilian real, Indian rupee, and Russian ruble with Bitcoin, suggesting upper tail dependence and lower tail independence. Therefore, during the COVID-19 period, we find asymmetric tail dependence with Bitcoin only for the Brazilian real, Indian rupee, and Russian ruble.

Our results indicate that the dependence between Bitcoin and major fiat currencies is significant during both normal and crisis periods, yet the pattern remains heterogeneous across the different currencies. Moreover, the dependence structure of Bitcoin with fiat currencies mostly retains a time-varying pattern during both tranquil and turbulent periods as evidenced across the majority of the fiat currency markets considered. This finding is again somewhat in line with earlier studies that found time-varying dependence between fiat currencies (e.g. Albulescu et al., 2018; Dias and Embrechts, 2010) as well as with studies that found a time-varying relationship

[10] The results of our sub-period analysis are presented in the supplementary material.

[11] It is worth noting that the second sub-period encompasses the cryptocurrency market bubble of 2021, which took place during the first half of 2021 (Yousaf and Yarovaya, 2021).

[12] It is worth noting that our COVID-19 period does not include only the 2020 stock market crash period, which took place in early 2020 during which stock markets across the world crashed due to the COVID-19 pandemic uncertainty, and therefore we cannot comment on the safe haven properties of Bitcoin.

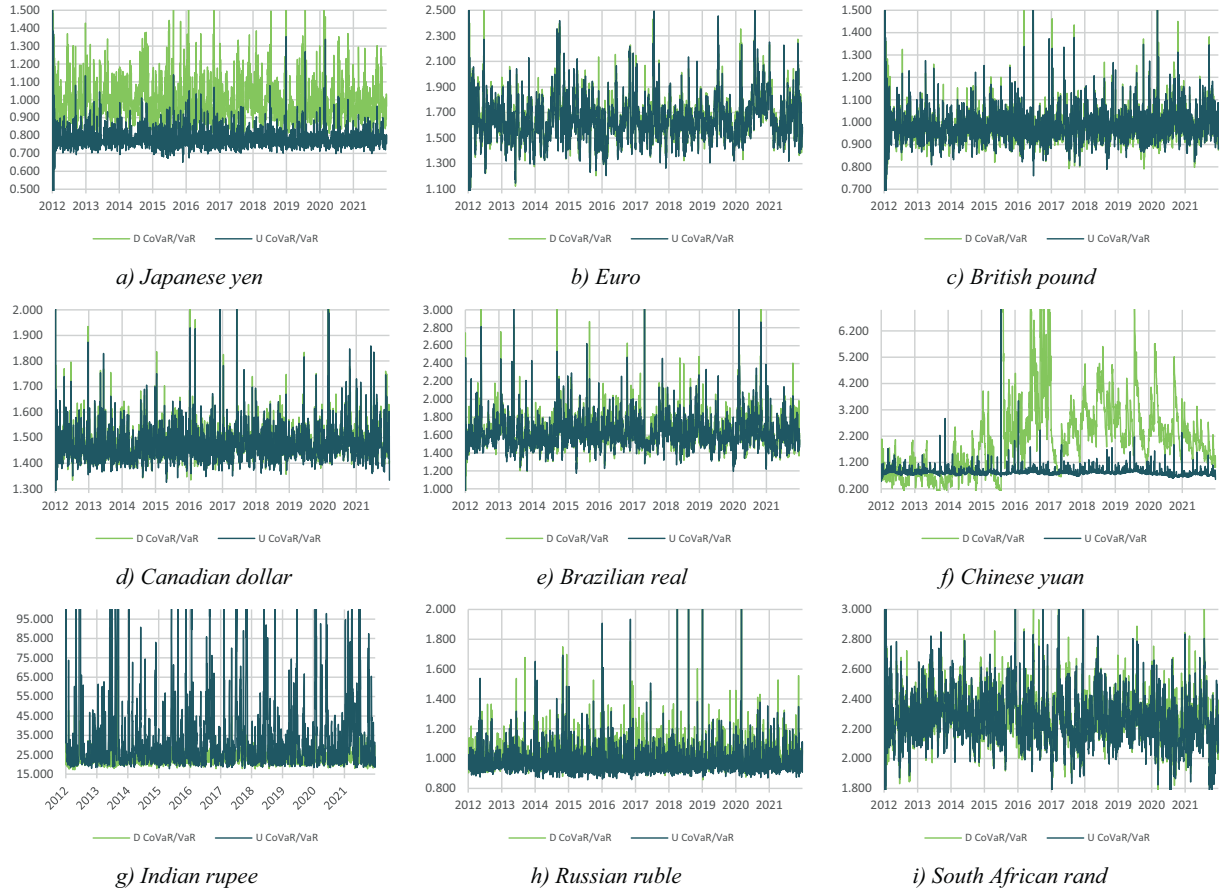

Fig. 6. Upside and downside ΔCoVaR (from Bitcoin to FX markets): Entire sample period (6th January 2012- 6th January 2022).

between Bitcoin and fiat currencies (e.g., Majdoub et al., 2021; Urquhart and Zhang, 2019).

Furthermore, the time evolution of the dependence parameter of the best fitted copula specification for Bitcoin with each sampled currency is depicted in Figs. S2 and S3, respectively. Overall, the dependence with Bitcoin seems to increase during the COVID-19 pandemic period for all FX markets except for the Chinese yuan and Russian ruble, as compared with the dependence before the COVID-19 outbreak. This result again supports earlier evidence that during the COVID-19 pandemic period Bitcoin is not isolated from fiat currencies (Aharon et al., 2021) and that Bitcoin has started becoming more correlated with financial assets (Corbet et al., 2020a; Maghyereh and Abdoh, 2021).

5.4.3. Risk analysis for the sub-periods

In our sub-period analysis of the *VaR* and *CoVaR* measures from Bitcoin to FX markets (Tables S6 and S7) and from FX markets towards Bitcoin (Tables S8 and S9), we find that all the results in both sub-periods are consistent with those from the entire sample period. However, when considering the risk measures from Bitcoin to FX markets, we notice that during the COVID-19 period (Table S7) the Brazilian real has the highest in absolute terms downside and upside *VaR* measures, followed by the South African rand. This result suggests that the Brazilian real became the riskiest fiat currency among those considered during the pandemic period, holding higher downside and upside risk than the South African rand. We further notice that the downside *VaR* measure increased in absolute terms during the COVID-19 period not only for the Brazilian real but also for the South African rand, British pound, and Canadian dollar. This result indicates that during the COVID-19 pandemic period, these four FX markets experience increased downside risk spillovers from Bitcoin. Similarly, the upside *VaR* measure of these four currencies as well as of the Chinese yuan increased during the COVID-19 pandemic period. Therefore, the Brazilian real, Chinese yuan, South African rand, British pound, and Canadian dollar are more exposed to upside risks, and thus to uncertain possibilities of gains, after the COVID-19 outbreak.

Moreover, when considering the risk measures from FX markets to Bitcoin, the downside *CoVaR* measure shows that the smallest in absolute terms downside spillovers towards Bitcoin returns come again from the Euro and Canadian dollar during the pre-COVID period (Table S8), but from the Chinese yuan during the COVID-19 period (Table S9). We also notice that the downside risk, as measured by the downside *CoVaR* measure, increased whereas the upside risk, as measured by the upside *CoVaR* measure, decreased during the COVID-19 period for all fiat currencies. Our results thus reveal Bitcoin's increased sensitivity to all fiat currencies during the

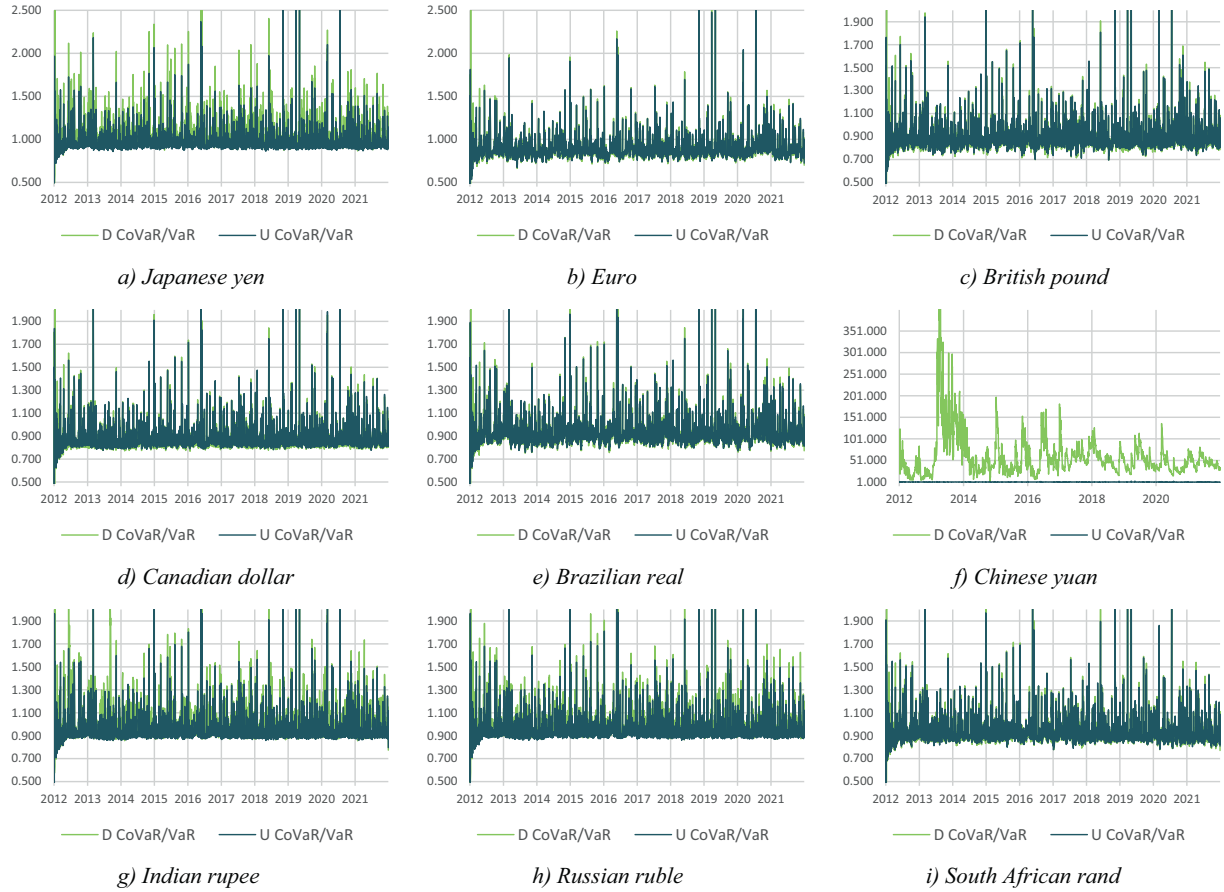

Fig. 7. Upside and downside ΔCoVaR (from FX markets to Bitcoin): Entire sample period (6th January 2012- 6th January 2022).

COVID-19 pandemic period when the overall market does not perform well (downside risk). Therefore, contagion, in terms of risk spillovers from FX markets to Bitcoin, appears more prominent during the pandemic period when the overall market is bearish. This result is somewhat in line with Le et al. (2021b) who found that Bitcoin is a large recipient of volatility spillovers from other financial assets during the COVID-19 pandemic and, therefore, should not be considered as a safe haven. However, our results indicate that risks in the upside price movements of FX markets have less influence over Bitcoin's upside risk (uncertain possibility of gains) during the COVID-19 period compared to the pre-COVID period, and the upside potential of Bitcoin's price is thus less sensitive to fiat currencies during the pandemic period.

As for the sub-period analysis of the $\Delta CoVaR$ measure, the results for the spillovers from Bitcoin to FX markets show that in the pre-COVID period (Table S10) the downside $\Delta CoVaR$ measure is higher than the upside $\Delta CoVaR$ measure for the Euro, British pound, Brazilian real, and Chinese yuan but the opposite is true for the remaining currencies. During the COVID-19 period (Table S11), the downside $\Delta CoVaR$ measure is higher than the upside $\Delta CoVaR$ measure for the Canadian dollar, Brazilian real, and Chinese yuan. With regard to the spillover effects from the FX markets to Bitcoin, we find that the downside $\Delta CoVaR$ is higher than the upside $\Delta CoVaR$ value for the Japanese yen, Chinese yuan, and Brazilian real during the pre-COVID period (Table S10). This is also true in the COVID-19 period (Table S11) for the Japanese yen, Euro, British pound, Brazilian real, and Chinese yuan. These results thus show asymmetric spillover effects between extreme upward and downward movements, which are confirmed again by the KS test results for most currencies in the two sub-periods as well.[13] Therefore, investors need to readjust their portfolios comprising Bitcoin and fiat currencies under different market conditions, since the risk spillovers are heterogeneous during normal and turbulent periods, and consider the increased risk when the overall market does not perform well.

[13] This finding is again consistent with previous studies that have found asymmetric downside and upside spillovers between currencies and financial markets (e.g., Ji et al., 2019; Reboredo et al., 2016).

6. Conclusions

In this study, we examined the dependence structure between Bitcoin and the currencies of the BRICS and G7 economies during upturn and downturn market periods by employing a wide range of time-invariant and time-varying copula specifications. We also measured and tested the impact of upward and downward movements of Bitcoin on FX markets and vice versa, by computing three different measures of upside and downside risk (VaR, $CoVaR$, and $\Delta CoVaR$).

Our copula results revealed time-varying dependence between Bitcoin and FX markets, with the dependence increasing during the COVID-19 pandemic period for all FX markets except for the Chinese yuan and Russian ruble. Moreover, our analysis for risk spillovers from Bitcoin to FX markets showed that, among the fiat currencies considered, the Chinese yuan holds the lowest downside and upside risk, as could have been expected from the effects of Chinese regulations on Bitcoin markets. On the other hand, the South African rand and Brazilian real hold both the highest downside and upside risk before the COVID-19 pandemic outbreak and during the COVID-19 pandemic period, respectively. Our results also showed that Bitcoin has significant influence over most of the considered currencies during both upward and downward market movements. As for risk spillovers from FX markets towards Bitcoin, we found that the Japanese yen exhibits the highest risk spillover effects. On the other hand, the lowest risk spillover effects come from the Canadian dollar and Euro before the COVID-19 pandemic outbreak but from the Chinese yuan during the COVID-19 period. Our results also showed Bitcoin's increased sensitivity to all fiat currencies during the COVID-19 pandemic period. Our results further revealed heterogeneity in the effects that the different FX markets have in the trading strategies adopted by investors in either short or long positions in Bitcoin and FX markets simultaneously. Finally, we found evidence of asymmetric spillovers from Bitcoin to FX markets and vice versa, as a result of discrepancies in the spillover effects between extreme upward and downward movements.

Understanding co-movements and risk spillovers between Bitcoin and exchange rates is of utmost importance to international investors for the formulation of portfolio strategies involving Bitcoin and currencies. Our results have thus important implications for international investors, who can benefit from understanding the asymmetric behaviour between Bitcoin and the different FX markets, especially when making decisions related to taking long or short positions in bearish and bullish markets. In contrast, adopting any trading strategy (either short or long position) without first considering the market conditions (bullish or bearish) can result in suboptimal decision-making. Furthermore, the presence of dynamic tail dependence suggests that investors in one market cannot ignore the risk associated with other markets, since such downside dependence may result in contagion phenomena. Finally, although Bitcoin is known as a more speculative asset, turbulent FX markets can also trigger Bitcoin returns due to the extreme underlying dependence. This has been confirmed by our results, which have shown that not only Bitcoin exhibits high downside risk spillovers towards traditional currencies but also that currencies, such as the Japanese yen, exhibit high downside risk spillover levels towards Bitcoin returns.

Future work could investigate the dependence structure and risk spillovers between different types of digital currencies and traditional financial markets, including both emerging and developed countries' stock indices and exchange rates. Given that digital currencies have different functions, with key differences among them, future research on this subject could account for their heterogeneous characteristics. For instance, Corbet et al. (2020b) and Katsiampa et al. (2022) classified digital currencies into three categories, namely currencies, protocols, and decentralised applications. It would be further interesting in the future to examine the dependence structure and risk spillovers between traditional financial markets and non-cryptocurrency applications of blockchain. The latter could include financial technology (FinTech) stocks, given the rapid growth and adoption of FinTech within the financial services industry recently (Le et al., 2021b), as well as Non-Fungible Tokens (NFTs), the market of which witnessed a significant increase in popularity in 2021 (Pinto-Gutiérrez et al., 2022).

CRediT authorship contribution statement

Mobeen Ur Rehman: Conceptualization, Methodology, Formal analysis. **Paraskevi Katsiampa:** Writing – original draft, Writing – review & editing, Project administration. **Rami Zeitun:** Conceptualization, Software, Writing – original draft. **Xuan Vinh Vo:** Data curation, Resources, Validation.

Data availability

We have explained where the data were downloaded from, and anyone with access to the databases can download the data.

Acknowledgement

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ememar.2022.100966.

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