The Interdependence of Bitcoin and Financial Markets: A Copula-Garch Approach*

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Abstract

This paper aims to examine the relationship between Bitcoin and preeminent financial indicators using Copula-GARCH method. In the study, we use closing prices of Bitcoin and US 10-Year Bond Yield, Gold Spot US Dollar, US Dollar Index, S&P 500, FTSE 100 and NIKKEI 225. To our knowledge, our paper is the first to examine this issue empirically. Analysis results show that there is no strong interdependence between Bitcoin and preeminent financial indicators. These findings provide new information that will benefit policy makers, banks, financial investors, and risk managers in trading activities for both long-term and short-term strategies.

Keywords: Bitcoin; Copula-GARCH; Financial Markets.

JEL Classification: G1, G15, E44, C14, C22

Finansal Piyasalar ve Bitcoin Bağımlılığı: Copula-Garch Yaklaşımı

Öz

Bu makale, Bitcoin ile kritik finansal göstergeler arasındaki ilişkiyi Copula-GARCH yöntemini kullanarak incelemeyi amaçlamaktadır. Araştırmada, Bitcoin ve ABD 10-Yıllık Tahvil Verim, Altın Piyasa, ABD Doları Endeksi, S&P 500, FTSE 100 ve NIKKEI 225'in kapanış fiyatları kullanılmaktadır. Bildiğimiz kadarıyla, bu konuyu ampirik olarak inceleyen ilk makale budur. Analiz sonuçları, Bitcoin ve önde gelen finansal göstergeler arasında güçlü bir karşılıklı bağımlılık olmadığını göstermektedir. Bu bulgular, hem uzun vadeli hem de kısa vadeli stratejilerde alım satım faaliyetlerinde politika yapıcılara, bankalara, finansal yatırımcılara ve risk yöneticilerine fayda sağlayacak yeni bilgiler sunmaktadır.

Anahtar Kelimeler: Bitcoin; Copula-GARCH; Finansal Piyasalar.

JEL Sınıflandırması: G1, G15, E44, C14, C22

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Introduction

Bitcoin is a peer-to-peer version of electronic cash (Nakamoto, 2008). Classified as cryptocurrency, Bitcoin has become popular in recent years. The currency can be said to have an intriguing logic (Eyal and Sirer, 2014). Although the Bitcoin world is prospering, there are several threats for users with regard to legal status and possible government sanctions (Grinberg, 2012). Despite having detractors, Bitcoin achieved an important role (Barber at al., 2012) and became a unique type of asset class in the financial markets within the last five years.

Rather than being issued by central organization such as a government or bank, it is completely reliant on cryptography, and the whole process of minting, storing and transfer is carried out by network of users (Ron and Shamir, 2013). Bitcoin was not created or controlled by a central organization, but by process called "mining", one of the key concepts in Bitcoin world. Valid transactions are compiled in blocks, then these and previously accepted blocks are added to the ledger. All transactions must take place in the network, called blockchain, thus preventing users from double spending (O'Dwyer and Malone, 2014).

A major problem with Bitcoin is the possibility of double-spending (Garay et al., 2015), and therefore delayed payment verification is required (Karame et al., 2012). To avoid the double spending problem, the system depends on digital signatures to confirm ownership, and a public history of transactions (Reid and Harrigan, 2013).

There are some important general assumptions with regard to Bitcoin, such as stakeholders must accept the rules and validity of transactions, and most importantly, it must be confirmed that Bitcoin has a value (Kroll et al., 2013).

Bitcoin is represented by a series of signals called transaction, which have several inputs and outputs (Bonneau et al., 2015) and established on a transaction registry dispersed across all participants (Böhme et al., 2015). Hence, this is a Proof-of-Work-based currency, in that users themselves can create crypto coin, requiring a heavy computational burden.

In this paper, we used the copula approach to describe the dependence structure of variables of interest. Sklar (1959) first introduced the copula theory to allow flexible description of the dependence between variables. Nelsen (1999) provided a thorough description of copulas from a mathematic perspective. The copula function is powerful since it states that the multivariate distribution function can be decomposed into marginal variables, and a density function copula, which completely describes the dependence framework of the variables. Embrechts et al. (2002) first employed the copula in the area of finance, and since has been widely applied in the field of financial risk management and portfolio decision problems. Cherubini et al. (2004) made a seminal contribution to the advent of pricing multivariate option by using copula. Mitchell et al. (2006) proposed Copula-GARCH models, which introduced the dynamic copula period. Patton (2006) reviewed the application of copula in financial time series. Bollersev (2009) supplied references, leading to the extensive list of ARCH acronyms used in the literature. Mitchell and McKenzie (2003) established model selection criteria with the ability to correctly identify the data generating process in simulated data. Brooks and Burke (2003) reproduced a group of appropriately adjusted information criteria for selection of models from the AR-GARCH family. Du and Lai (2017) examine the dependence between electricity spot markets in core European countries including France, Germany, Austria and Switzerland based on copula models. Of the ten different copulas with both time invariant and varying parameters currently in use, the empirical results show that time-varying Student-t copula is the best model for the sample data Albulescu et. al. (2018) explores the bivariate dependence structure between the US Dollar and four major currencies (EUR, GBP, CAD, JPY) using daily data for the time-span 1999–2014, and utilize different time-invariant and time-varying copula functions with different forms of tail dependence, and find a positive dependence between all exchange rates.

We also investigated the volatility effect US 10-Year Bond Yield, Gold Spot US Dollar, US Dollar Index, S&P 500, FTSE 100 and NIKKEI 225 stock indices. Volatility of each stock market are modeled based on the multivariate GARCH(p,q), EGARCH, GJR- GARCH, PGARCH, and CGARCH models. We employ a two-step Copula-GARCH model to examine the dependence structure of daily stock markets returns. Firstly, we filter log-return daily data using univariate EGARCH, GJR-GARCH and PGARCH models to obtain standard residuals and construct the marginal distributions. Secondly, copulas are selected to join the estimated marginal distributions. The Akaike information criteria (AIC) and Schwartz information criteria (SIC) methods are then used to determine which copula provides best fitness to the market data.

Although many empirical studies have been conducted in the literature about Bitcoin, these studies are mostly based on Bitcoin price estimation, (Munim et al., 2019; McNally et al., 2018; Pant et al., 2018; Azari, 2019; Urquhart, 2017), return and volatility analysis (Dyhrberg, 2016; Katsiampa, 2017; Symitsi ve Chalvatzis, 2018; Ardia et al., 2019; Balcilar et al., 2017;

Lahmiri et al., 2018; Chaim ve Laurini, 2018; Katsiampa, 2018) and its use as a hedging instrument against other financial assets. (Dyhrberg, 2016; Bouri et al., 2017a; Bouri et al., 2017b; Urquhart ve Zhang, 2019; Pal ve Mitra, 2019; Wu et al., 2019). This study aims to eliminate uncertainty in the market as the first study that analyzes both volatility and dependency between bitcoin and leading financial markets. We aim to provide better insights of the volatility of Bitcoin returns, its dependence structures to financial markets in recent years. This paper will be a deeper extension to current literature in Bitcoin volatility modeling and forecasting with the financial time series GARCH model and different variations.

The main research theme of this study is to select a model capable of supporting our efforts to determine whether there is a connection between Bitcoin and preeminent financial markets. Employing such a model will provide an opportunity to reduce market uncertainty, and hence make a modest contribution to the current literature.

The structure of this paper is as follows. The second section presents literature review. The third and fourth sections discusses the model and the data, consecutively. In the fifth section, the empirical results are analysed. The last section provides final remarks.

Literature Review

After its creation, much research followed on Bitcoin, generally conducted in the context of conceptual explanations, the introduction of cryptocurrency and the relationship between general economic indicators. In a study by Yermack (2015), Bitcoin was reviewed in terms of historical trading prices and it was described as acting more as an investment instrument than a currency, a finding supported by a similar study by Baur et al. (2015). Wijk (2013) used a statistical tool to establish a relationship between Bitcoin and the world's largest stock market indices (FTSE 100, Dow Jones, Nikkei 225), Dollar/Euro, Dollar/Yen and oil, to detect the short and long term effects of indicators on Bitcoin, and found that WTI oil price and Dollar/Euro exchange rates have long-term effects, and the Dow Jones index has short-term effect. Dyhrberg (2016a) studied the financial asset properties of Bitcoin by using the GARCH model. The author considered Bitcoin as a method of hedging, similar to gold or the dollar, and used the FTSE index, Dollar / Euro, Dollar / Pound exchange rate and federal fund rates to explain price volatility. In study by Dyhrberg (2016b), the asymmetric GARCH model was used to investigate the ability of Bitcoin to protect investors against market volatility and proposed that

Bitcoin could be used as a hedging tool against the US dollar in the short term, and against stocks in the FTSE index in the long term. Georgoula et al. (2015) attempted to identify the determinants of Bitcoin price, conducting a time series and sensitivity analysis which explored the short and long term relationships between Bitcoin price, basic economic variables, technological factors and tweets. Gronwald (2014) conducted a deeper analysis of Bitcoin price and behaviour using GARCH model to capture the more serious price movements that caused market shocks, showing that the model is very suitable for their proposed purpose and that the excessive price movements characterize the Bitcoin price. In a study by Bouri et al. (2016), a Dynamic Conditional Correlation Model was used to determine whether Bitcoin acted as a hedging tool and safe haven for large world stock indices, treasuries, oil, gold, general commodity index and US dollar index. The results demonstrate that Bitcoin is a weak protection tool, suitable only for diversification. However, it was found to have strong potential as a safe haven in one particular context, that is, against extreme weekly movements on Asian equities. Baek and Elbeck (2015) attempted to model the Bitcoin price using the S&P 500 index, the consumer price index, the Euro exchange rate and other economic indicators, but none of these economic variables were shown to affect the price. The authors reached the conclusion that Bitcoin is a purely speculative vehicle, with prices driven by investor intuition. Cheah and Fry (2015) pointed out that Bitcoin prices contain a substantial speculative component, and that Bitcoin markets are susceptible to bubbles. Examining the market efficiency of Bitcoin, Urquhart (2016) concluded that it does not currently have full efficiency, although further investigation found recent progress towards an efficient market. In another study, Urquhart (2017) reviewed Bitcoin price clustering, and found significant evidence of clustering at round numbers. A study by Nadarajah and Chu (2017) found that efficient market hypotheses are not valid for Bitcoin returns. Bariviera (2017) noted that daily returns exhibit persistent behaviour until 2014, after which the market became more informative. Katsiampa (2017), in the study of the volatility of Bitcoin returns, highlighted the importance of the AR-CGARCH model as the most appropriate for the inclusion of a long-running component of the short-term and conditional variance. Bouri et al. (2017) investigated the relationship between uncertainty and the Bitcoin market, revealing that Bitcoin acted as a hedge against uncertainty, a result echoed in a recent study by Demir et al. (2018). Yonghong et al. (2018) investigate time-dependent long-term memory in the Bitcoin market by using a rolling window approach and a new productivity index. Baur et al. (2018) find that Bitcoin exhibits distinctly different return, volatility and correlation characteristics compared to other assets, including gold and US dollars. Holub and Johnson (2018) emphasizes that peer-to-peer (P2P) exchange plays an important role in global Bitcoin trade, while Dastgir et al. (2018) examines the causal relationship between Bitcoin (measured by Google Trends search queries) and Bitcoin returns in the period between January 2013 and December 2017.

Model specification and estimation

Copula Functions

The copula function is proposed to measure dependence of multivariate variables. Based on Sklar's well-known theorem (Sklar 1959), copulas allow the implementation of the division of the specification of a multivariate model into two parts: the marginal distributions on one side, the dependence structure (copula) on the other. Let X and Y be random variables with continuous distribution functions F_X and F_Y, which are uniformly distributed on the interval $[0,1]$. Then, there is a copula such that for all $x, y \in R$,

$$F_{XY}\left(X,Y\right)=C(F_X\left(X\right),F_Y\left(Y\right) \tag{1}$$

The copula C for $\left(X,Y\right)$ is the joint distribution function for the pair $F_X\left(X\right)$, $F_Y\left(Y\right)$ provided F and F continuous.

The joint probability density of the variables X and Y is obtained from the copula density $(u,v)=\frac{\partial^2 C(u,v)}{\partial u \partial v}$, as follows:

$$f_{xy}(x,y)=c(u,v)f_x(\mathrm{x})f_y(y), \tag{2}$$

where $f_x(\mathrm{x})$ and $f_y(y)$ are the marginal densities of the random variables X and Y. According to Sklar (1959), an n-dimensional joint distribution can be decomposed into its n-univariate marginal distributions and an n-dimensional copula. In the extension of Sklar's theorem to continuous conditional distributions, Patton (2006) shows that the lower (left) and upper (right) tail dependence of two random variables is given for the copula as:

$$\lambda_l = \lim_{u \to 0} P(F_X(x) \le u \mid F_Y(x) \le u) = \lim_{u \to 0} C(u,u)/u \tag{3}$$

$$\lambda_u = \lim_{u \to 1} P(F_X(x) > u \mid F_Y(x) > u) = \lim_{u \to 1} 1 - 2u - C(u,u)/1 - u \tag{4}$$

where λ_l and $\lambda_u \in [0,1]$.

Copula Models

We introduce several copula models in this section (Nelsen, R. B. 1999); Gumbel copula, Clayton copula, Frank copula, Gaussian copula Student t copula, Suvival Clayton Copula and Joe copula.

Gumbel Copula: This Archimedean copula is defined based on the generator function $\phi(t) = (-lnt)^{\theta}$, $\theta \ge 1$;

$$C_\theta(u,v) = \exp\left(-[(-\ln u)^\theta + (-\ln v)^\theta]^{1/\theta}\right) \tag{5}$$

where is the copula parameter restricted to. This copula is asymmetric, with more weight in the right tail. In addition, it is an extreme value copula.

Clayton Copula: This Archimedean copula is defined based on the generator function $\phi(t) = \dfrac{t^{-\theta} - 1}{\theta}$,

$$C_\theta(u,v) = (u^{-\theta} + v^{-\theta} - 1). \tag{6}$$

where θ is the copula parameter restricted to $(0, \infty)$. This copula is also asymmetric, but with more weight in the left tail.

Frank Copula: This Archimedean copula is defined based on the generator function: $\phi(t) = -\ln \dfrac{-e^{-\theta t} - 1}{e^{-\theta} - 1}$;

$$C_\theta(u,v) = -\frac{1}{\theta} \ln\left(1 + \frac{\left(e^{-\theta u} - 1\right)\left(e^{-\theta v}\right.}{\left(e^{-\theta} - 1\right)}\right. \tag{7}$$

where θ is the copula parameter restricted to $\left(0, \infty\right)$.

Gaussian copula: The copula function can be written as:

$$C(u,v;\rho)=\int_{-\infty}^{\Phi^{-1}(u)}\int_{-\infty}^{\Phi^{-1}(v)}\frac{1}{2\pi\sqrt{1-\rho^2}}\exp\left(\frac{2\rho rs-r^2-s^2}{2(1-\rho^2)}\right)drds \quad (8)$$

where $u=F_{Y_1}(\mathrm{y}_1)$, $v=F_{Y_2}(\mathrm{y}_2)$ is the inverse of the standard normal distribution and ρ is the general correlation coefficient..

Student-t copula: The Student's-t copula allows for joint fat tails and an increased probability of joint extreme events compared with the Gaussian copula. This copula can be written as:

$$C_{\rho,v}(u,v)=\int_{-\infty}^{t_v^{-1}(u)}\int_{-\infty}^{t_v^{-1}(v)}\frac{1}{2\pi(1-\rho^2)^{1/2}}\left\{1+\frac{x^2-2\rho xy+y^2}{v(1-\rho^2)}\right\}^{-(v+2)/2}dsdt \quad (9)$$

where ρ, v parameters of the t copula.

Joe Copula: This Archimedean copula is defined with based on the generator function: $\phi(t)=-\ln[1-(1-t)^\theta]$

$$C_\theta(u,v)=1-[(1-u)^\theta+(1-v)^\theta-(1-u)^\theta(1-v)^\theta]^{1/\theta} \quad (10)$$

where θ is the copula parameter restricted to $[1,\infty)$.

The BB8 (Frank-Joe): Copula is

$$C(u_1,u_2,\theta,\delta)=\frac{1}{\delta}(1-[1-\frac{1}{1-(1-\delta)^\theta}(1-(1-\delta u_1)^\theta)(1-(1-\delta u_2)^\theta)]\frac{1}{\theta}) \quad (11)$$

with $\theta\in[1,\infty)\cap\delta\in(0,1]$.

Marginal Modelling

In order to build the model for bivariate distribution with the copula, the marginal distribution for the series must initially be formed. There are various models for commonly accepted financial time series returns. Engle and Bollerslev (1986) and Engle and Kroner (1995) propose ARCH and GARCH model, which have been widely applied to financial series. In their extensive review, Poon and Granger (2003) consider that important methodological viewpoints needed to be discussed, particularly regarding the evaluation of forecasts and classified volatility forecasts as belonging in one of the four categories. There are a number of GARCH models; in this study, we combine ARMA (m,n) and GARCH (p,q), EGARCH, GJR-GARCH (p,q), PGARCH and CGARCH models for modeling daily financial returns, respectively. These models' specifications are as follows:

$$r_t = \lambda_0 + \sum_{j=1}^{m} \lambda_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{n} \theta_i \varepsilon_{t-i} \tag{12}$$

$$r_t = w_0 + \sum_{i=1}^{q} \alpha_i u_{t-1}^2 + \sum_{j=1}^{p} \beta_j u_{t-1}^2 \tag{13}$$

$$\log(r_t) = w_0 + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{r_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{r_{t-i}}} + \sum_{j=1}^{p} \beta_j \log(u_{t-j}) \tag{14}$$

$$r_t = w_0 + \sum_{i=1}^{p} \beta_i r_{t-i} + \sum_{j=1}^{q} \alpha_j u_{t-j}^2 + \sum_{i=1}^{q} \gamma_j u_{t-j}^2 I_{t-j} \tag{15}$$

$$r_t^{\delta} = w_0 + \sum_{i=1}^{p} \alpha_i (|\varepsilon_{t-i}| - \gamma \varepsilon_{t-i})^{\delta} + \sum_{i=1}^{q} \beta_j r_{t-j}^{\delta} \tag{16}$$

where m,n,p, q are positive integers $, u_t = \eta_t \sqrt{h_t}$, η_t □ $f(0,1)$, respectively λ_j $, \theta_i$ parameters of (AR) and (MA), $w_0, \beta_i, \alpha_j, \gamma_j$ and δ are ARCH(p,q), GARCH (1,1), EGARCH, GJR-GARCH (p,q) and PGARCH model parameters.

Data

Daily Bitcoin (BTC) prices covers the period 07.08.2015-19.09.2018 and were downloaded from www.coinmarketcap.com. For consistency, we eliminated weekend data due to the lack of corresponding data from other datasets. Bloomberg was the source of the other data (US 10-Year Bond Yield, Gold Spot US Dollar, US Dollar Index, S&P 500, FTSE 100 and NIKKEI 225). The observations, in total 787, reflect the daily prices between 07.08.2015-19.09.2018. Table 1 summarizes statistics of financial series and summarizes statistics of returns series, while Table 2 shows sizeable differences in the mean values for the seven markets, and also in the corresponding standard deviations. Skewness of returns out of Gold Spot is negative, indicating that financial returns are skewed left, i.e. that the left tail is longer relative to the right. Gold Spot is skewed right. The high kurtosis of returns reveals that extreme value changes often occur when the tail of return distributions shows fatness. The Jarque-Bera (JB) test shows that the normality of each return series distribution is strongly rejected at 0.05 level, which means all price index distributions are non-normal. Finally, the Autoregressive Conditional Heteroscedasticity –Lagrange Multiplier (ARCH-LM) test indicates that strong ARCH effects exist in all financial return series. Graphical representations of the data employed are shown in Figures 1-7.

Table 1. Summary Statistics (Price Series)

	BTC	**US10-Year Bond Yield**	**Gold Spot**	**US Dollar Index**	**FTSE 100**	**NIKKEI 225**	**S&P 500**
Mean	3424,655	2,272382	1,242523	95,72571	6,967637	19,49177	2,351210
Median	1058,840	2,273000	1,254350	95,42000	7,176350	19,41537	2,347835
Max	19118,30	3,115000	1,364900	103,2900	7,877450	24,12415	2,914040
Min	210,0700	1,358000	1,050800	88,50000	5,536970	15,95202	1,829080
Std. Dev.	3993,569	0,422652	0,074587	3,247193	0,577587	2,300957	0,291264
Skewness	1,388055	-0,000340	-0,700688	0,054261	-0,504242	0,086467	0,224957
Kurtosis	4,398057	2,211989	2,759570	2,587043	1,890523	1,881396	1,799128
Jarqure Bera	316,4092	20,33652	66,20939	5,970654	73,62128	41,95866	53,85794
Probability	0,000000	0,000038	0,000000	0,040523	0,000000	0,000001	0,000000

Table 2. Summary Statistics of return series

	Bitcoin	Year Bond Yield	Gold Spot	US Dollar Index	FTSE 100	NIKKEI 225	S&P 500
Mean	0,003986	0,000443	0,000127	-4,65e-050	0,000111	0,000170	0.000428
Median	0,004305	0,000426	-7,66e-05	0,000000	0,000323	0,000000	0.000493
Max	0,223513	0,107081	0,045568	0,021577	0,035150	0,074262	0.038291
Min	-0,202077	-0,110214	-0,033752	-0,024185	-0,047795	-0,082529	-0.041843
Std. Dev	0,046821	0,019463	0,008256	0,004446	0,009078	0,013106	0.008120
Skewness	-0,133615	-0,092512	0,234740	-0,152676	-0,155529	-0,215980	-0.699039
Kurtosis	7,066050	5,649610	6,177275	5,253610	5,895575	9,778923	7.354931
Jarqure Bera	543,0948	230,7464	337,4024	169,1675	277,4030	1509,175	684.2597
Probability	0,00000	0,000000	0,000000	0,000000	0,000000	0,000000	0.000000
ARCH LM	37,04137	28,69334	2,603280	6,049454	112,1329	18,33321	86,78615
Probability	0,00000	0,00000	0,1066	0,0139	0,00000	0,00000	0,00000

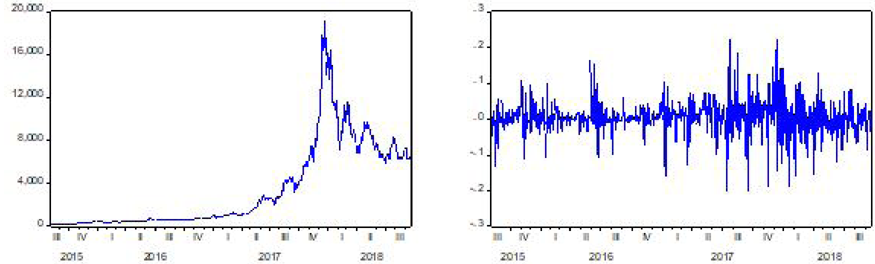

Figure 1. Change over years of BTC series and BTC return series

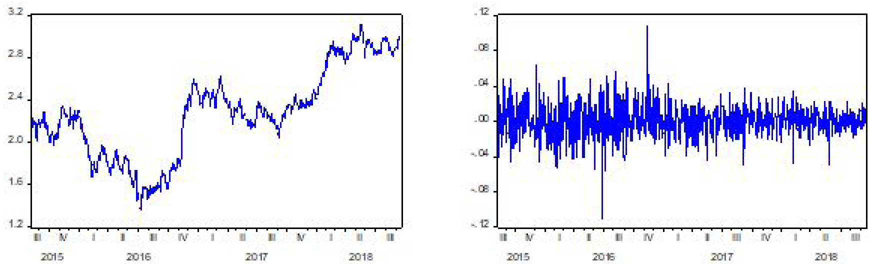

Figure 2. Change over years of US10-Year Bond Yield series and US10-Year Bond Yield return series

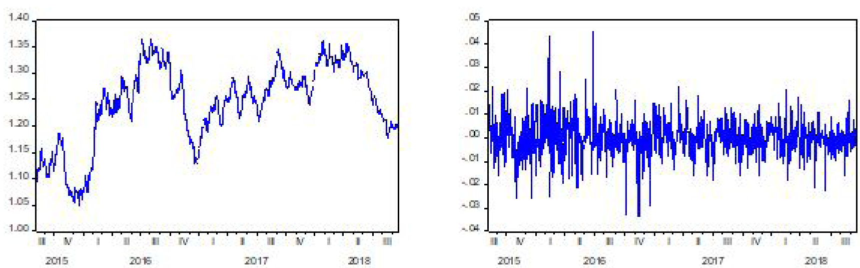

Figure 3. Change over years of Gold Spot series and Gold Spot return series

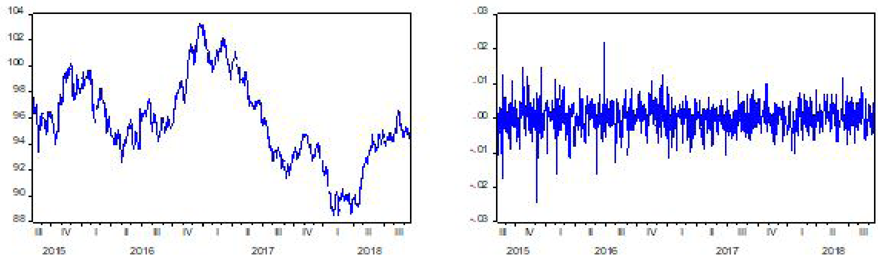

Figure 4. Change over years of US Dollar Index series and US Dollar Index return series

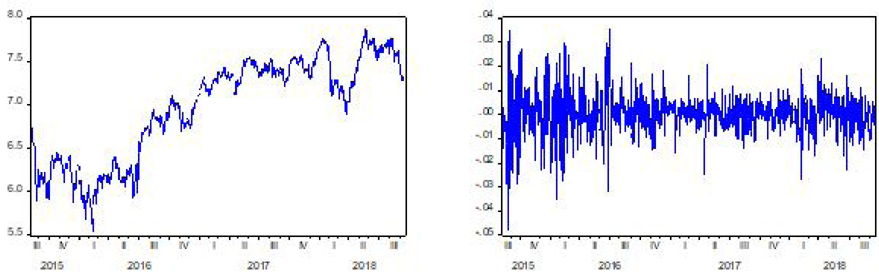

Figure 5. Change over years of FTSE 100 series and FTSE 100 Index return series

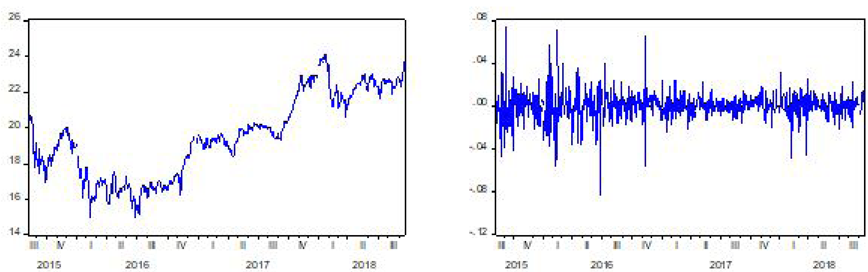

Figure 6. Change over years of NIKKEI 225 series and NIKKEI 225Index return series

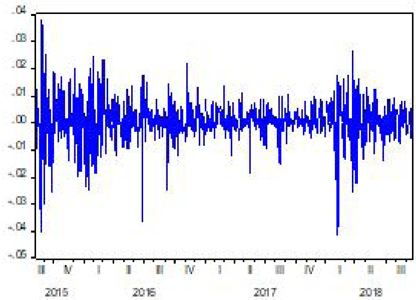

Figure 7. Change over years of S&P 500 series and S&P 500 Index return series

Empirical Results

Results of marginal distributions

We used the ARMA, GARCH, EGARCH, GJR-GARCH, PGARCH and CGARCH models for financial return series, and selected the most suitable model based on AIC and SIC model selection criteria. All the parameters estimate of marginal distributions are included in Table 3 and Table 4, which summarize the best fit model for all marginal distributions employed: the best models for the marginal; BTC, US 10-Year Bond Yield, Gold Spot, US Dollar Index, FTSE 100, Nikkei 225 and S&P 500 ARMA (0,0)-EGARCH(1,1,1) ARMA (3,4)- GJR-GARCH, ARMA (2,2)-CGARCH, ARMA (3,4)- GJR-GARCH, ARMA (4,0)- GJR-GARCH, ARMA (3,3)- CGARCH and ARMA (2,2)- PGARCH respectively. Based on the obtained results, Bitcoin and SP500 is modelled used PGARCH. In the PARCH model, from equation (17), δ and γ parameters represent the power parameter of standard deviation and the asymmetric effect, respectively. From Table 4, for BTC γ parameter is negative and for SP500 γ parameter is positive. US 10-Year Bond Yield, US Dollar Index and FTSE 100 are modelled via GJR- GARCH model. This model shows that good news and bad news might have different effects on volatility. The leverage effect is obtained as $(\alpha+\gamma)$ of negative shocks which is larger than $(\alpha)$of positive shocks. In this model, if $\gamma > 0$, the leverage effect exists. As can be seen from Table 4, for US 10-Year Bond Yield, US Dollar Index and FTSE 100, γ parameter is positive, namely, this series has leverage effect and Gold Spot and Nikkei 225 are modelled via CGARCH. For US 10-Year Bond Yield, US Dollar Index, FTSE 100, Nikkei 225 and S&P 500, the results of ARCH-LM test show that neither autocorrelation nor ARCH effects exist in the residuals; however, for Bitcoin and Gold Spot series, it is seen that the variance problem and the ARCH effect are not completely removed (figure-8).w

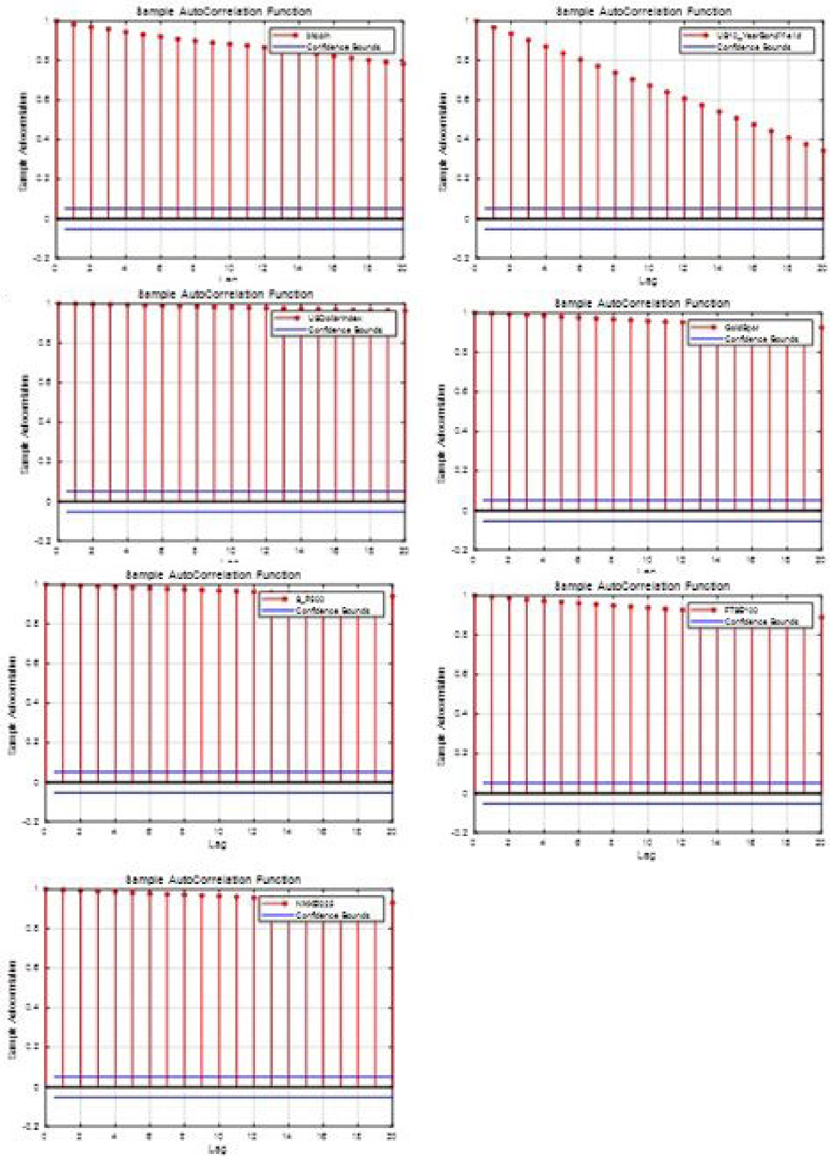

Figure 8. For BTC-US10-Year Bond Yield, Gold Spot, US Dollar Index FTSE 100, NIKKEI 225, S&P 500 pairs Auto Correlation Function, respectively

Table 3. Mean Equation for marginal distribution model of financial series

	Bitcoin	US10-Year Bond Yield	Gold Spot	US Dollar Index	FTSE 100	NIKKEI 225	S&P 500
Mean Equation	**0**	**-3,4**	**-2,2**	**-3,4**	**-4**	**-3,3**	**-2,2**
λ_1	-	-0,99609	-0,06296	-0,39664	-0,0008	-1,17431	0,012023
λ_2	-	0,985021	-0,96117	0,380491	-0,03956	0,588045	0,925081
λ_3	-	0,984231	-	0,981819	0,006898	0,779244	-
λ_4	-	-	-	-	-0,10636	-	-
θ_1	-	0,954115	0,034028	0,418426	-	1,157923	-0,01662
θ_2	-	-1,01899	0,954018	-0,39702	-	-0,66248	-0,98338
θ_3	-	-0,95503	-	-1,00615	-	-0,83443	-
θ_4	-	0,01993	-	-0,01526	-	-	-
AIC	-3,27465	-5,04828	-6,32842	-7,98112	-6,55623	-5,8264	-6,78597
SIC	-3,26277	-4,99484	-6,2928	-7,92768	-6,5206	-5,7789	-6,75034
HQIC	-3,27008	-5,02774	-6,31473	-7,96058	-6,54253	-5,80814	-6,77227

Table 4. Variance Equation for marginal distribution model of financial series

Variance Equation	Bitcoin		US10-Year Bond Yield		Gold Spot		US Dollar Index		FTSE 100		NIKKEI 225		S&P 500	
GARCH(1,1)	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	4,84E-05	1,66E-05	-2,15E-07	-3,12E-08	7,20E-08	6,81E-05	-4,72E-08	-1,65E-08	4,13e-06	3,54E-06	4,72E-06	5,72e-06	4,08E-06	1,88E-06
α	0,130220	0,286071	0,014553	0,015425	0,011166	0,150000	-0,012587	-0,006684	0,138861	0,155648	0,141161	0,150095	0,216926	0,191235
β	0,859554	0,835415	0,984377	0,982639	0,986749	0,600000	1,015272	1,006925	0,803929	0,803979	0,840360	0,840398	0,721880	0,799239
AIC	-3,526193	-3,778732	-5,157599	-5,184364	-6,811004	-6,388604	-8,061315	-8,062087	-6,827085	-6,866868	-6,104631	-6,233669	-7,141728	-7,240619
SIC	-3,502418	-3,748732	-5,133824	-5,154646	-6,787230	-6,258886	-8,037540	-8,037369	-6,803310	-6,837150	-6,080857	-6,203951	-7,117953	-7,210901
ARCH LM	0,031351 (0,8595)	0,241986 (0,6224)	11,24368 (0,0008)	10,32589 (0,0013)	6,163800 (0,0130)	4,667890 (0,0307)	1,065758 (0,3019)	1,315723 (0,2514)	0,633203 (0,4262)	0,191259 (0,6619)	0,358831 (0,5492)	0,520834 (0,4705)	2,120340 (0,1454)	2,220915 (0,1362)
EGARCH(1,0,1)	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	-6,399519	-4,899216	-8,160876	-8,144547	-9,594871	-9,378735	-10,87168	-10,88077	-9,913396	-9,801548	-8,898207	-8,698642	-10,12317	-9,774804
α	0,334568	1,184449	0,327533	0,304969	0,010000	-0,284902	0,043846	0,048173	0,520237	0,510303	0,232786	0,411796	0,504347	0,696190
γ	-0,060158	-0,024168	0,060749	0,016598	0,010000	0,137904	-0,085489	-0,090126	-0,060415	-0,169263	-0,180775	-0,178860	-0,091489	-0,067465
AIC	-3,330158	-3,597059	-5,064303	-5,103488	-6,745946	-6,859077	-7,990379	-8,039703	-6,684400	-6,765704	-5,894191	-6,144710	-6,924648	-7,082006
SIC	-3,306383	-3,567341	-5,40528	-5,093770	-6,722171	-6,829359	-7,966605	-8,009985	-6,660626	-6,735986	-5,870417	-6,114992	-6,900874	-7,052288
ARCH LM	0,278255	1,076494	0,244938	0,289072	2,763392	0,014545	2,315353	2,105010	1,029375	1,111504	0,193869	0,112260	0,616215	0,073781

	(0,5978)	(0,2995)	(0,6207)	(0,5908)	(0,0964)	(0,9040)	(0,1281)	(0,1468)	(0,3103)	(0,2918)	(0,6597)	(0,7376)	(0,4325)	(0,7859)
EGARCH(0,1,1)	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	-3,490870	-2,736289	-0,001711	-0,000982	0,002342	-0,650757	-2,583111	-2,443507	-0,049057	-0,040708	-0,574369	-0,517164	-0,812072	-0,217918
γ	-0,031384	-0,136554	-0,024845	-0,023404	0,019891	0,075816	-0,111603	-0,114730	-0,095948	-0,101952	-0,230646	-0,248116	-0,251989	-0,227922
β	0,430126	-0,402619	1,000087	1,000203	1,000464	0,932214	0,761941	0,774930	0,994803	0,995959	0,937036	0,943043	0,918962	0,978913
AIC	-3,278014	-3,553556	-5,176632	-5,196474	-6,807689	-6,859347	-8,000556	-8,047843	-6,863122	-6,887600	-6,128086	-6,257900	-7,086778	-7,186422
SIC	-3,268873	-3,523838	-5,152858	-5,166756	-6,783915	-6,829629	-7,967781	-8,018126	-6,840122	-6,857882	-6,104312	-6,228182	-7,063004	-7,156704
ARCH LM	40,69711 (0,00000)	36,65540 (0,00000)	13,07175 (0,0003)	12,90383 (0,0003)	5,047514 (0,0247)	2,620660 (0,1055)	2,747701 (0,0974)	2,604845 (0,1065)	13,25304 (0,0003)	11,52540 (0,0007)	2,080785 (0,1492)	2,065303 (0,1507)	22,98819 (0,00000)	13,02091 (0,0003)
EGARCH(1,1,1)	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	-0,543258	-0,196351	-0,003133	-0,002511	-9,840995	-9,764328	-2,451004	-2,330523	-0,489377	-0,444281	-0,724915	-0,716993	-0,888305	-0,636024
α	0,282732	0,261797	-0,001915	-0,014787	-0,267467	-0,291296	0,048830	0,048193	0,138276	0,146300	0,174428	0,177366	0,213869	0,227372
γ	0,001944	0,083985	-0,027597	-0,031316	0,075011	0,133884	-0,105945	-0,108370	-0,128895	-0,142483	-0,197396	-0,235328	-0,215817	-0,193523
β	0,945031	0,993727	0,999740	0,999216	-0,044030	-0,040707	0,777584	0,788787	0,960318	0,966078	0,934206	0,934966	0,927568	0,953700
AIC	-3,527697	-3,788876	-5,174363	-5,195185	-6,761413	-6,856587	-7,999818	-8,046655	-6,867791	-6,896212	-6,176453	-6,286947	-7,185365	-7,267692
SIC	3,497980	3,753215	5,144645	5,159524	6,731969	6,820926	7,970101	8,010994	6,838198	6,860551	6,146735	6,251286	7,155648	7,232031
ARCH LM	0,001744 (0,9667)	0,015885 (0,8997)	12,58100 (0,0004)	11,64770 (0,0006)	0,019482 (0,8890)	0,005332 (0,9418)	0,620774 (0,4308)	0,575952 (0,4479)	0,749820 (0,3865)	0,584006 (0,4447)	0,031028 (0,8602)	0,150535 (0,6980)	2,240168 (0,1345)	2,323516 (0,1274)
GJR-GARCH	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	4,49E-05	7,54E-06	**-3,14E-07**	**-4,14E-07**	1,75E-07	5,44E-07	**5,67E-10**	**-3,51E-09**	**2,93E-06**	**2,98E-06**	9,55E-06	9,28E-06	4,23E-06	2,57E-06
α	0,134956	0,349753	**-0,013768**	**-0,011918**	0,016119	0,025506	**-0,004226**	**-0,005077**	**-0,021857**	**-0,018503**	-0,056212	-0,056554	0,057640	0,029797
γ	-0,027558	-0,207904	**0,019812**	**0,016630**	-0,020632	-0,021797	**0,000688**	**0,000123**	**0,213856**	**0,243834**	0,466397	0,495691	0,299822	0,327596
β	0,868741	0,861113	**1,002199**	**1,002142**	0,990037	0,976099	**1,003686**	**1,004378**	**0,871196**	**0,853057**	0,787294	0,792588	0,727371	0,781353
AIC	-3,524670	-3,787739	**-5,181662**	**-5,196201**	-6,815646	-6,879224	**-8,042222**	**-8,062645**	**-6,872595**	**-6,899536**	-6,172946	-6,289441	-7,173000	-7,266602
SIC	-3,494952	-3,752077	**-5,151944**	**-5,160540**	-6,785928	-6,843563	**-8,012505**	**-8,026984**	**-6,842877**	**-6,868875**	-6,143228	-6,253780	-7,143283	-7,230941
ARCH LM	0,064461 (0,7996)	0,085570 (0,7699)	**11,56972 (0,0007)**	**11,68622 (0,0006)**	5,922012 (0,0150)	5,791855 (0,0161)	**1,123736 (0,2891)**	**1,285396 (0,2569)**	**0,094799 (0,7582)**	**0,009568 (0,9221)**	0,433103 (0,5105)	0,626681 (0,4286)	1,034518 (0,3091)	1,002612 (0,3167)
PGARCH	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	**0,000253**	**0,000268**	-7,55E-05	-1,57E-06	0,006256	0,006883	-8,65E-09	8,46E-09	7,23E-05	6,15E-05	0,001466	0,001719	**0,002785**	**0,000429**
α	**0,133966**	**0,163649**	0,007076	0,006453	-0,123742	-0,077544	-0,002479	-0,002242	0,073159	0,080886	0,122984	0,131968	**0,140484**	**0,135214**
γ	**-0,051522**	**-0,367603**	0,999261	0,999136	0,224203	0,998612	0,944496	0,926012	0,999884	0,999937	0,999943	0,999841	**0,996718**	**0,991182**
β	**0,868474**	**0,901841**	0,995849	0,990820	0,014808	0,180969	1,003368	1,002706	0,880817	0,873557	0,860056	0,861335	**0,851015**	**0,859118**

AIC	**-3,525219**	**-3,792430**	-5,164512	-5,187237	-6,760446	-6,851179	-8,034770	-8,056426	-6,872058	-6,898813	-6,189902	-6,295171	**-7,200875**	**-7,274595**
SIC	**-3,489558**	**-3,750826**	-5,128850	-5,145632	-6,724785	-6,809574	-7,999109	-8,014821	-6,836397	-6,857208	-6,154241	-6,253566	**-7,165214**	**-7,232990**
ARCH LM	**0,058553 (0,8088)**	**0,026835 (0,8699)**	14,38796 (0,0001)	12,32558 (0,0004)	0,055842 (0,8132)	0479833 (0,4885)	1,530258 (0,2161)	1,744576 (0,1866)	0,075620 (0,7833)	0,001059 (0,9740)	0,312276 (0,5763)	0,252751 (0,6151)	**5,438830 (0,0197)**	**4,043979 (0,0443)**
CGARCH	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**	**Gaussian**	**Student t**
ω_0	0,004264	0,133065	0,002380	-4,51E-05	**3,26E-05**	**5,68E-05**	8,00E-06	1,05E-05	6,94E-05	8,87E-05	**0,000287**	**0,000225**	5,78E-05	5,69E-05
α	0,988999	0,999862	1,000452	0,998023	**0,998160**	**0,994592**	0,999260	0,998944	0,967021	0,970545	**0,981147**	**0,995165**	0,956209	0,995410
γ	0,124096	0,141657	-0,001481	0,000669	**0,015656**	**0,023294**	-0,006934	-0,006338	0,094871	0,130628	**0,161968**	**0,039984**	0,135687	0,047074
β	0,017968	0,039989	0,086450	0,079463	**-0,061114**	**-0,063617**	0,015811	0,023477	0,120803	0,101371	**-0,056161**	**0,146572**	0,137520	0,172977
ξ	-0,159894	-0,090079	0,641391	-0,493453	**0,143147**	**0,208452**	-0,237465	-0,004551	-0,397153	-0,573178	**-0,624196**	**0,662904**	-0,187214	0,654011
AIC	-3,521265	-3,763519	-5,169556	-5,190938	**-6,827846**	**-6,891138**	-8,043947	-8,061613	-6,828821	-6,866843	**-6,103420**	**-6,236246**	-7,145757	-7,250115
SIC	-3,485603	-3,721914	-5,133894	-5,149333	**-6,792185**	**-6,849533**	-8,008286	-8,020008	-6,793160	-6,825238	**-6,067759**	**-6,194641**	-7,110096	-7,208510
ARCH LM	0,006796 (0,9343)	0,179555 (0,6718)	0,141445 (0,7068)	0,297775 (0,5853)	**1,516585 (0,2181)**	**2,503808 (0,1136)**	0,026993 (0,8695)	0,007439 (0,9313)	7,67E-05 (0,9930)	0,069180 (0,7925)	**1,072496 (0,3004)**	**0,05433 (0,9412)**	0,448850 (0,5029)	1,422144 (0,2331)

Results for the copula models

The empirical distribution functions used in modelling the dependence of BTC-US10-Year Bond Yield, BTC-Gold Spot, BTC-US Dollar Index, BTC-FTSE 100, BTC-NIKKEI 225, BTC-S&P 500 pairs are as shown in figure 9, 10, 11, 12, 13 and 14, respectively. We used Clayton, Gumbel Frank, Joe, Gaussian, Student-t, BB8, Survival BB8 and Rotated Tawn Type BB8 270 Degrees copula family. In table 5, it is observed that the relationship between BTC and US Dollar Index is negative, the relationship between BTC and US10 Year Bond Yield, Gold Spot is weak in the positive direction, and the relationship between BTC and FTSE100, Nikkei 225, S&P500 is in the? strong positive direction. From table 5, it is clear that the BB8, Survival BB8, Frank and Rotated Tawn Type BB8 270 Degrees copula performs best for the pairs BTC- US10-Year Bond Yield, BTC-Nikkei 225, BTC-Gold Spot, BTC-FTSE 100, BTC-S&P 500 and BTC- US Dollar Index, according to the AIC, and BIC criteria, respectively. In table 5, the calculated tail dependence values for the pairs BTC- US10-Year Bond Yield, BTC-Nikkei 225, BTC-Gold Spot, BTC-FTSE 100, BTC-S&P 500 and BTC- US Dollar Index, when λ_l =0, λ_u = 0, symmetric tail dependency is observed in the tail of these pairs. The graphical representations of BTC and used pairs with their three and two dimensional empirical distribution functions are given in figures 10-14, while Clayton, Gumbel Frank, Joe, Gaussian, Student-t, BB8, Survival BB8 and Rotated Tawn Type BB8 270 Degrees copula scatter graphs are shown in figures 15-20, respectively.

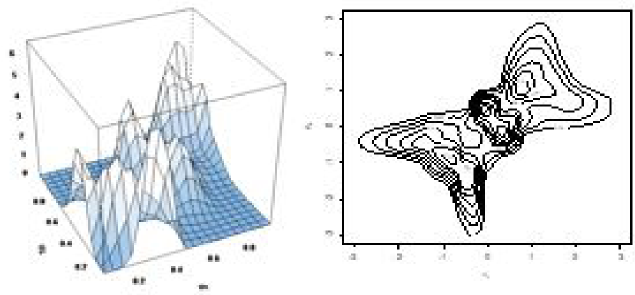

Figure 9. For BTC-US10-Year Bond Yield pair three and two dimensional empirical distribution function, respectively

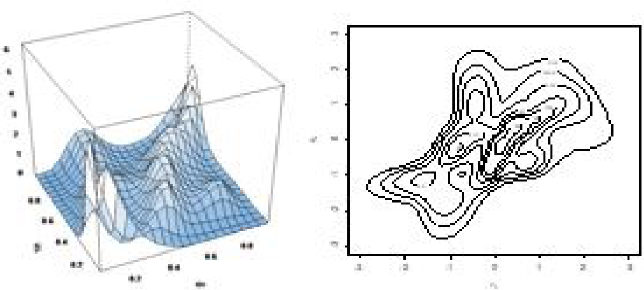

Figure 10. For BTC-Gold Spot pair three and two dimensional empirical distribution function, respectively

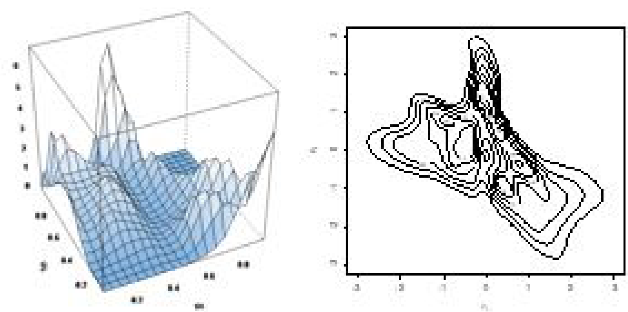

Figure 11. For BTC-US Dollar Index pair three and two dimensional empirical distribution function, respectively

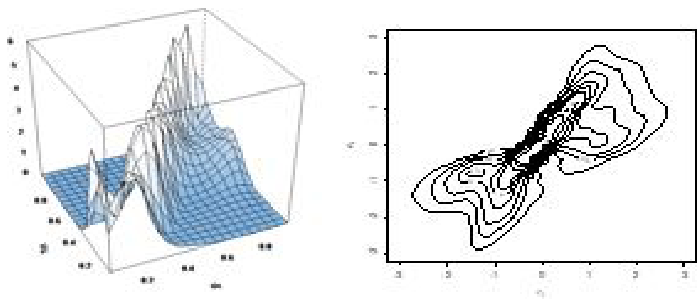

Figure 12. For BTC-FTSE 100 pair three and two dimensional empirical distribution function, respectively

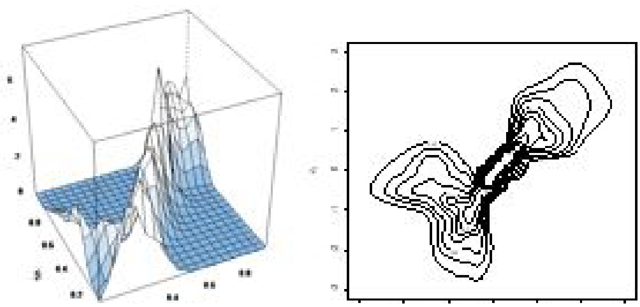

Figure 13. For BTC-NIKKEI 225pair three and two dimensional empirical distribution function, respectively

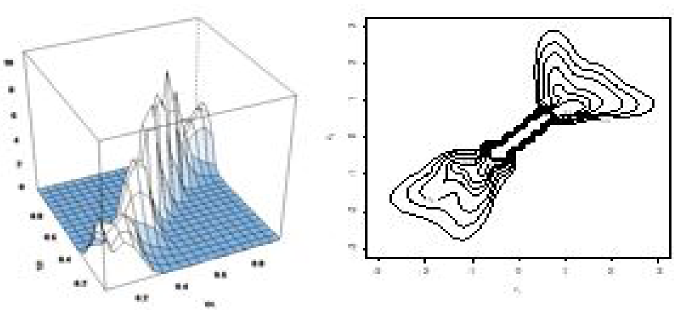

Figure 14. For BTC- S&P 500 pair three and two dimensional empirical distribution function, respectively

Table 5. Estimates for the copula models

	BTC-US10-Year Bond Yield	BTC – Gold Spot	BTC-US Dollar Index	BTC-FTSE 100	BTC-NIKKEI 225	BTC-S&P 500
τ	0,47	0,36	-0,36	0,66	0,61	0,8
Clayton θ	0,7	0,89	-	1,6	0,83	2,58
Logl	80,54	134,81		266,16	103,09	415,21
AIC	-159,09	-267,62		-530,31	-204,18	-828,43
BIC	-154,02	-262,95		-525,65	-199,52	-823,76
λ_u	0	0		0	0	0
λ_l	0,37	0,46		0,65	0,43	0,76
Gumbel θ	1,7	1,49	-	2,13	2,22	2,72
Logl	178,9	101,99		305,84	345,35	440,14
AIC	-355,8	-201,99		-609,69	-688,71	-878,28
BIC	-351,13	-197,32		-605,02	-684,04	-873,61
λ_u	0,5	0,41		0,61	0,63	0,71
λ_l	0	0		0	0	0
Frank θ	5,6	3,93	-3,73	9,64	8,36	17,81
Logl	252,12	136,77	133,83	467,66	383,85	801,45
AIC	-502,23	-271,54	-265,66	-933,32	-765,71	-1600,9
BIC	-497,57	-266,88	-261	-928,65	-761,04	-1596,23
λ_u	0	0	0	0	0	0
λ_l	0	0	0	0	0	0
Joe θ	2,02	1,53	-	2,3	3,01	2,84
Logl	157,88	56,76		209,44	359,58	290,21
AIC	-313,77	-111,51		-416,88	-717,16	-578,42
BIC	-309,1	-106,85		-412,22	-712,5	-573,76
λ_u	0,59	0,42		0,65	0,74	0,72
λ_l	0	0		0	0	0
Gaussian θ	0,63	0,54	-0,51	0,78	0,72	0,86
Logl	191,59	131,73	118,17	368,88	284,15	512,61
AIC	-381,18	-261,46	-234,33	-735,7	-566,31	-1023,22
BIC	-376,51	-256,79	-229,66	-731,09	-561,64	-1018,55
λ_u	0	0	0	0	0	0
λ_l	0	0	0	0	0	0
Student t ν	0,62	0,54	-0,51	0,78	0,74	0,88
ρ	30	24,23	30	30	12,75	7,3
Logl	185,66	132,52	114,5	365,68	288,19	524,76

AIC	-367,32	-261,05	-225,01	-727,36	-572,39	-1045,53
BIC	-357,99	-251,71	-215,67	-718,03	-563,05	-1036,19
λ_u	0,01	0,01	0	0,06	0,17	0,48
λ_l	0,01	0,01	0	0,06	0,17	0,48
BB8 θ	6	6	-	6	6	6
δ	0,66	0,49		0,74	0,84	0,83
Logl	269,16	124,23		387,18	460,48	566,31
AIC	-534,33	-244,45		-770,36	-916,97	-1128,63
BIC	-524,99	-235,12		-761,03	-907,63	-1119,29
λ_u	0	0		0	0	0
λ_l	0	0		0	0	0
Survival BB8 θ	6	2,83	-	6	6	6
δ	0,57	0,86		0,8	0,64	0,88
Logl	211,49	156,17		446,65	282,44	641,81
AIC	-419,49	-308,34		-889,3	-560,89	-1279,62
BIC	-410,16	-299		-879,97	-551,56	-1270,28
λ_u	0	0		0	0	0
λ_l	0	0		0	0	0
Rotated Tawn Type BB8 270 degrees θ	-	-	-2,71	-	-	-
δ			-0,93			
Logl			201,65			
AIC			-399,31			
BIC			-389,98			
λ_u			0			
λ_l			0			

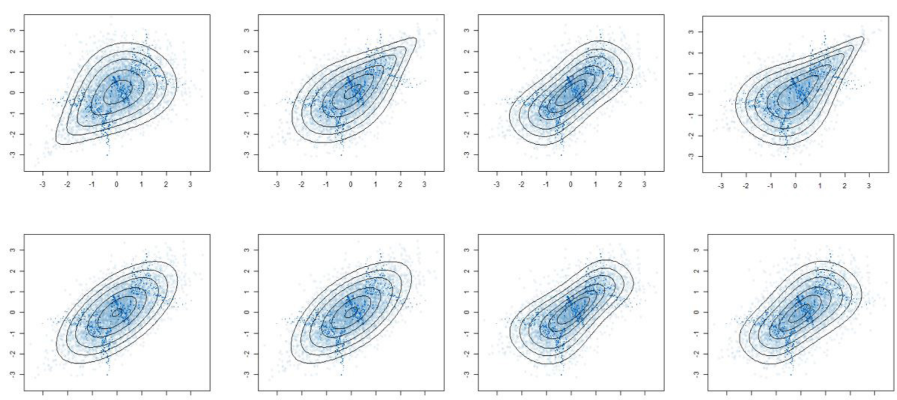

Figure 15. For BTC-US10-Year Bond Yield pairs Clayton, Gumbel, Frank, Joe, Gaussian, Student-t, BB8 and Survival BB8 copula scatter graph, respectively.

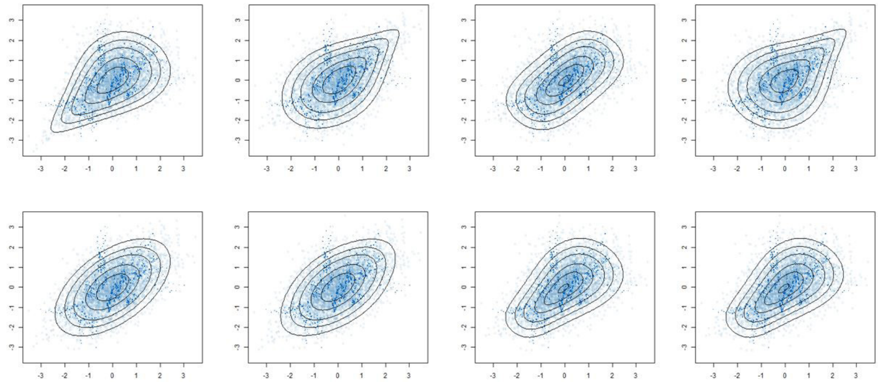

Figure 16. For BTC-Gold Spot pairs Clayton, Gumbel, Frank, Joe, Gaussian, Student-t, BB8 and Survival BB8 copula scatter graph, respectively.

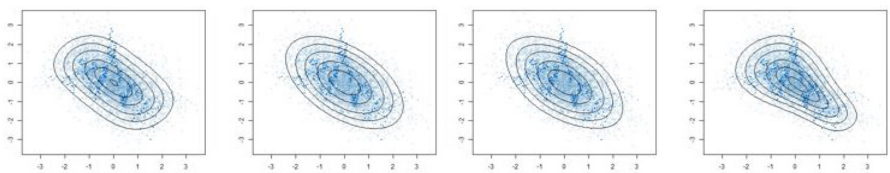

Figure 17. For BTC-US Dollar Index pairs Frank, Gaussian, Student-t and Rotated Tawn Type BB8 270 degrees copula scatter graph, respectively.

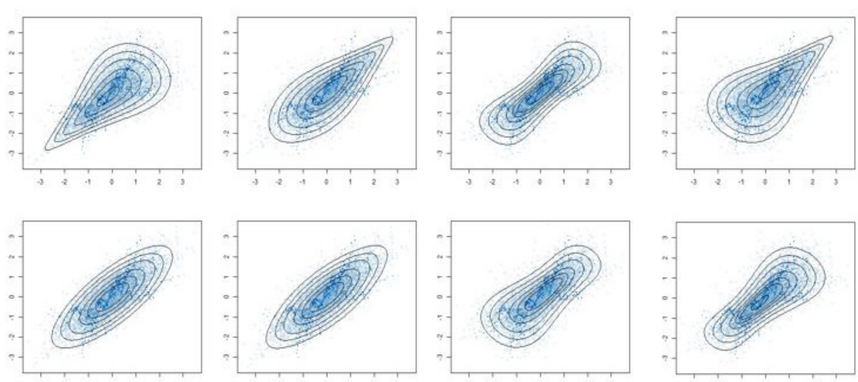

Figure 18. For BTC-FTSE 100 pairs Clayton, Gumbel, Frank, Joe, Gaussian, Student-t, BB8 and Survival BB8 copula scatter graph, respectively.

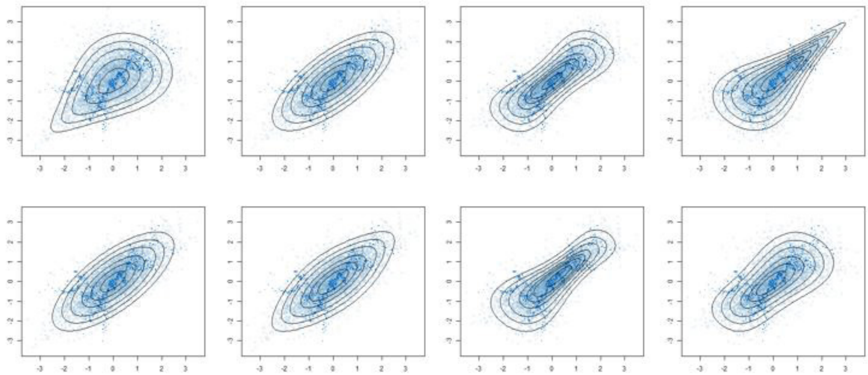

Figure 19. For BTC-NIKKEI 225 pairs Clayton, Gumbel, Frank, Joe, Gaussian, Student-t, BB8 and Survival BB8 copula scatter graph, respectively.

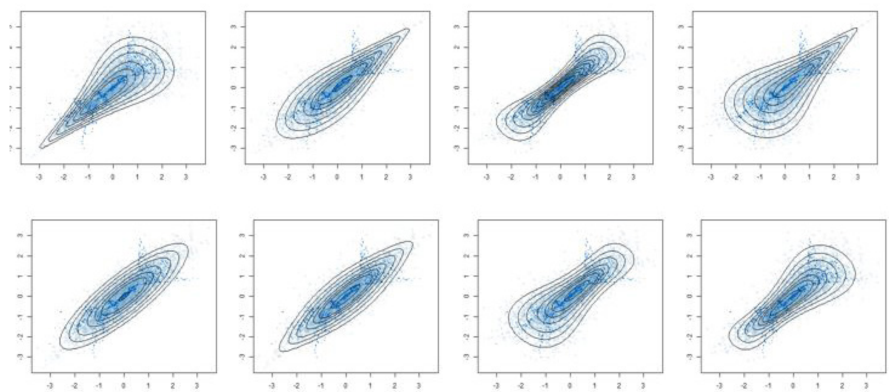

Figure 20. For BTC-S&P 500 pairs Clayton, Gumbel, Frank, Joe, Gaussian, Student-t, BB8 and Survival BB8 copula scatter graph, respectively.

Interpretation of Findings

In this study, Copula-Garch model was used to measure the relationship between Bitcoin and various preeminent indicators. Firstly, Bitcoin and various preeminent indicators were modelled by CGARCH, GJR- GARCH and PGARCH models, which take into account asymmetric effect. It can therefore be clearly said that negative conditions are more effective than positive conditions on serial volatility. In the next stage, the relationship between Bitcoin and various preeminent indicators were modelled by copula, a nonparametric method. We showed that the relationship between BTC and various preeminent indicators is negative, weak positive, and strong positive (Table 5). BTC- US10-Year Bond Yield, BTC-Nikkei 225 pairs were modelled by BB8 copula, and BTC-FTSE 100, BTC-S&P 500 pairs were modelled by Frank copula, BTC-Gold Spot pairs were modelled by Survival BB8 (180 Degrees) copula, and BTC-US Dollar Index pairs were modelled by Rotated Tawn Type BB8 270 Degrees copula. The tails of these pairs show that the Frank copula has zero tail dependence, therefore, BTC-Gold Spot pairs have symmetric tail dependence. The BTC-FTSE 100, BTC-NIKKEI 225, BTC-S&P 500 pairs have upper tail dependency, and BTC-S&P 500 pair has greater upper tail dependency than BTC-FTSE 100 and BTC-NIKKEI 225. Closer linear relationships were found between BTC-FTSE 100, BTC-NIKKEI 225, BTC-S&P 500 when compared to BTC- US10-Year Bond Yield, BTC-Gold Spot, BTC-US Dollar Index.

Conclusions

Bitcoin, created by a person or group under the pseudonym Nakamoto (2008), in 2009, reached its maximum price on 17 December 2017, at US$19.780. It is now traded in over 8000 markets, and by 03 January 2018, its total market value surpassed 180 billion dollars. Increasing market share, increasing price and high volatility make Bitcoin appealing for individual users, investors and economists alike. Our analysis supports the findings of Baek and Elbeck (2015) that there is no strong dependence between Bitcoin and other financial indicators. It was observed that Bitcoin's relationship with the Gold Index was much weaker than with other indicators (table 5), supporting the view that Bitcoin is generally regarded as currency rather than an investment tool.

National regulations on Bitcoin differ widely across countries. For example, it is prohibited in Bolivia, and its use is officially restricted in China. In contrast, in Israel, it is subject to the same taxation rules as the local currency and Venezuela has started to initiate a cryptocurrency with the aim of completely replacing the traditional currency. Institutions such as the IMF, World Bank and the central banks were conceived of to exert economic control through traditional forms of money. However, expected improvements in cryptocurrency systems, and their increasing use globally in the near future will allow the general public to play a more active role in the economic system. Many investment institutions currently avoid cryptocurrencies, but others are in the process of investing in the cryptocurrency business; Goldman Sachs is setting up trading centre for cryptocurrencies, while Chicago Board of Exchange is running Bitcoin Futures. Nevertheless, it should also be noted that, after the entrance of CBOE into Bitcoin Future Market, the Bitcoin price reached a peak, but started to fall dramatically as soon as expectations were fulfilled (Hale et. al., 2018).

In the current situation, it would seem irrational to use Bitcoin as a hedging instrument due to its highly volatile nature. Nevertheless, leading players in the international financial markets are beginning to seriously consider Bitcoin and other cryptocurrencies as a portfolio item and a device to decrease transaction costs. However, its future role is unclear, and will depend on both its movements, and also on the attitude and approaches of governments.

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