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Hedge and safe haven status of Bitcoin: copula-DCC approach

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Abstract

We investigate the financial assets status (diversifier, hedge and safe haven) of Bitcoin and gold against the world and U.S. stock markets. We employ the copula-DCC approach to consider the tail dependence between Bitcoin or gold return and stock return. Our results indicate that Bitcoin is a weak hedge against the world and U.S. stock markets, while gold is a diversifier against the world stock market, but a strong hedge against the U.S. stock market. Moreover, we employ the threshold model toinvestigate whether there exist contagion effects between Bitcoin or gold market and stock markets. Our results show that the increase in market uncertainty weakens the role of Bitcoin as a weak hedge and Bitcoin becomes a diversifier, while it changes the role of gold as a diversifier into a hedge or a safe haven. The above results mean that although Bitcoin is called as “new gold”, the financial assets status of Bitcoin and gold are different.

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1. Introduction

Since the global financial crisis, global economic risks stemming from economic uncertainties have increased markets' risk aversion and have disrupted financial markets intermittently. Along with the widespread fear of global economic risks, studies of safe haven currencies have been receiving increasing attention. According to Kaul and Sapp (2006), a safe haven currency is defined as a currency that appreciates when a hike in the global risk aversion decreases the value of the reference portfolio of risky assets. Based on this definition, Ranaldo and Söderlind (2009), De Bock and de Carvalho Filho (2015), Fatum and Yamamoto (2016), and Masujima (2017) use the implied volatility of S&P 500 options (VIX) as an indicator of market uncertainty and investigate the relationship between the behavior of the main currencies (including the EUR, the JPY, the SEK, the CHF, and the GBP), and the VIX.

Besides major currencies, gold has been considered as a safe haven although its price is more volatile than currencies. Thus, it is difficult to explain why investors purchase riskier alternative gold when markets' risk aversion increases. Baur and McDermott (2016) explain this puzzle based on behavioral biases called "cognitive limitations". They argue that if shocks are large and its implications are difficult to assess, investors only consider a subset of all available alternatives which have positive information. The positive information for gold is that it has been used as a reliable store of value and worked well in the past financial crises. Some properties of gold enhance its role as a store of value and a safe haven. One is scarcity, which is determined by recoverable reserves and extraction. The other is non-centrality and independence from central banks or government authorities, which implies that the financial turmoil stemming from the collapse of financial system or failure of economic policy may have little effect on gold.

Bitcoin named "new gold" or "digital gold" shares features with gold; scarcity verified by an automatic and deterministic "mining" rule, non-centrality, and independence from central banks or government authorities. Due to these characteristics, Bitcoin might have a safe-haven status when the financial system and market are disrupted. However, there are some key differences between gold and Bitcoin. For example, gold is primarily used as a store of value, while Bitcoin is regarded as a speculative investment (Baur, *et al*., 2018). Therefore, whether Bitcoin can be considered as a safe haven needs more analysis.

Some studies investigated the safe currency status of Bitcoin. For example, Bouri *et al*. (2017) follow the financial asset classification proposed by Baur and Lucey (2010), in which financial assets are classified into three main categories: a diversifier, a hedge, and a safe haven. According to their definition, a diversifier is an asset that is weakly and positively correlated with another asset on average. A weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average. A weak (strong) safe haven is an asset that is uncorrelated (negatively correlated) with another asset during times of stress. This definition is more convincing than that of Kaul and Sapp (2006), because correlation may be crucial information when building an efficient portfolio. Bouri *et al*. (2017) use a dynamic conditional correlation (DCC) model introduced by Engle (2002) to show that Bitcoin is a poor hedge and is suitable for diversification purposes only.

This study extends Bouri *et al*. (2017) in terms of the following four points to investigate the financial assets status (diversifier, hedge, and safe haven) of Bitcoin and gold.

First, we employ a copula-Dynamic Conditional Correlation (copula-DCC) approach. The DCC model employed in Bouri *et al*. (2017) is estimated under an unrealistic assumption of multivariate normality. However, it is well known that the correlation between stock returns is higher in a high-volatility regime than in a low-volatility regime, meaning the existence of asymmetric dependence structures. However, a normal distribution cannot capture such an asymmetric dependence. These problems can be treated easily by using copulas. The copula was introduced by Sklar (1959) and defined as a function that provides a mapping between the marginal distribution of each univariate series and the multivariate distribution of all series. This implies that it is not necessary that the marginal distribution and the multivariate distribution must follow the same type of distribution as in the DCC model[1].

Second, we estimate the dynamic conditional betas using the copula-DCC approach to investigate the riskiness of gold and Bitcoin with respect to market portfolio. As Bali, *et al*. (2017) state, the dynamic conditional beta estimated by DCC family has a dynamic feature that puts more weight on more recent observations and varies each day in the estimation; therefore, it can be a better measure of risk.

Third, we also investigate the contagion effect by using the threshold approach. Forbes and Rigobon (2002) define contagion as a significant increase in cross-market linkages after a shock to one country or group of countries. They argue that under the situation that two markets have a high degree of co-movement during tranquil periods, even if the markets display a high degree of co-movement after a shock to one of them, this may not mean contagion. This situation is regarded as interdependence, namely the long-run dependence between markets. On the other hand, contagion is a short-run phenomenon that occurs in the period of financial crises, which can cause a statistically significant increase in correlation known as "correlation breakdown". In our context, if there exists a threshold value above which the proxy for market uncertainty has statistically significant effects on the estimated dynamic correlation, it can be interpreted as evidence of "correlation breakdown", namely contagion.

Forth, we use not only the VIX but also the Equity Market-related Economic Uncertainty (EMEU) index proposed by Baker *et al*. (2016) as an indicator of market uncertainty. EMEU is one of the Economic Policy Uncertainty (EPU) indices which is calculated from the

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[1] Patton (2006) explains the copula approach for the application of analyzing the dependence structure.

frequency of articles in ten leading US newspapers that contain the following triple: (1) "economic" or "economy"; (2) "uncertain" or "uncertainty"; and one or more of "equity market", "equity price", "stock market" or "stock price". As the main global economic risks stem from economic policy uncertainty, the EMEU can be a good indicator of market uncertainty.

The remainder of this study is organized as follows: Sections 2 and 3 discuss the empirical methods and data, respectively. Section 4 presents the results. The last section concludes the study.

2. Empirical Methods

As the first step, we investigate the asset correlation by using the copula-DCC approach. We assume that the 3×1 vector $Y_t \equiv [\Delta bitcoin_t, \Delta gold_t, \Delta stock_t]'$ follows the VAR(p) model,

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + u_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + H_t^{1/2}\varepsilon_t, \tag{1}$$

where $\Delta bitcoin_t$, $\Delta gold_t$ and $\Delta stock_t$ is the first difference in the log of the Bitcoin price, the gold price, and the stock price index. $H_t^{1/2}$ is an 3×3 positive definite matrix such that H_t is the conditional covariance matrix of Y_t, and ε_t is an 3×1 random vector whose expected value is $E[\varepsilon_t]=0$ and variance-covariance matrix is $Var[\varepsilon_t]=I_n$. Since the conditional mean of Y_t is $E\left[Y_t|\Omega_{t-1}\right] = A_0 + \sum_{i=1}^{p} A_i Y_{t-i}$, the conditional covariance matrix of Y_t can be defined as

$$Var\left[Y_t|\Omega_{t-1}\right] = Var\left[u_t|\Omega_{t-1}\right] = H_t^{1/2} Var_{t-1}\left[\varepsilon_t|\Omega_{t-1}\right]\left(H_t^{1/2}\right)' = H_t,$$

where Ω_{t-1} is the information set available at time $t-1$. We decompose the conditional covariance matrix H_t into

$$H_t = D_t R_t D_t = \begin{pmatrix} h_{11,t} & \rho_{12,t}\sqrt{h_{11,t}h_{22,t}} & \rho_{13,t}\sqrt{h_{11,t}h_{33,t}} \\ \rho_{12,t}\sqrt{h_{11,t}h_{22,t}} & h_{22,t} & \rho_{23,t}\sqrt{h_{22,t}h_{33,t}} \\ \rho_{13,t}\sqrt{h_{11,t}h_{33,t}} & \rho_{23,t}\sqrt{h_{22,t}h_{33,t}} & h_{33,t} \end{pmatrix}, \tag{2}$$

where D_t is a 3×3 diagonal matrix of time-varying standard deviations with $\sqrt{h_{ii,t}}$ ($i = bitcoin, gold, stock$) as an element of the diagonal. We obtain D_t by assuming that the conditional covariance $h_{ii,t}$ follows the univariate Exponential GARCH(1, 1) model. This assumption is based on the empirically stylized fact that negative shocks at time $t-1$ have a stronger impact on the variance at time t than positive shocks, which is called as the leverage effect,

$$\ln h_{i,t} = \alpha_i + \beta_i \ln h_{i,t-1} + \gamma_i \varepsilon_{i,t-1} + \delta_i \left(\left| \varepsilon_{i,t-1} \right| - E \left| \varepsilon_{i,t-1} \right| \right) \tag{3}$$

R_t is a 3×3 symmetric time-varying correlation matrix,

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}, \tag{4}$$

where Q_t is defined as the following exponential smoother equation, which is used solely to provide R_t

$$Q_t = (1-a-b)\bar{Q} + a\varepsilon_{t-1}\varepsilon'_{t-1} + bQ_{t-1} \tag{5}$$

where a and b satisfy the condition to ensure stationarity and positive definiteness of Q_t, and $\bar{Q}$ denotes the unconditional covariance matrix of the standardized residuals.

We model the joint distribution of the standardized residuals vector $D_t^{-1}u_t$ by using copulas.[2] Let x_i ($i = 1.\cdots, n$) be a random variable with a marginal distribution function F_i ($i = 1.\cdots, n$). Each multivariate distribution $F(x_1, \cdots, x_n)$ can be represented as its marginal distribution function by using a copula such as

$$F(x_1, \cdots, x_n) = C(F_1(x_1), \cdots, F(x_n)) \tag{6}$$

An n-dimensional copula C determined in $[0,1]^n$ for distributions F can be defined by:

$$C(u_1, \cdots, u_n) = F(F_1^{-1}(x_1), \cdots, F_n^{-1}(x_n)) \text{ for } u_i \in [0,1],\ i = 1.\cdots, n \tag{7}$$

Then, the density functions of F and C are given by:

[2] The following discussions are based on Ghalanos (2019), and copula-DCC model are estimated using R program with the “rmgarch” written by Ghalanos.

$$f(x_1,\cdots,x_n)=c(F_1(x_1),\cdots,F(x_n))\prod_{i=1}^{n}f_i(x_i) \tag{8}$$

$$c(u_1,\cdots,u_n)=\frac{f(F_1^{-1}(u_1),\cdots,F_n^{-1}(u_n))}{\prod_{i=1}^{n}f_i(F_i^{-1}(u_i)} \tag{9}$$

where f_i are the marginal densities and F_i^{-1} are the quantile functions of the margins.

We test the fit of four typical copulas, namely Normal, Student-t, Clayton, and Gumbel copulas, and select the family that best fits the data by using the Akaike's Information Criterion (AIC). As for the marginal distribution, we use the empirical distribution estimated by the non-parametric method.

As the second step, we estimate the conditional capital asset pricing model (conditional CAPM) with time-varying beta based on the copula-DCC approach above. The conditional CAPM is defined as

$$E\left[r_{i,t}\,|\Omega_{t-1}\right]=\frac{\operatorname{cov}\left[r_{i,t},r_{m,t}\,|\Omega_{t-1}\right]}{\operatorname{var}\left[r_{m,t}\,|\Omega_{t-1}\right]}E\left[r_{m,t}\,|\Omega_{t-1}\right]=\beta_{i,t}E\left[r_{m,t}\,|\Omega_{t-1}\right], \tag{10}$$

where $r_{i,t}$ and $r_{m,t}$ denote the excess return on the asset i and the market portfolio, respectively. $\beta_{i,t}$ calculated as $\operatorname{cov}\left[r_{i,t},r_{m,t}\,|\Omega_{t-1}\right]/\operatorname{var}\left[r_{m,t}\,|\Omega_{t-1}\right]$ is the dynamic conditional beta, which could be a better measure of the riskiness of an asset in comparison to the overall stock market.

As Lewellen and Nagel (2006) and Fama and French (2006) show, the conditional beta can be estimated using rolling regression as follows:

$$r_{i,t}=\alpha_{i,\tau}+\beta_{i,\tau}r_{m,t}+\varepsilon_{i,t}$$

where τ stands for estimation window.[3] However, Boguth *et al.* (2011) point out that this approach could generate an *overconditioning* bias in beta because the empirical estimate of $\beta_{i,\tau}$ depends on information not available to investors at time *t*-1[4]. On the other hand, the conditional beta estimated by DCC-GARCH approach, which is proposed by Bali, *et al.*

[3] Fama and French (2006) include the lagged market return to take into account the first-order autocorrelation in returns, and estimate $r_{i,t}=\alpha_{i,\tau}+\beta_{i1,\tau}r_{m,t}+\beta_{i2,\tau}r_{m,t-1}+\varepsilon_{i,t}$. The beta is calculated as the sum of $\beta_{i1,\tau}$ and $\beta_{2i,\tau}$.

[4] Boguth *et al.* (2011) define the *overconditioning* bias as $-\operatorname{cov}\left[\left(\beta_{i,\tau}-\beta_{i,\tau|t-1}\right)\left(r_{m,\tau}-\overline{r}_{m,\tau}\right)\right]$, and show that the bias could be reduced by using only information contained in Ω_{t-1}.

(2017), depends only on lagged information, and thus can eliminate the *overconditioning* bias. Moreover, Bali, *et al*. (2017) argue that the conditional beta estimated by DCC-GARCH family has a dynamic feature that puts more weight on more recent observations and varies each day in the estimation; therefore, it can be a better measure of risk. Following Bali *et al*. (2017), we calculate the conditional variance of market portfolio $\mathrm{var}\left[r_{m,t} \middle| \Omega_{t-1}\right]$ based on univariate Exponential GARCH(1, 1) model, and estimate the conditional covariance $\mathrm{cov}\left[r_{i,t}, r_{m,t} \middle| \Omega_{t-1}\right]$ using the copula-DCC approach described above.

As the third step, we investigate the contagion effect by using the threshold approach developed by Hansen (2000). In the concrete, we regress the estimated dynamic conditional correlation on the proxy of market uncertainty, the VIX or the EMEU. If market uncertainty has statistically significant effects on the estimated dynamic conditional correlation, but the threshold does not exist, it means that the degree of the role of the currency as a diversifier or hedge changes as the market uncertainty changes. If there exist thresholds above which market uncertainty has statistically significant effects on the estimated dynamic correlation, it can be interpreted as the evidence of "correlation breakdown", namely contagion. However, if market uncertainty does not have statistically significant effects and there are no threshold effects, it can be regarded as the interdependence when the correlations are high on average, or no-interdependence when the correlations are close to zero on average.

We specify the estimation equation as follows:

$$\begin{aligned} dcc_{is,t} &= \alpha_i + \beta_{1,i} \ln MU_t I_1(\theta_0 < \ln MU_t \le \theta_1) + \cdots \\ &\quad + \beta_{m+1,i} \ln MU_t I_{m+1}(\theta_m < \ln MU_t \le \theta_{m+1}) + \delta_i dcc_{is,t-1} + \varepsilon_{i,t} \end{aligned} \tag{11}$$

with *m* thresholds and *m*+1 regions, where *j* indicates the regions, and $I_j(\theta_{j-1} < \ln MU_t \le \theta_j)$ is an indicator for the *j*th region. MU_t denotes market uncertainty, which is proxied by the VIX or the EMEU. $dcc_{is,t}$ stands for the estimated dynamic conditional correlation between asset *i* (Bitcoin, gold) and the stock price index *s* (World, U.S.). θ_j is the threshold parameter to be estimated.

3. Data

Our sample period runs from 3 January 2011 to 31 December 2019 due to data availability. The prices of Bitcoin and gold (the London Bullion Market) are denominated in terms of USD. As for the stock price indices, we consider MSCI World and MSCI U.S. as proxies for the world stock market condition. In estimating the conditional beta, we use U.S. 3-months treasury bill rate for riskless interest rate. The data are sourced from Investing.com (Bitcoin), *Datastream* (gold price, stock indices, treasury bill rate), Cboe (VIX), and the Federal Reserve Bank of St. Louis (EPEU).

Table I provides descriptive statistics of the first difference in the log of the prices of gold and Bitcoin, and two stock price indices. The average, the range, and the standard deviation of Bitcoin are much larger than those of gold and stock price indices. Table II provides unconditional correlations. We can see that the correlations of Bitcoin returns with stock price indices are lower than those of gold, which means that the behavior of the Bitcoin return is more independent from stock markets. Moreover, World and U.S. indices are highly correlated with each other and are negatively correlated with the VIX and the EMEU. The VIX and the EMEU are positively correlated, with a correlation coefficient of 0.374.

Table I. Descriptive Statistics

	Bitcoin	GOLD	World	U.S.
Observations	2,346	2,346	2,346	2,346
Mean	0.0072	0.0001	0.0003	0.0004
3rd Quantile	0.0234	0.0049	0.0043	0.0048
Median	0.0004	0.0001	0.0005	0.0003
1st Quantile	-0.0145	-0.0043	-0.0031	-0.0030
Max	3.3675	0.0558	0.0420	0.0497
Min	-0.5721	-0.0966	-0.0512	-0.0672
Standard Deviation	0.0954	0.0095	0.0079	0.0089
skewness	19.0662	-0.6699	-0.5561	-0.4748
kurtosis	662.2006	11.0367	7.8019	8.1898

Table II. Unconditional Correlations

	Bitcoin	gold	World	U.S.	VIX(level)	EMEU(level)
Bitcoin	1					
gold	0.002	1				
World	0.008	0.061	1			
U.S.	0.015	-0.031	0.919	1		
VIX(level)	-0.043	0.029	-0.199	-0.177	1	
EMEU(level)	0.002	0.049	-0.085	-0.067	0.374	1

Notes: (1) The prices of gold and Bitcoin and stock price indices are in the first difference in the logarithm. The VIX and the EMEU are the actual values.

4. Empirical Results

Table III shows the results of the selection of copulas. We test four typical copulas—Normal, Student-t, Clayton, and Gumbel copulas—and select the best-fitted family based on the AIC for each pair of Bitcoin or gold with the world or U.S. stock price index. We can see that all pairs are well described by Student-t copula. It is well known that Student-t copula can better capture dependence between extreme values, namely tail dependence, than Normal copula. The density of the Student-t copula with the shape parameter τ is defined by

$$c(u_1,\cdots,u_n;R_t,\tau)=|R_t|^{-\frac{1}{2}}\frac{\Gamma\left(\frac{\tau+n}{2}\right)\Gamma\left(\frac{\tau}{2}\right)^n\left(1+\frac{1}{\tau}t_\tau^{-1}(u)'R_t^{-1}t_\tau^{-1}(u)\right)^{-\frac{\tau+n}{2}}}{\left\{\Gamma\left(\frac{\tau+n}{2}\right)^n\right\}^n\Gamma\left(\frac{\tau}{2}\right)\prod_{i=1}^n\left(1+\frac{(t_\tau^{-1}(u_i))^2}{\tau}\right)^{-\frac{\tau+1}{2}}} \tag{12}$$

where $t_\tau^{-1}(\cdot)$ is the quantile function.

The correlation parameters and Kendall's τ are close to zero for the pair (Bitcoin, World) and (Bitcoin, U.S.), which means that Bitcoin is uncorrelated with stock prices on average. As for gold, the correlation parameter and Kendall's τ is positive for the pair (gold, World) while negative for (gold, U.S.).[5] From the above results, we can infer that Bitcoin is a weak hedge, and gold is a diversifier against the world stock market, while it is a strong hedge against the U.S. stock market.

Table III. Selections of Copula

	WORLD		U.S.	
	BTC	GOLD	BTC	GOLD
Copula	t	t	t	t
Correlation Parameter	0.01	0.07	0	-0.03
The Degree of Freedom	14.05	4.43	14.86	5.41
Kendall's τ	0	0.04	0	-0.02
Upper Tail Dependence	0	0.08	0	0.04
Lower Tail Dependence	0	0.08	0	0.04

Figure 1 displays the estimated dynamic conditional correlations (left axis) and the estimated conditional betas (right axis). In the estimation, we choose a multivariate *t* copula based on the previous results. From the figures, we can see that the estimated dynamic conditional correlations are relatively smaller for Bitcoin than for gold, which means that the behavior of the Bitcoin return is more independent than stock markets. The average of the dynamic correlation is 0.004 for the pair (Bitcoin, World) and 0.001 for (Bitcoin, U.S.). Therefore, we can infer that Bitcoin is a weak hedge because it is uncorrelated with stock price indices on average. However, the average of the dynamic correlation is 0.07 for the pair (Gold, World) and -0.03 for (Gold, U.S.). Therefore, we can reconfirm that Bitcoin is a weak hedge, and

5 Kendall's τ is a rank correlation coefficient, which is defined as

$$\Pr\left\{(x_1^i-x_1^j)(x_2^i-x_2^j)>0\right\}-\Pr\left\{(x_1^i-x_1^j)(x_2^i-x_2^j)<0\right\}.$$

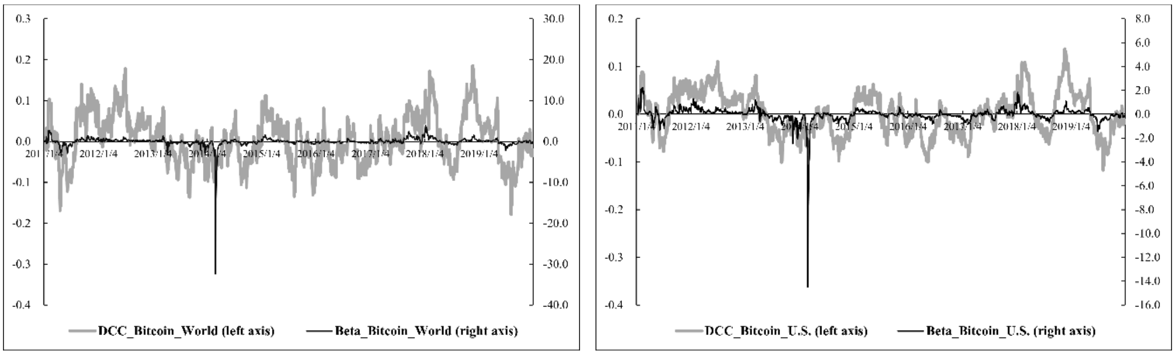
for two random variables (x_1,x_2). If the condition $x_1^i>x_1^j$ and $x_2^i>x_2^j$ is always satisfied, then $\tau=1$. On the other hand, if the condition $x_1^i>x_1^j$ and $x_2^i<x_2^j$ is always satisfied, then $\tau=-1$.

gold is a diversifier against the world stock market, while it is a strong hedge against the U.S. stock market.

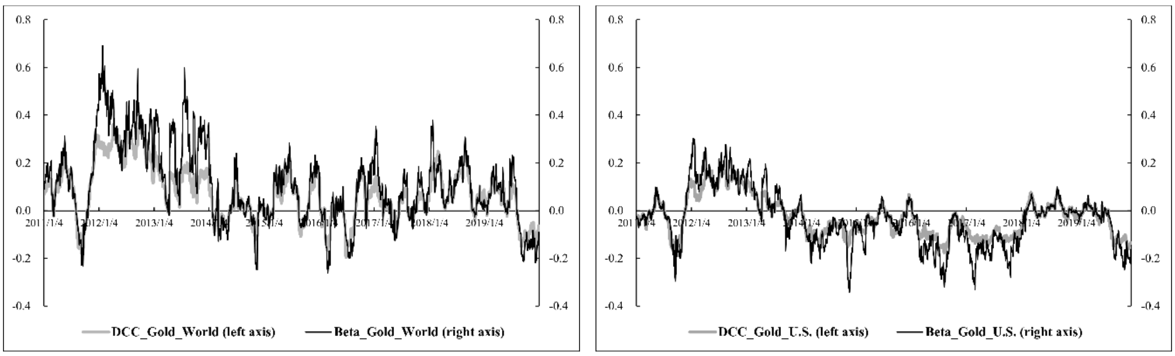
As for the conditional betas, the average of the conditional betas of Bitcoin with respect to World and U.S. is -0.048 and -0.032, respectively. However, as we can see from the figures, these results are due to the outliers between late February and early March 2014, when Mt. Gox, the world's largest bitcoin trading exchange at the time, missed 850,000 bitcoins (around $480 million at the time) and eventually collapsed. If we remove these outliers, the average turns into 0.02 and 0.004. The average of the conditional bates of gold with respect to World and U.S. is 0.109 and -0.037, respectively. These results imply that Bitcoin moves in the same direction as world and U.S. stock markets, while gold moves in the same direction as the U.S. stock market but in the opposite direction with the world stock market. It also indicates that the returns of Bitcoin and gold are not sensitive to changes in the value of market portfolio, and thus the riskiness of Bitcoin and gold with respect to the market portfolio is relatively low.

Figure 1. Estimated Dynamic Conditional Correlation and Conditional Beta

(a) Bitcoin



(b) Gold



In the next step, we estimate the threshold model described by equation (10) to investigate whether market uncertainty measured by the VIX or the EMEU has significant effects on the estimated dynamic conditional correlation and whether there exists a threshold effect.

Table IV shows the results. For Bitcoin, the threshold effect does not exist, but the correlations with the World and the U.S. are positively affected by the increase in the VIX. These results mean that an increase in market uncertainty would weaken its role as a weak hedge and Bitcoin would become a diversifier. Contrastingly, the EMEU does not have significant effects on the correlation. For gold, the threshold does not exist, but the correlations of gold with both stock indices are affected negatively by both the VIX and the EMEU. These results mean that an increase in market uncertainty changes the role of gold as a diversifier into a hedge or a safe haven. These results are consistent with those of Bouri *et al*. (2017).

The above results mean that although Bitcoin is called as "new gold", the financial assets status of Bitcoin and gold are different. Bitcoin can offer a medium of weak hedge in the tranquil period, but the Bitcoin return decreases when market uncertainty increases and stock returns also decrease. However, gold prices are positively related to stock prices in the tranquil period, but they can offer a medium of hedge or safe haven when market uncertainty increases.

Table IV. Estimation Results of Threshold Model

	World		U.S.	
	BTC	GOLD	BTC	GOLD
Number of Threshold	0	0	0	0
l_vix	0.00212*	-0.00348***	0.00117*	-0.00124*
	(0.00117)	(0.00127)	(0.00066)	(0.00069)
dcc(-1)	0.96446***	0.98892***	0.97944***	0.99449***
	(0.00543)	(0.00314)	(0.00412)	(0.00240)
constant	-0.00569'*	0.01033***	-0.00320*	0.00321*
	(0.00322)	(0.00349)	(0.00183)	(0.00193)

	World		U.S.	
	BTC	GOLD	BTC	GOLD
Number of Threshold	0	0	0	0
l_emeu	0.00022	-0.00113***	0.00012	-0.00055***
	(0.00031)	(0.00035)	(0.00018)	(0.00019)
dcc(-1)	0.96647***	0.98829***	0.98124***	0.99433***
	(0.00530)	(0.00314)	(0.003976)	(0.00237)
constant	-0.00060	0.00445***	-0.00036	0.00158**
	(0.00105)	(0.00120)	(0.00059)	(0.00064)

Notes: (1) Standard errors are in parentheses.

(2) The asterisks ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively.

5. Conclusions

In this study, we employ the copula-DCC approach to investigate the financial assets status of Bitcoin and gold. Our results indicate that Bitcoin is a weak hedge against the overall stock markets, while gold is a diversifier against the world stock market, but a strong hedge against the U.S. stock market. We also estimate the dynamic conditional betas and find that the returns of Bitcoin and gold are not sensitive to changes in the value of market portfolio. Moreover, we employ the threshold model to investigate whether there exist contagion effects between Bitcoin or gold market and stock markets. Our results show that the increase in market uncertainty weakens its role as a weak hedge and Bitcoin becomes a diversifier, while it changes the role of gold as a diversifier into that of a hedge or a safe haven.

Nevertheless, there are some topics for future research. In the analysis of the contagion, we calculate the correlations from which we cannot infer causation; therefore, it might be useful to employ the causality in the quantile method to analyze the contagion between foreign exchange markets and the stock markets by considering tail dependence.

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