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Co-movements between Bitcoin and Gold: A wavelet coherence analysis

Sang Hoon Kang [a,b,*], Ron P. McIver [b], Jose Arreola Hernandez [c]

[a] Department of Business Administration, Pusan National University, Busan 609-735, Republic of Korea
[b] School of Commerce, University of South Australia, Australia
[c] Rennes School of Business, Rennes, Brittany, France

HIGHLIGHTS

- We examine the structure of correlation and co-movements between the gold futures and Bitcoin markets.
- We employ both the DCC–GARCH and wavelet coherence methods.
- We find evidence of volatility persistence, causality, and phase differences between Bitcoin and gold futures prices.
- The contagion hypothesis is observed to increase during the 2010–2013 European-debt crisis.
- Wavelet coherence results indicate a relatively high degree of co-movement across the 8–16 week frequency band between Bitcoin and gold futures prices.

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ABSTRACT

In this paper, we use dynamic conditional correlations (DCCs) and wavelet coherence to examine the hedging and diversification properties of gold futures vis-à-vis Bitcoin prices. Our research aims to reveal whether the bubble patterns of behavior in gold futures prices can be used to hedge against the bubble behavior in the Bitcoin market in the short-term, and vice versa; as well as whether each can be used to manage and hedge overall market and sector downside risk of the other asset/commodity. We find evidence of volatility persistence, causality, and phase differences between Bitcoin and gold futures prices. Contagion is observed to increase during the European sovereign debt crisis. Wavelet coherence results indicate a relatively high degree of co-movement across the 8–16 weeks frequency band between Bitcoin and gold futures prices for the 2012–2015 time period.

1. Introduction

In the finance literature, gold's roles as a surrogate currency, inflation hedge, safe-haven asset, and its use in achieving greater risk diversification in investors' portfolios, have received increased attention from policy makers, portfolio

* Corresponding author at: Department of Business Administration, Pusan National University, Busan 609-735, Republic of Korea
E-mail addresses: sanghoonkang@pusan.ac.kr (S.H. Kang), ronald.mciver@unisa.edu.au (R.P. McIver), jose.arreola-hernandez@rennes-sb.com (J.A. Hernandez).

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investors and risk managers. This is especially the case following the abandonment of gold convertibility. Gold's role as a surrogate currency reflects its historic roles as a store of value and medium of exchange [1], being a scarce resource and highly valued across different cultures. Gold's surrogate currency role is also associated with its more recent functions as a dollar hedge, due to U.S. dollar pricing [2–5], and that its price volatility is strongly linked to monetary rather than other macroeconomic and financial variables [6].

Although varying in effectiveness over time, gold's potential as a long-term inflation hedge has been suggested, particularly against changes in the U.S. CPI [7–9]. This is particularly the case during periods of very high inflation. A limited stock and short-run inelasticity of supply increase perceptions of gold as a hard currency; one that will maintain its purchasing power in the presence of positive, particularly high, inflation rates [10]. This is evidenced in investors' initial purchases of gold as a potential hedge against the expected inflationary effects of the first two waves of quantitative easing by the U.S. Federal Reserve [11]. An extension, also argued by Lucy et al. [12], is that gold can serve as a hedge asset against an increase in the money supply.

Gold has also become widely regarded as a safe-haven asset (albeit weak) for equity investors, especially under adverse market circumstances [1,13–15]. However, this is again with varying levels of effectiveness, both across different equity markets and time periods [16–19]. Importantly, this role is strongest over a short time horizon, and is particularly evident during crisis periods [20]. Like gold, Bitcoin, the most recognized and valuable of the cryptocurrencies available globally, possesses the characteristics of both a limited stock and short-run inelasticity of supply [21]. Bitcoin's scarcity is a reason for it being argued to be synthetic commodity money, in addition to it sharing an absence of intrinsic value with fiat money [22]. Baeck and Elbeck [23] posit that Bitcoin is just a speculative commodity rather than a currency. Cheah and Fry [24] provide evidence that as with many asset classes, Bitcoin exhibits speculative bubbles and its fundamental price is zero. Assuming its potential as synthetic commodity money, Weber [25] explores the possibility of a global Bitcoin standard. Baur, et al. [26] suggest that Bitcoin's excess returns and volatility rather resemble a highly speculative asset than gold or the US dollar. The study concludes that, given Bitcoin and gold's distinguishing characteristics, a Bitcoin standard would lead to a macro-financial scenario where constant exchange rates and low deflation occur.

Additionally, unlike standard forms of currencies in circulation, Bitcoins' liquidity and volatility do not appear to be influenced by a centralized system of financial institutions (e.g., central banks) [26] or other major macroeconomic factors [23,27]. Instead, supply–demand factors within the Bitcoin market itself dominate price behavior [27], with both major market developments and price manipulation having been associated with bubble behavior in the Bitcoin market [28]. Bitcoin's price may, therefore, potentially be detached from the economic and business cycles stemming from monetary policy and central bank management of the money supply. It is this last property that suggests Bitcoin may serve as a dynamic diversification and hedging tool, and therefore for managing volatility exposures in the gold markets [29,30]. However, potential variation in cryptocurrency market efficiency and volatility persistence over the short-term, medium-term, and long-term, suggest that any analysis must account for variations in price dynamics over alternative time-scales [31].

Based on the above insights, we assess the co-movement between gold futures and Bitcoin prices markets. To do this, we utilize both a dynamic conditional correlation (DCC) with GARCH specification model and the wavelet coherence method. The combination of the DCC–GARCH and wavelet modeling strategies allows us to extract information about both the time-varying and time–frequency structure of correlation and co-movements between the markets under consideration. Specifically, the use of wavelet decomposition allows disaggregation of the homogeneous relationship assumed between returns within the time domain, into relationships between returns over different investment time-scales [32,33]. In doing so we aim to address the need to recognize variations in price dynamics [31], preference levels for risk [34], and diversification and thus risk management properties [35], over differing time-scales. We then use the phase difference approach to provide further information on the direction of co-movements, as well as to detect potential causal relationships between gold future and Bitcoin returns. Our research aims to reveal whether gold futures' price bubble behavior can hedge against bubble behavior in the Bitcoin market in the short-term, and vice versa; as well as whether either market can be used to manage and hedge the overall market risk of the other asset/commodity.

Our motivation for analyzing the co-movement between gold and Bitcoin is that both markets are heavily subject to speculation and market expectations. On the other hand, as gold price patterns are partially determined by the effects of monetary policy and financial regulation, in contrast to Bitcoin prices, the duration of Bitcoin price bubble cycles may be expected to differ from gold price bubble cycles in the short-run. Additionally, while gold is used as a safe-haven asset in times of financial uncertainty, Bitcoin, does not appear to be influenced by macroeconomic factors. This may make it possible for both markets to hedge against each other in the short term, under specific market circumstances.

Our study is broadly linked to recent research by Dyhrberg [36,37], and Bouri, et al. [29]. Dyhrberg [36] examines Bitcoin's hedging properties in relation to gold and currency market behaviors, and identifies similarities between the Bitcoin, gold, and the US dollar markets. Using asymmetric GARCH models, Dyhrberg [37] examines Bitcoin's use as a hedge against equity and currency price fluctuations, finding that Bitcoin possesses some of gold's hedging properties. As a result, it is suggested as an alternative financial instrument and tool for financial risk management. Finally, Bouri, et al. [29] investigate the diversifying, hedging and safe heaven properties of Bitcoin against fluctuations in energy commodity markets. They find that while Bitcoin displays marked hedging characteristics for investable energy commodity portfolios in the pre-crisis period, post-crisis Bitcoin functions only as a diversifier. Bouri et al. [38] also suggest the important roles of Bitcoin in diversifying and hedging against the risk of stock markets.

We contribute to the limited recent empirical literature firstly by examining the time–frequency structure of correlation and co-movements between the gold futures and Bitcoin markets using both the DCC–GARCH and wavelet coherence methods, respectively. Secondly, with respect to the diversification and hedging properties of the gold and Bitcoin markets, this study is the first to employ phase differences from wavelet coherence to provide information on the direction of co-movement and causal relationships between the Bitcoin and gold futures markets. We find evidence of volatility persistence, causality and phase differences between Bitcoin and gold futures. The contagion effect is confirmed for the 2010–2013 European debt crisis. The wavelet coherence results indicate a relatively high degree of co-movement between Bitcoin and gold futures for the 2012–2015 time period, across the 8-week to 16-week frequency band.

The remainder of this paper is organized as follows. Section 2 explains the modeling framework implemented. Section 3 describes the data, justifies the financial variables considered, and conducts some preliminary analyzes. Section 4 discusses the empirical results. Section 5 provides concluding remarks.

2. Econometric modeling framework

2.1. DCC-GARCH model

We estimate the time-varying correlations between Bitcoin and gold futures using the DCC–GARCH model of Engle [39]. Let us consider an autoregressive process of the mean equation using a 2×1 vector of r_t return series:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t, \tag{1}$$

where μ is a vector of constant terms, and ε_t is the 2×1 vector of error terms. Next, the conditional variance $h_{i,t}$ is estimated from the univariate GARCH(1,1) process defined as:

$$h_{i,t} = \omega_1 + \alpha_1 \varepsilon^2_{i,t-1} + \beta_1 h_{i,t-1}, \tag{2}$$

where $\omega_1 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$. To examine the dynamic conditional correlations (DCC) between gold futures and Bitcoin returns, we assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}\left[\varepsilon_t \varepsilon'_t\right] = H_t$, where $E_t[\cdot]$ is the conditional expectation for using the information set available at time t. The conditional variance–covariance matrix (H_t) can be written as follows:

$$H_t = D_t P_t D_t, \tag{3}$$

where P_t denotes the 2×2 symmetric matrix of dynamic conditional correlation, and $D_t = diag\left(h^{1/2}_{11,t}, \ldots, h^{1/2}_{NN,t}\right)$, $h_{ii,t}$ represents as the conditional variances of each return series. The dynamic conditional correlation matrix P_t decomposes to

$$P_t = (diagQ_t)^{-1/2}\, Q_t\, (diagQ_t)^{-1/2}, \tag{4}$$

$$Q_t = [q_{ij,t}] = (1 - a - b)\, S + a u_{t-1} u'_{t-1} + b Q_{t-1}, \tag{5}$$

where Q_t defines the covariance matrix of the standardized residuals $u_t = \left(u_{i,t}, \ldots, u_{k,t}\right)$. $S = \mathrm{Cov}\left(u_t u'_t\right) = E\left(u_t u'_t\right)$ is the 2×2 unconditional covariance matrix of u_t, and a and b are non-negative scalars and $a + b < 1$. The time-varying DCCs are defined as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}, \tag{6}$$

The final estimation is performed by maximizing the log-likelihood of the model given by:

$$L = \left(\frac{1}{2}\right) \sum_{i=1}^{T} \left(n \ln(2\pi) + \ln|D_t| + \varepsilon'_t D_t^{-1} \varepsilon_t\right) - \left(\frac{1}{2}\right) \sum_{i=1}^{T} \left(\ln|R_t| + \varepsilon'_t R_t^{-1} \varepsilon_t - \varepsilon'_t \varepsilon_t\right). \tag{7}$$

2.2. Wavelet coherence

In contrast to the GARCH–DCC model, the wavelet coherence method allows us to capture the co-movement between Bitcoin and gold futures in both the time and frequency domains. The wavelet coherence method implements a bivariate framework based on a continuous wavelet transform (with Morlet set to 6), allowing for various scaled forms of localization [40]. In addition, the wavelet coherence method sheds more light on co-movement between Bitcoin and gold futures, in comparison to conventional casualty and correlation analysis [41].

To characterize co-movement between time series in the time and frequency domains, we estimate the wavelet coherence by using the cross-wavelet transform and cross-wavelet. Following the approach of Torrence and Compo [42],

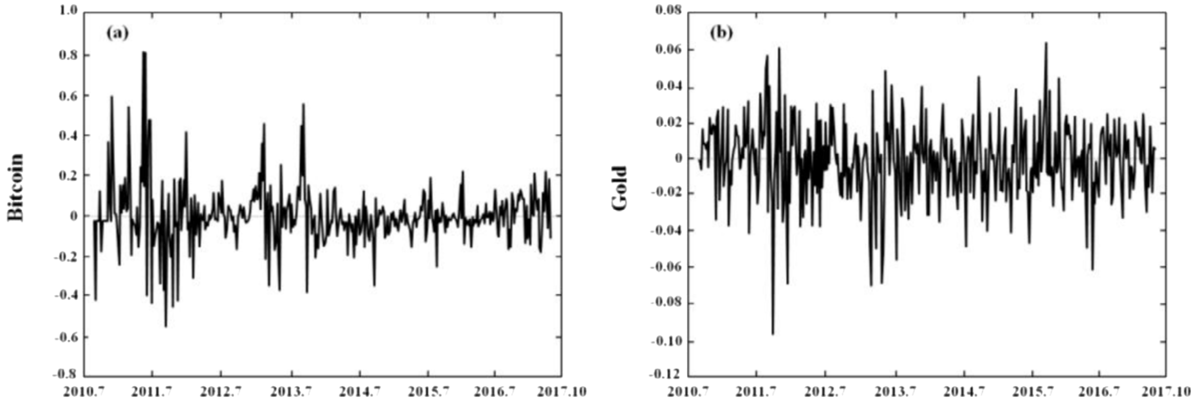

Fig. 1. The dynamics of Bitcoin and gold futures returns.

we define the cross wavelet transform of time-series$x(t)$ and $y(t)$ with the continuous wavelet transforms (CWT) $W_n^x(u,s)$ and $W_n^y(u,s)$ as follows:

$$W_n^{xy}(u,s) = W_n^x(u,s)\, W_n^{y*}(u,s) \tag{8}$$

where u refers to the location and s is the scale. The * denotes the complex conjugate. The CWT reveals areas in the time–frequency domain where time series show a high common power; that is, it represents the local covariance between the time series at each scale.

The wavelet coherence can detect co-movement between time-series in the time–frequency domain. Following Torrence and Webster [43], the wavelet coherence of time-series can be defined as:

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W^{xy}(u,s)\right)\right|^2}{S\left(s^{-1}\left|W^x(u,s)\right|^2\right) S\left(s^{-1}\left|W^y(u,s)\right|^2\right)} \tag{9}$$

where S is considered as a smoothing operator over time as well as scale, with $0 \le R^2(u,s) \le 1$ [40]. The value of the wavelet squared coherence $R^2(u,s)$ gives a quantity between 0 and 1, with a high value showing strong co-movement between time series and vice versa.[1] However, unlike the standard correlation coefficient, the wavelet squared coherence only takes positive values. The graphical presentation of the wavelet squared coherence enables us to identify areas of co-movement between time series in the time–frequency space. In this context, we cannot distinguish between positive and negative correlation. Thus, we use the phase difference of Terrence and Compo [42] to provide information on positive and negative co-movements, as well as on causal relationships between time series. The wavelet coherence phase difference is determined as follows:

$$\Phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W^{xy}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W^{xy}(u,s)\right)\right\}}\right) \tag{10}$$

where, $\Im$ and $\Re$ are the imaginary and real parts of the smoothed cross-wavelet transform, respectively. Phase is indicated by black arrows on the wavelet coherence plots. A zero phase-difference means that the time series move together. The arrows point to the right (left) when time series are in-phase (out of phase) or are positively (negatively) correlated. An upward pointing arrow means that the first time series leads the second by $\pi/2$, whereas an arrow pointing down indicates that the second time series leads the first by $\pi/2$. A combination of positions is generally more common.

3. Data and summary statistics

This study applies the wavelet method to weekly data of Bitcoin and gold futures prices from 26th July 2010 to 25th October 2017. Bitcoin price data is sourced from the Coindesk Price Index while gold futures data are drawn from the Thomson Reuters database. We calculate the continuously compounded weekly returns by finding the difference between logarithms of two consecutive prices: $r_{i,t} = ln\left(P_{i,t}/P_{i,t-1}\right)$. $r_{i,t}$ denotes the continuously compounded percentage returns and $P_{i,t}$ the price level of index i at time t. Fig. 1 depicts the evolution dynamics of the return series and illustrates the stylized factors (e.g., volatility clustering) for the Bitcoin and gold futures return series.

Our motivation for selecting gold futures prices against Bitcoin prices in analyzing the hedging properties of gold and Bitcoins is that both markets are heavily subject to speculation and market expectations. The motivation behind the

[1] On the wavelet coherence plots, red colors represent strong co-movement whereas blue colors corresponds to weak co-movements.

Table 1
Summary descriptive statistics.

	Bitcoin	Gold
Mean	0.0293	0.00021
Maximum	0.8671	0.0681
Minimum	−0.5409	−0.1013
Std. dev.	0.1572	0.0227
Skewness	1.0167	−0.4124
Kurtosis	9.2329	4.3643
Jarque–Bera	684.16***	40.456***
ADF	−10.189***	−17.562***
PP	−18.154***	−17.518***
KPSS	0.2110	0.1798

Notes: The Jarque–Bera test checks for normality. ADF, PP and KPSS are the empirical statistics of the Augmented Dickey and Fuller [45], and the Phillips and Perron [46] unit root tests and the Kwiatkowski et al. [47] stationarity test, respectively.
***Denotes the rejection of the null hypothesis at the 1% significance level.

Table 2
Toda–Yamamoto test for $d_{max} = 1$.

Null hypothesis	MWALD statistic	Decision
Gold does not Granger cause Bitcoin	8.0875**	Reject H_0
Bitcoin does not Granger cause Gold	4.2896	Accept H_0

Note:
**Denotes significance at 5% level.

selected data sample time period is that it accounts for two financial and economic events of regional and global scale, namely, the Eurozone sovereign debt crisis which extended from 2010 to around 2013, and the most recent oil price crisis that started in August 2014. Due to the financial market uncertainty caused by each of these events, it is possible that spillover effects were received by gold and Bitcoin prices. Gold prices for instance, are well-known for being a hedge against the inflation caused by oil price increases [8,44].

Table 1 presents the descriptive statistics of the return series. As shown in Table 1, Bitcoin has far higher values for the mean and volatility. Both return series are skewed with excess kurtosis. These findings indicate that the probability distributions of these return series are asymmetric and leptokurtic, rejecting normality, which is also confirmed by the Jarque–Bera statistics (J–B). Furthermore, this analysis also considers the Augmented Dickey–Fuller [45] and Phillips–Perron [46] unit root tests along with the Kwiatkowski et al. [47] stationarity test. The results indicate that all return series are stationary.

Table 2 reports the results of Toda–Yamamoto causality test to examine the causal relationship between Bitcoin and gold futures returns. We make use of modified Wald (MWALD) statistics to estimate H_0 of Granger causality. The MWALD statistics follow a chi-square distribution with k degrees of freedom. From Table 2, we reject Granger non-causality from gold to Bitcoin, implying gold futures returns have an influence on Bitcoin returns. In contrast, we observe that Bitcoin returns do not contain any information for gold futures returns, since the null hypothesis of Granger non-causality from gold to Bitcoin returns cannot be rejected at any conventional levels of significance.

4. Empirical results

4.1. Estimation of DCC-GARCH model

The results of the estimation of the DCC–GARCH (1,1) model between Bitcoin and gold futures markets are summarized in Table 3. Looking at the estimates of the univariate GARCH model (Panel A), the ARCH and GARCH terms are significant, and the sum of ARCH and GARCH terms are very close to unity. This implies volatility persistence in both Bitcoin and gold futures returns. Panel B of Table 3 reports the estimates of the DCC model. The coefficient a is positive and significant, underlying the importance of shocks between the precious metal and the stock markets. The parameter b is significant and very close to one, confirming the higher persistence of volatility between Bitcoin and gold. It is worth noting that the significance of the parameters a and b confirms the appropriateness of the DCC–GARCH model.

Based on the diagnostic tests (Panel C), the Ljung–Box test statistics for the standardized residuals and the squared standardized residuals do not reject the null hypothesis of no serial correlation at the 1% significance level, providing no evidence of misspecification in our model. Moreover, the Hosking [48] and Mcleod and Li [49] test results suggest rejection of the alternative hypothesis of no serial correlation in the conditional variances estimated by the DCC–GARCH model and, therefore, there is no evidence of statistical misspecification of the DCC–GARCH model.

Fig. 2 plots the dynamic conditional correlations obtained from the DCC–GARCH model. We observe time-varying correlations over the sample period, meaning that investors require frequent adjustment of their portfolio structures

Table 3
Empirical results of the DCC–GARCH model.

	Bitcoin	Gold
Panel A: Estimates of AR(1)-GACH (1,1) model		
Const.(m)	0.0165 (0.0055)***	0.0002 (0.0011)
AR(1)	0.0778 (0.0588)	0.0804 (0.0541)
Const.(ν)	0.0004 (0.0002)*	0.3638 (0.1614)**
ARCH(1)	0.1716 (0.0820)**	0.0744 (0.0332)**
GARCH(1)	0.8291 (0.0625)***	0.8558 (0.0405)***
Panel B: DCC estimates		
Average Corr.	0.0713 (0.1038)	
a	0.0178 (0.0029)***	
b	0.9670 (0.0132)***	
Panel C: Diagnostic tests		
Q(20)	31.134 [0.0534]	13.053 [0.8750]
Qs(20)	20.985 [0.3979]	31.045 [0.0545]
Hosking(20)	93.013 [0.1179]	
Li–McLeod(20)	92.778 [0.1213]	

Notes: Qs(20) are the Ljung–Box test statistics applied to the squared standardized residuals and 20 lags. Hosking [48] and McLeod and Li [49] multivariate Portmanteau statistics checks for the null hypothesis of no serial correlation (using 20 lags). The p-values are in brackets and the standard errors are in parentheses.

*Indicate significance at the 10% levels.

**Indicate significance at the 5% levels.

***Indicate significance at the 1% levels.

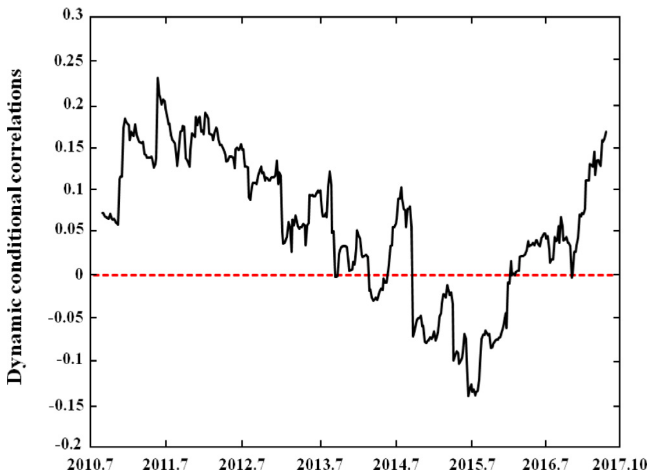

Fig. 2. Dynamic conditional correlations (DCC) between the Bitcoin and gold.

between Bitcoin and gold. More importantly, the level of DCC increases during the 2010–2013 European debt crisis, supporting the presence of contagion effects. This effect can be particularly visible during periods of turmoil, which diminish the benefits of international portfolio diversification for investors. However, we view a significant decrease and negative correlations during 2014–2016, indicating a decoupling between the Bitcoin and gold markets. This reflects that this was a period of low average return and volatility in the Bitcoin market [28]. These results support improved diversification benefits between Bitcoin and gold during the 2014–2016 period.

4.2. Wavelet coherence

We employ the continuous wavelet power spectrum and coherence between Bitcoin and gold futures returns in Figs. 3 and 4, respectively. Technically, the definition of the wavelet power spectrum is the absolute value of the square of the wavelet transform, which provides a measure of the time series variance at each time and at each scale (frequency). The horizontal axis denotes the time component while the vertical axis represents the frequency component, from scale 1 (a week) up to scale 64 (more than 1-year). The black contours indicate regions with significance at the five percent level, as estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence, shown by a

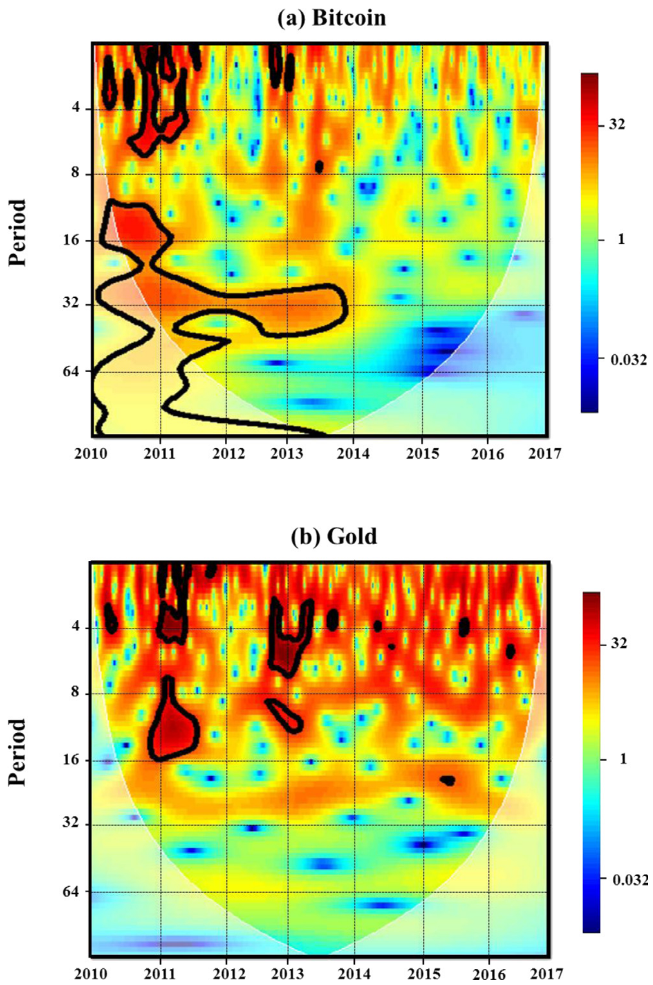

Fig. 3. Continuous wavelet transforms for Bitcoin (a) and gold (b). Notes: The horizontal axis shows time, while the vertical axis refers to the period in weeks. The white line refers to the cone of influence, and where edge effects might distort the picture is shown as a lighter shade. The black contour denotes the 5% significance level. The color code of power varies from red (high power) to blue (low power).

solid curved line indicates the zone affected by edge effects. The range of power is from red (high power) to blue (low power).

As shown in Fig. 3, both series demonstrate high power between 2011 and 2013 over short-run and medium-run scales. This implies a relatively high level of variation during the period of the European sovereign debt crisis. At all other times and frequencies variability was low. To investigate the co-movement and causality, Fig. 4 plots the wavelet coherence and phase difference between Bitcoin and gold futures returns. The interpretation of Fig. 4 is consistent with that of Fig. 3. The coherency ranges from red (high coherency) to blue (low coherency) to measure the degree of co-movement. We observe a significant high degree of co-movement between Bitcoin and gold for the 2012–2015 period across the 8–16 weeks frequency band. Some evidence of relatively weaker, but significant coherence above the 4 weeks frequency cycle is also observed during 2010 and mid-2012. This supports the contagion effect during the global financial crisis and European sovereign debt crisis, and the reduced short-run effectiveness of hedge/diversification benefits from combining Bitcoin and gold futures during crisis periods. Our results and conclusions therefore contrast to those of Baur et al. [26] and Corbet et al. [50], who suggest the presence of limited correlations between Bitcoin and gold markets, with the latter authors suggesting a general decoupling of the Bitcoin and gold markets in recent time periods.

We also identify causality and phase differences between Bitcoin and gold returns. Arrows indicate the phase differences between the Bitcoin and gold futures returns. For example, $\longrightarrow$ and $\longleftarrow$ indicate that both Bitcoin and gold returns are in phase and out of phase, respectively. $\nearrow$ and $\swarrow$ indicate Bitcoin returns are leading those of gold, while $\searrow$ and $\nwarrow$ indicate Bitcoin returns are lagging those of gold.

As shown in Fig. 4, we observe the most significant degree of co-movement between Bitcoin and gold futures returns for the 2012–2015 period across the 8–16 weeks frequency band. Co-movement appears to be relatively weak for the 64

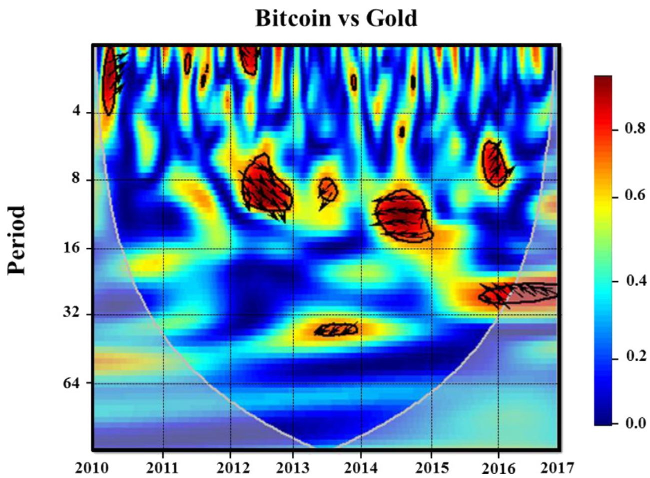

Fig. 4. Wavelet coherency between Bitcoin and gold returns. Notes: The horizontal axis shows time, while the vertical axis refers to the period in weeks. The white line refers to the cone of influence, an edge below which wavelet power is affected due to discontinuity and hence, difficult to interpret. The black contour denotes the 5% significance level. The level of correlation is indicated by the color on the right side of the charts; the hotter the color (moving from cool (blue) to hot (red)) the higher the absolute correlation value with respect to $R^2\,(u, s)$ in Eq. (9).

weeks and above time-scale, while co-movement in the short run (0–4 weeks band), although low on average, is highly variable. Thus, while a strategy of combining Bitcoin and gold futures in portfolios may generally offer diversification benefits across the short-run, the effectiveness of such strategies will vary, and may fail during periods of crisis.

We also identify causality and phase differences between Bitcoin and gold futures returns. We observe the arrow point $\longleftarrow$ signifying an out-of-phase relationship in the 8–16 weeks band, indicating the negative correlation between Bitcoin and gold returns during 2014–2015. We see the arrow point $\nearrow$ around 2010 in the 0–4 weeks band, indicating Bitcoin returns led those of gold in the short run during the global financial crisis. However, between 2012 and 2013 we observe the arrow point $\searrow$ in the 8–16 weeks band, implying that gold returns led Bitcoin returns in the medium run during the European debt crisis.

5. Conclusions

Bitcoin has emerged as an alternative currency that may be used to purchase goods within an increasing network of buyers and sellers who accept it as a means of payment. Its appeal reflects its distinctive characteristics. It operates within a digital network system, largely detached from the effects of monetary policy and central bank regulation. Thus, its liquidity (and number of Bitcoin), and consequently volatility, are dependent on the decentralized decision making of those who participate in the market. In addition, participants can access information on the number of transactions taking place daily, a feature not found in dealing with standard currencies.

Bitcoin's characteristics open the possibility for the Bitcoin market to be a source of diversification and hedging against the cycles caused by the design of the current financial system. Additionally, in parallel with gold future prices, it might be used to improve the hedging of risk in investable financial security portfolios. Although the performance of the gold market, unlike that of Bitcoin, is partially determined by business bubble cycles caused by monetary policy and the financial system, it shares with Bitcoin that it can be used for diversification and hedging in market downturns.

The above motivates testing for the correlation between gold futures and Bitcoin prices. Gold is used as a safe-haven asset in times of financial uncertainty, due to its contrarian performance to the downside of the business cycle. Bitcoin, by not being subject to the influence of business cycle patterns derived from monetary policy and central bank control, may also display a negative correlation with overall financial market movements. Another reason to test correlations between gold futures and Bitcoin prices is that, although both types of markets have performed in times of financial uncertainty, there seems to be a difference in the duration of their price bubbles and in the expectations of traders in each market. Given those reasons, this paper examined the hedging and diversification properties of gold futures prices and Bitcoin prices, in relation to each other, by implementing DCC–GARCH and wavelet coherence models.

We find evidence of volatility persistence, causality and phase differences between Bitcoin and gold futures. The contagion hypothesis is observed to increase during the 2010–2013 European-debt crisis. The wavelet coherence results indicate a relatively high degree of co-movement between Bitcoin and gold futures for the 2012–2015 period, across the 8–16 weeks frequency band. Finally, although co-movement in the 0–4 weeks band is relatively low on average, its variability may reduce the short-run diversification benefits available from Bitcoin-gold future portfolio combinations.

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