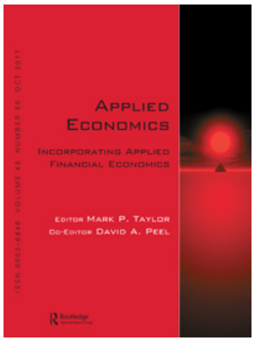

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Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven?

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ABSTRACT

We study the relationship between Bitcoin and commodities by assessing the ability of Bitcoin to act as a diversifier, hedge, or safe haven against daily movements in commodities in general, and energy commodities in particular. We focus on energy commodities because energy, in the form of electricity, is an essential input in the Bitcoin production. For the entire period, results show that Bitcoin is a strong hedge and a safe-haven against movements in both commodity indices. We further examine whether that ability is also present for non-energy commodities and our analysis show insignificant results when energy commodities are excluded from the general commodity index. We also account for the December 2013 Bitcoin price crash and our results reveal that Bitcoin hedge and safe-haven properties against commodities and energy commodities are only present in the pre-crash period, whereas in the post-crash period Bitcoin is no more than a diversifier. In addition to uncovering the time-varying role of Bitcoin, we highlight the dissimilarity in the dynamic correlations between the extreme downward and extreme upward movements.

KEYWORDS
Cryptocurrency; Bitcoin crash; commodities; energy commodities; diversifier; hedge; safe haven

JEL CLASSIFICATION
C1; G1; Q4

I. Introduction

Unlike conventional currencies that are designed and controlled by a governing body, Bitcoin has emerged as a fully decentralized cryptocurrency that depends on a sophisticated protocol. This protocol assures that supply of Bitcoins is and will remain limited.[1] Since Bitcoin's induction in 2009 following its proposal in Nakamoto (2008), the size and popularity of this 'peer-to-peer electronic cash system' has never climaxed. Figures from coinmarketcap.com show that as of 31 March 2016, the Bitcoin market capitalization exceeds 6.40 billion US dollars, making it by far the largest digital currency.[2]

Due to increasing popularity and importance of Bitcoin, as well as its volatility (See Figure 1), practitioners and researchers have recently started to assess Bitcoin from the perspective of economics and finance. Rogojanu and Badea (2014) explore the advantages and disadvantages of Bitcoin and compare it with other alternative monetary systems. Brandvold et al. (2015) focus on the contributions of Bitcoin exchanges to price discovery. Ciaian, Rajcaniova, and Kancs (2016) examine BitCoin price formation by focusing on market forces of supply/demand and digital currencies specific factors. Few studies have emerged from the view that Bitcoin presents an alternative to conventional currencies in times of weak trust, such as during the global financial crisis in 2008, thus referring to Bitcoin as digital gold (Rogojanu and Badea 2014; Popper 2015). Others have examined the benefits of including Bitcoin in an equity portfolio (Halaburda and Gandal 2014; Eisl, Gasser, and Weinmayer 2015). Baur, Lee, and Hong (2015) argue that Bitcoin is a hybrid between precious metals and conventional currencies. They also highlight its role as a useful diversifier (i.e. uncorrelated with traditional assets) and an investment.

If Bitcoin is regarded as an investment, then we need to know more about its properties and particularly about its relation to other assets. However, what renders an asset interesting from diversification and hedging perspectives is its correlation with other assets or portfolios not only on average but also during times

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[1]For detailed information on the principles of Bitcoin, the reader can refer to Segendorf (2014) and Dwyer (2015).

[2]Other digital currencies include, among others, Ethereum, Ripple, and Litecoin. Each of these three currencies has a market capitalization in excess of 100 million US dollars.

Figure 1. Daily price evolution of the Coindesk Bitcoin index.

of market stress. Accordingly, we differentiate between a diversifier, hedge and safe haven (Baur and Lucey 2010; Ratner and Chiu 2013). A diversifier is an asset that has a weak positive correlation 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 on average during *times of stress*. While gold has been widely seen as a hedge and a safe haven (Baur and Lucey 2010), the ability of Bitcoin to hedge and act as a safe haven against other assets remains understudied. To date, Dyhrberg (2016) examine whether Bitcoin is related to USD/EUR, USD/GBP exchange rates and the FTSE 100 index; whereas Bouri et al. (2017) consider the relation between Bitcoin and various assets with a focus on major world equity indices.

In this article, we study the relationship between Bitcoin and commodities by assessing the ability of Bitcoin to act as a diversifier, hedge, or safe haven against the commodities in general, and specifically against energy commodities. We focus on energy commodities because energy, in the form of electricity, is an essential input in Bitcoin production.[3] O'Dwyer and Malone (2013) estimate that electricity consumed in Bitcoin production is comparable to the electricity consumption of the whole Ireland. Notably, Hayes (2016) and Li and Wang (in press) indicate that Bitcoin value reflects the cost of production (mining). Garcia et al. (2014) use the cost of the energy involved in Bitcoin mining to indicate a lower-bound estimate of Bitcoin's fundamental value. Accordingly, a linkage between energy commodities and Bitcoin may be potentially established.[4] Furthermore, and from a different perspective, Ciaian, Rajcaniova, and Kancs (2016) provide evidence that oil price, as a measure of global macro-financial development, has a significant impact on Bitcoin price in the short run.

However, it is generally unclear which relationship should we expect between Bitcoin and energy commodities. On the one hand, as indicated above, Bitcoins are produced by using energy and, therefore, low energy prices could lead to higher production of Bitcoins and thus to low Bitcoin prices. If this supply link is strong enough, we could observe a positive correlation between energy prices and Bitcoin prices. On the other hand, even though the price of Bitcoin is determined by supply and demand, speculative demand might be a key determinant of Bitcoin price. Furthermore, part of the relationship may be due to the fact commodities are held as assets as well,[5] and therefore the relationship between Bitcoin and energy commodities might be similar to the relationship between Bitcoin and other assets.[6] In addition to the relationship between Bitcoin and commodities in general and energy commodities in particular, we also examine whether this relationship changed after the Bitcoin crash of December 2013 (Cheah and Fry 2015).

Our analyses provide first empirical findings on the hedging and safe-haven ability of Bitcoin against movements in commodities in general and energy

[3]That energy expenditure secures Bitcoin from attacks by speculators or criminals: it is required to increase security for the network by solving series of cryptographic puzzles, hereby raising the computer power needed to attempt to gain control of Bitcoins transactions on the network.
[4]Computer cooling firm Allied Control estimates the power consumption per Bitcoin transaction to be equivalent to around 1.6 times the daily usage of electricity of an average US household. Thus, a Bitcoin transaction requires 5,000 times more energy than, for instance, a VISA transaction.
[5]We thank the referee for mentioning this important point.
[6]Several studies so far find very weak relation between Bitcoin and conventional assets (e.g. Baur, Lee, and Hong 2015), suggesting that Bitcoin is a useful diversifier.

commodities in particular. We also examine whether energy commodities are the main driver of that ability and our results show insignificant results when energy are excluded from the general commodity index. Furthermore, the main overall results differ between pre- and post-crash periods.

The rest of the article is structured as follows. Section II describes the Bitcoin price formation. Section III discusses the Bitcoin mining. Section IV describes the empirical model. Section V presents the data and discusses the results. Finally, Section VI concludes.

II. Bitcoin price formation

As for the case of any other assets, the price of Bitcoin is determined by demand and supply. Demand for Bitcoin can be divided, at least theoretically, into transaction and speculative demand. Concerning the supply of Bitcoins, it is useful to consider separately the supply of old Bitcoins and the supply of newly produced Bitcoins. Therefore, in order to understand the determinants of Bitcoin price (or alternatively price changes), we should ideally identify the determinants of transaction and speculative demand as well as the supply of old and new Bitcoins.

Transaction demand for Bitcoin exists because Bitcoin is used for actual transactions and therefore serves as money. At first sight, transaction demand for Bitcoin seems to be an easily available variable, because all the Bitcoin transactions are recorded and publicly available across the Bitcoin exchanges. Accordingly, total value of Bitcoin transactions for each day is an easily available summary statistic. However, this number does not represent actual economic transactions when Bitcoins are exchanged for some goods or services. Large part of the transactions in the Bitcoin network happens for anonymizing purposes. For example, if one person wants to send a large amount of Bitcoins to another person, the amount can be divided into small amounts, and sent through many addresses, including randomizing services, before it reaches the final destination. Therefore, determining value of Bitcoin from its transaction demand would be very challenging.

Speculative demand for Bitcoin exists because many Bitcoin users and enthusiasts believe that Bitcoin is the future of money in general; and since Bitcoin supply is limited, its value will keep rising. Supply of old Bitcoins is determined by the people who currently own Bitcoin and whether they are willing to sell it. Both speculative demand and supply of old Bitcoins are influenced mostly by expectations. Understanding or predicting expectations of investors is inherently difficult, and therefore we focus on the most tractable determinant of Bitcoin price – supply of new Bitcoins.[7] New Bitcoins are produced in a process called mining. In this process, Bitcoin producers use their hardware and electricity to produce Bitcoins. Therefore, in a completive equilibrium, the price of the Bitcoin should equal to the marginal cost of its production, which is the electricity cost (Hayes 2016). We discuss this relationship further in the next section.

III. Bitcoin mining

Similar to fiat money, Bitcoin has value because its holders use it for transactions and also because they expect that Bitcoin will have value in the future. However, there is a big difference between fiat money and Bitcoin. There is always some central authority behind fiat money, usually a government via central bank, but in principle, it could be anybody. For example, in the case of virtual currency such as M-Pesa, it is a telecom company. Central authority can create additional fiat money.

Bitcoin, on the contrary, does not have any central authority. The backbone of Bitcoin is a decentralized peer-to-peer computer network. The software running on these computers allow Bitcoin transactions to happen. In addition, this software produces new Bitcoins through a process called *mining*. However, the rule for producing new Bitcoins is set up in such a way that total number of Bitcoins ever produced has a specific upper limit.

People run this mining software on their computers because running this software offers a reward in form of transaction fees as well as new Bitcoins. In the future, after almost all Bitcoins have been mined out, transaction fees will be the only income for miners. However, so far, the new Bitcoins has been strongly dominating the reward. Accordingly, the

[7]For further discussion of Bitcoin price determinants, readers can refer to Kristoufek (2015) and Ciaian, Rajcaniova, and Kancs (2016).

reward from transaction fees can therefore be neglected.

Initially, Bitcoin mining started at ordinary computers, in first stage on processors (CPU), later Bitcoin mining moved to graphic cards (GPU). Some people were mining Bitcoins on their personal computers when they were not using them, whereas others were using large servers and were mining Bitcoins continuously. Later on, specialized computers, Field Programmable Gate Arrays (FPGAs) and Application-Specific Integrated Circuits (ASICs), were introduced just for mining Bitcoins and even mining using GPUs become obsolete. Regarding Bitcoin mining hardware, it is useful to define efficiency as a computational power per unit of energy. In case of Bitcoin mining, the relevant computational power is a *hashrate*. For a very rough comparison, we can consider that each move to new technology (from CPU to GPU to FPGA to ASIC) was accompanied by a ten times increase in efficiency, see Hayes (2016). Since specialized Bitcoin mining machines are extremely efficient in Bitcoin mining, mining on ordinary computers (whether using CPU or GPU) stopped, because it would be very unprofitable.

Calculation of profitability of Bitcoin mining is in principle simple, for details see Hayes (2016). In a competitive market, the marginal product of mining should theoretically equal its marginal cost, which is the cost of electricity.[8] Once an investor has a mining device, he simply compares the price of one Bitcoin with the (electricity) cost of producing one Bitcoin. If the price of Bitcoin is above the electricity cost of mining, then the investor should keep mining. Conversely, if the price of Bitcoin is below the (electricity) cost of mining, then he should interrupt the mining. Therefore, there should be a co-movement between the Bitcoin price and energy (electricity) price.

However, there are several reasons why the seemingly obvious relationship between the Bitcoin price and energy price does not need to exist or might be significantly weakened. First, we investigate the correlation between the Bitcoin price and the prices of energy commodities, not electricity price. Electricity, unlike most of other energy commodities, is always priced and traded on local markets, and therefore cannot be used in our analysis as no global market (and therefore price) exists for electricity. There is often a strong positive correlation between the prices of electricity and energy commodities. However, this correlation is not perfect suggesting that the relationship between Bitcoin and energy commodities could be weaker than the relationship between Bitcoin and electricity.

Second, the relationship that the price of Bitcoin equals the cost of electricity needed to produce its holds in a competitive equilibrium. Market for a dynamic commodity, such as Bitcoin, does not need to be in a permanent equilibrium. Disequilibrium may happen, especially when speculations related to future expectations are much stronger than equilibrium forces coming from mining incentives. Imagine that the price of electricity goes up (or the price of Bitcoin goes down) and mining becomes unprofitable for some miners. These miners will simply stop mining, and the equilibrium will be restored. If the electricity price goes down (or the Bitcoin price goes up), mining will become profitable again. However, unless an investor already owns mining devices, it requires time to start new mining operations. This is particularly the case for 'new' miners who need to learn a lot before they may start mining. Even for people already involved in mining, obtaining new mining hardware may take a considerable time. In this case, it might explain a longer time before the market equilibrium is restored. Because of this asymmetry, the correlation between Bitcoin price and energy prices could depend on whether Bitcoin is becoming more or less valuable relatively to its energy cost. In this study, we therefore investigate the correlation between Bitcoin and the energy index not only for the whole period, but also for two sub-periods: before the Bitcoin crash of December 2013 (a period of increasing Bitcoin price) and afterward (a period of decreasing Bitcoin price).

Third, the Bitcoin mining is very different form production of other goods. If there is suddenly much more factories producing cars, this will put a downward pressure on the price of cars. However, if there are suddenly more people mining Bitcoins, new

[8]This is confirmed also empirically by Hayes (2016), who estimates that at the time of his calculation, the marginal cost of mining one Bitcoin was $415, whereas the Bitcoin price was $420.

equilibrium will be restored primarily via automatic increase in mining difficulty, not via large increase in Bitcoin production. Therefore, Bitcoin price does not need to be correlated with the energy prices.

Altogether, even though the main input in Bitcoin production is energy, it is unclear whether Bitcoin should be correlated with energy prices and how should this relationship depend on Bitcoin market being in rising or falling periods. We address this literature gap.

IV. Empirical model

The empirical analysis is conducted in two stages. In the first stage, pairwise dynamic conditional correlations (DCCs) between Bitcoin and each of the three commodity indices are estimated. In the second stage, the hedge and safe-haven properties of Bitcoin against these commodities are assessed via the regression of those pairwise DCCs on dummy variables representing extreme *downward* movements in the return distribution. Although the empirical analysis is broadly along the lines of Ratner and Chiu (2013), it also differs in several ways.

First, this article employs a bivariate asymmetric DCC model proposed by Cappiello, Engle, and Sheppard (2006) in extension of the standard DCC of Engle (2002) used by Ratner and Chiu (2013). We specify the conditional mean equation of the asymmetric DCC model as an autoregressive-moving-average (ARMA) process. This methodological extension that this article adopts is important for avoiding biased estimates of dynamic correlations coefficients.

Second, in addition to focusing on extreme *downward* movements in the return distribution, the diversification properties of Bitcoin against energy commodities are examined against extreme *upward* movements. Furthermore, we assess whether the potential diversification benefits of Bitcoin differ across two particular sub-periods, before and after the December 2013 Bitcoin crash (Cheah and Fry 2015).

The DCC model

It is well documented that the dynamic conditional correlation (DCC) model of Engle (2002) can capture the time-varying and dynamic relationship across return series (Parhizgari and Cho 2008). However, for the purpose of this study and given the large number of return series, the DCC model is estimated separately for pairs of return series and not for all the return series simultaneously. In doing so, the minor possibility of getting biased estimates of parameters in higher dimensions is prevented (Hafner and Reznikova 2012).

The estimation of the bivariate DCC model is conducted in two steps. In the first step, a univariate GARCH (1,1) model is estimated. In the second, a time-varying correlation matrix is computed using the standardized residuals from the first-step estimation. However, we introduce asymmetry in the correlation dynamics of the DCC and translate the resultant model (called the ADCC model) into a quadratic form, in line with Cappiello, Engle, and Sheppard (2006). The mean equation of the ADCC model (1) is specified as an ARMA process. This is in line with the work of Kyrtsou and Labys (2007), who suggests that overlooking this characteristic may undermine some of the dynamics of the relationships between the examined variables.

$$r_t = \mu_t + \omega r_{t-1} + \psi \varepsilon_{t-1} + \varepsilon_t, \tag{1}$$

where r_t is the vector of the price return of Bitcoin and that of the energy commodity, μ_t is the conditional mean vector of r_t, and ε_t is a vector of residuals. The variance equation is specified as

$$h_t = c + a\varepsilon_{t-1}^2 + bh_{t-1} + \gamma\varepsilon_{t-1}^2 I_{t-1}, \tag{2}$$

where h_t is the conditional variance; c is the constant; a is the parameter that captures the ARCH effect; b represents the GARCH effect; γ is the parameter that measures the asymmetric effect, with a symmetric impact if $\gamma = 0$, and otherwise, the asymmetric impact is significant if $\gamma \neq 0$.

The ADCC(1,1) equation is specified for Q_t, which is an asymmetric square positive-definite matrix:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} - \zeta\bar{N} + \theta_1\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \theta_2 Q_{t-1} + \zeta n_{t-1}n_{t-1}^{'}, \tag{3}$$

where θ_1, θ_2, and ζ are $K \times K$ parameter matrices, $\overline{Q}$ is the sample covariance matrix of the standardized residuals ε_t, $n_t = \mathrm{I}\,[\varepsilon_t < 0] \circ \varepsilon_t$, $\mathrm{I}\,[\bullet]$ is a $K \times 1$ indicator function taking value 1 if the argument is true and 0 otherwise, $\circ$ indicates the Hadamard product, and $\overline{N} = E[n_{t-1}n'_{t-1}]$.[9]

The pairwise dynamic conditional correlation between assets i and j is given by

$$\rho_{ij,t} = \frac{q_{ij,t}}{\left(\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}\right)} \quad (4)$$

Diversifier, hedge or safe haven

Potential diversifying, hedge, and safe-haven properties of Bitcoin are examined using regression analyses. Practically, pairwise DCCs are extracted from the ADCC model into separate time series and then regressed on dummy variables (D) representing extreme *downward* movements in the lower 10th, 5th or 1st percentile as well as extreme *upward* movements in the 90th, 95th and 99th percentile of the return distribution.

For extreme downward and extreme upward movements, the regression is specified as

$$\begin{aligned} ADCC_t = c &+ m_1 D(r_{commodity\ index}\ q_{10}) \\ &+ m_2 D(r_{commodity\ index}\ q_5) \\ &+ m_3 D(r_{commodity\ index}\ q_1) \\ &+ m_4 D(r_{commodity\ index}\ q_{90}) \\ &+ m_5 D(r_{commodity\ index}\ q_{95}) \\ &+ m_6 D(r_{commodity\ index}\ q_{99}) \\ &+ m_4 D(r_{commodity\ index}\ q_{90}) \\ &+ m_5 D(r_{commodity\ index}\ q_{95}) \\ &+ m_6 D(r_{commodity\ index}\ q_{99}) + v_t \end{aligned} \quad (5)$$

where ADCC is the pairwise conditional correlation between Bitcoin and each of the three commodity indices under study (general commodity index, index for energy commodities and index for non-energy commodities), $r_{commodity\ index}$ is the return of each of the other index, and v_t is the disturbance term. Bitcoin is a diversifier against movements in the other index if c is weakly positive. Bitcoin is a weak hedge against movements in the other index if c is zero or a strong hedge if c is negative. Bitcoin is a weak safe haven against movements in the other index if the m_1, m_2, or m_3 coefficients are not significantly different from zero, or a strong safe haven if these coefficients are negative.

V. Empirical analysis

The dataset

To cover the December 2013 Bitcoin crash, daily data on Bitcoin and the commodity indices span from 18 July 2010 to 28 December 2015. Accordingly, the entire sample period is divided into two sub-periods, relating to before and after the December 2013 Bitcoin crash (Cheah and Fry 2015). Bitcoin prices are obtained from Coindesk Price Index. We utilize three commodity indices initially developed by Goldman Sachs and currently owned and published by Standard & Poor's: (1) the Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI), a general – aggregate- commodity index, (2) the S&P GSCI energy commodities index, and (3) the S&P GSCI non-energy commodities index. The S&P GSCI general commodity index represents the most widely recognized benchmark for the global commodity market. It contains 25 commodities, seven of which are energy commodities representing a 63% weight of the aggregate S&P GSCI index, whereas the remaining weight of 37% is for non-energy commodities (agriculture, livestock, industrial metals, and precious metals). The empirical analysis is conducted using return series, calculated as the log difference in price. It is worth noting that the data have been filtered so that only common observations across all the four return series are used. This filtering was important, especially given that, unlike commodities, Coindesk Price Index provides data on Bitcoin prices on all days of the week.

Table 1 provides descriptive statistics for the return series in the entire period and two sub-periods under study. In particular, in the pre-crash period, Bitcoin experiences by far the highest return and volatility relative to energy commodities. It also has the highest value for skewness and kurtosis. The negative values of skewness statistics indicate that large negative returns in Bitcoin are more probable than large positive returns. Regarding the two sub-periods, before and after the Bitcoin crash of December 2013, Bitcoin has the highest volatility in

[9] For a detailed explanation on the ADCC model and its estimation, the reader can refer to Cappiello, Engle, and Sheppard (2006).

Table 1. Summary statistics of daily return.

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Obs.
Panel A: Entire period (19 July 2010–28 December 2015)							
Bitcoin	0.0057	0.4246	−0.4700	0.0665	−0.2177	11.3837	1365
Commodity	−0.0004	0.0548	−0.0674	0.0118	−0.3560	6.0488	1365
Energy	−0.0006	0.0808	−0.0935	0.0158	−0.3128	6.6535	1365
Non-energy	−0.0001	0.0417	−0.0462	0.0085	−0.1660	5.6280	1365
Panel B: Before the Bitcoin crash (19 July 2010–30 November 2013)							
Bitcoin	0.0098	0.4246	−0.4700	0.0757	−0.2361	9.8407	844
Commodity	0.0002	0.0548	−0.0674	0.0115	−0.4787	6.1401	844
Energy	0.0003	0.0711	−0.0848	0.0141	−0.4141	6.1886	844
Non-energy	0.0001	0.0417	−0.0462	0.0097	−0.2391	5.2125	844
Panel C: After the Bitcoin crash (1 December 2013-28 December 2015)							
Bitcoin	−0.0011	0.2908	−0.2696	0.0475	−0.6788	12.1102	521
Commodity	−0.0014	0.0526	−0.0659	0.0123	−0.1664	6.0162	521
Energy	−0.0020	0.0808	−0.0935	0.0183	−0.1350	6.2988	521
Non-energy	−0.0004	0.0206	−0.0164	0.0063	0.1045	3.1527	521

Bitcoin prices are represented by the Coindesk Price Index from Bitcoindesk.com; commodity prices are represented by the S&P GSCI general commodity index; energy and non-energy prices are respectively represented by the S&P GSCI Energy index and the S&P GSCI Non-Energy index.

both cases. In both sub-periods, the high value of kurtosis statistics across all the return series, relative to a normal distribution, suggests the presence of extreme upward and downward movements.

Diversifying, hedge and safe-haven properties of Bitcoin

In the ADCC model, we relied on the Schwarz information criterion (*SIC*) and found that the ARMA(1,1) specification of the mean Equation (1) was the optimal choice to control for historical patterns in returns, whereas the ADCC(1,1) was the best model for the conditional correlation. Given that our main purpose of ADCC modelling is to extract the pairwise conditional correlations, we do not elaborate on the results of the remaining estimated model coefficients, especially those estimated from the first step univariate GARCH model. However, we present in Table 2 the estimated coefficients of the ADCC model from the second step described in Equation (3). As shown in Table 2, all parameters except for ζ in the equation of Bitcoin and no-energy commodities are statistically significant at the 5% level. The results from the Ljung-Box diagnostics test on the residuals and squared standardized residuals show that the models do not exhibit significant lack of fit. We also compare the ADCC model to the DCC and the constant conditional correlation (CCC) models. Based on a log-likelihoods and *SIC* values, we show that the ADCC is a better choice than both the CCC and ADCC models as it produces smaller *SIC* values and larger log-likelihoods values.

Table 2. Estimation results of the ADCC model.

	Bitcoin-Commodity	Bitcoin-Energy	Bitcoin-Non energy
ADCC parameters			
θ_1	**0.0133**	**0.0230**	**0.0317**
θ_2	**0.9720**	**0.9602**	**0.9539**
ζ	**0.0035**	**0.0022**	0.0018
Diagnostics checks			
Q(10)	6.740	8.123	7.799
$Q^2(10)$	12.089	14.031	12.702
Log likelihood	−3,811.0	−3,889.0	−3,775.0
SIC	5.679	5.731	5.707
Log likelihood of the CCC model	−3825.0	−3898.0	−3782.0
SIC of the CCC model	5.729	5.742	5.799
Log likelihood of the DCC model	−3814.0	−3.891.0	−3.778.0
SIC of the DCC model	5.702	5.736	5.728

The estimations results are based on the ADCC model. Q(10) and $Q^2(10)$ are the Q-statistics test for serial correlation in the residuals and squared standardized residuals, respectively. Figures in bold indicate statistical significance at the 5% level. *SIC* (Schwarz information criterion). CCC (constant conditional correlation). DCC (dynamic conditional correlation).

Following the estimation of the ADCC model, the pairwise dynamic conditional correlations are generated into separate times series and then used in Equation (5) to assess the diversifying, hedge, and safe-haven properties of Bitcoin. For example, the series of the ADCC between Bitcoin and the S&P GSCI general commodity index is regressed on: a constant (c), three dummy variables (m_1, m_2, m_3) that represent extreme *downward* movements in the general commodity index prices in the 10th, 5th and 1st quantiles of the return distribution, respectively, and another three dummy variables (m_4, m_5, m_6) that represent extreme *upward* movements in the general commodity index prices in the 90th, 95th and 99th quantiles of the return distribution, respectively. The same analysis is conducted individually for the ADCC series of the Bitcoin and energy commodities as well as for the

ADCC series of the Bitcoin and non-energy commodities. In addition to the entire period, the analysis is conducted for the two periods before and after the December 2013 Bitcoin crash.

Table 3 presents the coefficient estimates from the regression model in Equation (5). We first discuss the diversification and hedging abilities of Bitcoin against commodities, as captured by the coefficient of the constant term. For the entire period, the coefficient of the constant term is significantly negative (−0.0197), suggesting that Bitcoin is a strong hedge against commodities in general. We then investigate energy and non-energy commodity indices separately and report the followings two results: Bitcoin is also a strong hedge for energy commodities (the coefficient of the constant term is significantly negative −0.0293); however, Bitcoin is no more than a diversifier against non-energy commodities (the coefficient of the constant term is significantly positive 0.0209). These two findings suggest that energy commodities are the main driver of that hedging ability.

We focus on the two sub-periods and the results provide evidence that the diversification and hedging abilities of Bitcoin differ between pre- and post-crash periods. For the pre-crash period, the results on the diversification and hedging abilities of Bitcoin for each of the three commodity indices under study are similar to that for the entire period. In other words, Bitcoin can act as a hedge for commodities and energy commodities, whereas it is just a diversifier for non-energy commodities. After the Bitcoin crash of December 2013, the results on the diversification and hedging abilities of Bitcoin differ. In fact, during the post-crash period, Bitcoin can act just as a diversifier, not only for non-energy commodities – as for the entire period and the pre-crash period – but also for commodities and energy commodities. This implies that, after the price crash of 2013, Bitcoin has no hedging ability against movements in commodities in general and energy and non-energy commodities.

Second, we concentrate on the safe-haven property of Bitcoin for the entire period and the two subperiods. Results for the entire period and the period before the crash of December 2013 indicate that Bitcoin can serve as a strong safe-haven against the general commodity index and the energy commodity index in the 1% quantile. As for the post-crash period, Bitcoin exhibits no safe-haven property against any of the three commodity indices under study.

Overall, the above results are in accordance with our discussion in Section III about the Bitcoin mining. We explain there that theoretically, there should be a positive correlation between Bitcoin price and energy price, but for several reasons, this relationship might be rather weak. The positive relationship between the Bitcoin price and energy prices is more likely to be found during period of decreasing Bitcoin prices, i.e. after the Bitcoin crash of 2013. The reason is that the response of Bitcoin mining to changed market conditions is asymmetric. When the economic conditions become unfavourable for mining (either due to decreased Bitcoin price or increased electricity price), mining can be decreased easily. Miners will simply interrupt mining on least profitable mining hardware. However, miners can start mining immediately as a response to favourable market conditions (either high Bitcoin price or low electricity price) only if they already own mining hardware that is idle at the moment. Therefore, Bitcoin mining activity should respond much faster to changes in Bitcoin or electricity price during the

Table 3. Estimation results from Equation (5).

	10% Q (m_1)	5% Q (m_2)	1% Q (m_3)	Constant (c)	90% Q (m_4)	95% Q (m_5)	99% Q (m_6)
Panel A: Entire period (19 July 2010–28 December 2015)							
Commodity	−0.0025	0.0030	**−0.0330**	**−0.0197**	−0.0032	0.0027	−0.0012
Energy	−0.0009	−0.0018	**−0.0212**	**−0.0293**	0.0019	−0.0021	0.0022
Non-energy	0.0005	0.0012	0.0035	**0.0209**	−0.0017	0.0012	−0.0018
Panel B: Before the Bitcoin crash (19 July 2010–30 November 2013)							
Commodity	−0.0002	−0.0032	**−0.0420**	**−0.0093**	−0.0070	0.0012	−0.0061
Energy	−0.0025	−0.0022	**−0.0391**	**−0.0171**	−0.0021	−0.0025	−0.0035
Non-energy	0.0034	−0.0171	−0.0059	**0.0142**	−0.0075	−0.0098	−0.0011
Panel C: After the Bitcoin crash (1 December 2013–28 December 2015)							
Commodity	−0.0135	−0.0198	−0.0705	**0.0277**	−0.0071	−0.0188	−0.0099
Energy	0.0037	0.0093	−0.0507	**0.0240**	0.0018	−0.0030	−0.0032
Non-energy	0.0127	−0.0081	−0.0233	**0.0012**	0.0041	−0.0021	0.0017

This table presents the estimation results from Equation (5); Figures in bold indicate statistical significance at the 5% level.

Table 4. Estimation results from Equation (5) – DCC model.

	10% Q (m_1)	5% Q (m_2)	1% Q (m_3)	Constant (c)	90% Q (m_4)	95% Q (m_5)	99% Q (m_6)
Panel A: Entire period (19 July 2010–28 December 2015)							
Commodity	−0.0061	0.0018	**−0.0306**	**−0.0175**	−0.0020	0.0098	−0.0031
Energy	−0.0022	−0.0023	**−0.0107**	**−0.0221**	0.0032	−0.0008	0.0039
Non-energy	0.0014	0.0019	0.0054	**0.0202**	−0.0009	0.0006	−0.0010
Panel B: Before the Bitcoin crash (19 July 2010–30 November 2013)							
Commodity	−0.0018	−0.0009	**−0.0434**	**−0.0101**	−0.0028	0.0017	−0.0068
Energy	−0.0041	−0.0019	**−0.0377**	**−0.0099**	−0.0003	−0.0029	−0.0044
Non-energy	0.0021	−0.0112	−0.0043	**0.0136**	−0.0071	−0.0069	−0.0002
Panel C: After the Bitcoin crash (1 December 2013–28 December 2015)							
Commodity	−0.0103	−0.0165	−0.0673	**0.0290**	−0.0055	−0.0163	−0.0088
Energy	0.0034	0.0086	−0.0543	**0.0226**	0.0011	−0.0036	−0.0037
Non-energy	0.0131	−0.0077	−0.0225	**0.0009**	0.0046	−0.0011	0.0012

This table presents the estimation results from Equation (5) based on the DCC (1,1) model; Figures in bold indicate statistical significance at the 5% level.

period of decreasing Bitcoin prices (after the crash). As a result, positive relationship between the Bitcoin and electricity prices is more likely to be observed during this period. Consequently, safe heaven properties are less likely to be observed during this period. Both these predictions are in accordance with our above-mentioned empirical results.

We can also identify another reason why the safe haven property is not present in the period after the Bitcoin crash. Notably, in the post-crash period, during which Bitcoin prices plunged, energy commodities also declined sharply especially from mid-2014 leading to a tandem movement between Bitcoin prices and energy commodities; as a result, the effect of safe haven property of Bitcoin against commodities in general and energy commodities vanished.

It is also interesting to consider the correlation between Bitcoin and the three commodity indices in extreme upward movements, such as 90, 95 and 99% quantiles in the return distribution. As shown in the last three columns of Table 3, all the coefficient estimates for the extreme upward movements are insignificant for the commodities, energy commodities and non-energy commodities, and this for the entire period and the two sub-periods.

Our findings add to prior studies and provide a more clearly empirical evidence on the association between energy, as an input into the Bitcoin production, and Bitcoin price (Garcia et al. 2014; Hayes 2016; Li and Wang in press). We also provide a nuanced picture about the relation between Bitcoin and the three examined commodities markets not seen in prior studies (Halaburda and Gandal 2014; Baur, Lee, and Hong 2015; Eisl, Gasser, and Weinmayer 2015; Dyhrberg 2016; Bouri et al. 2017). While our results confirm some of the findings from Ciaian, Rajcaniova, and Kancs (2016) that indicate energy (oil) price has a significant impact on Bitcoin price in the short-run, we were able to relate this impact to Bitcoin mining and account for the role of the Bitcoin crash of 2013 (Cheah and Fry 2015).

Further analysis

We examine the robustness of our above-mentioned results reported in Table 3 to the choice of the dynamic correlation model by considering the case of a standard DCC model. As shown in Table 4, the new estimated results do not change significantly from those reported earlier in Table 3. To sum, the general outcome from this robustness section implies that our results are sufficiently independent from the model specification in the first stage, and thus are fairly robust.

VI. Conclusions

This article addresses a considerable void in the literature by assessing whether Bitcoin can serve as diversifier, hedge or safe haven for commodities in general and for energy commodities in particular. The reason why we focus on energy commodities in particular is that the only variable cost in Bitcoin production (Bitcoin mining) is the electricity cost (Garcia et al. 2014; Hayes 2016). Therefore, the relationship between Bitcoin and energy commodities could be different from that between Bitcoin and non-energy commodities. Using daily data from 18 July 2010 to 28 December 2015, and accounting for the price crash of December 2013, we document interesting results that can be summarized as follows. Bitcoin exhibits hedge and safe-haven properties for the general commodity index and for the energy commodity index, for the entire period and the pre-crash period. After the Bitcoin crash of December 2013, Bitcoin acts only as a diversifier for those two commodity indices. To further confirm that our findings are mainly driven by energy commodities, we consider the non-energy commodity index and our results show that for the non-energy commodities, Bitcoin is just a diversifier, independent of the sample periods. Overall, the weak correlation between Bitcoin and energy commodities, non-energy commodities or commodities in general could mean that the large traditional investors have not yet considered Bitcoin as an investment prospect. The reason for this result could be that traditional investors do not consider Bitcoin as an investment (Bouri et al. 2017).Further, the results show that the hedge and safe-haven properties of Bitcoin differ between the two sample periods as well as in extreme downward and upward movements in the return distribution. This suggests that the December 2013 Bitcoin crash has brought substantial changes in the dynamics between Bitcoin and energy commodities. This is in accordance with our intuition that positive correlation is more likely be found during the period of decreasing Bitcoin prices. The novel findings of this study can be used by policy-makers and market participants in their decision-making.

This article has at least two limitations. The first is related to the employment of a Bitcoin Price Index – from Coindesk – representing an average of Bitcoin prices across several exchanges. In this sense, the use of other Bitcoin prices from individual Bitcoin exchanges could alter some of our empirical findings. A second limitation is related to the use of daily data to the detriment of less noisy data such as weekly data. However, given that the available number of weekly observations on Bitcoin prices so far does not exceed 500, then it is difficult to obtain reliable GARCH estimates in smaller samples (Hwang and Pereira 2006).

It is worth noting that although the above-mentioned findings are important to economic actors, a final word of caution is needed regarding the liquidity of Bitcoin. Compared to conventional assets, Bitcoin is far less liquid and accessible to retail investors. However, this can improve with the potential emergence of Bitcoin derivatives following the U.S. Commodity Futures Trading Commission's decision to classify Bitcoin as a 'commodity'. This would induce a new stream of research on Bitcoin and its financial derivatives.

Highlights

- We uncover the time-varying diversification ability of Bitcoin
- Bitcoin is a strong hedge and safe haven for energy commodities, but not for non-energy commodities.
- The price crash of 2013 affects the relation between Bitcoin and energy commodities
- Dynamic correlations between the extreme downward and upward movements are dissimilar

Disclosure statement

No potential conflict of interest was reported by the authors.

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