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On the return-volatility relationship in the Bitcoin market around the price crash of 2013

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Abstract
The authors examine the relation between price returns and volatility changes in the Bitcoin market using a daily database denominated in US dollar. The results for the entire period provide no evidence of an asymmetric return-volatility relation in the Bitcoin market. The authors test if there is a difference in the return-volatility relation before and after the price crash of 2013 and show a significant inverse relation between past shocks and volatility before the crash and no significant relation after. This finding shows that, prior to the price crash of December 2013, positive shocks increased the conditional volatility more than negative shocks. This inverted asymmetric reaction of Bitcoin to positive and negative shocks is contrary to what one observes in equities. As leverage effect and volatility feedback do not adequately explain this reaction, the authors propose the safe-haven effect (Baur, *Asymmetric volatility in the gold market*, 2012). They highlight the benefits of adding Bitcoin to a US equity portfolio, especially in the pre-crash period. Robustness analyses show, among others, a negative relation between the US implied volatility index (VIX) and Bitcoin volatility. Those additional analyses further support the findings and provide useful information for economic actors who are interested in adding Bitcoin to their equity portfolios or are curious about the capabilities of Bitcoin as a financial asset.

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Keywords Bitcoin; price crash of 2013; asymmetric GARCH; safe haven

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1 Introduction

Since its controversial inception in 2009, Bitcoin has attracted the attention of the media and economic actors. Debate on this decentralized cryptocurrency[1] soared in particular during the European sovereign debt crisis (ESDC) of 2010–2013, as some practitioners turned their backs on conventional currencies and used Bitcoin instead. Interestingly, the Commodity Futures Trading Commission's (CFTC) approval in September 2015 to regulate Bitcoin as a commodity provides important evidence of the acceptance of Bitcoin as a commodity and financial product by a US regulatory agency.[2]

Few studies have been conducted on the financial characteristics of Bitcoin. Brandvold et al. (2015) and Bouoiyour et al. (2016) focus on price discovery in the Bitcoin market. Interestingly, the latter authors reveal some lead-lag relationship between Bitcoin prices, transactions use, and investors' attractiveness. Other studies also show that Bitcoin price formation is subject to unique factors that substantially differ from that affecting conventional assets. These factors include internet search (see, among others, Kristoufek, 2013), word-of-mouth information on social media, and information on google trends (Garcia et al., 2014). Eisl et al. (2015) concentrate on the benefits of adding Bitcoin to an equity portfolio. Bitcoin is considered to be a speculative investment by Yermack (2013) and digital gold by Popper (2015). In his remarkable book entitled "Digital Gold: The Untold Story of Bitcoin", Popper covers bitcoin's evolution beginning with cryptocurrencies' antecedents and the fascinating stories of Bitcoin architects, users and investors. The author then explains the technical concepts at the heart of cryptography which helped with the design and construction of this 21st century money. In another interesting paper, Baur et al. (2015) argue that Bitcoin is a hybrid between precious metals and conventional currencies. The authors also show that Bitcoin is a useful diversifier (i.e. uncorrelated with traditional assets) and highlight its role as an investment. Bouri et al. (2016) examine the volatility persistence in the Bitcoin market. However, Dyhrberg (2015a) highlights the hedging ability of Bitcoin against the USD/EUR and USD/GBP exchange rates and UK equities, whereas Dyhrberg (2015b) situates the hedging capability of Bitcoin somewhere

[1] Dwyer (2015) explained in detail the principles of Bitcoin.

[2] https://www.bloomberg.com/news/articles/2015-09-17/bitcoin-is-officially-a-commodity-according-to-u-s-regulator; http://www.coindesk.com/us-swap-platform-registration-cftc/

between gold and the US dollar. It is worth noting that Bitcoin and gold differ in several aspects. Unlike gold, Bitcoin is an intangible asset that bears a significant counterparty risk. Notably, the latter aspect has shaken the Bitcoin market given the recent collapse of the Mt. Gox, one of the most widely used Bitcoin exchanges.

However, the safe-haven property of Bitcoin remains unexplored, especially the effect of the Bitcoin price crash of December 2013 on such a property. We therefore address this literature gap by examining whether Bitcoin can be considered as a valuable asset in downturn periods. Such an examination is important for economic actors who are searching for an ultimate asset that provides insurance against downward market movements.

Methodologically, we test the asymmetric impact of shocks (news) on Bitcoin volatility within an asymmetric-GARCH framework in line with Baur (2012). We also argue that the economic explanations for asymmetric volatility for equities are not relevant for Bitcoin.

The results point toward a positive relation between return shocks and volatility in the pre-crash period. We argue that this inverse asymmetric volatility phenomenon, which is the opposite of that found in equities,[3] is related to the safe-haven property of Bitcoin. However, this property has ceased in the post-crash period, suggesting that the price crash of 2013 has caused Bitcoin to lose its ability to compensate investors for losses in equities during stress periods. Furthermore, the findings are found to be robust when considering the relation between the US stock market uncertainty and Bitcoin volatility. Notably, investors should be cautious about the lack of liquidity in Bitcoin relative to conventional assets, as shown in the presence of serial correlation in the Bitcoin return series.

The rest of the paper is structured as follows. Section 2 introduces the data. Section 3 describes the econometric model. Section 4 presents the results. Section 5 provides the conclusion.

2 Data

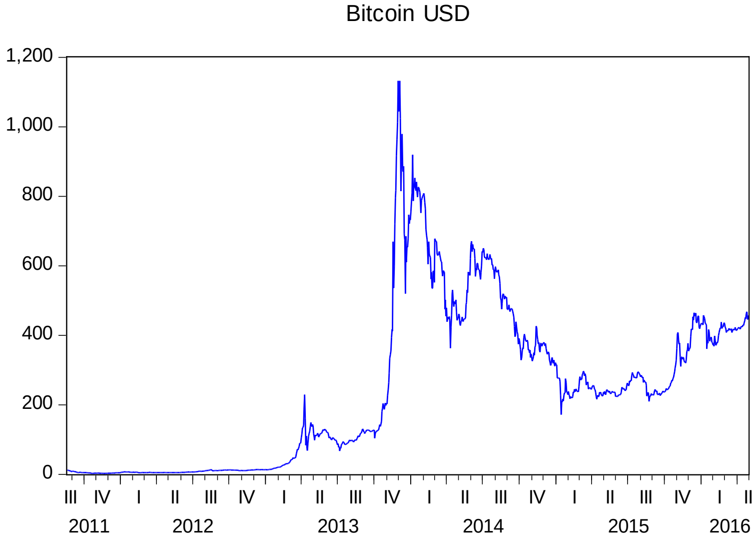
We use daily returns on Bitcoin from August 18, 2011 to April 29, 2016, calculated as the log difference in prices multiplied by 100. The data is compiled

[3] There is consensus on the negative return-volatility relation in equities (Bollerslev et al., 2007).

from Bitstamp, the largest Bitcoin exchange (Brandvold et al., 2015), and covers a daily database denominated in US dollar. The latter represents the currency against which Bitcoin is the most traded.

The database for the entire period (1,226 daily observations) covers the Bitcoin crash of December 2013[4] (Cheah and Fry, 2015) and thus allows us to examine how the safe-haven property of Bitcoin was affected as a result. Accordingly, the pre-crash period (596 daily observations) and the post-crash period (630 daily observations) are defined.[5] Figures 1 and 2 plot the level and return series respectively of Bitcoin price. Figure 2 clearly shows that large changes in prices tend to cluster together, resulting in persistence of volatility.

Figure 1. Bitcoin daily price



[4] Using the Bai and Perron's (2003) approach, results from tests for structural breaks (not reported here but available from the authors) point towards a structural break around the Bitcoin price-crash of December 02, 2013 (Cheah and Fry, 2015).

[5] Each sub-period includes more than 500 observations to ensure a proper GARCH estimation (Hwang and Pereira, 2006).

Figure 2. Bitcoin daily return

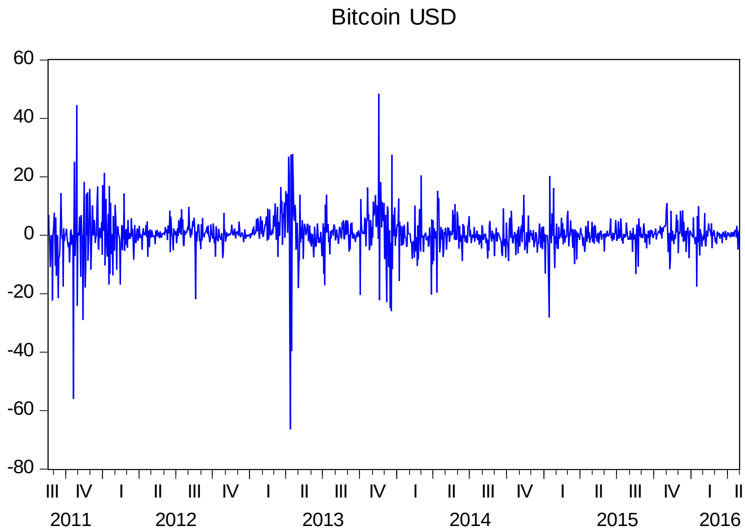


Table 1. Summary statistics of Bitcoin daily return

	Mean	Std. Dev.	Skewness	Kurtosis	Q(10)	ARCH(10)
Panel A: Entire period (August 18, 2011 – April 29, 2016)						
Bitcoin	0.305	6.566	–1.168	23.796	33.309***	20.007***
Panel B: Pre-crash period (August 18, 2011 – November 30, 2013)						
Bitcoin	0.779	8.006	–1.299	20.856	25.507***	9.071***
Panel C: Post-crash period (December 1, 2013 – April 29, 2016)						
Bitcoin	–0.144	4.787	–0.629	11.640	21.808**	13.673***

Note: Statistics for Engle's heteroskedasticity test and Ljung−Box up to 10 lags. ***, ** indicate statistical significance at 1% and 5% levels, respectively.

As reported in Table 1, Bitcoin return during the pre-crash period is positive, but it becomes negative in the post-crash period. The volatility of Bitcoin is highest during the pre-crash period, and lowest during the post-crash period. The return distribution is negatively skewed and more peaked than a normal distribution. Interestingly, the presence of serial correlation as confirmed by the Ljung−Box Q statistic, is probably due to the lack of liquidity in the Bitcoin market. Results from Engle's ARCH test justify the appropriateness of using a GARCH framework to model the conditional volatility.

3 The model

3.1 The asymmetric GARCH

Following Baur (2012), the asymmetric-GARCH model of Glosten et al. (1993) is used. The conditional mean of Bitcoin returns is calculated using Eq. (1), and the conditional volatility of Bitcoin returns is calculated using Eq. (2):

$$R_t = \mu + R_{t-P} + \varepsilon_t \tag{1}$$

$$h_t = \omega + \alpha\,(\varepsilon_{t-1}^2) + \beta(h_{t-1}) + \gamma\,(\varepsilon_{t-1}^2)\,I(\varepsilon_{t-1} < 1 \tag{2}$$

In Eq. (1), R_{t-p} is the lagged daily returns that takes into account the presence of serial correlation, In Eq. (2), ω is the constant volatility, α represents the ARCH term which measures the impact of past innovations on current variance, β represents the GARCH term which measures the impact of past variance on current variance, $\mathcal{E}$ is the error term, and γ captures any potential symmetric effect of lagged shocks on the volatility of Bitcoin. If γ is positive and significant, then a negative shock generates more volatility than a positive shock of the same magnitude; in contrast, if γ is significantly negative, then a positive shock generates more volatility than a negative shock of the same magnitude. To ensure stationarity and positivity, the following constraints must be respected: $\omega > 0$; $\alpha \geq 0$; $\beta \geq 0$; $\alpha + \gamma \geq 0$; $\alpha + \beta + 0.5\gamma < 1$. The asymmetric-GARCH model is estimated by the maximum likelihood approach under three distribution densities: Gaussian, Student-*t*, and generalized error distribution (GED). The order of the lagged returns in Eq. (1) is selected to ensure that no serial correlation is left in the residuals. We also conduct several diagnostic tests for the residuals and squared residuals to evaluate the goodness of fit of the selected models.

3.2 Asymmetry and safe-haven property

There is ample evidence that negative shocks to equities generate more volatility than positive shocks of the same magnitude (Glosten et al., 1993; Bollerslev et al., 2007). Two theories have been used to explain this negative return-volatility relation in equities. The first is the leverage hypothesis, which argues that a drop in a company's stock value makes the stock riskier, as the ratio of equities to the company value becomes smaller, while the ratio of debt to the company value becomes larger. Black (1976) and Duffee (1995) argue that this negative relation leads to a spike in the stock volatility. The second is volatility feedback (Campbell and Hentschel, 1992), which suggests that positive shocks to volatility first cause a decline in equity returns, which in turn increases the time-varying risk premium. In other words, an anticipated increase in volatility would raise the required rate of return on equity, resulting in a decline in the equity price. Nevertheless, the negative change in expected returns tends to be more intensified compared to the positive change in the expected returns, leading to an asymmetric volatility phenomenon.

Baur (2012) shows that the volatility of gold returns, contrary to equities, reacts inversely to negative shocks (i.e., positive shocks generate more volatility than negative shocks of the same magnitude). Baur (2012) argues that this positive return-volatility relation for a commodity, such as gold, cannot be explained properly by the leverage effect or volatility feedback (Bollerslev et al., 2007), but is instead related to a safe-haven property. When gold prices increase during downward market movements, investors interpret this as an increase in the uncertainty of the macroeconomic environment and thus transmit the increased uncertainty and volatility of the stock market to the gold market. By contrast, if gold prices decrease in periods of rising stock markets, the uncertainty/volatility will similarly be transmitted by investors to the gold market.

With the acceptance of Bitcoin as a commodity by the CFTC, any evidence of a positive return-volatility relation in the Bitcoin market may point toward a safe-haven property. Such evidence can be used to extend the usefulness of Bitcoin as a hedge against equity market turbulence (Dyhrberg, 2015b).

4 Results

4.1 Results of asymmetry and safe-haven property

Coefficient estimates for the mean and variance equations are reported in Tables 2 and 3, respectively. Based on the Schwarz information criterion, the asymmetric-GARCH (1,1) model and non-normal densities are found to be the best fit. In the entire and post-crash periods, the generalized error distribution is the best fit whereas the Student-*t* distribution show a much better fit in the pre-crash period. In the mean equation, the coefficients of lagged returns are significant and there is no serial correlation left in the residuals. This suggests that, except for the post-crash period, the inclusion of lagged return in the mean equation has removed the presence of serial correlation (see Table 2). In the entire period, for example, we include four lagged returns (i.e. 4, 5, 9 and 10). Regarding the variance equation, the stationarity and positivity conditions are respected in all periods and there is no evidence of conditional heteroscedasticity in the squared residuals. Across all Panel estimates, the ARCH and GARCH terms are highly significant, with the GARCH term dominating the ARCH term, indicating that the volatility of Bitcoin is highly persistent (see Table 3). Over the entire period (Panel A), the coefficient for the asymmetric term (γ) is negative but insignificant. However, this same coefficient varies between pre- and post-crash periods (see Panels B and C). Interestingly, in the pre-crash period, it is negatively significant at the 1% level.

Table 2. Coefficient estimates of the asymmetric-GARCH model – mean equation

	Constant	R_{t-4}	R_{t-5}	R_{t-9}	R_{t-10}	Q(10)
Panel A: Entire period (August 18, 2011 – April 29, 2016)						
Bitcoin	0.218**	0.051*	0.055**	0.044*	0.066***	15.107
Panel B: Pre-crash period (August 18, 2011 – November 30, 2013)						
Bitcoin	0.528***	-	-	0.100**	0.082**	11.997
Panel C: Post-crash period (December 1, 2013 – April 29, 2016)						
Bitcoin	0.051	-	-	-	-	10.181

Notes: This table reports the estimation results from Eq.(1); statistics for Ljung−Box test up to 10 lags; ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

Table 3. Coefficient estimates of the asymmetric-GARCH model– variance equation

	Constant	ARCH	GARCH	Asymmetry	ARCH(10)
Panel A: Entire period (August 18, 2011 – April 29, 2016)					
Bitcoin	0.403***	0.158***	0.840***	–0.027	0.146
Panel B: Pre-crash period (August 18, 2011 – November 30, 2013)					
Bitcoin	0.374***	0.236***	0.804***	–0.119***	0.054
Panel C: Post-crash period (December 1, 2013 – April 29, 2016)					
Bitcoin	0.864**	0.116**	0.805***	0.071	0.552

Notes: this table reports the estimation results from Eq.(2); Statistics for Engle's heteroskedasticity test up to 10 lags; ***, ** indicate statistical significance at 1% and 5% levels respectively.

Before the price crash of 2013, Bitcoin was characterized by an inverse asymmetric volatility phenomenon, meaning that shocks to return were positively correlated with shocks to volatility. This result is contrary to that found in equities (Bollerslev et al., 2007). As indicated by Baur (2012), such findings for commodities cannot be adequately explained by the leverage effect or volatility feedback. We therefore follow Baur (2012) and propose the safe-haven hypothesis, which is more likely to explain our finding. If Bitcoin prices increase in periods of economic/financial turmoil, during which stock markets fall, investors purchase Bitcoin and transmit the increased uncertainty and volatility of the stock markets to the Bitcoin market. Similarly, if Bitcoin prices decrease in times of rising stock markets, then investors sell Bitcoin, signaling that uncertainty is low; thereby, investors transmit the decreased volatility to the Bitcoin market. Accordingly, the volatility of Bitcoin decreases less as the price of Bitcoin increases, leading to an inverted asymmetry phenomenon. This interesting finding concurs with that reported for gold (Baur, 2012), and adds further evidence to the similarities between gold and Bitcoin (Dyhrberg, 2015b). Another plausible explanation of the findings relates to investors' quest for a safe-haven asset in an environment of weak trust, such as during the global financial crisis (GFC) and post-GFC periods, in particular during the ESDC. At that time, the systematic weakness of the global financial system and fear of European monetary union collapse predominated; central banks in developed economies adopted a series of rapid cuts in interest rates and massive purchases of long-term securities, known as quantitative easing (QE). In such an environment, Bitcoin has represented a decentralized alternative monetary system, and therefore a safe haven against market risk.

In the post-crash period, however, the inverse asymmetric effect disappeared, suggesting that the price crash of 2013 has ended the safe-haven capabilities of Bitcoin.[6]

Further, we estimate the Exponential-GARCH, an alternative to the asymmetric-GARCH model of Glosten et al. (1993), for the entire period and two sub-periods. Results indicate that the asymmetric term of the Exponential-GARCH model is positive and significant in the pre-crash period. This finding, which is consistent with the inverse asymmetric effect as positive return shocks in the Bitcoin market generate more volatility than negative shocks of the same magnitude, shows that the volatility asymmetry is not affected by the choice of the asymmetric-GARCH model.[7]

We also estimate the asymmetric-GARCH models for the S&P 500 returns in the entire period and the two periods before and after the price crash of 2013, and compare the coefficients for the asymmetric term (γ) to that of Bitcoin reported in Table 3. As expected and argued in subsection 3.2, the asymmetric term of the S&P 500 conditional volatility is significantly positive at the 1% level in all the three periods under study,[8] suggesting that negative return shocks to US equities lead to an increased volatility (i.e. this is contrary to that found in the Bitcoin market).

4.2 News impact curves

The news impact curves are defined by the functional relationship between $\sigma^2_{n|n-1}$ and ε_{n-1} holding all other variables constant. This provides a simple way of characterizing the influence of the most recent shock on the next period's conditional volatility. Figure 3 plots the asymmetric volatility effect of the differential impact

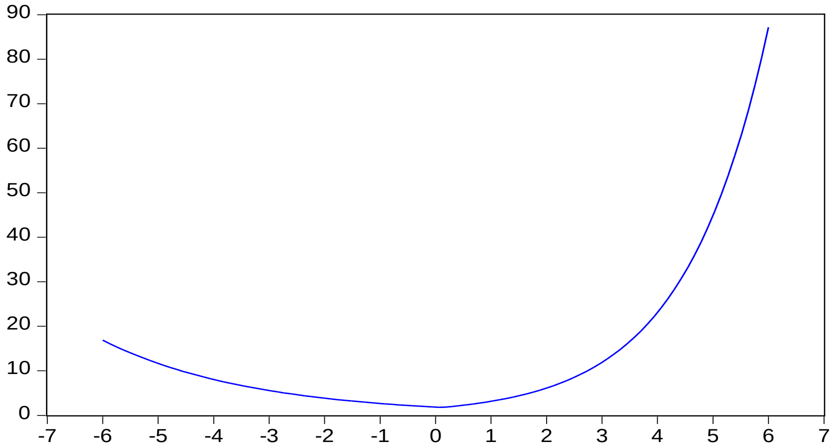
[6] We also consider Bitcoin return in different various currency denominations (Australian dollar, the Canadian dollar, the British pound, the euro, and the Japanese yen) to account for any potential influence of changes in the value of currency on the asymmetric effect. Unreported results are homogenous results across various currency denominations of Bitcoin returns, further supporting our previous findings about the safe-haven property of Bitcoin.

[7] The results of the Exponential-GARCH model are not reported here, but are available from the authors.

[8] The coefficient for the asymmetric term in the S&P 500 return is 0.362 for the entire period, 0.285 for the pre-crash period, and 0.478 for the post-crash period.

of negative and positive returns with news impact curves for Bitcoin returns from Panel B. The x-axis illustrates the lagged returns, while the contemporaneous volatility is indicated on the y-axis. Figure 3 shows that the impact of positive shocks on the conditional volatility of Bitcoin return is far larger than that of negative shocks.

Figure 3. News impact curve for Bitcoin



4.3 Portfolio implications

We illustrate the portfolio implications of our empirical findings for the stake of investors holding Bitcoin and US equities, and this in order to provide practical evidence that Bitcoin could reduce equity downside risk. Therefore, we consider a benchmark portfolio A, composed 100% of US equities represented by the S&P 500, against an equally weighted portfolio B composed of 50% Bitcoin and 50% in the S&P 500 and another portfolio C of Bitcoin and the S&P 500 constructed to have the minimum risk without reducing the expected return. Following Kroner and Ng (1998), the optimal weight of Bitcoin in portfolio C is given by:

$$\omega_{i,t} = \frac{h_{j,t} - h_{ij,t}}{h_{i,t} - 2h_{ij,t} + h_{j,t}} \tag{3}$$

with $\omega_{i,t} = 0 \; if \; \omega_{i,t} < 0$; $\omega_{i,t} = \omega_{i,t} \; if \; 0 \leq \omega_{i,t} \leq 1$; $\omega_{i,t} = 1 \; if \; \omega_{i,t} > 1$; where $\omega_{i,t}$ is the portfolio weight for Bitcoin at time t, $h_{i,t}$ denotes the conditional variance of Bitcoin, $h_{j,t}$ denotes the conditional variance of the S&P 500, and $h_{ij,t}$ denotes the conditional covariance between Bitcoin and the S&P 500 at time t. Therefore, the weight of S&P 500 in portfolio C is $1–\omega_{i,t.}$

Next, we focus on the risk reduction effectiveness (RRE) in portfolios B and C. To this end, we compare the percentage reduction in the risk of these two portfolios with respect to the benchmark portfolio A.

$$RRE = 1 - \frac{Risk\ Portfolio_{\ k}}{Risk\ Portfolio_{\ \mathrm{A}}} \tag{4}$$

where k = B, C.

The results reported in Table 4 show large reductions in risk for both portfolios B and C during all the periods under study. Interestingly, the optimal weighted portfolio C outperforms the equally weighted portfolio B. More importantly, the reduction in risk is the largest during the pre-crash period when we found statistical evidence of an inverse asymmetric effect. This practical portfolio implication supports the effectiveness of Bitcoin in reducing equity risk, especially in the pre-crash period of 2013, and further reinforces our earlier findings on Bitcoin's safe haven property (see Table 2).

Table 4. Risk reduction effectiveness – Bitcoin and US equities

	Entire period	Pre-crash period	Post-crash period
	US equities	US equities	US equities
Portfolio B	0.093	0.112	0.043
Portfolio C	0.107	0.129	0.035

Notes: Based on Eq. (4), this table reports the RRE for portfolios B and C composed of Bitcoin and US equities with respect to the benchmark portfolio composed 100% of US equities. Portfolio B is an equally weighted portfolio of 50% Bitcoin and 50% in the S&P 500. Portfolio C is composed of Bitcoin and US equities according to the optimal weights given by Eq. (3).

4.4 Further analysis

In this subsection, we examine the robustness of our main findings.

First, we assess whether our findings are robust to the choice of the asymmetric GARCH model. We therefore compare the estimated asymmetric-GARCH model with its symmetric-GARCH counterpart to indicate the preferred GARCH model according to the log-likelihood function. Intuitively, the asymmetric-GARCH model has larger values for the log-likelihood function in all the sample periods under study,[9] suggesting that asymmetric-GARCH model outperforms the simple symmetric-GARCH model and explains better the conditional volatility of Bitcoin returns.

Second, we estimate in Eq. (5) an extension version of the asymmetric-GARCH model presented earlier in Eq. (2) by adding the return series on the US implied volatility index (VIX). Several studies report a negative relation between the VIX and safe haven assets such as gold (see, among others, Jubinski and Lipton, 2013). The VIX index is a forward-looking measure of US market uncertainty published by the Chicago Board Options Exchange (CBOE). It is backed out from option prices, and accordingly, it doesn’t only reflect historical volatility information, but also investors’ expectation on future market conditions (Liu et al., 2013).

$$h_t = \omega + \alpha\,(\varepsilon_{t-1}^2) + \beta(h_{t-1}) + \gamma\,(\varepsilon_{t-1}^2)\,I(\varepsilon_{t-1} < 1) + \varphi\,VIX_{t-1}^2 \qquad (5)$$

If the parameter φ is negatively significant, then there exists an inverse relation between the US stock market uncertainty and the Bitcoin volatility. This means that in an environment of high uncertainty in the stock market, market participants moved into Bitcoin to hedge any possible stock market losses. Because our focus here is on the relation between the VIX and Bitcoin volatility, coefficient estimates from Eq. (5) are not all reported here but available from the authors. Interestingly, the coefficient estimate for the VIX is negative but insignificant in both the entire and post-crash periods (–0.001 and –0.002 respectively). Only the results from the pre-crash period show a significant inverse relation between the US stock market uncertainty and the Bitcoin

[9] The asymmetric-GARCH model leads to higher values of the log-likelihood function than the symmetric GARCH model in all periods (–3387.72 versus –3389.68 in the entire period).

volatility; interestingly, the coefficient estimate (φ) is negatively significant at the 5% level (–0.008). This finding supports the findings previously reported in Table 3. Bitcoin volatility has a statistically negative response to the US implied volatility.

5 Conclusion

Using a different methodological approach to prior studies, this paper focuses on the safe-haven property of Bitcoin and its relationship to the price crash of December 2013. Based on an asymmetric-GARCH framework, the main results indicate that in the pre-crash period, Bitcoin has a safe-haven property. The results also show an inverse relation between the US VIX and the Bitcoin volatility. After the price crash, however, the safe-haven property disappears. We also illustrate that adding Bitcoin to US equity portfolios leads to an effective risk reduction, in particular before the price-crash of 2013. Several robustness analyses support the findings. However, investors should be cautious about the lack of liquidity in Bitcoin relative to conventional assets. Finally, future studies using higher-frequency data, when available, are necessary to assess the robustness of our findings.

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