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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 various currencies. The results for the entire period provide no evidence of an asymmetric return-volatility relation in the Bitcoin market. They 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 the authors observe in equities. As leverage effect and volatility feedback don't adequately explain this reaction, they propose the safe-haven effect (Baur, *Asymmetric volatility in the gold market*, 2012). The authors 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 their 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; 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<sup>1</sup> 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 approval by the Commodity Futures Trading Commission (CFTC) in September 2015 of the temporary listing of an over-the-counter swap product based on the price of a Bitcoin provides important evidence of the acceptance of Bitcoin as a commodity and financial product by a US regulatory agency.

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, while 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). 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 between gold and the US dollar.

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, like gold, 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.

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<sup>1</sup> Dwyer (2014) explained in detail the principles of Bitcoin.

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<sup>2</sup>, 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. Homogenous results across various currency denominations of Bitcoin returns further support our findings. Furthermore, the findings are found to be robust when considering the relation between the US stock market uncertainty and Bitcoin volatility.

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.

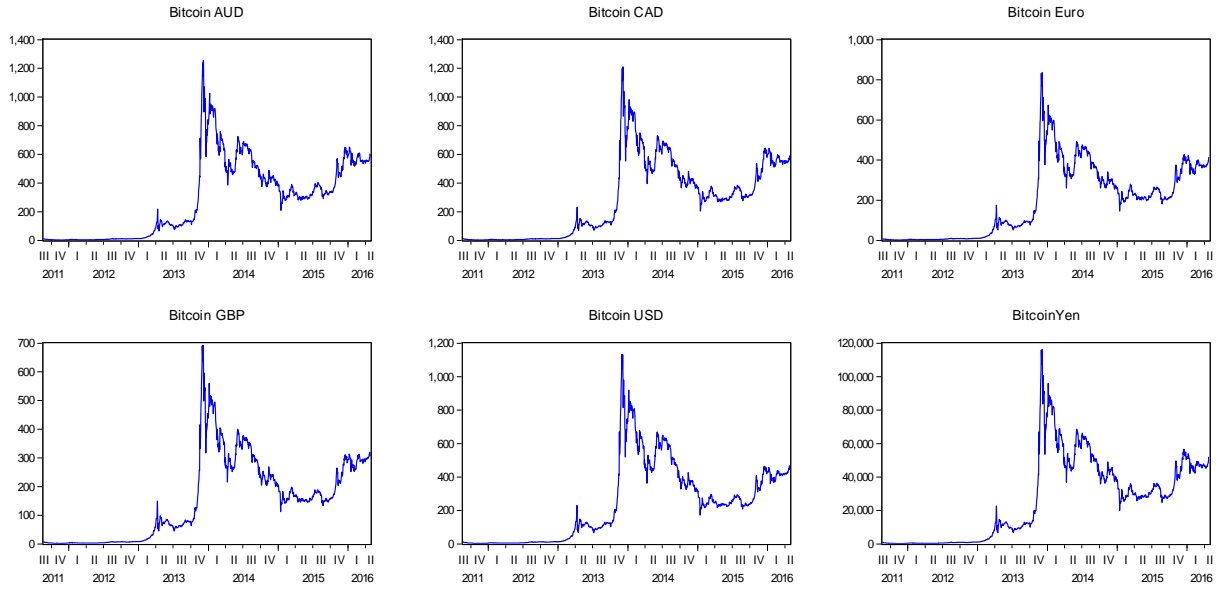
## **2. Data**

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 from Bitstamp, the largest Bitcoin exchange (Brandvold et al., 2015), and covers various currency denominations to account for any potential influence of changes in the value of currency on the asymmetric effect. We selected the currencies against which Bitcoin is the most traded. These include the American dollar, the Australian dollar, the Canadian dollar, the British pound, the euro, and the Japanese yen.

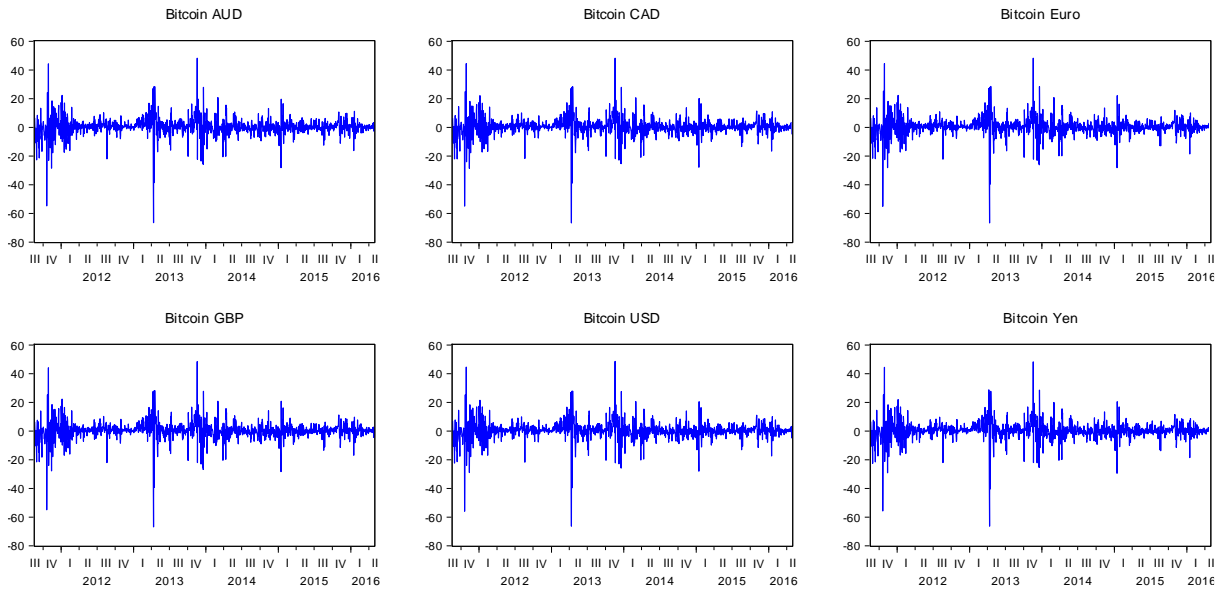
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<sup>2</sup> There is consensus on the negative return-volatility relation in equities (Bollerslev et al., 2007).

**Figure 1. Bitcoin daily prices**



**Figure 2. Bitcoin daily returns**



The database for the entire period (1,226 daily observations) covers the Bitcoin crash of December 2013<sup>3</sup> (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<sup>4</sup>. Figures 1 and 2 plot the level and return series respectively of Bitcoin prices in different currency denominations. Figure 2 clearly shows that large changes in prices tend to cluster together, resulting in persistence of volatility.

**Table 1. Summary statistics of Bitcoin daily returns**

	Mean	Std. Dev.	Skewness	Kurtosis	ARCH(10)
Panel A: Entire period (August 18, 2011 – April 29, 2016)					
Bitcoin-AUD	0.330	6.582	-1.144	23.155	20.006***
Bitcoin-CAD	0.324	6.578	-1.147	23.357	19.823***
Bitcoin-Euro	0.323	6.593	-1.147	23.307	20.126***
Bitcoin-GBP	0.314	6.573	-1.166	23.556	20.115***
Bitcoin-USD	0.305	6.566	-1.168	23.796	20.007***
Bitcoin-Yen	0.332	6.601	-1.159	23.347	19.859***
Panel B: Pre-crash period (August 18, 2011 – November 30, 2013)					
Bitcoin-AUD	0.801	7.999	-1.283	20.506	9.061***
Bitcoin-CAD	0.790	8.003	-1.289	20.630	8.992***
Bitcoin-Euro	0.787	8.012	-1.287	20.622	9.147***
Bitcoin-GBP	0.780	7.993	-1.295	20.792	9.138***
Bitcoin-USD	0.779	8.006	-1.299	20.856	9.071***
Bitcoin-Yen	0.828	8.021	-1.298	20.680	9.088***

<sup>3</sup> 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).

<sup>4</sup> Each sub-period includes more than 500 observations to ensure a proper GARCH estimation (Hwang and Pereira, 2006).

Panel C: Post-crash period (December 1, 2013 – April 29, 2016)

Bitcoin-AUD	-0.116	4.841	-0.601	11.345	13.907***
Bitcoin-CAD	-0.117	4.826	-0.581	11.344	13.328***
Bitcoin-Euro	-0.117	4.853	-0.596	11.601	14.148***
Bitcoin-GBP	-0.126	4.827	-0.649	11.697	14.040***
Bitcoin-USD	-0.144	4.787	-0.629	11.640	13.673***
Bitcoin-Yen	-0.137	4.854	-0.644	11.651	13.456***

Note: Statistics for Engle's heteroskedasticity test up to 10 lags. \*\*\* indicates statistical significance at the 1% level.

As reported in Table 1, Bitcoin returns during the pre-crash period are positive, but they become 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. Results from Engle's ARCH test justify the appropriateness of using a GARCH framework to model the conditional volatility. Interestingly, there are no major variations of specific statistics among the different currency denominations of Bitcoin returns.

### 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. (1a), and the conditional volatility of Bitcoin returns is calculated using Eq. (1b):

$$R_t = \mu + \varepsilon_t \quad (1a)$$

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

In Eq. (1b),  $\omega$  is the constant volatility,  $\alpha$  represents the ARCH term which measures the impact of past innovations on current variance,  $\beta$  represents the GARCH term which measures the impact

of past variance on current variance,  $\varepsilon$  is the error term, and  $\gamma$  captures any potential symmetric effect of lagged shocks on the volatility of Bitcoin. If  $\gamma$  is positive and significant, then a negative shock generates more volatility than a positive shock of the same magnitude; in contrast, if  $\gamma$  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).

### **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 are reported in Table 2. Based on the Schwarz information criterion, the asymmetric-GARCH (1,1) model and the GED density are found to be the best fit<sup>5</sup>. Furthermore, the stationarity and positivity conditions are respected for all cases and there is no evidence of conditional heteroscedasticity in the squared residuals<sup>6</sup>. 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. Over the entire period (Panel A), the coefficient for the asymmetric term ( $\gamma$ ) is negative but insignificant. However, this same coefficient

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<sup>5</sup> Based on Schwarz information criterion (SIC), results, not reported here but available from the authors, show no evidence of an auto-regressive dynamic in the return series.

<sup>6</sup> Results of residual diagnostics tests are not reported here, but are available from the authors.



varies between pre- and post-crash periods (see Panels B and C). Interestingly, in the pre-crash period, it is negatively significant in all cases.

**Table 2. Coefficient estimates of the asymmetric-GARCH model**

	Constant	ARCH	GARCH	Asymmetry
<b>Panel A: Entire period (August 18, 2011 – April 29, 2016)</b>				
Bitcoin-AUD	0.618***	0.193***	0.829***	-0.036
Bitcoin-CAD	0.653***	0.217***	0.819***	-0.050
Bitcoin-Euro	0.651***	0.214***	0.818***	-0.049
Bitcoin-GBP	0.694***	0.203***	0.821***	-0.045
Bitcoin-USD	0.559***	0.229***	0.818***	-0.057
Bitcoin-Yen	0.689***	0.218***	0.819***	-0.061
<b>Panel B: Pre-crash period (August 18, 2011 – November 30, 2013)</b>				
Bitcoin-AUD	0.312**	0.219***	0.868***	-0.120**
Bitcoin-CAD	0.367**	0.255***	0.851***	-0.138*
Bitcoin-Euro	0.495*	0.255***	0.839***	-0.123*
Bitcoin-GBP	0.531**	0.255***	0.840***	-0.130*
Bitcoin-USD	0.400*	0.269***	0.839***	-0.137*
Bitcoin-Yen	0.412*	0.256***	0.852***	-0.147**
<b>Panel C: Post-crash period (December 1, 2013 – April 29, 2016)</b>				
Bitcoin-AUD	1.112**	0.098*	0.794***	0.096
Bitcoin-CAD	1.147**	0.096*	0.790***	0.107
Bitcoin-Euro	1.091**	0.115**	0.789***	0.085
Bitcoin-GBP	0.998***	0.084*	0.815***	0.088
Bitcoin-USD	0.906**	0.113**	0.803***	0.078
Bitcoin-Yen	1.182**	0.109*	0.789***	0.088

Notes: this table reports the estimation results from Eq.(1b); \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10% 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. As such, it mirrored the role of gold.

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. Furthermore, the variation in

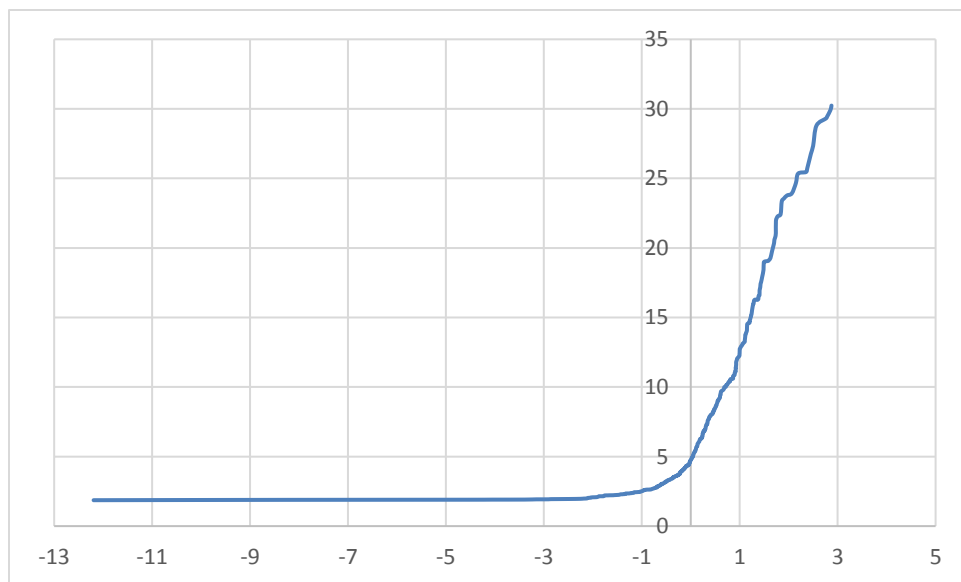
the results across Panel B indicates that the currency denomination doesn't matter to the safe-haven property of Bitcoin, which further support our findings.

#### 4.2 News impact curves

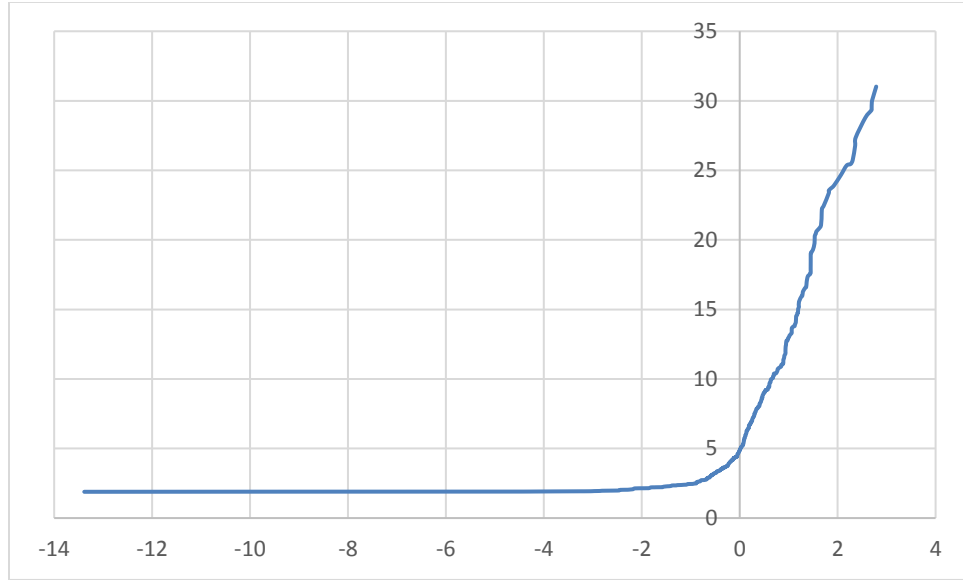
The news impact curves are defined by the functional relationship between  $\sigma^2_{n|n-1}$  and  $\varepsilon_{n-1}$  holding all other variables constant. This provides a simple way of characterizing the influence of the most recent shock on the next period's conditional volatility.

Figures 3 and 4 plot the asymmetric volatility effect of the differential impact of negative and positive returns with news impact curves for AUD- and yen-denominated 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 volatility of the AUD-denominated Bitcoin returns is 2 for shocks equal to  $-12.5\%$ , and 30 for shocks equal to  $+2.8\%$ . Hence, the impact of positive shocks on the conditional volatility is 15 times larger than that of negative shocks. A similar pattern for yen-denominated Bitcoin returns is shown in Figure 4.

**Figure 3. News impact curve for Bitcoin in AUD**



**Figure 4. News impact curve for Bitcoin in yen**



### 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:

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

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.

$$RRE = 1 - \frac{Risk\ Portfolio\ k}{Risk\ Portfolio\ A} \quad (4)$$

where  $k = B, C$ .

The results reported in Table 3 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 3. 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<sup>7</sup>, suggesting that asymmetric-GARCH model outperforms the simple symmetric-GARCH model and explains better the conditional volatility of Bitcoin returns.

Second, 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.

Third, we 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 ( $\gamma$ ) to that of Bitcoin reported in Table 2. As expected and argued in subsection 3.2, the asymmetric term of the S&P 500 conditional volatility is significantly positive at the 1%

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<sup>7</sup> 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).

level in all the three periods under study<sup>8</sup> (i.e. it is contrary to that found in the Bitcoin market), suggesting that positive return shocks to US equities lead to an increased volatility.

Fourth, we focus on the USD-denominated Bitcoin returns and estimate in Eq. (2) an extension version of the asymmetric-GARCH model presented earlier in Eq. (1) by adding the return series on the US implied volatility index (VIX). Several studies report a negative relation between the VIV 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).

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

If the parameter  $\varphi$  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 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 volatility; interestingly, the coefficient estimate ( $\varphi$ ) is negatively significant at the 5% level (−0.008). This finding supports the findings previously reported in Table 2. Bitcoin volatility has

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<sup>8</sup> 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.

a statistically negative response to the US implied volatility, as in the case of gold (Jubinski and Lipton, 2013).

## 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 somewhat similar to gold. After the price crash, however, this safe-haven property disappears. The results also indicate that the currency denomination of Bitcoin has no effect on its safe-haven capability. We also show 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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