



# Can volume predict Bitcoin returns and volatility? A quantiles-based approach<sup>☆</sup>



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## ABSTRACT

Prior studies on the price formation in the Bitcoin market consider the role of Bitcoin transactions at the conditional mean of the returns distribution. This study employs in contrast a non-parametric causality-in-quantiles test to analyse the causal relation between trading volume and Bitcoin returns and volatility, over the whole of their respective conditional distributions. The nonparametric characteristics of our test control for misspecification due to nonlinearity and structural breaks, two features of our data that cover 19th December 2011 to 25th April 2016. The causality-in-quantiles test reveals that volume can predict returns – except in Bitcoin bear and bull market regimes. This result highlights the importance of modelling nonlinearity and accounting for the tail behaviour when analysing causal relationships between Bitcoin returns and trading volume. We show, however, that volume cannot help predict the volatility of Bitcoin returns at any point of the conditional distribution.

## 1. Introduction

Studying the relationship between volume and returns is important in generating a better understanding of how market information is transmitted and then embedded in asset prices. It also helps increase the utility of forecasting asset returns and volatility. In times of stress, in particular, it is critical to examine the return-volume relationship to better understand market booms and crashes (Marsh and Wagner, 2000).

While the volume–return relationship has been extensively covered for equities (Karpoff, 1987; Li et al., 2016; Todorova and Souček, 2014), bonds (Balduzzi et al., 2001), commodities (Chiarella et al., 2016), interest rates and currency futures (Puri and Philippatos, 2008), and real estate (Tsai, 2014), it remains unexplored for the Bitcoin market. The latter has recently attracted the attention of the media and scholars, given the rising importance of Bitcoins not only as an electronic payment system but also as financial and speculative assets (Kristoufek, 2014).

In a speculative market, such as that of Bitcoin, understanding the volume–return paradigm is essential to shedding light on potential implications for trading strategies. Practically, if the transaction

volume in the Bitcoin market has a predictive power for its returns, this suggests that practitioners will be able to construct volume-based strategies to increase profits (Chen et al., 2001). This is particularly important given that many traders and practitioners have relied on technical analysis as an alternative tool to study Bitcoin prices, as no reliable, fundamental valuation technique is available to quantify the intrinsic value of Bitcoin. The fact that market technicians employ models and trading rules based on the relation between return and volume further underscores the need for a better understanding of the Bitcoin volume–return relationship.

Since its inception in 2009, Bitcoin has been characterized by sharp upward and downward price movement associated with high transaction volumes. On 19 November 2013, the price of Bitcoin on Bitstamp, the largest European Bitcoin exchange, plunged almost 20% (19.88%) on the highest volume ever recorded (71,560 Bitcoins). Furthermore, on 7 December 2013, the Bitcoin price plunged almost 15% (14.92%) and recorded a new all-time trading volume high of 79,852 Bitcoins. Again, on 18 December 2013, Bitcoin price plunged almost 23% (22.80%) and hit a new daily volume record high of 137,070 Bitcoins.<sup>1</sup> These trends suggest a strong relationship between the magnitudes of price movement and transaction volume. However, no

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<sup>1</sup> For a detailed explanation on the negative and positive bubbles in the Bitcoin market, please refer to Fry and Cheah (2016).

study thus far to explore this relationship in depth for Bitcoin. To address this research gap, we use the novel, nonparametric causality-in-quantiles test from [Balcilar et al. \(2016a\)](#) to examine the predictability of Bitcoin returns and volatility based on trading volume. For our purpose, we use daily data covering the period of 19 December 2011 to 25 April 2016. The nonparametric causality-in-quantiles approach has three main novelties: First, our approach is robust to misspecification errors as it detects the underlying dependence structure across the variables under study. This novelty arises from the view that stock returns are inherently non-linear (see [Bekiros et al., 2016](#), for a detailed discussion in this regard) – a fact we confirm in our data. Second, our methodology allows for the detection of not only the causality-in-mean but also for any potential causality in the tails of the joint distribution of the variables. This novelty is crucial if the dependent variable has proven to have fat-tails – a fact that has been shown to exist for Bitcoin returns (and volume). Third, our nonparametric causality-in-quantiles approach allows us to examine causality-in-variance and, thus, study higher-order dependency. Such an investigation is important because during some periods, causality in the conditional-mean may not exist, while, at the same time, higher-order interdependencies may turn out to be significant.

Note that we could have also used nonlinear causality tests (for example, [Hiemstra and Jones, 1994](#), and [Diks and Panchenko, 2005](#)) and GARCH models to analyse the impact of volume on Bitcoin returns and/or volatility, as used recently by [Bampinas and Panagiotidis \(2015\)](#) while analyzing causality between gold and oil markets. As pointed out by [Diks and Panchenko \(2005\)](#), Himestra-Jones test is generally not compatible with the definition of Granger causality and over-rejects the null of no Granger causality. [Diks and Panchenko \(2005\)](#) rectify the over-rejection problem of the Himestra-Jones test by using the average of local dependence measures. However, these approaches rely on conditional-mean based estimation, and hence, fail to capture the entire conditional distribution of returns and volatility – something we can do with our nonparametric causality-in-quantile approach. Indeed, [Bampinas and Panagiotidis \(2015\)](#) find evidence that mean-based test cannot deal with the time dependent causality linkages due to structural breaks. In the process, our nonparametric causality-in-quantiles test is a more general procedure of detecting causality in both returns and volatility simultaneously at each point of their respective conditional distributions. Hence, we are able to capture existence or non-existence of causality at various states of the Bitcoin market: bear (lower quantiles), normal (median), and bull (upper quantiles). As a more general test, our nonparametric causality-in-quantile approach is more likely to pick up causality when conditional mean-based tests might fail to do so. In addition, since we do not need to decide on the number of regimes as in a Markov-switching model, and can test for causality at each point of the conditional distribution characterising specific regimes, our test also does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes. An important issue however, is that like standard causality tests, existence of causality would imply that it holds at all horizons. As discussed in [Bampinas and Panagiotidis \(2015\)](#), a more informative causality test would be to use the approach of [Hill \(2007\)](#), which allows us to detect causality in tri-variate system and at multiple horizons and in a time-varying fashion using recursive or rolling windows. While the advantages in terms of multiple-horizons are undeniable, the approach of [Hill \(2007\)](#) remains a conditional mean based approach restricted to only the first-moment.

Indeed, certain studies, such as [Chuang et al. \(2009\)](#), [Chiang and Li \(2012\)](#), [Gebka and Wohar \(2013\)](#), [Lin \(2013\)](#), and [Chen et al. \(2016\)](#), have used quantile based methodologies to study the relationship between returns and volatility based on the volume of traditional stock indices of Pacific Basin and Asian countries. However, to the best of our knowledge, this is the first study that analyses the predictability of returns and volatility of Bitcoin based on trading volume using a nonparametric method that covers the entire conditional distribution

of returns and volatility, and is free from misspecification due to nonlinearities and structural breaks.

The rest of the paper is organized as follows: [Section 2](#) reviews related literature on the finance and economics of Bitcoin. [Section 3](#) presents our methodology, while [Section 4](#) discusses the data and the results. Finally, [Section 5](#) concludes.

## 2. Literature review

Bitcoin is an open source software-based online payment system. Its popularity among practitioners and economic actors has soared in response to the perceived failures of governments and central banks during the global financial crisis of 2008 and the European sovereign debt crisis (ESDC) of 2010–2013. While central authorities and central banks guarantee or have control over conventional currencies, Bitcoin is fully decentralized and depends on a sophisticated protocol that uses only cryptography to control transactions, manage its supply, and prevent harmful actions that may endanger the system. All transactions are stored digitally and recorded in a shared ledger data technology known as *blockchain*. While the algorithm behind Bitcoin represents a solid safeguard against counterfeiting, the system has proved to be vulnerable to illicit activities such as the massive theft of 350 million USD worth of Bitcoins from the Mt. Gox exchange in February 2014. The principles of Bitcoin are explained by [Dwyer \(2015\)](#) and at [bitcoin.org](#). Bitcoin is the first cryptocurrency to come into existence. While other cryptocurrencies, such as Feathercoin and Peercoin, now exist, Bitcoin has managed to maintain its leading position in this particular market.<sup>2</sup> At the end of June 2016, Bitcoin market capitalisation exceeded 10 billion USD ([coinmarketcap.com](#)), which represents more than 80% of the total market capitalisation of all cryptocurrencies on the market.

In addition to the early, extensive literature on the technical and legal aspects of Bitcoin, the economics and finance debate on Bitcoin have recently intensified. [Kristoufek \(2014\)](#) argues that Bitcoin represents a unique asset, possessing properties of both a standard financial asset and a speculative one. On the other hand, [Popper \(2015\)](#) considers Bitcoin to be digital gold and [Bouri et al. \(2017a, 2017b\)](#) highlight some valuable characteristics of Bitcoin as an investment. Regardless of whether Bitcoin is a financial or a speculative asset, digital gold, or a commodity, some studies have been interested in the ‘moneyness’ of Bitcoin. [Yermack \(2013\)](#) argues that Bitcoin has no intrinsic value but behaves more like a speculative investment than a currency because its market capitalisation is high compared to the economic transactions it facilitates. The author also concludes that Bitcoin volatility adversely affects its usefulness as a currency. [Glaser et al. \(2014\)](#) find that most of the interest in Bitcoin is due to its ‘asset’ aspect and not its currency aspect. [Hanley \(2013\)](#) also indicates that Bitcoin has no fundamental value to support its pure market valuation against conventional currencies. In contrast, [Woo et al. \(2013\)](#) argue that Bitcoin has some fair value due to its money-like properties. [Garcia et al. \(2014\)](#) and [Hayes \(2016\)](#) show that the cost of producing a Bitcoin via mining adds some fundamental value to Bitcoins.

Other studies have examined the price formation in the Bitcoin market. [Kristoufek \(2013\)](#) reports a strong bidirectional causality between the prices of Bitcoin and the search queries for Bitcoin on Google Trends and Wikipedia. [Bouoiyour and Selmi \(2015\)](#) illustrate the significant role of a lagged Google search for the word ‘Bitcoin’ in explaining the Bitcoin price, whereas the velocity of Bitcoin, measured by data transactions, fails to explain the Bitcoin price. Similar results regarding the roles of the two above-mentioned variables (the volume of daily searches for Bitcoin on the Internet and the number of Bitcoin transactions) in explaining the Bitcoin price are reported by [Polasik](#)

<sup>2</sup> By the end of June 2016, there were more than 700 cryptocurrencies traded in the market.

et al. (2015). Within the same research subject, Kristoufek (2014) finds that the trade-exchange ratio plays an essential role in driving Bitcoin price fluctuations in the long run. Bouoiyour et al. (2015) examine the relations between Bitcoin price and transactions proxied by the exchange-trade ratio. The authors find that Bitcoin price Granger causes an exchange-trade ratio in the short- and medium-terms. Like Kristoufek (2014), they find that the increasing use of Bitcoin in the exchange-trade ratio expands Bitcoin's price in the long term. They also show a significant link that runs from the exchange-trade ratio to the Bitcoin price. An interesting paper by Ciaian et al. (2016) focuses on the determinants of Bitcoin price fluctuations. It shows that the total number of unique Bitcoin transactions per day – a demand side variable – has more impact on the Bitcoin price than the number of Bitcoins – a supply side variable.

We argue that the above literature presents an incomplete picture of the role of trading volume in predicting the Bitcoin returns because the Bitcoin volume–return relationship at the tails may be different from that near the mean of the return distribution. Furthermore, prior studies have overlooked the dependency between the second moment of Bitcoin returns and trading volume. These issues suggest the appropriateness of using the nonparametric causality-in-quantiles test of Balcilar et al. (2016a) to investigate this further.

### 3. Methodology

In this section, we present a novel methodology for detecting nonlinear causality in the mean and the variance proposed by Balcilar et al. (2016a) in their extension of the models of Nishiyama et al. (2011) and Jeong et al. (2012). This methodological approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies.

We start by denoting Bitcoin returns by  $y_t$  and the predictor variable (in our case the traded volume) as  $x_t$ .

Let  $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$ ,  $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$ ,  $Z_t = (X_t, Y_t)$ , and  $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$  and  $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$  denote the conditional distribution functions of  $y_t$  given  $Z_{t-1}$  and  $Y_{t-1}$ , respectively. If we represent  $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$  and  $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$ , then we have  $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$  with probability one. It follows that the (non)causality in the  $\theta$ -th quantile hypotheses to be tested are

$$H_0: P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1, \quad (1)$$

$$H_1: P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1. \quad (2)$$

Following Jeong et al. (2012), we use the distance measure  $J = \{e_i E(e_i|Z_{t-1})f_z(Z_{t-1})\}$ , where  $e_i$  is the regression residual term and  $f_z(Z_{t-1})$  is the marginal density function of  $Z_{t-1}$ . The regression residual  $e_i$  emerges based on the null hypothesis in (1), which can only be true if and only if  $E[1\{y_i \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$  or, equivalently,  $1\{y_i \leq Q_\theta(Y_{t-1})\} = \theta + e_i$ , where  $1\{\cdot\}$  is an indicator function. According to Jeong et al. (2012), the feasible kernel-based sample analogue of  $J$  is given by

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{e}_t \hat{e}_s. \quad (3)$$

where  $K(\cdot)$  is the kernel function with bandwidth  $h$ ,  $T$  is the sample size,  $p$  is the lag order, and  $\hat{e}_t$  is the estimate of the unknown regression residual. The latter is estimated as

$$\hat{e}_t = 1\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \quad (4)$$

$\hat{Q}_\theta(Y_{t-1})$  is an estimate of the  $\theta$ th conditional quantile of  $y_t$  given  $Y_{t-1}$ , and we estimate  $\hat{Q}_\theta(Y_{t-1})$  using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta|Y_{t-1}), \quad (5)$$

where  $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$  is the Nadarya-Watson kernel estimator specified as

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L((Y_{t-1} - Y_{s-1})/h) 1(y_s \leq y_t)}{\sum_{s=p+1, s \neq t}^T L((Y_{t-1} - Y_{s-1})/h)}, \quad (6)$$

with  $L(\cdot)$  denoting the kernel function and  $h$  the bandwidth.

However, we extend the work of Jeong et al. (2012) by developing a test for the *second* moment. As such, we can test the volatility causality running from the traded volume to Bitcoin returns. Adopting the approach in Nishiyama et al. (2011), higher order quantile causality is given by:

$$H_0: P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} = 1 \text{ for } k = 1, 2, \dots, K \quad (7)$$

$$H_1: P\{F_{y_t^k|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\} < 1 \text{ for } k = 1, 2, \dots, K \quad (8)$$

Incorporating the whole framework, we state that  $x_t$  Granger causes  $y_t$  in quantile  $\theta$  up to the  $k$ th moment using (7) to construct the test statistic of (6) for each  $k$ . The causality-in-variance test can be calculated by replacing  $y_t$  in (3) and (4) with  $y_t^2$ . However, it can be shown that it is not easy to combine the different statistics for each  $k = 1, 2, \dots, K$  into one statistic for the joint null in (7) because the statistics are mutually correlated (Nishiyama et al., 2011). To address this issue, we follow Nishiyama et al. (2011) and include a sequential-testing method. First, we test for the nonparametric Granger causality in the *first* moment (i.e.  $k=1$ ). However, failure to reject the null hypothesis in the mean (i.e.  $k=1$ ) does not automatically lead to no-causality in the *variance* (i.e.  $k=2$ ). We therefore extend the nonparametric Granger causality to detect the *variance*.

Practically, three choices must be specified in order to apply the causality test based on quantiles: the bandwidth  $h$ , the lag order  $p$ , and the kernel type for  $K(\cdot)$  and  $L(\cdot)$ , respectively. In this study, we make use of a lag order of 7 based on the Schwarz Information Criterion (SIC) under a VAR involving Bitcoin returns and traded volume. Moreover, when it comes to choosing lags, the SIC is considered as being parsimonious compared to other lag-length selection criteria. The SIC helps overcome the issue of over-parameterisation usually arising with nonparametric frameworks.<sup>3</sup> We choose the bandwidth value via the use of the least squares cross-validation technique.<sup>4</sup> Finally, for  $K(\cdot)$  and  $L(\cdot)$  Gaussian-type kernels are employed.

### 4. Data and empirical findings

#### 4.1. Data

In this study, we use two variables, namely, the Bitcoin index and the trading volume, as measures of the level of trading activity. The Bitcoin price index is denominated in USD, the currency in which Bitcoin is generally traded on Bitstamp – the largest European Bitcoin exchange (Brandvold et al., 2015). Daily price and volume data for Bitcoin traded on Bitstamp are sourced from [www.bitcoincharts.com](http://www.bitcoincharts.com).

Both the Bitcoin index and volume are non-stationary in log-levels as indicated by standard unit root tests.<sup>5</sup> Since our methodology requires stationary data, we work with Bitcoin returns, obtained as the first-differences of the natural logarithmic values of the index expressed in percentage. The squared values of returns measure the volatility of the Bitcoin returns. Previous studies have shown the existence of deterministic time trends, both linear and nonlinear, in the volume data (Gallant et al., 1992; Chen et al., 2001; Gebka, 2012). To control for these trends, and following Gebka and Wohar (2013), we use a detrended measure of volume. Specifically, we consider the natural log of the volume series and remove its trend by regressing it on

<sup>3</sup> Hurvich and Tsai (1989) examine the Akaike Information Criterion (AIC) and show that it is biased towards selecting an over-parameterised model, while the SIC is asymptotically consistent.

<sup>4</sup> For each quantile, we determine the bandwidth  $h$  using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

<sup>5</sup> Complete details of the unit root tests are available upon request from the authors.



a constant,  $(t/T)$  and  $(t/T)^2$ , where  $T$  is the total sample size. Our period of analysis covers the daily period of 19 December 2011 to 25 April 2016 (i.e. 1587 observations).<sup>6</sup> Interestingly, the sample period covers the Bitcoin crash of December 2013 (Cheah and Fry, 2015) and the recovery that started in the fourth quarter of 2014. Thus, as a result, it allows us to examine how the return-volume relationship in the Bitcoin market was affected.

Table 1 presents the descriptive statistics for the Bitcoin returns and traded volume. We observe that volume is more volatile than returns in the Bitcoin market. More importantly, for our context of causality-in-quantiles, both the variables are skewed to the left, with excess kurtosis, resulting in non-normal distributions (see also the results from the Jarque-Bera test). The heavy-tails in the distributions of both the returns and the volume further confirm our choice of employing a causality-in-quantiles test. Furthermore, results from the Augmented Dickey-Fuller (ADF) test show that the two series are stationary.

The natural logarithm of the data for the Bitcoin index and traded volume and their respective transformations to returns and detrended volume are presented in Fig. 1. We clearly notice that the long bull market lasted almost three years before it ended in December 2013 – the month during which we captured a major structural break in Bitcoin prices (see the next sub-section for more details), with such an observation also made by Bouri et al. (2016).

Fig. 2 provides a scatterplot of Bitcoin returns against the detrended volume. In Fig. 2, we also present the fit from a local polynomial regression (LOESS) with polynomial degree 2 (solid line). The shaded region in Fig. 2 denotes the 95% confidence band for the LOESS fit. The LOESS fit in Fig. 2 is indicative of no relationship between the detrended volume and Bitcoin returns. However, the relationship of the return dispersion with the detrended volume level in Fig. 2 indicates a positive relationship between the return volatility and the level of the detrended volume.

#### 4.2. Empirical findings

Before conducting the causality-in-quantiles tests running from volume to the Bitcoin returns and their volatility, we first present the results from the standard linear Granger causality test based on a VAR(7) model. The resulting  $\chi^2(7)$  statistic for the null that volume does not Granger cause returns is 9.4305 with a  $p$ -value of 0.2232. In other words, volume cannot be used to predict Bitcoin returns based on the linear causality test even at the 10% level of significance.<sup>7</sup>

Next, we examine whether the relationship between the Bitcoin returns and volume is non-linear in order to further confirm our reliance on the nonparametric quantile-in-causality approach. To this end, we apply the Brock et al. (1996, BDS) test on the residuals of an AR(7) model for returns, and the returns equation in the VAR(7) model involving traded volume. As can be seen from Table 2, based on 10,000 bootstrap replications, we find strong evidence, at the highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions ( $m$ ).<sup>8</sup> These results suggest the presence of nonlinearity in the returns as well as in the relationship between the returns and volume. Accordingly, the equation for testing the null of

<sup>6</sup> While Bitcoin prices from Bitstamp are available as of 13 September 2011, the associated volume data for the period from 13 September 2011 to 19 December 2011 were not usable because they contained many errors, (i.e. values equal to ‘infinity’). This led us to start our sample period as of 19 December 2011.

<sup>7</sup> The  $\chi^2(7)$  statistic for the null that returns do not Granger cause volume is 9.9290 with a  $p$ -value of 0.1926, that is, returns do not cause volume based on the linear causality test at conventional levels of significance.

<sup>8</sup> Similar results were obtained for the AR(7) model of volume, and for the volume equation in the VAR(7) model involving the returns series. Hence, not only is volume nonlinear but it also has a nonlinear relationship with returns, implying non-reliability of the linear test of causality running from returns to volume. Complete details of these results are available upon request from the authors.

**Table 1**  
Summary statistics.

Statistic	Variable	
	Returns	(Detrended) Volume
Mean	0.0031	0.0013
Median	0.0020	0.0554
Maximum	0.3375	2.7966
Minimum	−0.6639	−6.6199
Std. Dev.	0.0516	0.9022
Skewness	−1.6387	−0.7632
Kurtosis	28.8730	6.7148
Jarque-Bera	44975.1100	1066.5960
Probability	0.0000	0.0000
ADF Test Statistics	−41.1059	−4.1223
$p$ -value	0.0000	0.0000

**Notes:** Std. Dev. stands for standard deviation. For Jarque-Bera test, the null hypothesis is of normality. For Augmented Dickey fuller (ADF) test, the null hypothesis is that the series has a unit root.

no-Granger causality in the linear model is misspecified and the results of the standard linear causality test are spurious.<sup>9</sup>

Now, we turn to the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003). These determine 1 to  $M$  (multiple) globally determined breaks with the error distributions differing across the breaks, applied again to the AR(7) model for Bitcoin returns, and the returns equation in the VAR(7) model involving the volume. There is only one break (19 December 2013) in the AR(7) model of returns that corresponds to the Bitcoin price crash of December 2013, identified in Cheah and Fry (2015). Two breaks (18 April 2013 and 18 December 2013) are detected for the returns equation in the VAR(7) model involving volume<sup>10</sup>: the first corresponds to the Bitcoin bubble of April 2013 following the technical glitch in the Bitcoin software (Fry and Cheah, 2016); the second break of December 2013 as mentioned above, identified in the return series. The results from the BDS test show that the standard linear Granger causality test is misspecified. Furthermore, evidence of nonlinearity and regime changes in the relationship between returns and volume leads us to employ the causality-in-quantiles test. The latter, being a nonparametric (i.e. data-driven) approach, is robust to linear misspecification.

In Fig. 3, we present the results obtained from the quantile causality test for Bitcoin returns and squared returns (i.e. volatility) from the traded volume over the quantile-range of 0.01–0.99.<sup>11</sup> As can be seen, the null that volume does not Granger cause returns is rejected, in general, at the five per cent level of significance (critical value of 1.96) over the quantile range ( $\tau$ ) of 0.24–0.66 of the conditional distribution of returns. The causality is rejected consistently over 0.24–0.51, namely, from below the median until just above it. Predictability is then observed intermittently until quantile 0.66. However, we fail to reject the null that volume does not Granger cause volatility over the entire conditional distribution.<sup>12</sup> In other words, volume can predict

<sup>9</sup> Based on the suggestion of an anonymous referee, we also conducted the RESET test, and found that both the AR(7) model of returns and the returns equation in the VAR(7) model are misspecified irrespective of the order of polynomial specified, that is, based on the highest possible allowed without the test running into singularity issues. Complete details of these results are available upon request from the authors.

<sup>10</sup> The AR(7) model for volume, as well as the volume equation in the VAR(7) model with Bitcoin returns, was found to have a regime change at 22 October 2013. Complete details of these results are available upon request from the authors. Thus, based on the BDS and the structural break tests, we can conclude that traded volume evolves in a nonlinear fashion and is also related nonlinearly to returns.

<sup>11</sup> The quantile causality test was been conducted using the open-source software *R* based on the codes written by the authors. The codes are available upon request.

<sup>12</sup> We also conducted the causality-in-quantiles test with detrended volume and its squared value as dependent variables. However, we could not detect any evidence of causality for either volume or squared volume resulting from returns at any point of the respective conditional distributions of the dependent variables. Complete details of these results are available upon request from the authors.

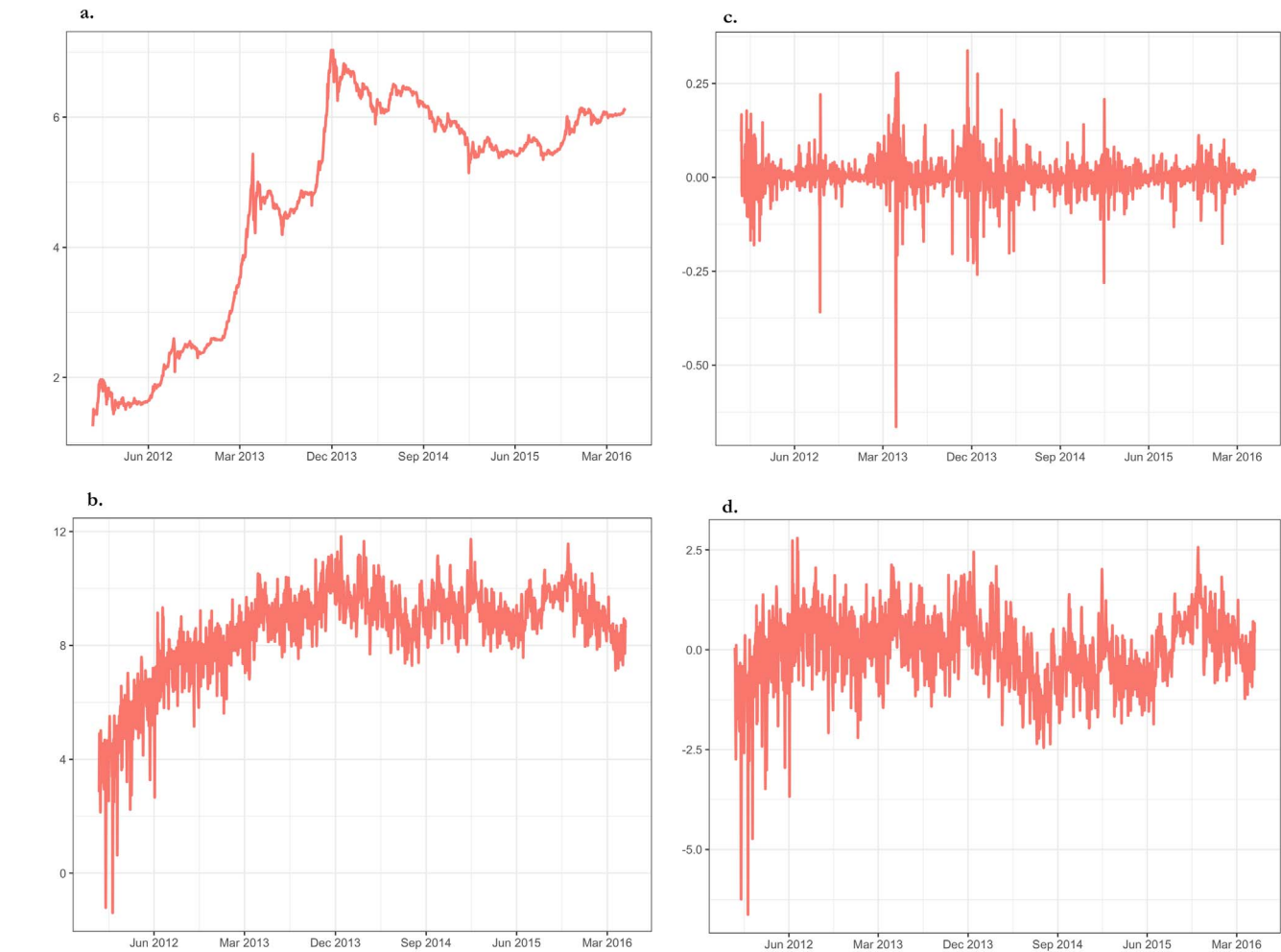


Fig. 1. a). Natural logarithm of closing price of Bitcoin. b). Natural logarithm of volume traded. c). Bitcoin returns. d). Detrended volume.

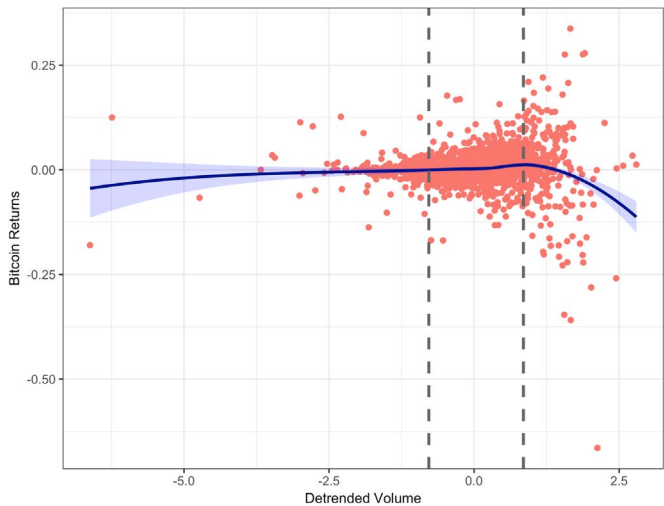


Fig. 2. Scatterplot of Bitcoin returns against detrended volume. Note: The fit from a local polynomial regression (LOESS) with polynomial degree 2 is denoted with the solid line. Shaded region denotes the 95% confidence band for the LOESS fit. Grey vertical dashed lines are drawn at the 0.18 (at value  $-0.78$ ) and 0.80 (at value  $0.85$ ) quantiles of the detrended volume.

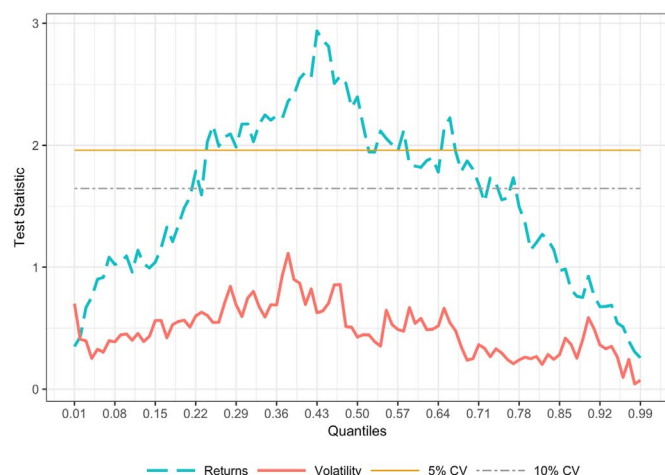
returns but not volatility, with the evidence of causality for returns holding over the entire conditional distribution barring the two ends. Specifically, volume has no predictive content for Bitcoin returns when the market is bearish (lower quantiles) or bullish (upper quantiles).

Table 2					
BDS test statistic.					
Model of returns equation	m	2	3	4	5
AR(7)		12.9500***	15.5327***	17.4181***	19.1123***
VAR(7)		13.0976***	15.6403***	17.5329***	19.2779***

Notes:  $m$  stands for the number of (embedded) dimensions that embeds the time series into  $m$ -dimensional vectors, by taking each  $m$  successive points in the series. Values in the cells represent BDS  $z$ -statistic; \*\*\* indicates rejection of the null of *i.i.d.* residuals at one per cent level of significance.

However, when the market is functioning around the normal (median) mode, volume can indeed predict returns.

The findings from the causality-in-quantiles tests can be intuitively seen from Fig. 2. The LOESS fit in Fig. 2 indicates no association between the Bitcoin returns and volume except at the very high end of the volume quantiles. The negative relationship at high values of detrended volume does not indicate significant test statistics as there are only a few observations at these high quantile ranges, leading to imprecise estimates. Fig. 2 also shows an increasing dispersion of Bitcoin returns with the level of the volume, particularly in the mid-ranges of the volume values. The insignificant test statistics at the 10% significance level for quantile causality in volatility in Fig. 3 corresponds to the quantile ranges below 0.18 (value of detrended volume equal to  $-0.78$ ) and above 0.80 (value of detrended volume equal to  $0.85$ ), which are marked with dashed vertical lines in Fig. 2. We see from Fig. 2 that the relationship between the Bitcoin return dispersion



**Fig. 3. Causality-in-Quantiles: Volume does not Granger cause Bitcoin Returns and Volatility.** Note: Vertical axis presents the test statistics corresponding to the null that volume does not *Granger* cause returns, and volume does not *Granger* cause volatility; Horizontal axis measures the quantiles; five per cent critical value is 1.96.

and the level of the volume is weak in the quantile ranges below 0.18 and above 0.80. Additionally, fewer observations fall into these quantile ranges. These two features lead to insignificant tests statistics presented in Fig. 3 for the causality in volatility.

Furthermore, we estimated a GARCH(1,1) model for Bitcoin returns and extracted the resulting GARCH variance series. We then conducted the causality-in-quantiles test using this GARCH-based estimate of volatility. As can be seen in Fig. A1 in the Appendix A, we find that barring the extreme lower (0.01–0.09) and upper quantile ranges (0.97–0.99), volume predicts volatility over its entire conditional distribution, with the strongest predictability observed at quantile 0.72. These results completely differ from those obtained using squared returns. However, we believe that since squared returns – as a measure of volatility – follow directly from the  $k$ -th order test, and are independent of a model-based estimate of volatility (which could vary depending on what model of volatility we choose), the use of squared returns is more appropriate in our context in capturing the risk involved in the Bitcoin market. Balcilar et al. (2016b) have also posited a similar line of reasoning. In light of this, we have presented the GARCH-based result of volatility in the Appendix A, and considered the model-free estimate of volatility using squared returns as a more robust estimate of Bitcoin market volatility. Naturally, the result based on squared returns is also more reliable; this is more so because we show that returns evolve in a nonlinear fashion, which the GARCH model does not take into account while capturing the volatility.

To summarize, evidence that volume predicts Bitcoin returns is non-existent in the linear model. However, this evidence is not robust to the presence of nonlinearity and structural breaks. We therefore employ the nonparametric causality-in-quantiles test, which is more appropriate and robust to misspecifications, and reveal that volume can predict returns around the median of the conditional distribution, but not volatility.

This result seems to suggest that investors in the Bitcoin market can obtain valuable predictive information for returns from traded volume, when the market is in normal mode. However, in bear and bull regimes, volume plays no role in predicting returns, with past (seven) lags of returns providing relatively more valuable information for future returns than volume. This finding partially implies that in stress periods, unlike in the case of equities, trading volume is not associated with extremely high/low returns in the Bitcoin market.

These findings on return predictability based on volume add to information documented in prior studies trying to define the underlying factors that determine the price of Bitcoin (Bouoiyour and Selmi,

2014; Bouoiyour et al., 2014; Polasik et al., 2014; Kristoufek, 2014; Ciaian et al., 2016). In fact, our findings provide a broader picture of the dependence between volume and returns in the Bitcoin market and uncover the insignificant role of trading volume in predicting Bitcoin price volatility. In terms of the finding of return predictability around the median, our result is different from what is observed in equity markets, where the predictability of returns from volume holds mostly at the tails (Chuang et al., 2009; Gebka and Wohar, 2013). This could possibly be due to the short-selling constraint in the Bitcoin market in the lower-end of the market. However, when the market is booming, there is more herding into the market and less interest in searching out relevant information (in this case on volume) on behalf of market agents. The lack of predictability of volatility from traded volume provides support to the so-called mixture of distribution hypothesis (MDH) developed by Clark (1973). MDH assumes that the volume-volatility relation is dependent on the rate of information flow into the market. The basic intuition is that because all traders simultaneously receive new information, there is no intermediate equilibrium. Since the variables contemporaneously change in response to new information, it is impossible to use past volume data to predict volatility. The possibility of MDH holding in the Bitcoin market rather than the sequential information arrival hypothesis (SIAH; Copeland, 1976) is likely to be higher due to possible easy dissemination of information across traders, given that Bitcoin involves an open source, software-based online payment system.

## 5. Conclusion

Although a large amount of literature has focused on the role of traded volume in predicting movement in stock returns and volatility (see Gebka and Wohar, 2013, for a detailed literature review), the predictability of traded volume for the returns and volatility in the Bitcoin market remains unexplored. To address this literature gap, we examine daily data covering the period of 19<sup>th</sup> December 2011 to 25 April 2016, which interestingly show that the Bitcoin returns and volume are non-normally distributed. Methodologically, we employ a novel nonparametric causality-in-quantiles test proposed by Balcilar et al. (2016a). It combines elements of the test for nonlinear causality of  $k$ -th order developed by Nishiyama et al. (2011) with the causality-in-quantiles test proposed by Jeong et al. (2012).

Our results are summarized as follows: First, the standard linear Granger causality test, which was conducted for comparison purposes, fails to detect any evidence of volume causing returns. Second, the nonlinearity test indicates that returns and their relationship with volume evolve in a nonlinear manner. Additionally, tests of multiple structural breaks show evidence of regime changes in returns and in the equation relating them to volume. Evidence of nonlinearity and structural breaks suggests that the linear Granger causality is misspecified, thus, leading to unreliable results. Third, the causality-in-quantiles approach, which emerges as a suitable choice given evidence of non-linearity, structural breaks, and fat tails, reveals that the null that volume does not *Granger* cause returns is rejected at the conventional levels of significance over the quantile range of 0.25 to 0.75 of the conditional distribution of returns. However, we fail to reject the null that volume does not *Granger* cause volatility over the entire conditional distribution. These results show that volume can predict returns, but not volatility, with causality for returns non-existent in bearish (lower quantiles) and bullish (upper quantiles) phases. Therefore, when the market is functioning around the normal (median) mode, volume can indeed predict returns, thus providing investors in the Bitcoin market with valuable predictive information. However, when the market is performing well or poorly, all that matters for predicting future returns is past values, and thus information about volume is irrelevant. Generally, our results, via the volume-returns causality in the Bitcoin market, highlight the importance of detecting and modelling nonlinearity when analysing predictability via

causal relationships. In the Bitcoin speculative market, our findings involve potential implications for trading strategies. Practically, under normal market conditions, practitioners and traders in the Bitcoin market will benefit from constructing volume-return based strategies to increase their profits. This evidence adds to prior studies that only associate Bitcoin price and transaction measures as well as search queries of Bitcoin on Google Trends and Wikipedia (Kristoufek, 2013; Bouoiyour and Selmi, 2015; Ciaian et al., 2016). However, in the bear and bull phases of the Bitcoin market, practitioners and traders can still rely on technical analysis.

## Appendix A

See Fig. A1.



**Fig. A1. Causality-in-Quantiles: Volume does not Granger cause Bitcoin GARCH-Based Volatility.** Note: Vertical axis presents the test statistic corresponding to the null that volume does not *Granger* cause volatility derived from a GARCH(1,1) model; Horizontal axis measures the quantiles; five per cent critical value is 1.96.

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