Relationship between price and volume in the Bitcoin market

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Abstract

Purpose – Bitcoin has recently become the focal point of investors as a digital currency and an alternative payment method. Despite Bitcoin being in the spotlight, a gap in the literature on its price-setting behaviors has been observed. This study aims to contribute to the literature by investigating the relationship between Bitcoin price and volume in the period between January 1, 2012 and April 7, 2018 through a symmetric and asymmetric causality test.

Design/methodology/approach – Daily price and volume data relevant to Bitcoin traded in the Bitstamp market were obtained from www.bitcoincharts.com. Within the framework of data applicable for analysis, the data set for this study includes a total of 2,286 observations for the period between January 1, 2012 and April 7, 2018.

Findings – Based on the results of the standard causality test, a causality relationship was determined from price to volume. Based on the results of the asymmetric causality test between positive and negative shocks of variables, a unilateral causality relationship was determined from negative shocks in Bitcoin prices to negative shocks in trading volume as well as from positive shocks in trading volume to positive shocks in prices. Furthermore, it was found that the relationship between Bitcoin price and volume is cointegrated.

Practical implications – The empirical results can be used by investors and portfolio managers to make trading decisions.

Originality/value – The contribution of this paper to the literature is that it is the first study on the symmetric and asymmetric causality relationship between Bitcoin price and volume. Moreover, this paper reveals short- and long-term behaviors of Bitcoin using the cointegration test used for determining the long-term relationship between Bitcoin price and volume.

Keywords Price-volume relationship, Asymmetric causality test, Bitcoin market

Paper type Research paper

1. Introduction

Bitcoin appeared for the first time in an article published in 2008 by an author or group of authors known as Satoshi Nakamoto. Bitcoin is basically described as a decentralized, peer-to-peer cryptocurrency and payment method that redefines money as an electronic monetary system. Despite being vastly different from official currencies (Brandvold *et al.*, 2015), Bitcoin's prominent feature is that circulating units of money is controlled by a software algorithm rather than a person, group, company, central administration or government (Ciaian *et al.*, 2016). At present, Bitcoins are traded in many independent markets available 24 h a day, seven days a week (Pieters and Vivanco, 2017). The review of literature reveals studies investigating Bitcoin from the economic aspect in addition to studies on its security, ethics and legal characteristics. Baek and Elbeck (2015) found in their studies on relative volatility using trend-adjusted rates for the period between July 2010 and

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February 2014 over daily returns of Bitcoin and S&P 500 indexes that Bitcoin markets were rather speculative for the period in hand. Cheah and Fry (2015) examined the Bitcoin prices starting from the daily closing prices, between July18, 2010 and July 17, 2014, it was determined that Bitcoin prices tend to be speculative bubble and the basic value was zero. Cheung *et al.* (2015) studied the period between July 17, 2010 and February 18, 2014 for presence of bubbles in the Bitcoin market by using daily closing prices, concluding three different bubbles, one short term between 2010 and 2014 in addition to another that lasted 66 to 106 days between 2011 and 2013. Corbet *et al.* (2018) examined the existence of price bubbles of two popular cryptocurrencies (Bitcoin and Ethereum) and found that bubbles were detected in the end of 2013 and the second period of 2017. Bouri *et al.* (2018b) studied explosions of seven cryptocurrencies (Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash and Stellar) and found several explosions in 2017 specifically. Geuder *et al.* (2018) studied the bubble behavior of Bitcoin prices during 2016-2018 and found that bubble behavior was a common and recurring feature of Bitcoin prices. Ciaian *et al.* (2016) studied Bitcoin price formation between 2009 and 2015 based on a daily data. They found that Bitcoin as an attractive investment tool for investors and users, which has a significant impact on the price of Bitcoin. However, this effect has been differentiated over the time.

Dyhrberg (2016) revealed in their study by using an asymmetric GARCH model that there are similar methods, as Bitcoin is a hedge tool against both gold and dollar and that responses given to good or bad news in the market are symmetric, so Bitcoin can be a productive tool in terms of portfolio management, risk management and sensitivity analysis by combining the advantages of currencies and commodities in the financial market. In addition, Bouri *et al.* (2017) studied the hedge effect of bitcoin between July 2001 and December 2015 in four major World stock indices, bond, oil, gold, general commodity index and the US dollar index. They found that bitcoin was a weak hedge but suitable diversification tool. Urquhart (2016) examined the efficiency of the Bitcoin market between August 1, 2010 and July 31, 2016. It was found that the Bitcoin market was not efficient in the weak form during the all period. Katsiampa (2017) determined that the perfect model would be AR-CGARCH in their study on the volatility of Bitcoin prices using a GARCH type of models. Following their study with eight different tests on Bitcoin market activities between August 1, 2010 and July 31, 2016, Nadarajah and Chu (2017) obtained findings that do not support the efficient market hypothesis. Consequent to their study price clustering in Bitstamp, the Bitcoin market, Urquhart (2017) observed that 10.81 per cent of the prices ended with the digits "00" and therefore obtained hard evidence on clustering over the digits "00."

On the other hand, there are also studies in the literature that take into account the relationship between the price, volume and returns of Bitcoin. In this context, Balcilar *et al.* (2017) examined the causality relationship between Bitcoin trading volume, return and volatility. They found that the trading volume outside of bear and bull market regimes could predict the returns. Bouri *et al.* (2018a) studied the Granger causality from trading volume to the returns along with volatility in the cryptocurrency market (Bitcoin, Riple, Ethereum, Litcoin, NEM, DASH and Stellar). The results indicated that trading volume Granger caused negative and positive returns on all cryptocurrencies. However when the volatility was low, volume was a Granger cause of return volatility for only three cryptocurrencies (Litecoin, NEM and Dash). Alaoui *et al.* (2018) studied the price–volume cross-correlation in the Bitcoin market during the period of July17, 2010-May 2, 2018. They found that the prices of Bitcoin were changed, and the changes in the trading volume mutually interacted in a nonlinear way. Corbet and Katsiampa (2018) examined Bitcoin's minute, hourly, daily and weekly returns of similar asymmetric return patterns (ANAR) during the period of June 2010-February 2018.

They found that the persistence of positive returns was higher than negative returns. They also obtained that the Bitcoin price returns represent asymmetric reverting behavior.

Based on the above previous studies, we aimed to analyze the first time of symmetric and an asymmetric causality relationship between Bitcoin price and volume. Moreover, this study reveals short- and long-term behaviors of Bitcoin using the cointegration test used for determining the long-term relationship between price and volume of Bitcoin.

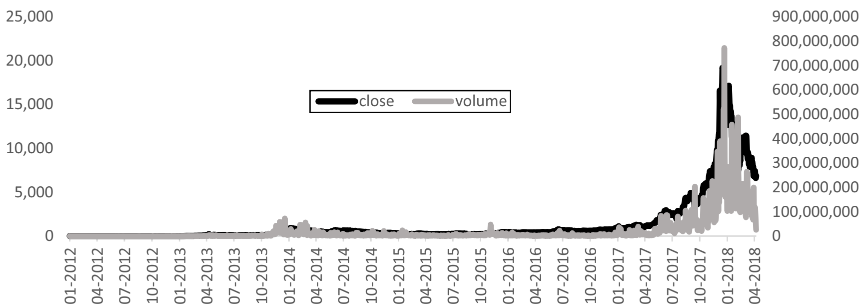
2. Data and methodology

Daily price and volume data relevant to Bitcoin traded in the Bitstamp market were obtained from www.bitcoincharts.com. Within the framework of data applicable for analysis, the data set for this study includes a total of 2,286 observations for the period between January 1, 2012 and April 7, 2018. Figure 1 displays Bitcoin prices and volumes for the investigated period.

Table I indicates descriptive statistics related to Bitcoin price and volume. Accordingly, the maximum price sample in the study was $19,187.78, whereas the minimum was $4.23.

2.1 Cointegration tests

Several methods can be used to determine a cointegration relationship in time series. The most commonly used are the Engle and Granger (1987) and Johansen (1988) cointegration



Note: Primary y-axis shows price, whereas secondary y-axis shows volume

Figure 1. Time series graph on Bitcoin's daily price and volume data

Statistic	Variable Price	Volume
Mean	1316.765	19433932
Median	400.025	2841386
Maximum	19187.78	7.72E + 08
Minimum	4.23	1.23
SD	2848.769	52565296
Skewness	3.427587	5.221235
Kurtosis	15.15002	41.97048
Jarque-Bera	18537.2	155042.6
Probability	0.0000	0.0000
N	2,286	2,286

Table I. Descriptive statistics on price and volume data at Bitstamp tests. The method developed by Engle and Granger (1987) is a single-equational cointegration test. This test accepts that there is a cointegration relationship between variables if the error term obtained from regression among non-stationary variables is stationary at level. However, when the number of variables is more than two, there can be more than two cointegrated vectors among variables. In such cases, the test may provide misleading results, as it is insufficient for differentiating relationships. This single-equational cointegration has been made multi-equational by expanding with the simultaneous equations system in the Johansen (1988) test. Accordingly, this test is considered to be strong in determining more than one cointegrated relationships when there are more than two variables. A restriction for this test is that all variables need to be sta at the same level. In this study, the Johansen (1988) test was used to identify a cointegration relationship between variables.

A vector error correction model (VECM) will need to be calculated if a cointegration relationship is identified among the variables using the Johansen (1988) test. This model considers all variables to be dependent variables while adding on them the error correction model (ECM), followed by an estimation at an optimal lag length. VECM is a limited vector autoregressive model (VAR) model used by Engle and Granger (1987) to identify the long-term relationship among variables in the VAR model. The equation for VECM is given in equation (1).

$$\Delta X_t = a + \mathrm{B(L)}\Delta X_{t-1} + d^{'}(e_{t-1}) + \eta_t \tag{1}$$

where,

$\Delta X_t = n \times t$ signifies dimensional variable vector, while $a = n \times 1$ indicates its dimensional constant vector;

$\mathrm{B(L)} = n \times n$ indicates the polynomial lag length processor matrix, whereas$d' = n \times 1$ indicates its dimensional constant vector; and

$e_{t-1} = n \times t$ the signifies error correction term vector $\eta_t = n \times t$ indicates residues' vector.

2.2 Causality tests

2.2.1 Toda-Yamamoto causality test. As one of the most commonly used causality tests in the literature, the Granger causality test necessitates that all variables are stationary at level. Otherwise, the results from the *F*-test cannot be considered valid. However, even if the variables in the Toda and Yamamoto (1995) test are not stationary, the VAR model can be implemented and the Wald test can be used through the level values of variables. The Wald test is implemented over the first k quantity in the matrix of coefficients by estimating a $[k + (d_{\mathrm{max}})]$ degree VAR model for the Granger causality test. From the VAR model, an optimal lag length is identified. Then, a cointegration degree (d_{max}) of the variable that has maximum cointegration is added to the k lag length. By estimating the VAR model, the Wald test is applied on the coefficients obtained from d_{max} afterward. The estimated VAR model is given in equations (2) and (3).

$$Y_t = \alpha_0 + \sum_{i=1}^{k+d_{max}} \alpha_{1i} Y_{t-i} + \sum_{i=1}^{k+d_{max}} \alpha_{2i} X_{t-i} + u_t \tag{2}$$

$$X_t = \beta_0 + \sum_{i=1}^{k+d_{max}} \beta_{1i} X_{t-i} + \sum_{i=1}^{k+d_{max}} \beta_{2i} Y_{t-i} + v_t \tag{3}$$

Here, equation (2) tests the causality from X to Y, while equation (3) does the same from Y to X.

2.2.2 Asymmetric causality tests. Engle and Granger (1987) and Toda and Yamamoto (1995) reveal that causality tests are symmetric. Hence, Hatemi-j (2012) developed the asymmetric causality test by considering that positive and negative shocks have different causal impacts and that impacts on series can be asymmetric.

Accordingly, two integrated variables as Bitcoin price PRC and Bitcoin volume VOL are as follows:

$$PRC_t = PRC_{t-1} + \varepsilon_{1t} = PRC_0 + \sum_{i=1}^{t} \varepsilon_{1i} \tag{4}$$

$$VOL_t = VOL_{t-1} + \varepsilon_{2t} = VOL_0 + \sum_{i=1}^{t} \varepsilon_{2i} \tag{5}$$

where PRC_0 and VOL_0 in the equations indicate initial values.

Positive and negative shocks are as follows:

$$\varepsilon_{1i}^{+} = \max(\varepsilon_{1i}, 0),\ \ \varepsilon_{2i}^{+} = \max(\varepsilon_{2i}, 0),\ \varepsilon_{1i}^{-} = \min(\varepsilon_{1i}, 0)\ ,\ \varepsilon_{2i}^{-} = \min(\varepsilon_{2i}, 0)$$

Reformulating the PRC_t and VOL_t equations with the help of the equations above:

$$PRC_t = PRC_{t-1} + \varepsilon_{1t} = PRC_0 + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{6}$$

And similarly:

$$VOL_t = VOL_{t-1} + \varepsilon_{2t} = VOL_0 + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{7}$$

Positive and negative shocks in each variable can be expressed in the cumulative form as follows:

$$PRC_i^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{+}, \qquad PRC_i^{-} \sum_{i=1}^{t} + \varepsilon_{1i}^{-}, \quad VOL_t^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}\ , \quad VOL_t^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{8}$$

To investigate the positive shocks between Bitcoin price and Bitcoin volume, in light of the assumption that $y_t^{+} = \left(PRC_i^{+},\ VOL_t^{+}\right)$, the causality relationship between these two series was tested using the lag length vector autoregressive model (VAR_p):

$$y_t^+ = \nu_t + A_1 y_{t-1}^+ + \cdots + A_p y_{t-1}^+ + \cdots + A_{p+d} y_{t-p-d}^+ + \varepsilon_t^+ \tag{9}$$

Optimal lag length was determined using HJC (Hatemi-J criterion), and the VAR_{p+d} model is simply constructed as follows:

$$Y = DZ + \delta \tag{10}$$

where:

$$Y = \left(y_1^+, \ldots, y_T^+\right) \quad (n \times T)\,\text{matrix} \tag{11}$$

$$D = \left(\nu, A_1, \ldots, A_p\right) \quad (n \times (1 + np))\,\text{matrix} \tag{12}$$

$$Z_t = \begin{bmatrix} 1 \\ y_t^+ \\ y_{t-1}^+ \\ \cdot \\ \cdot \\ \cdot \\ y_{t-p+1}^+ \end{bmatrix} \quad ((1 + np) \times 1)\,\text{matrix}, \quad \text{for}\, t = 1, \ldots, T, \tag{13}$$

$$Z = (Z_0, \ldots, Z_{T-1}) \quad ((1 + np) \times T)\ \text{matrix, and} \tag{14}$$

$$\delta = \left(\varepsilon_1^+, \ldots, \varepsilon_T^+\right) \quad (n \times T)\,\text{matrix} \tag{15}$$

The null hypothesis of H_0: $C\beta = 0$, which has no Granger causality can be tested with Wald statistics as follows:

$$Wald = (C\beta)' \left[C\left(\left(Z'Z\right)^{-1} \otimes S_U\right)C''\right]^{-1} (C\beta) \tag{16}$$

where $\otimes$ signifies the Kronecker product, an indicate function involving C limitations or $\beta = \text{vec}(D)$ and vec indicates the column stacking operator. S_U indicates the variance covariance matrix calculated for the unlimited VAR model as in $S_U = \frac{\hat{\delta}_U' \hat{\delta}_U}{T-q}$.

3. Empirical results

The unit root test in this study was performed using the ADF unit root test developed by Dickey and Fuller (1979), which disregards breaks, and Perron (1997), which regards breaks in variables. Results from these two tests are given in Table II.

According to the results from the ADF and Perron unit root tests, both variables contained unit root with their level values. However, it was determined when the first difference was taken between variables that both variables became stationary at the 1 per cent level value.

Variables	ADF Model with constant t-statistics	ADF Model with constant and trend t-statistics	PP Model with constant t-statistics	PP Model with constant Break date	PP Model with constant and trend t-statistics	PP Model with constant and trend Break date
Level						
Volume	−2.457	−2.522	−3.280	1.2.2012	−3.823	26.2.2014
Price	−1.181	−1.500	−2.247	25.3.2017	−3.042	19.7.2014
First differences						
Volume	−13.640***	−13.700***	−13.972***	7.12.2013	−14.058***	7.12.2013
Price	−48.875***	−48.872***	−52.732***	11.4.2013	−52.994***	11.4.2013
		Critical values				
	1%	−3.433	−3.962		−4.949	−5.719
	5%	−2.863	−3.412		−4.444	−5.176
	10%	−2.567	−3.128		−4.194	−4.894

Note: ***Indicates 1% level of significance. Maximum lag length was assumed to be 26 with Schwarz criteria as the information criteria

Table II. Results from the unit root tests

A regression estimate between non-stationary variables may not reflect their true relationship. Yet if the variables are cointegrated with each other, the regression result will be accurate. The variables used in the study were non-stationary with their level values. Accordingly, before the relationship between variables was estimated, a cointegration analysis would be needed. For this reason, as the most commonly used test in literature, the Johansen cointegration test was used, and the results are given in Table III.

As both trace and max-eigen statistics were larger than the critical value at 1 per cent level of significance, it was decided consequent to the Johansen cointegration test, as seen in Table III, that there is a long-term relationship between variables. Indeed, it can be stated that Bitcoin price and trade volumes act in unison in the long-term.

As variables are cointegrated, it will be possible to estimate long-term coefficients. Furthermore, it is possible for variables that act in unison in the long-term to experience short-term deviations in dynamic behaviors. The resulting model is referred to as the VECM. In this model, the error term will need to be negative and significant for deviations to re-converge. If the error term is not negative and significant, it is understood that the VECM does not function properly. In this study, two variables were considered dependent variables in different models while estimating the long-term coefficient between variables and the

Null hypothesis	Alternative hypothesis	Trace statistic	Critical value %5	Critical value %1	Max-eigen statistic	Critical value %5	Critical value %1
$r = 0$	$r = 1$	27.421***	15.494	19.937	24.134***	14.264	18.520
$r \leq 1$	$r = 2$	3.286	3.841	6.634	3.286	3.841	6.634

Note: ***Indicates 1% level of significance. Assuming the maximum lag length as 26, the lag length in accordance with Schwarz information criteria was determined to be 14

Table III. Results from the Johansen cointegration test short-term vector error correction term by using the VECM estimation method. The results obtained from the models are given in Table IV.

The negative and significant coefficients of the error correction terms given in Table IV indicate that the error correction mechanism of the model functions properly and that short-term deviations in variables do not re-converge in the long-term. At the same time, this proves that the long-term relationship found between variables is reliable. The coefficients of the error correction terms indicate that a 1 per cent deviation between variables reflects a convergence of 0.64 per cent from price to volume and 0.04 per cent from volume to price the next day. Considering the long-term relationship between variables, it was determined that 1 per cent increase in Bitcoin prices causes approximately 1.32 per cent increase in Bitcoin volume, whereas 1 per cent increase in Bitcoin volume causes approximately 0.76 per cent increase in Bitcoin prices. The fact that ECMs function properly indicates a causality between the variables. Besides, to clearly determine a causality relationship, the causality relationship between the variables was also studied using the Toda and Yamamoto (1995) causality method. The results obtained are given in Table V.

Table IV.
Short- and long-term coefficient estimate results from the VECM method

Independent variables	Dependent variables: Price	Dependent variables: Volume
Price	–	1.3167*** (15.5783)
Volume	0.7594*** (17.5456)	–
Constant	−5.2720	6.9416
ECM_{t-1}	−0.0036** (−2.2997)	−0.0636*** (−4.5701)
R^2	0.0248	0.3633

Note: *** and ** indicate 1% and 5% levels of significance, respectively. Assuming the maximum lag length in both models to be 26, the lag length in accordance with Schwarz information criteria was decided to be 14. Parentheticals indicate t-statistics

Table V.
Results from the Toda-Yamamoto causality test

Null hypothesis	Test statistics	p-value
Price $\nRightarrow$ Volume	61.673***	0.000
Volume $\nRightarrow$ Price	10.859	0.697

Note: ***Indicates 1% statistical significance

Table VI.
Results from the asymmetric causality test

Null hypothesis	Test statistics	k	1%	5%	10%
$PRC^+ \nRightarrow VOL^+$	14.134	15	30.639	25.233	22.545
$PRC^- \nRightarrow VOL^-$	59.056***	22	43.349	35.21	31.463
$VOL^+ \nRightarrow PRC^+$	38.110***	15	34.453	25.028	22.313
$VOL^- \nRightarrow PRC^-$	21.521	22	42.494	34.842	31.163

Notes: *, ** and *** indicate 10, 5 and 1% statistical significance, respectively. Critical values were obtained via 10,000 bootstrap

According to the Toda-Yamamoto test, the causality relationship from Bitcoin volume to Bitcoin prices was not statistically significant, whereas a causality at 1 per cent level of significance was found from Bitcoin price to Bitcoin volume. In other words, it was identified that variance in Bitcoin prices is the cause of variance in trade volume, whereas variance in Bitcoin trade volume is not the cause of variance in prices. Causality was identified from volume to price using the VECM method; in contrast, no causality was identified using the Toda-Yamamoto method. Hence, using the causality test that investigates this hidden causality between variables, an asymmetric causality relationship was tested from positive and negative shocks in Bitcoin prices to positive and negative shocks in Bitcoin trade volume as well as from positive and negative shocks in Bitcoin trade volume to positive and negative shocks in Bitcoin price. The results are given in Table VI.

As can also be seen in Table VI, a significant causality relationship was not identified from positive shocks in Bitcoin prices to positive shocks in Bitcoin trade volume as well as from negative shocks in Bitcoin trade volume to negative shocks in Bitcoin price. However, a unilateral causality relationship at 1 per cent level of significance was found from negative shocks in Bitcoin prices to negative shocks in Bitcoin trade volume as well as from positive shocks in Bitcoin trade volume to positive shocks in Bitcoin price.

4. Conclusion

In this study, the relationship between Bitcoin prices and trade volume was investigated. To begin with, the cointegration relationship between price and trade volume was investigated. It was observed through the cointegration test that Bitcoin trade volume and price are cointegrated in the long-term. Afterward, long- and short-term coefficients were estimated by using the VECM method, which determined that Bitcoin price has a stronger impact on trade volume. After the long-term relationship and coefficients were identified, the symmetric relationship between variables was investigated using causality tests, concluding a unilateral causality from price to trade volume. It was understood that the more Bitcoin prices increase, the more it attracts investors, resulting in an increase in trade volume.

Finally, asymmetrical causality of negative and positive shocks was investigated between variables. According to the results from the test, unilateral causality relationships from negative shocks in Bitcoin prices to trade volume as well as from positive shocks in trade volume to price were observed at 1 per cent level of significance. It can be said that, as Bitcoin is a high-risk investment tool, its price increases as it assures investors with increases in trade volume. However, as decreasing trade volume does not trigger too much discontent, it is possible that it will not have an impact on the decrease in prices. Further, the increase in Bitcoin prices and trade volume within the relevant period could be the reason for no decrease in prices caused by any decrease in trade volume. It can be put forward that as investors hope to further increase Bitcoin prices, they hesitate to trade when prices decrease, which causes further decrease in trade volume; however, as they opt out of selling together with an increase in prices, increasing prices do not trigger another increase in trade volume. The empirical results can be used by investors and portfolio managers to make trading decisions.

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