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The Intraday Dynamics of Bitcoin

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Abstract

Bitcoin has received much investor attention in recent years, however, there remains a lot of scepticism and lack of understanding of this cryptocurrency. We contribute to the growing literature of Bitcoin by examining the intraday variables of the leading Bitcoin exchange with the highest information share from 1st November 2014 to 31st October 2016 to reveal the intraday stylized facts of Bitcoin and also study the intraday interaction between returns, volume, bid-ask spread and volatility. Employing GMT-stamped tick data aggregated to the 5-minutely frequency, we find that volume, bid-ask spread and volatility all experience n-shaped patterns throughout the day which suggests that European and North American traders are the main drivers of Bitcoin trading and volatility. It also suggests that volatility and the bid-ask spread are highly related as suggested by Roll (1984), which is probably due to the lack of market makers in Bitcoin markets. We also find that all intraday variables are highly correlated, possess significant lead-lag relationships and there is significant bilateral Granger causality.

Keywords: Bitcoin; Cryptocurrency; Intraday Patterns; Granger causality; Lead-Lag; High-Frequency

JEL classification: F30; G02; G15
1. Introduction

Bitcoin is a cryptocurrency, which has received a lot of publicity given its innovative features, simplicity, transparency, and its increasing use. Bitcoin was first outlined in a paper by Nakamoto (2008) and since first going online in 2009, has grown dramatically with the Bitcoin user base becoming increasingly global and diversified, as are the currency exchanges. The Bitcoin protocol sends and receives payment information by directly linking individuals who wish to exchange funds without having to involve a third party. Individuals who participate in transactions are anonymous users assigned a public key as an identity and timestamp proofs transactions enabling records to be secure and unchangeable. This method has been seen as superior to transactions involving a third party as costs, such as transaction costs, are removed and trust is replaced by a cryptographic proof which is the chronological timestamp. Therefore the two parties involved in the exchange need not know each other and the security of the transaction is not dependent on the trust provided by a third party executing the exchange.¹ Unlike fiat currencies that trust the central bank to guarantee the value of the money, with Bitcoin the trust is that the cryptographic proofs provided by the network are correct. Given the recent financial crisis and the bailouts of some European countries and their banks, trust in central banks has diminished and Bitcoin has gained a lot of publicity and surged in value with Bitcoin price increasing by over 21,000% between January 2012 and March 2017. However, Bitcoin is traded on many exchanges and regulatory issues still influence the Bitcoin exchange rate meaning that different exchanges offer different prices for Bitcoin.

This substantial public interest in Bitcoin leads to enormous legal (Plasaras 2013), regulatory (European Central Bank 2012; Ali et al 2014) and ethical (Angel and McCabe 2015) challenges.

¹ For a discussion on the economics of mining Bitcoin, see Kroll et al (2013).
Bitcoin markets have been extremely volatile with the market share and market capitalisations of several cryptocurrencies fluctuating wildly (White 2014). Although initially dominated by literature on the safety, ethical and legal aspects of Bitcoin, recent literature has examined Bitcoin from a financial and economic viewpoint. Cheah and Fry (2015) argue that if Bitcoin were a true unit of account, or a form of store of value, it would not display such volatility expressed by bubbles and crashes. Brandvold et al (2015) employ a multivariate model to study the price discovery process of Bitcoin and find that six Bitcoin exchanges are cointegrated and that Mt.Gox and BTC-e are the market leaders with the highest information share. They also show that the information share is dynamic and evolves significantly over time. Dwyer (2015) studies the economics of Bitcoin and finds that the average monthly volatility of Bitcoin is higher than for gold or a set of foreign currencies in dollars, but the lowest monthly volatilities for Bitcoin are less than the highest monthly volatility for gold and foreign currencies. Smith (2015) shows that the implied exchange rates of Bitcoin are cointegrated with nominal exchange rates, and there is causality running from the nominal to the implied exchange rates. Dyhrberg (2016a; 2016b) report that Bitcoin has similar hedging capability as gold and the dollar, and as such the currency is an exchange medium and can be used for risk management. Fry and Cheah (2016) develop an econophysics model to reveal that Bitcoin and the Ripple (another cryptocurrency) are characterised by negative bubbles. Khairuddin et al (2016) study the motivation of Bitcoin users through interviews and find that the main motivations for users are Bitcoin’s predicted role in a monetary revolution, users’ increased empowerment, and their perception of a real value of Bitcoin currency. Urquhart (2016) finds that Bitcoin is not an efficient market, but in the latter subsample period, some tests suggest that Bitcoin is moving towards efficiency. Recently, Bouri et al (2017) find that Bitcoin is a poor hedge but suitable for diversification purposes only for major stock market indices, bonds, oil, gold, the commodity index and US dollar.
Although Bitcoin was created as an alternative currency, it can also be used as an investment and thus leads to the question whether Bitcoin acts more like a currency or an investment. Recently, the EU ruled that Bitcoin must be treated like a currency and not a commodity for tax purposes (Skatteverket v Hedqvist, EU Press Release 128/15) suggesting that the market is starting to treat Bitcoin like a currency. However, academic evidence has suggested that Bitcoin should be treated as an investment with Yernack (2013) arguing that it needs to become more stable so it can reliably serve as a store of value and as a unit of account in commercial markets. They also show that the excess volatility is more consistent with the behaviour of a speculative investment than a currency, and therefore Bitcoins behaviour resembles Internet stocks in the late 1990s. Baur et al (2015) also examine whether Bitcoin is a currency or an investment by analysing the value of Bitcoin’s financial characteristics relative to a large number of different assets and whether Bitcoin is used as an investment or currency to pay for goods. They find that Bitcoin returns are essentially uncorrelated with all major asset classes and therefore offer great diversification benefits. They also find that about a third of Bitcoins are held by investors not interested in using them as a currency but as an investment. Therefore, they suggest that Bitcoin is mostly used as an investment rather than a currency.

We add to the growing literature on Bitcoin by examining the intraday dynamics of the most popular Bitcoin exchange, BTCE. We collect GMT-stamped tick data and aggregate it to the 5-minutely frequency to examine intraday stylized facts of Bitcoin as well as the lead-lag relationship between returns, volume, bid-ask spread (BAS) and volatility of Bitcoin. There is a large literature documenting intraday patterns in financial time series such as intraday variations in returns, volatility, volume and bid-ask spreads. Some papers on North American markets report that trading activity exhibit a U-shaped pattern (McInish and Wood 1990a; Brock and Kleidon 1992; Hamao and Hasbrouck 1993) while some studies on UK markets report a M-shape where volume is high around the opening of US markets (Ellul et al 2002; Cai et al 2004). Elevated opening and
closing returns have also been reflected in the volatility patterns, where a U-shape is reported by Wood et al (1985), McInish and Wood (1990a and 1990b) and Madhavan et al (1997). For currencies, Danielsson and Payne (2001) find an M-shaped volume pattern while Baillie and Bollerslev (1990) find that volatility for major currency pairs peaks twice during the day, when London and New York open, yielding an M-shaped plot. Low and Muthuswamy (1996) find similar peaks in the price change volatility for three major currency pairs when London and New York open and close while McGroarty et al (2009) find an M-shaped intraday pattern for trading volume and volatility of currencies. Ranaldo (2009) and Breedon and Ranaldo (2013) find that currencies tend to depreciate during local trading hours and that this pattern is reflected in the order flow. Ap Gwilym and Sutcliffe (1999) divide these observed patterns in intraday trading patterns into two categories. The first, documented by Brock and Kleidon (1992), attributes these patterns to differing trader behaviour at the open and close, while the second, documented by Admati and Pfleiderer (1988), attribute the patterns to the strategic behaviour of informed traders.\(^2\)

Another stylized fact about financial returns is an asymmetric relationship between returns and volatility, where volatility tends to increase following negative returns and decreases following positive returns. The first one is called the leverage effect, while the second is called the volatility feedback effect which argues that if volatility is priced, an anticipated increase in volatility raises the rate of the return, implying an immediate stock price decline in order to allow for higher future returns (see French et al 1987; Bekaert and Wu 2000). There is also a growing literature reporting stock index returns are negatively correlated with changes in volatility and that the negative relationship is even more pronounced in falling than in rising markets. There have been attempts to explain this relationship, such as Black (1976) and Christie (1982) arguing that positive stock returns increase the market value of the firm’s equity and therefore diminish its financial leverage.

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\(^2\) Since there is no daily open or close in the Bitcoin market, our focus follows Admati and Pfleiderer (1988).
ratio which in turn lowers the volatility of stock returns. Another explanation is that bad news might have different implications for future uncertainty than good news (Glosten et al 1993; Chen and Ghysels 2007). Whether this relationship is return-driven or volatility-driven is open to debate (see Masset and Wallemier 2010) as most of the recent studies show evidence of both. Clark’s (1973) mixture of distributions hypothesis (MDH) argues that volatility and volume move together in response to common but not directly observable external stimuli, which is associated with public information. This is supported by Copeland (1976) and Jennings et al (1981) who show that traders receive a signal ahead of the market and trade on it, thereby creating volume and moving price (volatility). Therefore, we expect to find that volatility is positively correlated with volume.

Intraday seasonality has been examined in some depth for equities, foreign exchange markets and precious metals yet Bitcoin has so far been ignored. Therefore, we contribute to the literature in the following ways. Firstly, we add to the modest but growing literature on Bitcoin by examining the intraday seasonality of Bitcoin, which is of high importance to investors and regulators alike. Given the increases in media coverage and trading volume of Bitcoin, an analysis of its intraday behaviour is required. Secondly, we examine the lead-lag relationship between intraday returns, volume and volatility of two Bitcoin exchanges to determine the relationship between the intraday variables. The relationships between these variables have been examined in some detail in the literature of equities, currencies and commodities, but this is the first on Bitcoin. Thirdly, we study the Granger causality between the intraday Bitcoin variables to examine the direction of any Granger causality between the intraday variables of Bitcoin.

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The rest of the paper is organized as follows. Section 2 reports the data and methodology employed in this paper while Section 3 reports the empirical results while Section 4 provides a summary and conclusions.

2. Data and Methodology

In this section, we present the data employed in this study as well as the calculation of the variables utilised to examine the high-frequency dynamics of Bitcoin.

2.1. Data

The data for this paper is downloaded from www.Bitcoincharts.com, which provides the complete historic trade data of various Bitcoin exchanges. It provides the unixtime, price and volume to the second of various Bitcoin exchanges. We study the the BTC-e exchange at the 5-minute frequency to examine the intraday dynamics of Bitcoin returns, volume, volatility and bid-ask spread (BAS). The BTC-e exchange is one of the largest exchanges denoted in US dollars and as Brandvold et al (2015) note, is the market leader with the highest information share along with Mt.Gox until its demise.\footnote{Mt.Gox went bankrupt on 26\textsuperscript{th} February 2014 and so is not included in our study. Mt.Gox was the largest exchange before its bankruptcy. Bitstamp is also studied and reports similar results. We do not report the results to conserve space but are available from the authors upon request.} We choose the 5-minute frequency since data at any higher frequency was often missing due to low liquidity which may lead to unreliable and spurious results. Also, as Anderson (2000) points out, this frequency is the best compromise between having enough observations to examine the intraday dynamics while also at the same time having enough data to avoid noise issues.

In order to generate 5-minutely intervals from the data, we aggregate the data into 5-minutely data so that we obtain high/low/open/close prices for each 5-minute period. Our sample period runs from 1\textsuperscript{st} November 2014 to 31\textsuperscript{st} October 2016 and is chosen since before this period, high frequency data was infrequent and spurious. Only a handful of 5-minutely data is missing over our
complete sample period, therefore enabling a complete examination of the intraday dynamics of Bitcoin.\textsuperscript{5} The BTC-e exchange trades 24-hours a day and anyone throughout the world can trade Bitcoin. An issue faced is what time zone to select since the data is provided in unixtime. Following Ranaldo (2009), we account for differences in daylight savings times by expressing time in terms of Greenwich Mean Time (GMT). Figure 1 and 2 show the time-series graph of the price, volume and volatility of Bitcoin throughout our sample period. The price of Bitcoin has generally increased during our sample period and especially since August 2015. Volume has stayed fairly constant, except for a few sharp jumps in the magnitude of trading activity. Similarly, volatility (measured by realized volatility) shows no discernible pattern, but there have been a number of jumps in volatility throughout the sample period.

2.2. Variables of Interest

The variables of interest in this paper are returns, volume, bid-ask spread and volatility. We calculate log returns as;

\[ r_{t,d} = (\ln P_{t,d} - \ln P_{t,d-1}) \times 100 \]  

where \( r_{t,d} \) is the return for the intraday period \( d \) on trading day \( t \) and \( P_{t,d} \) is the price for the intraday period \( d \) on trading day \( t \). We employ the popular realised volatility (RV) as our measure of volatility such that;

\[ RV = \ln \left( \frac{P_t}{P_{t-1}} \right)^2 \]  

Since we do not have information on the bid or ask prices, we calculate the BAS by employing the methodology of Corwin and Schultz (2012). Once we aggregate our data to the 5-minutely frequency, we can also derive the high and low prices over each 5-minute frequency. From these

\textsuperscript{5} BTC-e has suffered some outages related to Distributed Denial service attacks and therefore no data is obtained during these periods. However, these periods are very infrequent and do not last long (Millet, 2014).
we use the Corwin and Schultz (2012) methodology that is based on the idea that high (low) prices are almost always buyer (seller) initiated trades and therefore the ratio of high-to-low prices reflect both the fundamental volatility of the stock and its bid-ask spread. Also, the component of the high-to-low price ratio that is due to volatility increases proportionately with the length of the trading interval, while the component due to the big-ask spreads does not. This implies that the sum of the high/low ranges over two consecutive periods reflects two periods’ volatility and twice the spread, while the price range over two periods reflects two days’ volatility and one spread. The measure is calculated by:

\[
BAS_{i,t} = \frac{2(e^\alpha - 1)}{(1 + e^\alpha)}
\]

where \(\alpha\) is defined as

\[
\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \frac{\gamma}{\sqrt{3 - 2\sqrt{2}}}
\]

and \(\beta\) and \(\gamma\) are calculated as

\[
\beta = \sum_{j=0}^{1} \left[ \ln \left( \frac{H_{t+j}}{L_{t+j}} \right) \right]^2
\]

\[
\gamma = \left[ \ln \left( \frac{H_{t,t+j}}{L_{t,t+j}} \right) \right]^2
\]
Where $H_{t+j}$ represents the high price for a given stock on day $t+j$, $L_{t+j}$ represents the low price for a given stock on day $t+j$, $H_{t,t+j}$ represents the high price for a given stock over two-periods from $t$ to $t+1$ and $L_{t,t+j}$ represents the low price for a given stock over two-periods from $t$ to $t+1$. 

### 2.3. Descriptive Statistics

Table 1 reports the descriptive statistics for BTC-e for the full sample period as well as the two equally sized subsample periods of 12 months each to determine whether the behaviour of Bitcoin has changed over our sample period. This is motivated by the fact Urquhart (2016) finds a change in the behaviour of returns of Bitcoin over a similar sample period. We can see that mean returns during the full sample period are positive, but in the first sample period, mean returns are negative indicating an increase in value of Bitcoin over our sample period. In addition, the skewness of returns in the first sample period is positive while the skewness is negative in the second subsample, indicating a change in the distribution of returns over the two sample periods. Interestingly, the mean trading volume has slightly decreased from the first sample period to the second, indicating that investor demand for Bitcoin has actually decreased over time. The mean RV and BAS also decrease over time between the two subsamples indicating that the variation returns and the spread of Bitcoin has decreased in recent times. Therefore, the descriptive statistics show that over our full sample period, the behaviour of our intraday variables changes and consequently we should look at both sample periods separately.

### 3. Empirical Results

This section provides the results for intraday patterns of Bitcoin as well as the correlation and lead-lag relationships between the intraday variables.

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6 For more information on this estimator, see Corwin and Schultz (2012).
3.1. Intraday Patterns

Figure 3 presents the intraday mean volume and we see that volume is fairly low until 07:00 when trading volume increases until 10:30, therefore suggesting an inverted U-shape for the full sample and the two subsample periods. Volume again peaks at 14:00 and then gradually decreases over the rest of the day. This pattern is consistent with the idea that volume of certain currency markets increase when European and North American markets open. This suggests that European and North American investors are the main drivers of the volume traded of USD denominated Bitcoin. Intraday RV is shown in Figure 4 and we can see that it is at its highest from 07:00 and declines after 18:00, again indicating that the variation in Bitcoin is at its strongest during the open periods of European and North American markets. These intraday patterns for volume and volatility are broadly reminiscent of patterns observed in the foreign exchange market and are consistent with the idea that volume and volatility are correlated. The intraday pattern for Bitcoin BAS is shown in Figure 5 and shows that the BAS increases throughout the day until 15:30 and then decreases constantly until the end of the day. This is unlike the vast majority of the literature which finds a U-shape for the BAS (ap Gwilym and Sutcliffe 1999), including foreign exchange rates.

Our observed Bitcoin intraday patterns find support from market microstructure theory, which suggests that the BAS should resemble volatility. Roll (1984) argues that high frequency return volatility and the BAS are broadly equivalent because successive trades bounce between bid-side and ask-side of the touch. Black (1991) presents a formal model of the BAS as a positive function of volatility. By contrast, microstructure theory predicts an inverse relationship between trading volume and the BAS (see O’Hara 1995). However, the core mechanism for this is competition among risk-averse market makers who seek to manage their inventories by adjusting their prices.

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7 Although investors can trade outside the usual trading hours of stock markets, consistent with the literature we assume that they will conduct most of their trading during normal stock market trading hours.
Bitcoin is not traded by banks or institutional investors and there is no evidence that any of the Internet venues, which facilitate Bitcoin trading, ever act as market makers (in the sense of risking their own capital to manage an inventory of the asset). These only provide electronic orderbooks via which customers can trade with each other, by either advertising the price-volume combination they want to buy (sell), or engaging an existing order posted by an earlier seller (buyer). Without market makers, there is no direct mechanism for BAS behaviour to be determined by trading volume.

All the intraday patterns are consistent across the sample periods, indicating that there hasn’t been a change in the intraday behaviour of Bitcoin over our sample period. In the next section, we examine the relationship between the intraday variables over the full sample. Analysis was conducted on the two subsample periods, however, there was qualitatively no difference in the results, therefore they are omitted to conserve space.

3.2. Correlation Matrix

We examine the correlation matrix for Bitcoin to determine how the intraday variables are related to each other. Table 2 shows that returns have a negative and significant relationship with volume and RV, while it has a positive and significant relationship with the BAS. The relationship of returns to volume and RV is statistically significant at the 1% level. We also find that Bitcoin volume has a positive and statistically significant relationship at the 1% level with RV and the BAS indicating that volume and RV/volume are highly and positively correlated. Finally, we also find that RV has a positive and significant relationship with the BAS, indicating that when RV is high, the spread also increases. Therefore, we find that all the intraday variables for each individual exchange are significantly correlated with one another and returns have a significant negative relationship with volume, RV but a significant positive relationship with the BAS.
3.3. Lead-Lag Relationships

In the previous section, we find that intraday returns, volume, volatility and BAS of Bitcoin are highly correlated with one another. We therefore examine the origins of these relationships to determine which variable is driving the relationships. We examine the cross-correlation coefficient where one variable is at time interval $t$ and the other at time interval $t + j$, where $j \in \{-12, \ldots, 12\}$, to include up to plus or minus 1-hour.\footnote{The lead-lag relationships at any higher lags are insignificant but are available upon request.} Figure 6 reports the cross-correlation between Bitcoin returns and volume and shows that the correlation is negative for a number of lagged volumes. This suggests that returns may be systematically related to the preceding volume. We also find that returns are correlated with volume in the proceeding 5-minutes, with the first two leads not near zero. This suggests a bilateral lead-lag relationship between returns and volume. Figure 7 shows the correlation coefficient is negative at a number of lagged RV, while returns are correlated with RV in the proceeding couple of leads, indicating a bilateral lead-lag relationship between returns and RV. Figure 8 presents a bilateral relationship between Bitcoin volume and RV which seems symmetrical in magnitude indicating a symmetric correlation between Bitcoin volume and RV. Figure 9 shows that proceeding returns are correlated with the BAS indicating a return-driven relationship, although the magnitude of the effect is small in comparison to the other cross-correlation relationships. Also, we show in Figure 10 that there is a volume driven relationship between volume and the BAS, while RV and the BAS in Figure 11 show a symmetric relationship.

Therefore our results suggest that there is strong evidence of some lead-lag relationships between the intraday variables of Bitcoin. However, one issue is that the cross-correlation analysis excludes partial cross-correlations (Masset and Wallmeier 2010). It could be the case that correlations computed for lags greater than 2 are completely due to the correlation at lag = 1. A more detailed

\footnote{The lead-lag relationship at the two-subsamples were also studied but there is no difference between the subsamples and the full sample results.}
study is therefore necessary to identify causality and the number of lagged intraday variables which have an impact on other intraday variables of Bitcoin.

3.4. Granger Causality

The Granger causality test is implemented to determine the causality between our intraday variables. Table 3 summarises the results of the Wald F-test for the full sample period for up to seven lags ($p = 7$). We report the $F$-statistic and their significance and find bi-directional causality between all of our variables. That is, each relationship studied rejects the null hypothesis of no causality indicating that one past variable does contribute to the explanation of the current variable. Although all are significant at least at the 5% level, some relationships are stronger than others are. For instance, the relationship between RV and returns is only significant at the 5% level, while all other relationships are significant at 1% level indicating that this is the weakest of the relationships found. Further, the strongest relationship we find according to the $F$-statistic is that RV granger causes BAS. Therefore, we find strong evidence of the bilateral relationship between intraday Bitcoin variables.

4. Summary and Conclusions

It is well known that equity markets and currencies exhibit intraday patterns and that there are relationships between intraday returns, volume and volatility. Bitcoin is a relatively new financial instrument which has created considerable debate in the media as well as the academic literature. However, there is relatively little known about Bitcoin from an investor and academic viewpoint. Therefore we add to the sparse literature by examining the intraday stylized facts of Bitcoin returns, volume, realised volatility and BAS throughout the day as well as the dynamics between these

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10 We choose seven lags as the market is open 7 days a week and the Akaike and Schwartz information criteria confirm this when the lag limit is set to 7. Other lag lengths were examined and confirm our results.
variables. We aggregate tick data to the 5-minutely frequency of the BTC-e exchange and find that Bitcoin returns have increased over time, while trading volume and volatility have gradually decreased. We also find that returns are highest during the hours of 8am to 4pm, which is consistent with the opening and closing of European and North American markets. Further, volume increases throughout the day and falls from around 4pm until midnight, which is consistent with the intraday patterns found in currency markets. Realised volatility shows a n-shape, as does the BAS, which can be explained through the lack of market makers in the Bitcoin exchanges.

We also examine the relationships between our variables and find a significant negative relationship between returns and volatility, which is consistent with the literature. However, we find that this relationship is not return- or volatility-driven, but is a bilateral relationship according to Granger causality. We find a significant positive relationship between volatility and volume, which is consistent with the mixture of distributions hypothesis (MDH) by Clark (1973) that argues that volatility and volume move together. Finally, we find that this relationship is bilateral according to the Granger causality test.

We attribute our findings to the European and North American trading of Bitcoin as well as the lack of a market maker in Bitcoin markets. These findings show the periodicity of Bitcoin and will be of great interest to regulatory authorities as well as Bitcoin investors who could use this information in their trading strategies.
References


Table 1: Descriptive statistics of BTC-e at the 5-minute frequency.

<table>
<thead>
<tr>
<th></th>
<th>Returns</th>
<th>Volume</th>
<th>RV</th>
<th>BAS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Full Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.0003562</td>
<td>26.925634</td>
<td>0.001434</td>
<td>0.001252</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.240341</td>
<td>55.906436</td>
<td>0.001929</td>
<td>0.001643</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>-0.0236</td>
<td>7.7144</td>
<td>5.320190</td>
<td>2.5647</td>
</tr>
<tr>
<td>25% quant</td>
<td>-0.00083</td>
<td>3.38456</td>
<td>0.00022</td>
<td>2.24e-8</td>
</tr>
<tr>
<td>50% quant</td>
<td>0.00000</td>
<td>9.872129</td>
<td>0.00085</td>
<td>0.00059</td>
</tr>
<tr>
<td>75% quant</td>
<td>0.000878</td>
<td>26.55577</td>
<td>0.00201</td>
<td>0.00199</td>
</tr>
<tr>
<td><strong>Panel B: 1st November 2014 – 31st October 2015</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>-0.000097</td>
<td>29.609531</td>
<td>0.00157</td>
<td>0.00146</td>
</tr>
<tr>
<td>Std. Dev</td>
<td>0.256337</td>
<td>61.58577</td>
<td>0.002023</td>
<td>0.001810</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.069295</td>
<td>7.85988</td>
<td>4.92993</td>
<td>2.122921</td>
</tr>
<tr>
<td>25% quant</td>
<td>-0.097022</td>
<td>3.318934</td>
<td>0.000279</td>
<td>0.000007</td>
</tr>
<tr>
<td>50% quant</td>
<td>0.00000</td>
<td>10.40375</td>
<td>0.000991</td>
<td>0.000774</td>
</tr>
<tr>
<td>75% quant</td>
<td>0.1006579</td>
<td>29.56296</td>
<td>0.002219</td>
<td>0.0024108</td>
</tr>
<tr>
<td><strong>Panel C: 1st November 2015 – 31st October 2016</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.0008012</td>
<td>24.29345</td>
<td>0.00129654</td>
<td>0.0010453</td>
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<tr>
<td>Std. Dev</td>
<td>0.223545</td>
<td>49.57004</td>
<td>0.00182106</td>
<td>0.0014305</td>
</tr>
<tr>
<td>Kurtosis</td>
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<td>5.837501</td>
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<td>25% quant</td>
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<td>3.440033</td>
<td>0.0001669</td>
<td>3.807e-9</td>
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<tr>
<td>50% quant</td>
<td>0.000000</td>
<td>9.406667</td>
<td>0.0007405</td>
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<tr>
<td>75% quant</td>
<td>0.07703995</td>
<td>24.11249</td>
<td>0.0017954</td>
<td>0.0016097</td>
</tr>
</tbody>
</table>

Table 2: Correlation matrix between the variables of BTC-e. ***, **, * indicate significance at 1%, 5% and 10% respectively.

<table>
<thead>
<tr>
<th></th>
<th>Returns</th>
<th>Volume</th>
<th>RV</th>
<th>BAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Returns</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume</td>
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<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RV</td>
<td>-0.028603***</td>
<td>0.445947***</td>
<td>1</td>
<td></td>
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<td>BAS</td>
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<td>0.242583***</td>
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</table>

Table 3: The Granger causality results along with the F-statistics. ***, **, * indicate significance at 1%, 5% and 10% respectively.

<table>
<thead>
<tr>
<th>Relationship</th>
<th>F-stat</th>
<th>Relationship</th>
<th>F-stat</th>
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</thead>
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<td>RV-Returns</td>
<td>4.2***</td>
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<tr>
<td>Returns-RV</td>
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<td>RV-Volume</td>
<td>217.8***</td>
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<tr>
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<td>5.9***</td>
<td>RV-BAS</td>
<td>817.9***</td>
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<tr>
<td>Volume-Returns</td>
<td>2.6**</td>
<td>BAS-Returns</td>
<td>2.4**</td>
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<tr>
<td>Volume-RV</td>
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<td>BAS-Volume</td>
<td>39.9***</td>
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<tr>
<td>Volume-BAS</td>
<td>590.8***</td>
<td>BAS-RV</td>
<td>72.8***</td>
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</table>
Figure 1: Time-series graph of the price of BTCe on the primary y-axis and volume on the secondary y-axis.

Figure 2: Time-series graph of the RV of BTCe on the primary y-axis.
Figure 3: Intraday mean volume of BTC-e over the full sample and two subsamples.

Figure 4: Intraday mean volatility of BTC-e over the full sample and two subsamples.

Figure 5: Intraday mean BAS of BTC-e over the full sample and two subsample periods.
**Figure 6:** The cross-correlation between Bitcoin returns and volume over the total sample period for different lead and lag intervals.

**Figure 7:** The cross-correlation between Bitcoin returns and RV returns over the total sample period for different lead and lag intervals.
**Figure 8:** The cross-correlation between Bitcoin volume and RV returns over the total sample period for different lead and lag intervals.

**Figure 9:** The cross-correlation between Bitcoin returns and BAS returns over the total sample period for different lead and lag intervals.
Figure 10: The cross-correlation between Bitcoin volume and BAS returns over the total sample period for different lead and lag intervals.

Figure 11: The cross-correlation between Bitcoin RV and BAS returns over the total sample period for different lead and lag intervals.