Economics Letters 159 (2017) 145–148

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Price clustering in Bitcoin

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HIGHLIGHTS

- We study the price clustering in Bitcoin.
- We find significant evidence of price clustering at round numbers.
- However there is no significant pattern in returns after round numbers.
- We also show that price and volume have a significant positive relationship with price clustering.
- Our analysis supports the negotiation hypothesis of Harris (1991).

ARTICLE INFO

Article history:
Received 13 July 2017
Received in revised form 25 July 2017
Accepted 30 July 2017
Available online 3 August 2017

JEL classification:
C22
G12
G14

Keywords:
Bitcoin
Price clustering
Cryptocurrency

ABSTRACT

Investor and media attention in Bitcoin has increased substantially in recently years, reflected by the incredible surge in news articles and considerable rise in the price of Bitcoin. Given the increased attention, there little is known about the behaviour of Bitcoin prices and therefore we add to the literature by studying price clustering. We find significant evidence of clustering at round numbers, with over 10% of prices ending with 00 decimals compared to other variations but there is no significant pattern of returns after the round number. We also support the negotiation hypothesis of Harris (1991) by showing that price and volume have a significant positive relationship with price clustering at whole numbers.

1. Introduction

Cryptocurrencies have received much attention by the media and investors alike, which can be attributed to their innovative features, transparency, simplicity and increasing popularity. As Katsiampa (2017) notes, Bitcoin is the most popular cryptocurrency with 41% of the estimated cryptocurrency capitalisation in Bitcoin. However little is known about the behaviour Bitcoin prices. Dwyer (2015) finds that the average monthly volatility of Bitcoin is higher than that of gold or a set of foreign currencies, and the lowest monthly volatility for Bitcoin are less than the highest monthly volatility for gold and currencies. Brière et al. (2015) show that Bitcoin offers significant diversification benefits for investors while Urquhart (2016) shows that Bitcoin returns do not follow a random walk. Recently, Balcilar et al. (2017) show that Bitcoin volume can predict returns except in bear and bull market regimes and that volume cannot predict the volatility of Bitcoin returns.

A well-known behavioural phenomenon in the literature is price clustering, where prices tend to congregate around some specific set of values, usually whole digits. Price clustering has been found in many markets, such as the spot foreign exchange market (Sopranzetti and Datar, 2002; Ahn et al., 2005; Mitchell, 2001), stock markets (Harris, 1991; Aşçıoğlu et al., 2007; Ikenberry and Weston, 2008), commodity markets (Ball et al., 1985; Narayan et al., 2011a; Bharati et al., 2012) and even betting markets (Brown and Yang, 2016). A number of potential hypotheses have been have put forward in an attempt explain price clustering, such as uncertainty due to a lack of information (Ball et al., 1985), attraction of investors to certain integers (Goodhart and Curcio, 1991), and the negotiation hypothesis which argues that investors deal with a smaller set of integers to minimise the negotiation process (Harris, 1991). In this paper, we are the first to examine Bitcoin prices for clustering, the potential trading benefit from such clustering and the determinants of the clustering.

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http://dx.doi.org/10.1016/j.econlet.2017.07.035

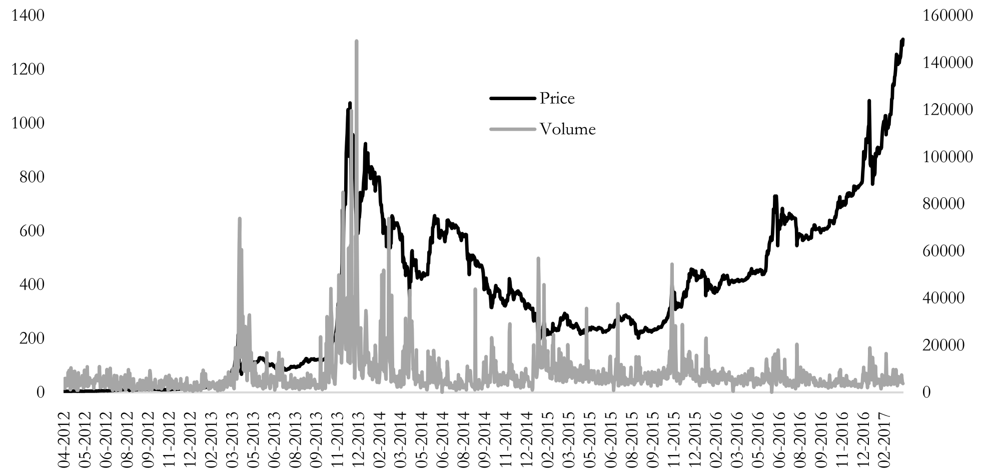

Fig. 1. Time-series graph of the daily price and volume of Bitstamp. Price is on the primary y-axis while volume is on the secondary y-axis.

Table 1
Descriptive statistics of the price and returns of Bitstamp.

	Mean	SD	Max	Min	Kurt	Skew	N
Price	383.0193	305.3206	1350.21	4.87	0.0974	0.7624	1823
Returns	0.0031	0.0472	0.3375	−0.6639	32.1465	−1.9170	1822

Table 2
Price clustering. 'XX' refers to the digits to the right of the decimal place, while 'freq' refers to its frequency. '%' refers to the frequency percentage while 'factor' refers to the frequency divided by the expected frequency and therefore is a test for a uniform distribution.

XX	Freq.	%	Factor
Panel A: Most Frequent			
00	197	10.81%	10.81
50	52	2.85%	2.85
99	50	2.74%	2.74
75	39	2.14%	2.14
19	33	1.81%	1.81
Panel B: Least Frequent			
73	4	0.22%	0.22
34	5	0.27%	0.27
37	5	0.27%	0.27
83	6	0.33%	0.33
46	7	0.38%	0.38
$\chi^2 = 153.81^{***}$			

*** refers to significance at the 5% level for the χ^2.

2. Data and methodology

We collect data from www.bitcoincharts.com which provides complete history of various Bitcoin exchanges denoted in various exchanges. The data consists of daily closing prices of Bitstamp from 1st May 2012 to 30th April 2017 therefore capturing 5 years of Bitcoin prices. Fig. 1 shows the Bitcoin prices and volume over this period and it shows that Bitcoin prices were relatively stable before late 2013. After this date prices moved quite dramatically, reflecting the increased attention of Bitcoin by investors. Table 1 reports the descriptive statistics of the prices and returns of Bitcoin and show that the maximum price in our sample is \$1350.21 and the minimum of \$4.87. The returns show that the mean return is positive, with quite a high standard deviation, while there is also evidence of a leptokurtic distribution and negative skewness.

Price clustering at whole numbers means that we are interested in the pair of digits to the right of decimal place. Therefore a price of \$156.00 is noted as a whole number while a price of \$156.01 is not considered a whole number. We broadly follow the methodology of Dowling et al. (2016) who examine psychological barriers in prices of energy markets, except we focus on price clustering rather than psychological barriers. Firstly, we employ a clustering test which is;

$$f(M) = \alpha + \beta D^i + \varepsilon \tag{1}$$

where $f(M)$ is the absolute frequency of digits to the right of the decimal place while D^i is a dummy variable taking the value of 1 for whole numbers and zero otherwise. Under the null hypothesis, β will be zero while the presence of clustering will result in a higher frequency of M-values at the cluster point and thus a positive and significant β. We also conduct a clustering kurtosis test whether there is a different frequency distribution shape around whole numbers such that;

$$f(M) = \mu + +\delta_1 M + \delta_2 M^2 + \varepsilon \tag{2}$$

where M is the M- digit values and M^2 is the square of their values. If there is a normal distribution around whole numbers then the coefficient δ_2 should have a value of zero, while the presence of abnormal whole number shapes would be suggested by a significant negative δ_2 and price clustering would be suggested through a significant positive δ_2.

The analysis so far tests for price clustering, but lacks any trading implications. Therefore we examine the conditional effects, similar to Dowling et al. (2016), where are examine the different reactions of prices depending on the conditionals related to the round numbers. That is, whether the cluster at a round number is being approached by rising or falling prices, or other relevant conditions that might influence the reaction. We distinguish two aspects related to days which cluster. First, we examine a cluster that is reached through prices falling or whether the cluster is caused by prices rising. Second, we examine separately the days before and after a cluster at round numbers to study the pre- and post-behaviour of prices. We create four dummy variables;

(1) BDZ^n, a dummy variable that equals 1 to the n days before a cluster through falling prices
(2) BUZ^n, a dummy variable that equals 1 to the n days before a cluster through rising prices

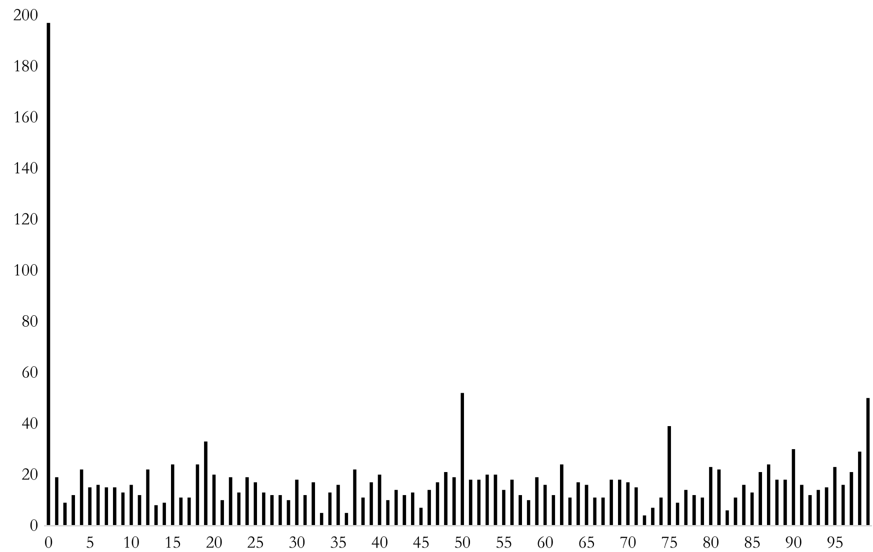

Fig. 2. Plot of M-values against their respective frequencies. The M-values are the two digits that bracket the decimal point.

Table 3
Clustering, clustering kurtosis, condition effects and determinants of round numbers.

Panel A: Clustering and clustering kurtosis test						
Clustering test			Clustering Kurtosis test			
α	β	Adjusted R^2	μ	δ_1	δ_2	Adjusted R^2
16.424***	180.576***	0.85	32.498***	−0.749***	0.007***	0.06
(0.00)	(0.00)		(0.00)	(0.01)	(0.01)	

Panel B: Conditional effects of round numbers					
Window	1	2	3	5	10
Constant	0.0027**	0.0022*	0.0022	0.0029*	0.0033**
	(0.03)	(0.10)	(0.12)	(0.08)	(0.05)
r_{t-1}	−0.0072	−0.0097	−0.0118	−0.0270	−0.0437*
	(0.78)	(0.71)	(0.65)	(0.32)	(−0.10)
BDZ_t^n	−0.0026	−0.0027	0.0008	−0.0026	−0.0045
	(0.61)	(0.50)	(0.82)	(0.43)	(0.16)
BUZ_t^n	0.0116**	0.0111***	0.0082**	0.0050*	0.0081***
	(0.02)	(0.00)	(0.01)	(0.09)	(0.00)
ADZ_t^n	−0.0023	0.0007	−0.0026	−0.0031	−0.0054*
	(0.67)	(0.16)	(0.48)	(0.35)	(0.10)
AUZ_t^n	−0.0008	−0.0013	−0.0007	0.0010	0.0003
	(0.87)	(0.74)	(0.84)	(0.75)	(0.93)

Panel C: Determinants of price clustering			
Model 1		Model 2	
Price	(Log)Volume	Price	Volatility
0.0005***	0.2334***	0.0006***	5.0606
(0.00)	(0.00)	(0.00)	(0.16)

* Indicate significance at the 10% respectively.
** Indicate significance at the 5% respectively.
*** Indicate significance at the 1% respectively.

(3) ADZ^n, a dummy variable that equals 1 to the n days after a cluster through falling prices
(4) AUZ^n, a dummy variable that equals 1 to the n days after a cluster through rising prices

In each case, we set n to 1, 2, 3, 4, 5 and days in order to allow us to identify the duration of any price impact. Therefore, the regression model is;

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 BDB_t^n + \beta_3 BUB_t^n + \beta_4 ADB_t^n + \beta_5 AUB_t^n + \varepsilon_t \quad (3)$$

where R_{t-1} is the previous days return to account for serial correlation. Finally, we also study the potential determinants of price clustering by following Narayan et al. (2011b) by estimating a standard probit model where the dependent variable in a binary variable taking the value of one when prices cluster at whole numbers. We estimate two models, where we firstly regress volume and price on the price clustering, while the second model regresses volume and price volatility on price clustering.

3. Empirical Results

Fig. 2 presents distribution of prices for Bitstamp, we find strong evidence of clustering at the 00 digit indicating clustering at round numbers. We also find smaller evidence of clustering around the 50 digit and the 99 digit however they are no where as large as the clustering at round numbers. To quantify this clustering,

Table 2 reports distribution of clustering for the most popular and least popular 5 digits. We can clearly see that 00 digits are the most popular, with 10.81% of the prices ending in 00 digits. We also see that the 50 and 99 digits are the next two popular digits while the least popular digits only occur between 4 and 7 times in the whole series. We also show the factor suggested by Sonnemans (2006) which is a simple test for a uniform distribution (actual frequency divided by expected frequency) and any number higher than 1 indicates clustering. We find clear evidence of clustering at 00, but we also find evidence of clustering at 99 and 50, albeit not as strong. In the last row, we also calculate the χ^2 for a uniform distribution and show that a uniform distribution is clearly rejected by the significant χ^2 statistic. Panel A of Table 3 also reports the clustering test and clustering kurtosis test results and we find positive and significant evidence of clustering at round numbers, while the clustering kurtosis test shows a significant positive coefficient indicating significant clustering at round numbers. Therefore our analysis shows strong evidence of clustering of prices around round numbers. In attempt to take an advantage of this, we examine the price reaction after round numbers and Panel B of Table 3 shows that in one, two, three, five and ten days before a round number from rising prices, the returns are positive and statistically significant. However we find not significant evidence of a return pattern after round numbers, but there is evidence of an insignificant next day negative reaction after round numbers. Finally in Panel C of Table 3, we examine the potential determinants of price clustering where we find the price and volume have a significant positive relationship with price clustering, indicating that as the price and trading volume of Bitcoin increases, the number of clustering at round numbers also increases. Therefore our results support evidence of Ikenberry and Weston (2008) and the negotiation hypothesis of Harris (1991) as when prices and volume increase, clustering also increases.

4. Conclusion

Price clustering has been found in many financial markets and this paper is the first to examine any potential price clustering in Bitcoin. We find significant evidence of price clustering around whole numbers, with over 10% of prices ending with decimal digits of 00. However prices after a round number show no predictable pattern and therefore cannot be taken advantage in the form of an investment strategy, however we find that the clustering in Bitcoin is consistent with the negotiation hypothesis of Harris (1991) as price clustering is significantly related to price and volume.

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