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PERSISTENCE IN THE CRYPTOCURRENCY MARKET

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1. Introduction

The exponential growth of BitCoin and other cryptocurrencies is a phenomenon that has attracted considerable attention

2. Literature Review

As already mentioned above, the cryptocurrency market has only been in existence for a few years, and therefore only a handful of studies have been carried out. ElBahrawy et al. (2017) provide a comprehensive analysis of 1469 cryptocurrencies considering various issues such as market shares and turnover. Cheung et al. (2015), Dwyer (2014), Bouoiyour and Selmi (2015) and Carrick (2016) show that this market is much more volatile than others. Halaburda and Gandal (2014) analyse its degree of competitiveness Urquhart (2016) and Bartos (2015) focus on efficiency finding evidence for and against respectively. Anomalies in the cryptocurrency market are examined by Kurihara and Fukushima (20171in04 511.7(nd)-39(a)-5(g)10(a)4(inst)-amin

3. Data and Methodology

We focus on the four cryptocurrencies with the highest market capitalisation and longest

2. This period is divided into contiguous A sub-periods with length n, such that $A_n = N$, then each sub-period is identified as I_a, given the fact that $a = 1, 2, 3. . . , A$. Each element I_a is represented as N_k with $k = 1, 2, 3. . . , N$. For each I_a with length n the average e_a is defined as:

$$e_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}, \quad k = 1,2,3,\ldots N, \quad a = 1,2,3\ldots, A. \tag{2}$$

3. Accumulated deviations $X_{k,a}$ from the average e_a for each sub-period I_a are defined as:

$$X_{k,a} = \sum_{i=1}^{k} (N_{i,a} - e_a). \tag{3}$$

The range is defined as the maximum index $X_{k,a}$ minus the minimum $X_{k,a}$, within each sub-period (I_a):

$$R_{Ia} = \max(X_{k,a}) - \min(X_{k,a}), \quad 1 \le k \le n. \tag{4}$$

4. The standard deviation S_{Ia} is calculated for each sub-period I_a:

$$S_{Ia} = \left(\left(\frac{1}{n}\right)\sum_{k=1}^{n} (N_{k,a} - e_a)^2\right)^{0,5}. \tag{5}$$

5. Each range R_{Ia} is normalised by dividing by the corresfanding by corresfandin(4)

7. The least square method is used to estimate the equation *log (R / S) = log (c) + H*log (n).* The slope of the regression line is an estimate of the Hurst exponent *H.* (Hurst, 1951).

The Hurst exponent lies in the interval [0, 1]. On the basis of the H values three categories can be identified: the series are anti-persistent, returns are negatively correlated (” +); the series are random, returns are uncorrelated, there is no memory in the series (H = 0.5); the series are persistent, returns are highly correlated, there is memory in price dynamics (0.5 + ” .

To analyse the dynamics of market persistence we use a sliding-window approach. The procedure is the following: having obtained the first value of the Hurst exponent (for example, for the date 01.04.2004 using data for the period from 01.01.2004 to 31.03.2004), each of the following ones is calculated by shifting forward

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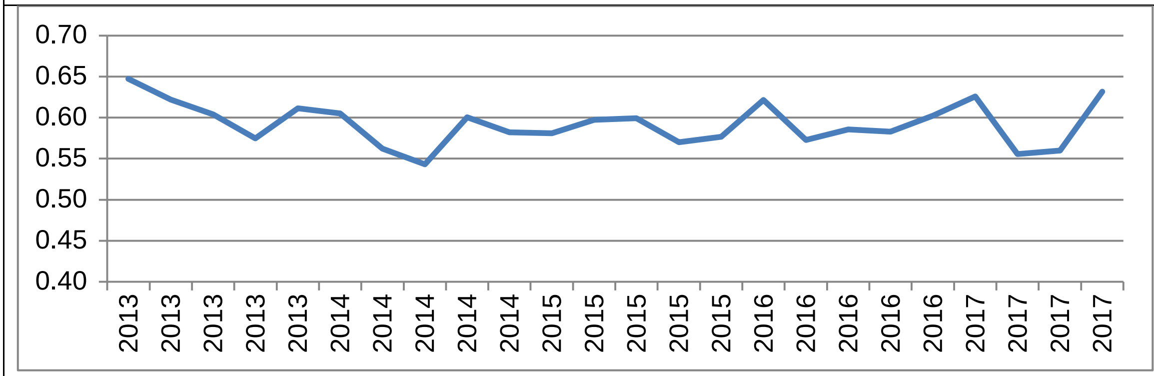
and a sufficient number of estimates is required to analyse the time-varying behaviour of the Hurst exponent. For example, if the shift equals 10, the second value is calculated for 10.04.2004 and characterises the market over the period 10.01.2004 till 09.04.2004, and so on.

In addition we also employ I(d) techniques for the log prices series, both parametric and semiparametric. Note that the differencing parameter d is related to the Hurst exponential described above through

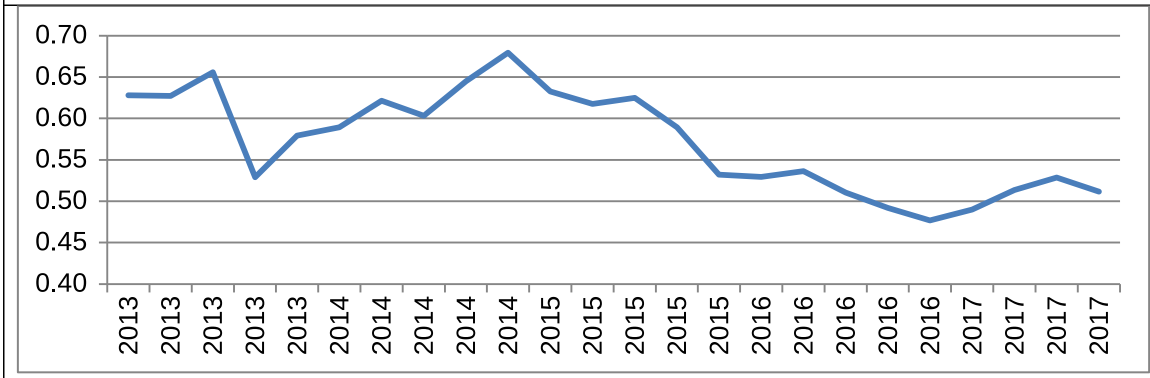
The dynamic R/S analysis shows the evolution over time of persistence in the cryptocurrency market (see Figure 1).

Figure 1: Results of the dynamic R/S analysis, (step=50, data window=300)

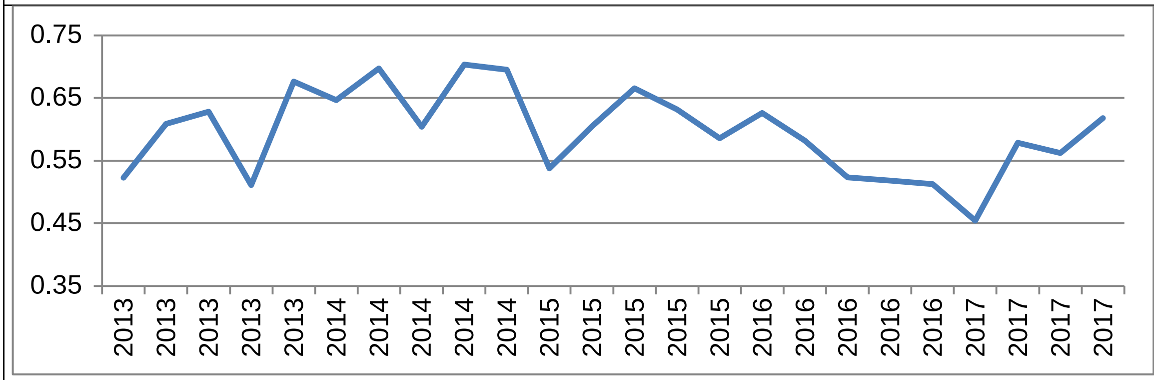
Bitecoin



Litecoin



Ripple



Dash

As can be seen the degree of persistence varies over the time, and fluctuates around its average. Time variation is particularly evident in the case of Litecoin, with the exponent dropping significantly from 0.7 in 2013 to 0.50 in 2017. This represents evidence in favour of the Adaptive Market Hypothesis (see Lo, 1991 for details) and also of efficiency increasing over time. In the case of Litecoin the market was initially rather inefficient, but after 2-3 years it became more liquid, and the number of participants, trade volumes and efficiency all increased.

Next we estimate an I(d) model specified as:

$$y_t = \alpha + \beta t + x_t, \quad (1 - B)^d x_t = u_t, \quad t = 1, 2, ..., \qquad (9)$$

and test the null hypothesis:

$$H_o: \ d = d_o, \qquad (10)$$

in (9) for d

Table 3: Estimates of d and confidence bands for the case of no autocorrelation

Log series	No terms

errors, a time trend is required for Bitcoin and Dash but not for the other two series. As before, the estimates of d are within the I(1) interval for all series except Ripple, for which the estimate of d is significantly higher than 1, which implies a high degree of persistence.

Table 5: Estimates of d and confidence bands for the case of autocorrelation

Log series	No terms	An intercept	A linear time trend

Ripple
Dash

Depending on the bandwidth parameters the estimates of d are within the I(1) interval or above 1. Therefore there is strong evidence that mean reversion does not occur, which suggests market inefficiency.

5. Conclusions

This paper uses R/S analysis and fractional integration long-memory cryptocurrency market is still inefficient, but is becoming less so. This is especially true of the Litecoin market, where the Hurst exponent dropped considerably over time.

The results obtained using I(d) methods are less conclusive, since the estimated values of d are higher than but not significantly different from 1 in a number of cases, the main exception being Ripple for which the parametric estimate of d is significantly higher than 1. The semiparametric I(d) results are very sensitive to the choice of the bandwidth parameter, and market inefficiency is found in a number of cases.

Persistence implies predictability, and therefore represents evidence of market inefficiency, suggesting that trend trading strategies can be used to generate abnormal profits in the cryptocurrency market.

References

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