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Persistence in the cryptocurrency market

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ABSTRACT

This paper examines persistence in the cryptocurrency market. Two different long-memory methods (R/S analysis and fractional integration) are used to analyse it in the case of the four main cryptocurrencies (BitCoin, LiteCoin, Ripple, Dash) over the sample period 2013–2017. The findings indicate that this market exhibits persistence (there is a positive correlation between its past and future values), and that its degree changes over time. Such predictability represents evidence of market inefficiency: trend trading strategies can be used to generate abnormal profits in the cryptocurrency market.

1. Introduction

The exponential growth of BitCoin and other cryptocurrencies is a phenomenon that has attracted considerable attention in recent years. The cryptocurrency market is rather young (BitCoin was created in 2009, but active trade only started in 2013) and therefore still mostly unexplored (see Caporale and Plastun, 2017 for one of the very few existing studies, with a focus on calendar anomalies). One of the key issues yet to be analysed is whether the dynamic behaviour of cryptocurrencies is predictable, which would be inconsistent with the Efficient Market Hypothesis (EMH), according to which prices should follow a random walk (see Fama, 1970). Long-memory techniques can be applied for this purpose. Several studies have provided evidence of persistence in asset price dynamics (see Greene and Fielitz, 1977; Caporale et al., 2016), and also found that this changes over time (see Lo, 1991), but virtually none has focused on the cryptocurrency market. One of the few exceptions is due to Bouri et al. (2016), who find lon- memory properties in the volatility of Bitcoin.

The present study carries out a more comprehensive analysis by considering four main cryptocurrencies (the most liquid ones: BitCoin, LiteCoin, Ripple, Dash) and applying two different long-memory methods (R/S analysis and fractional integration) over the period 2013–2017 to investigate their stochastic properties. Moreover, it also examines the evolution of persistence over time (by looking at changes in the Hurst exponent). Any predictable patterns could of course be used as a basis for trading strategies aimed at making abnormal profits in the cryptocurrency market.

The layout of the paper is the following. Section 2 provides a brief review of the relevant literature. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the empirical results. Section 5 provides some concluding remarks.

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Table 1
Capitalisation of the cryptocurrency market (27.10.2017).
Source: https://coinmarketcap.com/coins/.

#	Name	Market Cap	Price	Circulating Supply	Data starts from
1	Bitcoin	$98 035 067 124	$5888.16	16 649 525 BTC	28 Apr 2013
2	Ethereum	$28 411 539 142	$297.97	95 350 974 ETH	07 Aug 2015
3	Ripple	$7 825 254 645	$0.203087	38 531 538 922 XRP	04 Aug 2013
4	Bitcoin Cash	$5 928 832 364	$354.52	16 723 313 BCEH	23 Jul 2017
5	Litecoin	$2 974 020 034	$55.53	53 556 032 LTC	28 Apr 2013
6	Dash	$2 179 887 702	$285.10	7 646 019 DASH	14 Feb 2014
7	NEM	$1 786 032 000	$0.198448	8 999 999 XEM	01 Apr 2015
8	BitConnect	$1 582 408 231	$216.50	7 308 910 BCEC	20 Jan 2017
9	NEO	$1 429 555 000	$28.59	50 000 NEO *	09 Sept 2016
10	Monero	$1 331 970 304	$87.21	15 273 032 XMR	21 May 2014

Cryptocurrency Market Capitalisation. Data.

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 (2017) and Caporale and Plastun (2017).

Bariviera et al. (2017) test the presence of long memory in the Bitcoin series from 2011 to 2017. They find that the Hurst exponent changes significantly during the first years of existence of Bitcoin before becoming more stable in recent times. Bariviera (2017) also use the Hurst exponent and detect long memory in the daily dynamics of BitCoin as well as its volatility; in addition, they find more evidence of informational efficiency since 2014. Bouri et al. (2016) examine persistence in the level and volatility of Bitcoin using both parametric and semiparametric techniques; they detect long memory in both measures of volatility considered (absolute and squared returns). Catania and Grassi (2017) provide further evidence of long memory in the cryptocurrency market, whilst Urquhart (2016) using the R/S Hurst exponent obtains strong evidence of anti-persistence, which indicates non-randomness of Bitcoin returns.

3. Data and methodology

We focus on the four cryptocurrencies with the highest market capitalisation and longest span of data (see Table 1 below): BitCoin, LiteCoin, Ripple and Dash. The frequency is daily, and the data source is CoinMarketCap (https://coinmarketcap.com/coins/).

The two approaches followed are R/S analysis and fractional integration respectively. The following algorithm is used for the R/S analysis (see Mynhardt et al., 2014 for additional details):

1. A time series of length M is transformed into one of length $N = M - 1$ using logs and converting prices into returns:

$$N_i = \log\left(\frac{Y_{t+1}}{Y_t}\right), \quad t = 1,2,3,... \ (M - 1) \tag{1}$$

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:

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

Table 2
Results of the R/S analysis for the different crypto currencies, 2014–2017.

Period	Daily frequency
Bitcoin	0.59
LiteCoin	0.63
Ripple	0.64
Dash	0.60