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On the inefficiency of Bitcoin

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HIGHLIGHTS

- A follow up study of Urquhart (2016), investigating the market efficiency of Bitcoin.
- Shows for the first time that a power transformation of Bitcoin returns can be weakly Efficient.
- Gives a rationale for the power transformation used.

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ABSTRACT

Urquhart (2016) investigated the market efficiency of Bitcoin by means of five different tests on Bitcoin returns. It was concluded that the Bitcoin returns do not satisfy the efficient market hypothesis. We show here that a simple power transformation of the Bitcoin returns do satisfy the hypothesis through the use of eight different tests. The transformation used does not lead to any loss of information.

1. Introduction

Introduced and first documented by Satoshi Nakamoto in 2009, Bitcoin is a form of cryptocurrency—an "electronic payment system based on cryptographic proof" (Nakamoto, 2009), instead of traditional trust. Several authors have modeled Bitcoin data in recent years. Garcia et al. (2014) studied the links between social signals and Bitcoin price through a social feedback cycle. Kristoufek (2013) studied the relationship between digital currencies, such as Bitcoin, and search queries through Google Trends and Wikipedia. Moore and Christin (2013) provided an empirical analysis of Bitcoin-Exchange Risk. Glaser et al. (2014)'s analysis looked into whether Bitcoin intra-network transaction and on-exchange trading volumes are linked, and also tries to determine if Bitcoin can be classed as an asset or a currency. Hencic and Gourieroux (2014) modeled and predicted the Bitcoin/USD exchange rate through the application of a non-causal autoregressive model. Kondor et al. (2014) looked at the structure and evolution of the Bitcoin transaction network. The study of Sapuric and Kokkinaki (2014) measured volatility of the exchange rate of Bitcoin against six major currencies. Using a known technique that is robust in detecting bubbles, Cheung et al. (2015) investigated the existence of bubbles in the Bitcoin market. Through wavelet coherence analysis, Kristoufek (2015) examined Bitcoin price formation and the main drivers of price.

One of the fundamental principals for modeling of financial data is the efficient market hypothesis due to Fama (1970). There are three forms of this hypothesis. The one most commonly used is the weak form of the efficient market hypothesis. The weak form implies that investors cannot use past information to predict future returns.

Urquhart (2016) was the first to test the weak form for Bitcoin data. He used five different tests and concluded that Bitcoin returns are market inefficient. We follow up Urquhart (2016)'s work here. We test the same hypothesis not on the Bitcoin returns but an odd integer power of the Bitcoin returns, note that powering to an odd integer does not lead to any loss of information. Our results show that the transformed Bitcoin returns are actually market efficient. So, after all, everything is not so negative about Bitcoin.

The contents of this note are organized as follows. The Bitcoin data used and a brief descriptive analysis are presented in Section 2. The tests performed and their results are discussed in Section 3. Finally, some conclusions are noted in Section 4.

2. Data

The data are as in Urquhart (2016), that is, daily closing prices for Bitcoin in USD from the 1st of August 2010 to 31st of July

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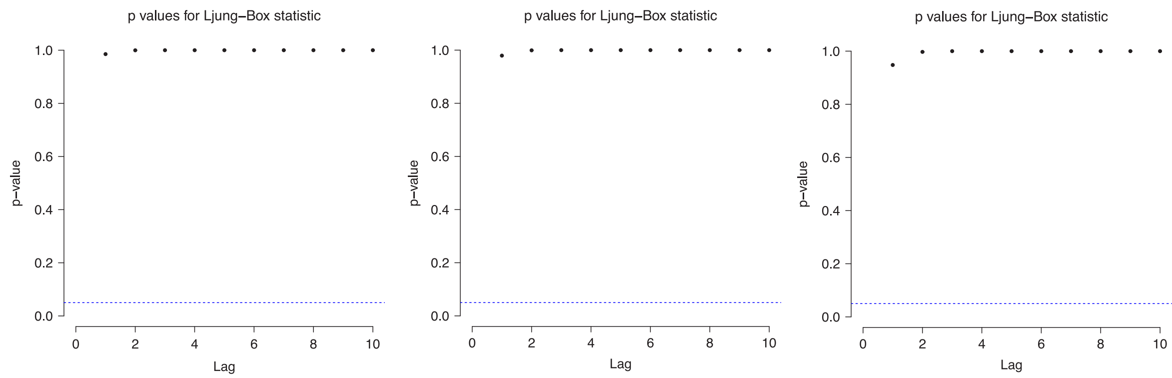

Fig. 1. *p*-values of the Ljung–Box test versus lag: full period (left), first subsample period (middle) and second subsample period (right).

2016. A plot of the data is shown in Fig. 1 in Urquhart (2016). As in Urquhart (2016), we consider data from three periods: the full period from the 1st of August 2010 to 31st of July 2016; the subsample period from the 1st of August 2010 to 31st of July 2013; the subsample period from the 1st of August 2013 to 31st of July 2016.

We computed the Bitcoin returns as

$$R_t = 100 \cdot \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where P_t and P_{t-1} denote the closing prices on days t and $t-1$, respectively.

To investigate the efficient market hypothesis, we propose dealing with R_t^m where m is an odd integer. This way no information is lost. If R_t is negative R_t^m will still be negative. If R_t is positive R_t^m will still be positive. If R_t is zero R_t^m will still be zero.

We choose $m = 17$, although smaller values could also be chosen. The following descriptive statistics of R_t^m are shown in Table 1: number of observations, minimum, first quartile, median, mean, third quartile, maximum, standard deviation, coefficient of variation, skewness and kurtosis.

The mean and median of the Bitcoin returns are approximately zero. The variability appears largest for the first subsample period and smallest for the second subsample period. The distribution of the Bitcoin returns are extremely skewed for all three periods. The full and the first subsample periods are negatively skewed. The second subsample period is positively skewed. The distribution of the Bitcoin returns are extremely peaked for all three periods. The degree of peakedness appears largest for the full period and smallest for the first subsample period.

3. Tests

We now test the efficient market hypothesis using various tests, including the ones used in Urquhart (2016).

Firstly, we performed the Ljung–Box (Ljung and Box, 1978) test for no autocorrelation. The *p*-values are plotted in Fig. 1 for lags from 1 to 10. There is no evidence against the hypothesis of no autocorrelation.

Secondly, we performed the runs test (Wald and Wolfowtiz, 1940) for independence of the returns. The *p*-values for the full, first subsample and second subsample periods were 0.019, 0.489 and 0.809, respectively. Hence, there is no evidence against the hypothesis of independence for the two subsample periods. The evidence against for the full period is not that strong.

Thirdly, we performed the Bartel's test (Bartels, 1982) also to test independence of the returns. The *p*-values for the full, first subsample and second subsample periods were 0.009, 0.011 and 0.388, respectively. Hence, there is no evidence against the hypothesis of independence for the second of the two subsample periods. The evidence against for the full period appears strong.

Fourthly, we performed the wild-bootstrapped automatic variance ratio test (Kim, 2009) to check whether the random walk hypothesis holds for the returns. The *p*-values for the full, first subsample and second subsample periods were 0.475, 0.465 and 0.5, respectively. Hence, there is no evidence against the random walk hypothesis.

Furthermore, plots of the variance ratios versus holding period are shown in Fig. 2 for the full, first subsample and second subsample periods. The variance ratios are within the 95% confidence bands. This gives further evidence to support the random walk hypothesis.

Fifthly, we performed the spectral shape tests (Durlauf, 1991; Choi, 1999) also to test if the random walk hypothesis holds for the returns. The *p*-values based on the Anderson–Darling statistic for the full, first subsample and second subsample periods were 1, 1 and 1, respectively. The *p*-values based on the Cramer–von Mises statistic for the full, first subsample and second subsample periods were 1, 1 and 1, respectively. Hence, yet again there is no evidence against the random walk hypothesis.

Sixthly, we performed the BDS test (Brock et al., 1996) that the returns are independently and identically distributed. The *p*-values for the full period were 0.932, 0.908, 0.932, 0.908, 0.932, 0.907, 0.966 and 0.954. The *p*-values for the first subsample period were 0.903, 0.870, 0.903, 0.870, 0.952, 0.935, 0.952 and 0.935. The *p*-values for the second subsample period were 0.952, 0.935, 0.952, 0.935, 0.952, 0.935, 0.976 and 0.967. Hence, there is no evidence against the hypothesis that the returns are independently and identically distributed.

Seventhly, we performed the robustified portmanteau test (Escanciano and Lobato, 2009) for no serial correlation. The *p*-values for the full, first subsample and second subsample periods were 0.513, 0.513 and 0.258, respectively. Hence, there is no evidence against no serial correlation.

Finally, we performed the generalized spectral test (Escanciano and Velasco, 2006) to check whether the martingale difference hypothesis holds for the returns. The *p*-values for the full, first subsample and second subsample periods were 0.287, 0.223 and 0.250, respectively. Hence, there is no evidence against the martingale difference hypothesis.

4. Conclusions

The tests in Section 3 have shown that an odd integer power of Bitcoin returns are largely weakly efficient over the full period as well as over the two subsample periods. We have used eight different tests: Ljung–Box test for no autocorrelation; runs test for independence; Bartel's test for independence; wild-bootstrapped automatic variance ratio test for the random walk