

Contents lists available at ScienceDirect

### **Economics Letters**

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



# The inefficiency of Bitcoin

## Andrew Urquhart

Southampton Business School, University of Southampton, Southampton, UK



#### HIGHLIGHTS

- We study the informational efficiency of Bitcoin.
- We employ a battery of tests and find evidence of market inefficiency.
- We find that some tests indicate market efficiency in the latter period.

#### ARTICLE INFO

# Article history: Received 24 August 2016 Received in revised form 12 September 2016 Accepted 17 September 2016 Available online 22 September 2016

JEL classification: G14

Keywords: Bitcoin Market efficiency Cryptocurrency Random walk

#### ABSTRACT

Bitcoin has received much attention in the media and by investors in recent years, although there remains scepticism and a lack of understanding of this cryptocurrency. We add to the literature on Bitcoin by studying the market efficiency of Bitcoin. Through a battery of robust tests, evidence reveals that returns are significantly inefficient over our full sample, but when we split our sample into two subsample periods, we find that some tests indicate that Bitcoin is efficient in the latter period. Therefore we conclude that Bitcoin in an inefficient market but may be in the process of moving towards an efficient market.

© 2016 Elsevier B.V. All rights reserved.

#### 1. Introduction

Bitcoin is a cryptocurrency that has received substantial attention given its innovative features, simplicity, transparency and its increasing popularity. Since it was first outlined in a paper by Nakamoto (2008) and went online in 2009, the price of Bitcoin has increased by over 5000% up July 2016. Investors have employed Bitcoin as currency as well as for investment purposes with Selgin (2015) and Baeck and Elbeck (2015) arguing that Bitcoin should be seen as a speculative commodity rather than a currency. Yet, the efficiency of Bitcoin within the meaning of Fama (1970) has not been investigated. Therefore we fill this gap and employ a battery of tests for weak form efficiency of Bitcoin.

The efficient market hypothesis (EMH) is one the key cornerstones of finance, developed by Fama (1970). A market is efficient if prices fully reflect all available information. Fama (1970) distinguishes between three forms of efficiency with the most commonly examined form the weak form, where a market is said

to be weak form efficient if investors cannot use past information to predict future returns. The weak form EMH has been examined substantially in the literature for many traditional financial assets as well as commodities (Kristoufek and Vosvrda, 2014) and even art (David et al., 2013), however Bitcoin has so far been unexplored.

The literature on Bitcoin was initially dominated by studies on the safety, ethical and legal aspects of Bitcoin, although recent literature has examined Bitcoin from an economic viewpoint. Cheah and Fry (2015) argue that if Bitcoin were a true unit or account, or a form of store of value, it would not display such volatility expressed by bubbles and crashes. Dwyer (2014) finds that the average monthly volatility of Bitcoin is higher than that for gold or a set of foreign currencies, and the lowest monthly volatilities for Bitcoin are less than the highest monthly volatility for gold and currencies. Cheung et al. (2015) show the existence of bubbles in the bitcoin market over the period and find a number of shortlived bubbles but also three huge bubbles, the last of which led to the demise of the Mt Gox exchange. Brière et al. (2015) show that Bitcoin offers significant diversification benefits for investors while Dyhrberg (2016a, b) show that Bitcoin has similar hedging

E-mail address: aju1y12@soton.ac.uk.

<sup>&</sup>lt;sup>1</sup> For an overview of Bitcoin, see Böhme et al. (2015).

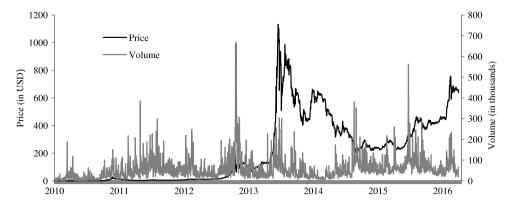


Fig. 1. Time-series graph the price of the daily price and volume of Bitcoin.

**Table 1**Descriptive statistics of Bitcoin over the full sample period, as well as two subsample periods.

| Sample period      | N    | Mean   | SD     | Max     | Min      | Kurt    | Skew    |
|--------------------|------|--------|--------|---------|----------|---------|---------|
| 1/8/2010-31/7/2016 | 2183 | 0.4245 | 5.4176 | 37.2239 | -44.5641 | 13.0323 | -0.3919 |
| 1/8/2010-31/7/2013 | 1089 | 0.6853 | 6.4539 | 37.2239 | -44.4607 | 8.4745  | -0.1400 |
| 1/8/2013-31/7/2016 | 1094 | 0.1681 | 4.1247 | 25.9477 | -44.5641 | 23.7367 | -1.5167 |

capabilities as gold and the dollar, and as such can be employed for risk management. Fry and Cheah (forthcoming) develop an econophyscis model to reveal that Bitcoin and Ripple (another cryptocurrency) are characterized by negative bubbles.

#### 2. Data and methodology

Many different Bitcoin exchanges are available, each with varying popularity and currencies that Bitcoin is denoted in. Therefore we collect data from www.bitcoinaverage.com, which is the first aggregated Bitcoin price index that aggregates rates from all available Bitcoin exchanges around the world and provides a volume weighted average Bitcoin price. Therefore this enables a worldwide perspective on the price, and therefore efficiency of Bitcoin. The data consists of daily closing prices for Bitcoin in USD from 1st August 2010 to 31st July 2016. Fig. 1 shows Bitcoin prices and volume over this period and it appears that Bitcoin prices are relatively stable before peaking dramatically in late 2013. However as Cheah and Fry (2015) show, even the earliest years of this period, the price rises are considerable and therefore we include the full sample period in our analysis. We examine the efficiency of Bitcoin over our full sample period, as well split our sample into two subsamples in order to whether the level of efficient has varied over time. Therefore our full sample period to study the efficiency of Bitcoin is from 1st August 2010 to 31st July 2016, and the two subsample periods are from 1st August 2010 to 31st July 2013 and 1st August 2013 to 31st July 2016.

We calculate Bitcoin returns in the following way;

$$R_t = \text{Ln}[(P_t)/(P_t - 1)] \times 100 \tag{1}$$

where  $R_t$  is the return of Bitcoin and  $\operatorname{Ln}(P_t)$  and  $\operatorname{Ln}(P_{t-1})$  are the natural logs of Bitcoin prices at time t and t-1. Table 1 reports the descriptive statistics of Bitcoin and shows that the mean return of Bitcoin is positive and over the full sample period with excess kurtosis and negative skewness. We also find that the mean return and standard deviation of Bitcoin returns are smaller in the second subsample while the kurtosis and negative skewness is much greater in the second subsample period.

In an efficient market, future prices are not foreseeable and variations are random due to the random nature of unpredictable events and therefore prices follow a random walk. To analyse whether Bitcoin is efficient, we employ a battery of highly powerful tests for randomness in order to avoid spurious results and

to capture all the dynamics of Bitcoin. Firstly, we examine the autocorrelation of returns which are assessed via the Ljung-Box (Ljung and Box, 1978) test that has the null hypothesis of no autocorrelation. Secondly, the runs test (Wald and Wolfowitz, 1940) and the Bartels test (Bartels, 1982) are employed to determine whether returns are independent, which has independence as the null hypothesis. Thirdly, we employ the variance ratio test (Lo and MacKinlay, 1988), which under the null hypothesis, the price process is a random walk and the variance of the price difference of order q equals p times the variance of the first difference. An issue with this test is the choice of parameters q and p and therefore we adopt the automatic variance test (AVR) of Choi (1999) where they are determined automatically using a data-dependent procedure. Further we utilize the wild-bootstrapped AVR test of Kim (2009). which greatly improves the small sample properties of the AVR test. Fourthly, the BDS (Brock et al., 1996) test is employed which is a popular non-parametric test for serial dependence in stock returns. The null hypothesis is that the data generating processes are i.i.d., while the alternative hypothesis is an indication that the model is misspecified (Brock et al., 1996). Embedding dimensions and metric bounds must be specified and we follow the literature by choosing embedding dimensions from 2 to 5 and metric bounds to a proportion of the standard deviation of the returns (Patterson and Ashley, 2000). We report the average p-values across our different specifications. Finally, the rescaled Hurst exponent (R/S Hurst) for long memory of stock returns is employed. We follow Urquhart (forthcoming), who suggest that strong evidence of persistence is evident with Hurst exponent values greater than 0.65 and strong anti-persistence with Hurst exponent values less than 0.45.

#### 3. Empirical results

Table 2 summarizes the results of our various tests. In each case we report the corresponding *p*-values, except the R/S Hurst exponent where we report the Hurst statistic.<sup>2</sup> For the full sample period, we find that weak-form informational efficiency of Bitcoin can be rejected, since all of the *p*-values reject the null hypothesis of randomness. The R/S Hurst exponent shows strong evidence of

 $<sup>^{2}</sup>$  There are no p-values associated with the Hurst exponent. Full results are available upon request.

**Table 2**Test results of weak form market efficiency with their *p*-values and R/S Hurst exponent.

| Test               | Ljung-Box test | Runs test | Bartels test | AVR test | BDS test | R/S Hurst |
|--------------------|----------------|-----------|--------------|----------|----------|-----------|
| 1/8/2010-31/7/2016 | (0.00)         | (0.00)    | (0.00)       | (0.01)   | (0.00)   | 0.353     |
| 1/8/2010-31/7/2013 | (0.00)         | (0.00)    | (0.00)       | (0.00)   | (0.00)   | 0.363     |
| 1/8/2013-31/7/2016 | (0.35)         | (0.00)    | (0.00)       | (0.64)   | (0.00)   | 0.406     |

anti-persistence, indicating the non-randomness of returns. Therefore our full sample period results indicate significant inefficiency in Bitcoin. When we split our full sample period into two subsamples we find that in the first subsample period, each of our tests rejects null hypothesis of randomness and the R/S Hurst statistic indicates strong anti-persistence. However when we study the second subsample period, the Ljung–Box and AVR tests both fail to reject their null hypotheses, indicating no autocorrelation and that Bitcoin is inefficient. The other tests all indicate that Bitcoin is inefficient. Therefore our results show that Bitcoin is an inefficient market over our full sample period but appears to becoming less inefficient in the second subsample period.

#### 4. Conclusion

The above analysis shows that the Bitcoin market is not weakly efficient over the full sample period. However we do show that Bitcoin may becoming more efficient with some of the tests for market efficiency suggesting that Bitcoin returns are random in the second subsample. Nevertheless, the inefficiency of Bitcoin is quite strong. Since it is a relatively new investment asset and still in its infancy, it is similar to an emerging market and therefore the inefficiency finding is not surprising. Consistent with this argument is that Bitcoin will become more efficient over time as more investors analyse and trade Bitcoin. Future work may involve further empirical analysis of the changing degree of market efficiency and comparing Bitcoin to emerging markets and other alternative investments.

#### References

Baeck, C., Elbeck, M., 2015. Bitcoins as an investment or speculative vehicle? A first look. Appl. Econom. Lett. 22, 30–34.

Bartels, R., 1982. The rank version of von Neumann's ratio test for randomness. J. Amer. Statist. Assoc. 77 (377), 40–46.

Bekaert, G., Harvey, C.R., 2002. Research in emerging markets finance: Looking to the future. Emerg. Mark. Rev. 3, 429–448.

Böhme, R., Christin, N., Edelman, B., Moore, T., 2015. Bitcoin: Economics, technology, and governance. J. Econom. Perspect. 29 (2), 213–238.

Brière, M., Oosterlinck, K., Szafarz, A., 2015. Virtual currency, tangible return: Portfolio diversification with bitcoin. J. Asset Manag. 16 (6), 365–373.

Brock, W.A., Dechert, W.D., Schieinkman, J.A., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econometric Rev. 15, 197–235.

Cheah, E.-T., Fry, J., 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econom. Lett. 130, 32–36.

Cheung, A., Roca, E., Su, J.-J., 2015. Crypto-currency bubbles: An application of the Phillips-Shi-Yu (2013) methodology on Mt.Gox bitcoin prices. Appl. Econom. 47, 2348–2358.

Choi, I., 1999. Test the random walk hypothesis for real exchange rates. J. Appl. Econometrics 14, 293–309.

David, G., Oosterlinck, K., Szafarz, A., 2013. Art market inefficiency. Econom. Lett. 121 (1). 23–25.

Dwyer, G.P., 2014. The economics of Bitcoin and similar private digital currencies. J. Financ. Stab. 17, 81–91.

Dyhrberg, A.H., 2016a. Bitcoin, gold and the dollar - a GARCH volatility analysis. Finance Res. Lett. 16, 85–92.

Dyhrberg, A.H., 2016b. Hedging capabilities of bitcoin. Is it the virtual gold? Finance Res. Lett. 16, 139–144.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. J. Finance 25 (2), 383–417.

Fry, J. and Cheah, E.-T., 2016. Negative bubbles and shocks in cryptocurrency markets, Int. Rev. Financ. Anal., forthcoming.

Kim, J.H., 2009. Automatic variance ratio test under conditional heteroskedasticity. Finance Res. Lett. 3, 179–185.

Kristoufek, L., Vosvrda, M., 2014. Commodity futures and market efficiency. Energy Econ. 42. 50–57.

Ljung, G.M., Box, G.E.P., 1978. On a measure of the lack of fit in time series models. Biometrika 65 (2), 297–303.

Lo, A.W., MacKinlay, C., 1988. Stock market prices do not follow random walks: Evidence from a simple specification test. Rev. Financ. Stud. 1, 41–66.

Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System.

Patterson, D.M., Ashley, R.A., 2000. A Nonlinear Time Series Workshop: A Toolkit for Detecting and Identifying Nonlinear Serial Dependence. Kluwer Academic, Boston, MA.

Selgin, G., 2015. Synthetic commodity money. J. Financ. Stab. 17, 92-99.

Urquhart, A., 2016. How efficient are precious metal returns? Eur. J. Financ., forthcoming.

Wald, A., Wolfowitz, J., 1940. On a test whether two samples are form the same population. Ann. Math. Stat. 11 (2), 147–162.

<sup>&</sup>lt;sup>3</sup> Bekaert and Harvey (2002) summarize the academic evidence for greater inefficiency in emerging markets.