ANALYSIS OF BITCOIN MARKET EFFICIENCY BY USING MACHINE LEARNING

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Abstract: The issue of market efficiency for cryptocurrency exchanges has been largely unexplored. Here we put Bitcoin, the leading cryptocurrency, on a test by studying the applicability of the Efficient Market Hypothesis by Fama from two viewpoints: (1) the existence of profitable arbitrage spread among Bitcoin exchanges, and (2) the possibility to predict Bitcoin prices in EUR (time period 2013-2017) and the direction of price movement (up or down) on the daily trading scale. Our results show that the Bitcoin market in the time period studied is partially inefficient. Thus the market process is predictable to a degree, hence not a pure martingale. In particular, the F-measure for XBTEUR time series obtained by three major recurrent neural network based machine learning methods was about 67%, i.e. a way above the unbiased coin tossing odds of 50% equal chance.

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Introduction

Bitcoin was the first open source distributed cryptocurrency released in 2009 after it was introduced in a paper "Bitcoin: A Peer-to-Peer Electronic Cash System" by a developer under the pseudonym Satoshi Nakamoto. It has been quickly followed by a number of alternative coins (altcoins), derivatives of the original concept, and other block-chain based cryptocurrencies of more or less sophisticated design, such as Ethereum. As of the writing of this article (Feb. 15, 2018), the market capitalization of all cryptocurrencies is about USD 475 billion, with Bitcoin share being around USD 166 billion, followed by Ethereum (USD 92 billion; Coinmarketcap 2018). Considering the fact that no cryptocurrency has become a regular means of payment in any national economy or global sector yet, cryptocurrencies present a remarkable speculative enterprise in cyberspace with a theoretical potential of disrupting financial systems by the emergent digital commodity aspiring to function as a global means of payment and value storage.

The future of Bitcoin and other currencies appears at stake however, because of the following problems. First, large prices of Bitcoin made micropayments impractical as the transaction fees for each payment rocketed, in spite of the original concept. Second, from the viewpoint of a stable currency, daily price fluctuations as high as 10 percent up or down on Bitfinex exchange market are a way too high; on 16 December 2017 the price of Bitcoin was more than 20 times higher relative to the same date a year earlier – just to fall down to a half of that maximum value 5 weeks later. Third, the Bitcoin mining process that sustains the integrity of the block chain has an enormous carbon footprint, consuming as much electric power as the entire country of Nigeria, according to CBS News (November 27, 2017). Therefore it is quite questionable whether the Bitcoin payment system can be scaled up in order to take the role of a national or even global currency. Consequently, some authorities maintain that cryptocurrencies, including Bitcoin, are just a pyramid scheme scam, whereas others proclaim the emergence of a new global monetary system.

Given the absence of a substantial economic sector behind Bitcoin, and the above mentioned volatility with abundant bubbles and crashes, it is an open question as to what extent is the Bitcoin market system efficient. The prices of Bitcoin are very sensitive to market making news, such as the recognition of Bitcoin as a legal payment method by Japan from April 1, 2017, or the ban of cryptocurrency exchanges in China effective from November 1, 2017.

The central question addressed in this article is whether Bitcoin exchange markets are efficient. In an efficient market, all the available information including the entire price history is fully reflected in the current price of the asset. Thus the Efficient Market Hypothesis (EMH) introduced by Eugene Fama (Fama, 1970 and 1991) implies that asset prices should follow a random walk which is impossible to forecast; in general, the price dynamics is then a martingale process, in which the expectation of the next value equals the current value of the asset, and the direction of price change is impossible to predict. Since the EMH assumes complete information efficiency with regard to price formation, it rules out the

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possibility of arbitrage transactions. In other words, if a profit-making arbitrage transaction is possible among markets, then it is a certain manifestation of partial inefficiency of the market system. In what follows we will show that in the case of Bitcoin, profitable arbitrage windows may open among Bitcoin exchanges to various fiat currencies, and that the next-day price-change direction (sign of logarithmic return) for a single time series may be predicted to a certain degree by using machine learning methods trained on the past daily data and at a prediction level that is higher than the equal odds of fair coin tossing.

Figure 1: Time series of XBT prices in EUR over a period of 927 trading days.

Source: Authors (Plot generated using R-package quantmod)

This paper is organized as follows. Following the literature review in the next section, in Section 3 we explain the dataset and outline the methods of its analysis. Section 4 wraps up our results and discussions, which are followed by the concluding section.

Literature Review

Scientific literature on Bitcoin has become abundant recently. Most of the papers are related to the statistical analysis of Bitcoin and other cryptocurrencies, using methods from econometrics and general data analysis. As of present, we are not aware of any article that would apply machine learning for the estimation of cryptocurrency market efficiency.

In a recent research work, Gkillas & Katsiampa, (2018) have studied the behavior of returns of five major cryptocurrencies using extreme value analysis, finding out that “Bitcoin Cash is the riskiest, while Bitcoin and Litecoin are the least risky cryptocurrencies”. In a statistical study by Phillip et al., (2018) diverse stylized facts such as long memory and heteroscedasticity have been explored for 224 different cryptocurrencies, which are found to “exhibit leverage effects and Student- error distributions”. The design issues of Bitcoin are revisited by Ziegeldorf et al., (2018) in a study proposing a novel oblivious shuffle protocol “to improve reliance against malicious attackers”. Their method is claimed to be “scalable, increasing anonymity and enabling deniability”. In a study of market efficiency, Alwarez-Ramirez et al., (2018) analyzed Bitcoin to find that the “Bitcoin market is not uniformly efficient, and asymmetries and inefficiency are replicated over different time scales”. In contrast to our work, their method is based on the detrended fluctuation analysis estimating long-range correlations for price returns, thus not covering the relation among Bitcoin exchanges and nonlinear dynamics patterns. Corbet et al., (2018) applied a time and frequency domain analysis to estimate the relationships between 3 major cryptocurrencies and a variety of financial assets, arriving to the conclusion that “cryptocurrencies may offer diversification benefits for investors with short investment horizons”.

In a work motivated by market efficiency reasons related to ours, Lahmiri et al., (2018) analyzed the Bitcoin time series in seven different exchanges, finding that “the values of measured entropy indicate a high degree of randomness in the series”. In contrary to this finding, they claim however, “strong evidence against the EMH”. Compared to the present approach, they do investigate nonlinear patterns in volatility dynamics, but the work is limited by broad assumption of the four diverse statistical distributions employed. The interdependence of Bitcoin and altcoin markets was studied on short- and long-term scales by Ciaian et al., (2018) who found the price relationship stronger in the short-term run. Bariviera et al., (2018) studied the statistical features and long-range dependence of Bitcoin returns, focusing on the behavior of the Hurst exponent computed in sliding windows, showing that it has a similar behavior at different time scales. Luther & Salter, (2017) examined the relationship of possible hedging in Bitcoin for countries with troubled financial systems, such as Cyprus, finding little significant evidence that would support such transitions.

Price clustering of Bitcoin at round numbers is found in the work of Urquhart, (2017) who also studies this effect in volume distributions and market liquidity. Hendrickson & Luther, (2017) employed a monetary model with endogenous search and random consumption preferences, in which they show that governments of sufficient size are capable of banning Bitcoin without serious consequences. The degree of synchronization of prices of Bitcoin across exchanges is studied by Pieters & Vivanco, (2017) who claim that the law of one price does not apply due to a reason ascribed to market efficiency failure, especially for markets with anonymous trading accounts. In a search for the determinants of Bitcoin price Hayes, (2017) argues that it closely follows the cost of production, in particular predominantly the energy consumption, which drives the relative value formation at the cost margin.

In summary, the above reviewed literature deals directly with the issue of market efficiency of Bitcoin only in two cases, Alwarez-Ramirez et al., (2018), and Lahmiri et al., (2018) neither of which consider arbitrage opportunities among Bitcoin exchanges or use machine learning algorithms to predict price movement direction. Thus the present work provides a novel complementary insight into the issue of Bitcoin market efficiency.

Data and Methods

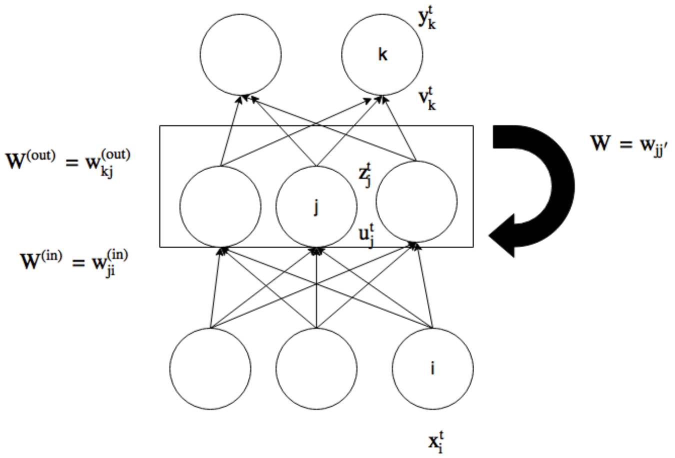
The dataset for triangular arbitrage has been retrieved from Yahoo finance using the R-package quantmod (R Core Team 2018; Ryan and Ulrich, 2017). It contains all 822 closing Bitcoin prices for the selected fiat currencies of AUD, CAD, CNY, EUR, GBP, JPY, and USD between January 1, 2015 and February 16, 2018. In order to analyze the triangular arbitrage of the type USD-XBT-CRC-USD, we retrieved the closing values of the USDAUD, USDCAD, USDCNY, USDEUR, USDGBP, and USDJPY exchange rates, correspondingly diminishing the amount of data points by the holidays of each particular foreign exchange market.

The profit rate of the trianguar arbitrage transaction, in which the USD currency is first used to buy one Bitcoin, which is then sold for CRC and converted by the exchange rate CRCUSD=1/USDCRC back to USD, normalized to the initial expense for 1 XBT (i.e. the value of XBTUSD), reads

$$\rho = \frac{XBTCRC}{XBTUSD}/USDCRC - 1 \equiv USDCRC(XBT)/USDCRC - 1 \qquad (1)$$

The dataset used for machine learning prediction of price trend of Bitcoin is the XBTEUR time series retrieved from Bloomberg, shown in Fig. 1. The three methods of machine learning applied for prediction are (1) a Recurrent Neural Network in Elman configuration (Elman, 1990), depicted in Fig. 2,

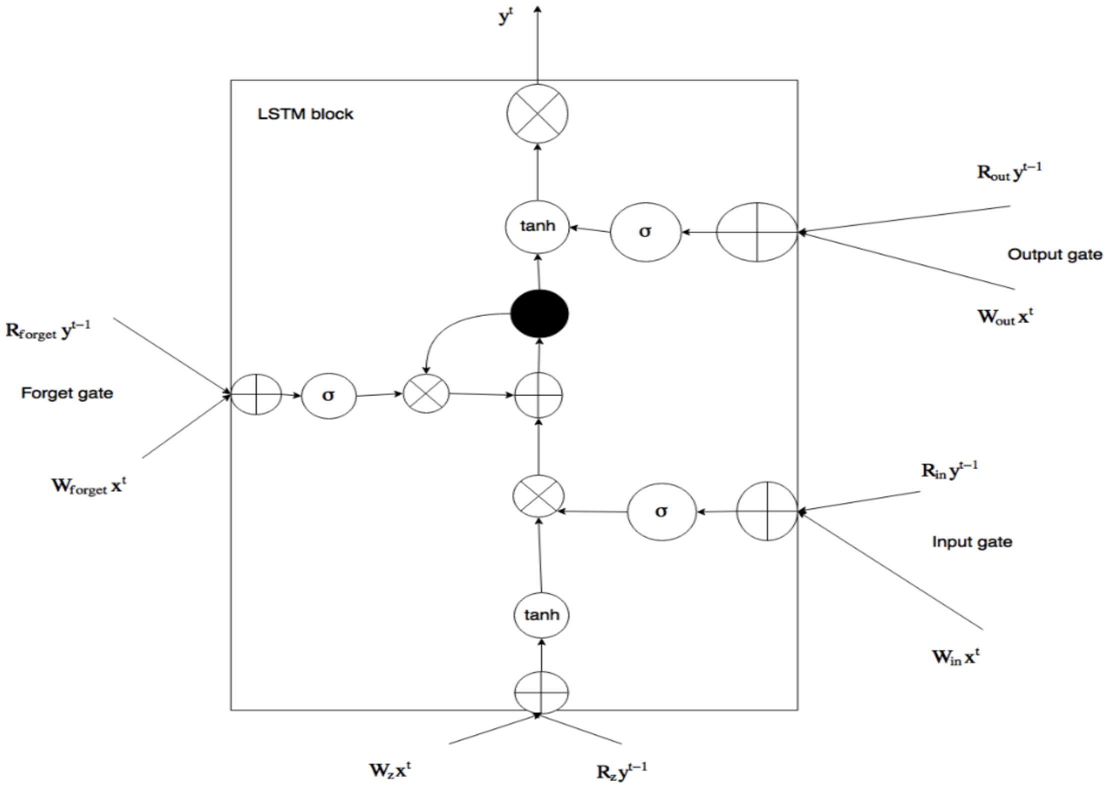
Figure 2: Recurrent neural network in Elman's topology.



Source: Authors

(2) a LSTM network depicted in Fig. 3, and (3) a GRU network shown in Fig. 4. Since these methods are standard in deep learning libraries, such as TensorFlow, which we applied, we do not repeat the equations, only briefly comment on the notation in the schematic figures. In particular, in Fig. 2, the input vector (components *i* taken from the time series as 20-element long moving window) at time *t* are fed to the hidden layer using a weight matrix of *W(in)*. Then hidden unit values are computed, which are fed back in a recurrent connection with parameter matrix *W* (recurrence shown by the bold arrow), and also passed over to the output layer with the weights *W(out)*. For the machine learning example, we assign 70% of the dataset to training, 15% of the dataset for validation (using early stopping criterion), and 15% of the dataset to testing (our result data). Figure 3 shows the far-more complicated design of the LSTM network. The recurrent unit is shown as the black circle. In addition to the input and output gates depicted on the right, there is an additional forget gate shown on the left, which regulates what data will be remembered and for how long. The addition and multiplication symbols are shared with Fig. 4. Finally, in Fig. 4 a design of the GRU network is presented, which is a simplification of the LSTM method that uses less parameters but is capable of producing results of similar accuracy as those by the LSTM algorithm in most cases. Reset and update gates regulate the flow of the neural signal through the network. Sigmoid and tangent-hyperbolic activation functions are used as shown in the legend.

Figure 3: Long Short-Term Memory (LSTM) neural network schematic



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Results and Discussions

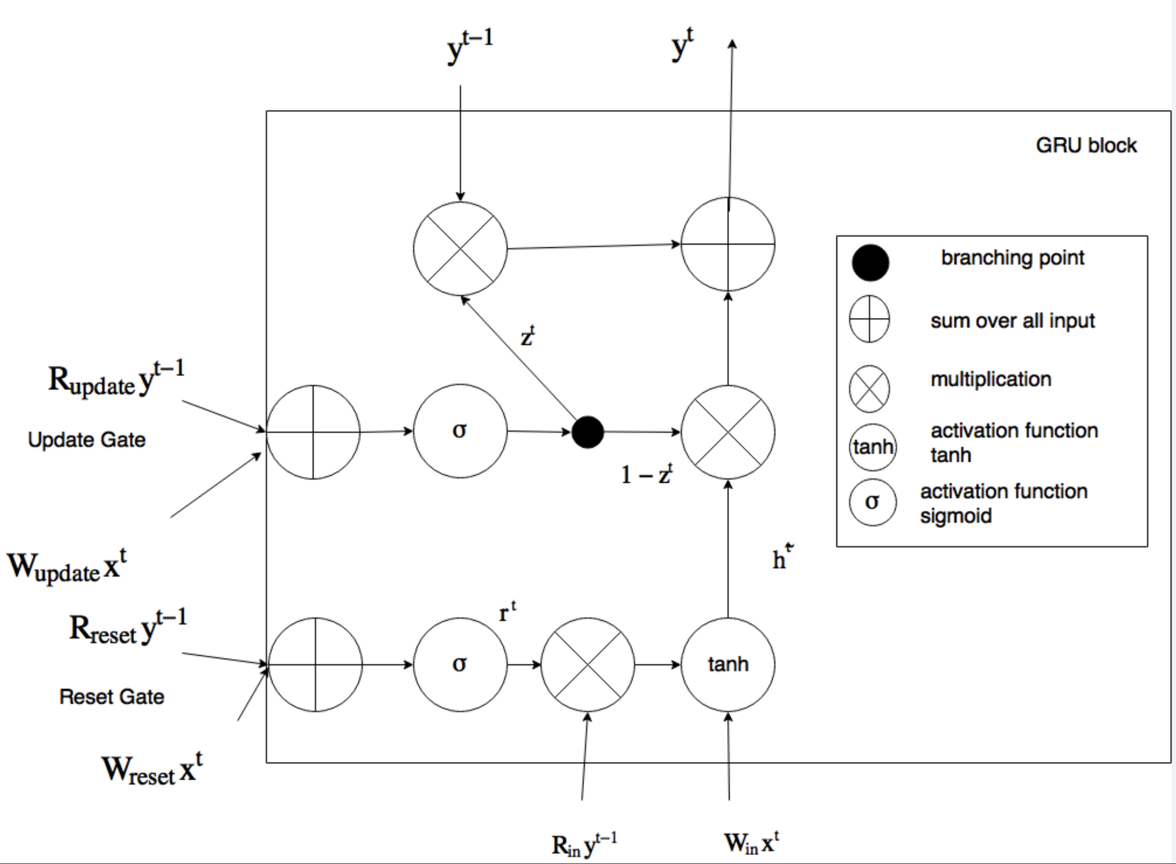
Table 1 shows the results for the triangular arbitrage. The medians of the distributions are very small, close to zero (i.e. never exceeding 1 percent, which, if transaction fees are considered, is probably not a profitable value). The main result are the standard deviation values, measuring the width of the distribution, which is often asymmetric and exhibits outliers. The minimum value, maximum value, mean, median, skewness and kurtosis parameters complement the standard-deviation based analysis. We can see that USD-EUR based Bitcoin arbitrage offers virtually no profit opportunities whereas the arbitrage window widens to almost 6% for the Chinese currency. It can be said that as the currency becomes minor, the arbitrage window broadens. Table 2 shows the information retrieval measures for the trend prediction results of the three ML algorithms, using 2 different predictors (prices and log returns).

Table 1: Summary of triangular arbitrage distributions (normalized profit rate) for the USD-XBT-CRC-USD scheme using 6 different currencies as CRC

Currency	Min	Max	Mean	Median	St. Dev.	Skewness	Kurtosis
AUD	-0.2405	0.3389	0.0308	0.0162	**0.0478**	1.6583	10.0418
CAD	-0.1655	0.3953	0.0232	0.0093	**0.0510**	2.4611	12.8804
CNY	-0.4321	0.3998	0.0053	0.0059	**0.0585**	0.5499	16.0649
EUR	-0.0817	0.0706	0.002	0.0021	**0.0101**	0.1192	14.3642
GBP	-0.1616	0.6654	0.0085	0.0065	**0.0298**	13.3933	290.9942
JPY	-0.1208	0.267	0.0219	0.0122	**0.0407**	3.3021	16.6164

Source: Authors

Figure 4: Gated Recurrent Unit (GRU) neural network schematic



Source: Authors

Table 2: Machine Learning Algorithm results for binary trend prediction of XBTEUR time series

	(a) Training by prices				(b) Training by logarithmic return			
Method	Accuracy	Recall	Precision	**F-measure**	Accuracy	Recall	Precision	**F-measure**
RNN	0.58	0.69	0.66	**0.67**	0.60	0.95	0.60	**0.73**
LSTM	0.57	0.69	0.64	**0.67**	0.54	0.73	0.58	**0.65**
GRU	0.58	0.69	0.66	**0.67**	0.56	0.85	0.58	**0.69**

Source: Authors

Conclusion

We have established partial information inefficiency of the Bitcoin market by means of triangular arbitrage between USD-XBT-CRC-USD where CRC stands for one of 6 major currencies. Whereas on the daily data trading scale, the profit window is very narrow in case of major currencies such as EUR, it widens up for currencies such as AUD, CAD and CNY, beyond the standard transaction fee levels. In addition, by using three machine learning algorithms, the RNN, LSTM and GRU methods, we have proved that machine learning algorithms are capable of predicting the direction of the price change for the next day based on the past data with the F-measure in the range of 67% to 73%. When compared to the USDEUR exchange rate values, the Bitcoin market shows a substantially greater deal of inefficiency. These results present a significant argument to question the validity of the EMH in case of Bitcoin exchanges.

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References

Alvarez-Ramirez, J., Rodriguez, E., Ibarra-Valdez, C. (2018) Long-range correlations and asymmetry in the Bitcoin market, Physica A: Statistical Mechanics and its Applications vol. 492, pp. 948-955.

Bariviera, A. F., M. J. Basgall, W. Hasperue, and M. Naiouf (2017) Some Stylized Facts of the Bitcoin Market, Physica A vol. 484, pp. 82-90.

Ciaian, P., Rajcaniova, M., Kancs d'A (2018) Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets, Journal of International Financial Markets, Institutions and Money vol. 52, pp. 173-195.

Coinmarketcap (2018) Cryptocurrency Market Capitalizations, https://coinmarketcap.com/, Accessed 2018/02/15.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., Yarovaya, L. (2018) Exploring the dynamic relationships between cryptocurrencies and other financial assets, Economics Letters, vol. 165 pp. 28-34.

Elman, J. L. (1990) Finding Structure in Time, Cognitive Science vol. 14 No. 2, pp. 179-211.

Fama, E.F. (1970) Efficient Capital Markets: A Review of Theory and Empirical Work, The Journal of Finance vol. 25, pp. 383-417.

Fama, E.F. (1991) Efficient Capital Markets: II, The Journal of Finance vol. 46, pp. 1575-1617.

Gkillas K., Katsiampa, P. (2018) An application of extreme value theory to cryptocurrencies, Economics Letters vol. 164, pp. 109-111.

Hayes, A. S. (2017) Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin, Telematics and Informatics vol. 34 No. 7, pp. 1308-1321.

Hendrickson, J. R., Luther, W. J. (2017) Banning bitcoin, Journal of Economic Behavior & Organization vol. 141, pp. 188-195.

Lahmiri, S., Bekiros, S.. Salvi A. (2018) Long-range memory, distributional variation and randomness of bitcoin volatility, Chaos, Solitons & Fractals vol. 107, pp. 43-48.

Luther, W. J., Salter, A. W. (2017) Bitcoin and the bailout, The Quarterly Review of Economics and Finance vol. 66, pp. 50-56.

Phillip, A., Chan, J. S. K., Peiris, S. (2018) A new look at Cryptocurrencies, Economics Letters vol. 163, pp. 6-9.

Pieters, G., Vivanco, S. (2017) Financial regulations and price inconsistencies across Bitcoin markets, Information Economics and Policy vol. 39, pp. 1-14.

R Core Team (2018). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.

Ryan, J. A., Ulrich, J. M. (2017). quantmod: Quantitative Financial Modelling Framework. R package version 0.4-12. https://CRAN.R-project.org/package=quantmod

Urquhart, A. (2017) Price clustering in Bitcoin, Economics Letters vol. 159, pp. 145-148.

Ziegeldorf, J. H., Matzutt, R., Henze, M., Grossmann, F., Wehrle, K. (2018) Secure and anonymous decentralized Bitcoin mixing, Future Generation Computer Systems vol. 80, pp. 448-466.