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Mean Sojourn and Mean Return Time of the Buy-hoard-sell Strategy of Bitcoin Exchange Prices

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ABSTRACT

A three state Markov chain procedure for testing the Bitcoin exchange rate prices via the mean return and mean sojourn times were applied in this study from January 2016 to February 2017. The data were of a daily basis. The analysis were conducted on the buy-hoard-sell strategies of the bitcoin exchange rate and it was discovered that the hoard state was a more difficult one to enter and once entered, it takes a longer time to come out. It was also discovered that the buy state and sell states were preferred because it has a high speed of transition. The steady state values also showed that in the long run, it takes 49% for the buy state to achieve its steady state level, 43% for the sell state and 8% for the hoard state. With these information, the hoard state was still not preferred in the bitcoin exchange market.

Keywords: Markov, Buy-Hoard-Sell, Bitcoin
JEL Classifications: C10, G15

1. INTRODUCTION

Bitcoin is a cryptocurrency that was presented at the tail end of 2008 by Japanese Satoshi Nakamoto and implemented in the beginning of 2009. Bitcoin, since then has grown from strength to strength and also has become a widely acceptable digital means of payment because it is decentralized. It is true that Bitcoin was originally designed and developed by Computer Scientist Satoshi Nakamoto but the real identity of Satoshi is still unknown (Cocco et al., 2015).There are other cryptocurrencies apart from Bitcoin, cryptocurrencies such as Litecoin, Ethereum, to mention but a few that have attracted significant attention as Bitcoin (Li and Wang, 2016) irrespective of the fact that most people believe that it would impact on the financial economy negatively. Bitcoin has remained the most widely used digital currency and also most significant of the other cryptocurrencies because of the extreme public attention it has received (Li and Wang, 2016) over the years.

On a general note, it is interesting to note that most people that are generally concerned and interested in Bitcoin do not really know how the Bitcoin system works. They are not familiar with the fact that there are people that introduce the cash into the system through the act of solving puzzles, the puzzles solved are hence used in the verification of past dealings or transactions (Vasek et al., 2014). The brains behind these acts are the "Miners" (Vasek et al., 2014). Thus, the attention of speculators are attracted as the act of the miners gives rise to Bitcoin exchange rate against other hard currencies (Vasek et al., 2014)."Uncrackable computer algorithm" (Cheung et al., 2013) are used to mine Bitcoins and this is what controls its supply (Cheung et al., 2013) since its maximum units is twenty-one million (Cheung et al., 013) and thus it cannot exceed that units. The miners are thus persons or group of volunteered persons that maintain what is called the "blockchain." These persons are paid with Bitcoins as their reward for a work well done, that is, for successful mining. The issue remains that what is been mined is "blocks" which in turn are added to the blockchain and thus brought to the notice of the chain or better still "network." With the above explanations, it is interesting to note that because there are no government backings on the Bitcoin economy because of its decentralized nature, most people that are in Bitcoin investments actually buy Bitcoins usually when the exchange price is high because the Bitcoin market is determined by the forces of demand and supply. Once they buy the Bitcoins and discover that the prices keep rising, they tend not to sell but rather use the hoarding strategy and thus apply the sell strategy whenever they view a price fall.

Therefore our concerns in this paper lies on the fact that we want to look at the mean sojourn and mean return times of the buy, hold and sell strategy of the Bitcoin exchange prices, that is, how long it takes when a person enters the buy state, what prompts people to sell their Bitcoin and what accelerates their hoarding strategy. We would first look at the buy-hoard-sell strategy via a three state markov-switching probabilities, then go ahead to calculate their mean sojourn and mean return times.

2. LITERATURE REVIEW

Past works reviewed really didn't address the issue of the buy-hoard-sell strategy of the Bitcoin exchange prices rather most of the past studies were on Bitcoin speculative or negative bubbles. Studies like that of (Cheung et al., 2013; Fry and Cheah, 2016; Li and Wang, 2016; Kelly, 2015) while (Kelly, 2015) was of the opinion that bitcoin is more of a bubble and shouldn't be considered a currency because the properties of money aren't actually met, there was support from (Li and Wang, 2016) who pointed out that since it is decentralized, that is "peer to peer" network in their own words, it really didn't serve as a payment medium nor a store of value. According to Li and Wang, (2016) payment system should require a central institution and not a decentralized one so that transactions made on such platform should have some sort of authentications. An econophysics technique was also developed by Fry and Cheah (2016) and later, it was applied to the two largest cryptocurrency markets, that is Bitcoin and Ripple so as to establish that negative bubbles actually exist in the market (Fry and Cheah, 2016). In 2013, references were made as regards the collapse of the Bitcoin's largest exchange market called Mt. Gox that gave more credence that the Bitcoin exchange and its market are characterized by bubbles and that these bubbles are ready to explode at the nearest future since it happened before (Cheung et al., 2013). Cheung et al. (2013) detected a number of short lived bubbles before the collapse of the Mt. Gox exchange which at that time was regarded as the biggest bubble that broke the camel's back.

Most recent studies didn't also address the issue of the Buy-Hoard-Sell strategy of the bitcoin exchange prices. Studies like Salman and Razzaq (2018) analyzed historical data (daily rates) of the bitcoin price, thereby showing that in the longrun, the financial intermediaries may become obsolete and the issue of middlemen wouldn't be in existence. Time series analysis and financial modeling were applied in studying the dynamic nature of the Bitcoin, its price volatility, market size and market capitalization. Another researcher looked at how cryptocurrencies should be regulated and monitored. They went further in bringing out the harm cryptocurrencies can inflect on people, thus, its market should be regulated to avoid theft and associated crimes (Anderson et al., 2018).

Gerlach et al. (2018) presented a robust bubble analysis of the Bitcoin via its dollar price, demystifying periods of draw ups and drawdowns so that imminent crash could be averted. They used the lagrange regularization method for detecting regimes, they went further in identifying three main peaks within the period under study.

The Bitcoin market have been reported by Kjærland et al. (2018) as not a safe market to trend financially, in their study to reveal the factors responsible for the volatile state of the Bitcoin's price. From their study, it was seen that the price of Bitcoin increased from zero USD (2009) to 19500 USD (December, 2017). They employed the two autoregressive distributed lag models to elucidate the price movements. Their findings were that political incidents and statements (shocks) were the major factors and drivers of the Bitcoin's increased price (Kjærland et al., 2018). From past and recent studies reviewed, it could be seen that the interest were more on the volatile nature of the Bitcoin's prices, its fluctuations, if Bitcoin can be referred to as money or treated as such and if Bitcoin would eventually crash but the thrust of our study is to look at the 3 main strategies that are inherent in the Bitcoin market and that is the Buy-Hoard-Sell strategies and thus see how the states transit amongst itself, thereby seeing how long on the average it takes for one state to transit to another or how long it can remain on a particular state once it enters that state.

3. METHODOLOGY

The cryptocurrency Bitcoin daily exchange rate price data ranging from 1st of January, 2016 to 20th February, 2017 was used and the source of the data is the bitcoin data from quandl from the quandl database. https://www.quandl.com/data/BITSTAMP-Bitstamp.

3.1. The Markov Chain (MC) Model

The daily observed Bitcoin exchange rate price data will follow 3 states, S_t; where $S_t = 0$, if the state, which would otherwise be referred to as the "BUY" state of the Bitcoin daily exchange rate price.

$S_t = 1$; if the state, which would henceforth be referred to as the "HOARD" state of the Bitcoin daily exchange rate price.

$S_t = 2$; if the state, which would henceforth be referred to as the "SELL" state of the Bitcoin daily exchange rate price. Thus, whether states $S_t = 0, 1, 2$; the process respectively would be regime 0, 1, 2; so that there would be an observed change between the period t and t + 1. Thus, the observed change Y_t is a random draw which follows a normal distribution. That is;

$Y_t \sim N(\mu_0, \sigma_0^2)$ distribution for the "Buy" state (1)

$Y_t \sim N(\mu_1, \sigma_1^2)$ distribution for the "Hoard" state (2)

$Y_t \sim N(\mu_2, \sigma_2^2)$ distribution for the "Sell" state (3)

Therefore the probabilities of the switching strategies amongst the three different states and regimes are defined by the P_{ij} which is the transition probability. Hence the transition probability state can be switched amongst the states or that a particular state (i) be followed by another state (j). The current Bitcoin exchange rate price depends on the preceding Bitcoin exchange rate price and not the past.

The MC is given as;

$$MC=P(X_{t+1}=x/X_1=x_1, X_2=x_2,\ldots,X_t=x_t) \quad (4)$$

Thus;

$$MC=P(X_{t+1}=x_{t+1}/X_t=x_t) \quad (5)$$

Where t ∈ N,

X is the Bitcoin exchange rate price at different time period. Therefore, the P_{ij} is given as;

$(P_{ij})=P(_{ji})$ where i and j ∈ S. The matrix of the transition probability P_{ij} becomes;

$$P_{ij}=\begin{bmatrix} P_{00} & P_{01} & P_{02} \\ P_{10} & P_{11} & P_{12} \\ P_{20} & P_{21} & P_{22} \end{bmatrix}$$

Mathematically; the transition probability matrix can be written as:

$$P=P_{ij}=\begin{bmatrix} P_{00} & P_{01} & 1-P_{00}-P_{01} \\ 1-P_{11}-P_{12} & P_{11} & P_{12} \\ P_{20} & 1-P_{20}-P_{22} & P_{22} \end{bmatrix}$$

Where i, j ∈ S and

$$P_{00}=P(\varphi_k=0/\varphi_{k-1}=0)=\alpha \quad (6)$$

$$P_{01}=P(\varphi_k=1/\varphi_{k-1}=0)=\beta \quad (7)$$

$$P_{02}=P\varphi_k=2/\varphi_{k-1}=0=1-\alpha-\beta \text{ etc.} \quad (8)$$

Such that $0 \le \alpha, \beta, \gamma, \delta, \varepsilon, \zeta \le 1$ and their sum, that is row wise cannot exceed 1.

$$P_{00}+P_{01}+P_{02}=1 \quad (9)$$

Therefore the three states observed frequency F_{ij} table would be given in Table 1.

Where F_{ij} is the observed frequency from the Bitcoin exchange rate price.

F_{BB}=Number of buy days coming from or switched from another buy days.

F_{BH}=Number of buy days coming from or switched from hoard days and so on.

$F_B=F_{BB}+F_{BH}+F_{BS}$, which is the total frequency or number of the buy days and so on.

The maximum likelihood estimators of P_{ij}, where i, j=b, h, s strategies; where b, h, s represent buy, hoard and sell respectively such that;

Table 1: 3 states observed frequency table

Current day				
	B	**H**	**S**	**Total**
B	F_{BB}	F_{BH}	F_{BS}	F_B
Previous day H	F_{HB}	F_{HH}	F_{HS}	F_H
S	F_{SB}	F_{SH}	F_{SS}	F_S

$$\hat{P}_{ij}=\frac{F_{ij}}{\sum_{j=b}^{s} f_{ij}} \quad (10)$$

The goodness of fit-test:

The goodness of fit test would be used to test for the independency assumption. The chi-square test would be applied and likewise the Wang and Maritz (2007) who used the Whittaker-Shannon (WS) test statistic for independence. To use these test, the hypothesis must first be formulated.

H_0: The Bitcoin exchange rate price on consecutive day is independent.

Versus,

H_1: The Bitcoin exchange rate price on consecutive day is not independent.

Thus the asymptotic Chi-square test statistic is:

$$Q^T=\sum_{t=1}^{T}\sum_{j\in N} n_i(t)\frac{(\hat{P}ij(t)-\hat{P}ij)^2}{\hat{P}ij} \quad (11)$$

$$asyx^2[\sum_{i=1}^{N}(ai-1)(bi-1)]$$

Where;

Q^T is the asymptotic chi square distribution with $(a_i-1)(b_i-1)$ degrees of freedom.

b_i is the number of the positive entries in the ith row of the matrix for the entire sample.

a_i is the number of positive entries in the ith row of the matrix for sub-samples T.

P_{ij} the probability of transition estimated from the entire sample.

$P_{ij}(t)$ the transition probability estimated from the T sub samples.

And the decision rule is given as: Reject H_0 if asymptotic χ^2 calculated > asymptotic χ^2 tabulated and accept if otherwise.

The WS test statistic is given as:

$$WS=\eta_\alpha+\eta_\beta-1\Big/\sqrt{V(\eta_\alpha+\eta_\beta-1)}\sim N(0,1) \quad (12)$$

Where;

$\eta_\alpha=P_{BB}+P_{HH}+P_{SS}$

$\eta_\beta=P_{SS}P_{BS}+P_{HS}P_{SH}+P_{BH}P_{HB}-P_{BB}P_{HH}-P_{BB}P_{SS}-P_{HH}P_{SS}$

The above test statistic is meant to test the validity of the Bitcoin exchange rate price data so as to ascertain the independence assumption of the 3-state MC.

The variance $(\eta_\alpha+\eta_\beta-1)$ in (3) above is given as:

$$V\left(\eta_\alpha+\eta_\beta-1\right)=\left(2\pi_0\pi_1\pi_2\right)\left(\frac{1}{F_{B.}F_{H.}}+\frac{1}{F_{H.}F_{S.}}+\frac{1}{F_{S.}F_{B.}}\right) \quad (13)$$

Where the π_0, π_1 and π_2 are stationary probabilities and thus it can be calculated as follows:

$\pi_0=[(1+p)+(1+s)p/q]^{-1}$

$\pi_1=[r+ps/q]\pi_0$

$\pi_1=[r+ps/q]\pi_0$

$\pi_2=[p/q]\pi_0$

Where, $p=[P_{SB}+P_{HS}(1\text{-}P_{BB})/P_{HB}][1/1\text{-}P_{SS}]$; $r=[P_{BH}/1\text{-}P_{HH}]$; $q=1+[P_{HS}P_{SB}/P_{HB}(1\text{-}P_{SS})]$ and $S=[P_{SH}/1\text{-}P_{HH}]$.

Decision rule: Reject H_0 if/WS cal/>Z tab. at an α level of significance.

Mean recurrence/return time (MRT) and mean sojourn time (MST).

With the stationary or steady state values through which all possible states i could switch to, the MRT can thus be computed as;

MRT for state i, it implies.

$$M_i = {}^{1}\!/_{\pi_i} \quad (14)$$

This is taking the inverse of the stationary or steady state values.

The MST is given as:

$$S_i=1/1-P_{ii} \quad (15)$$

Where;

M_i=The mean return or recurrence time

π_i=The steady state values or stationary values

S_i=The mean sojourn time

P_{ii}=The transition probability values

The rules of the B-H-S strategies.

The Buy state is characterized by increase in the price of the Bitcoin exchange rate and thus, more Bitcoins are purchased at the prevailing increased prices. The Hoard state is a state where there tend to be a hold on the Bitcoin. This is characterized by a persistent steady increase after three time periods, thus the fourt period of steady increase brings about the hoard state. This is because people would tend to hoard the Bitcoin and see what the prices would turn out to be. In the hoard state, one is expected to remain there for a period of 3 time periods as far as there is steady increase. A little decrease or change in the Bitcoin exchange rate, that is a drop in price would necessitate the sell state. The sell state is maintained as long as the Bitcoin price keeps dropping. The sell state can switch to the hoard state after a 5 time period. These rules were applied to the data so as to gather the switching strategies of each state for each month.

4. ANALYSIS

Below is the Bitcoin exchange rate Bitcoin versus dollar exchange rate for different prices and dates (from January 1st, 2016 to February 20th, 2017).

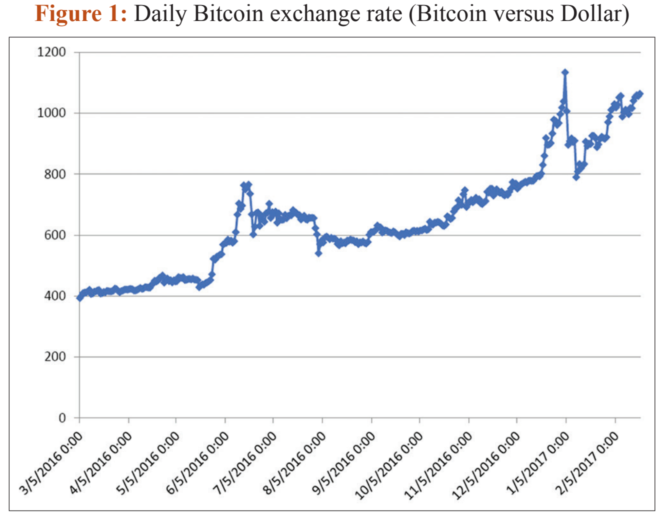
From the Figure 1, it can be seen that the Bitcoin exchange rate prices for January 2016 to February 2017 is very volatile. It peaked to a point in January 4th, 2017, where it had one Bitcoin exchanged for \$1133.219 and later dropped to \$789.884 in January 11th, 2017.

Applying the B-H-S rules, the following frequencies were obtained via months from January 2016 to February, 2017. The hypothesis for independence was tested via the asymptotic chi square distribution and the WS test statistic. The assumption of independence or the assumption of memoryless tells us that the current price is dependent on the immediate past price of the Bitcoin exchange rate and not on all other past prices. From the asymptotic chi square results in Table 2, it can be seen that the hypothesis was accepted which shows that the hypothesis that the current Bitcoin exchange rate price is dependent on just the immediate past Bitcoin exchange rate price and not other past prices of the Bitcoin exchange rate. It goes to imply that the assumption of memoryless is accepted for both the asymptotic chi square test statistic and also WS test statistic (Table 3).

Table 4 shows the state switching strategies, the state frequencies and the transition probability values corresponding to the state switching strategies.

From the Table 4, it could be seen that before the Easter celebration in March 2016, there are hoarding strategies applied in the Bitcoin exchange rate price via Dollar, that is, from the Buy to Hoard and Hoard to Hoard states but different for the Sell to Hoard states. After the Easter season, the hoarding state became difficult to ply, that is difficult to enter except for the Sell to Hoard state that had a

Figure 1: Daily Bitcoin exchange rate (Bitcoin versus Dollar)



Source: Authors computations; data from Quandl

Table 2: Asymptotic χ^2 results for the assumption of memoryless

Samples	Asy is χ^2 calculated	Asy χ^2 tabulated (5% level of significance)	Decision
T-sub samples (January-July 2016)	3.703	9.49	Accept H_0
T-sub samples (August-February 2017)	0.56	9.49	Accept H_0

Table 3: WS test statistic results for the assumption of memoryless

WS calculated	P<0.05	P<0.01	P<0.10
102.9	It is significant; accept H_0	It is significant; accept H_0	It is significant; accept H_0

WS: Whittaker-Shannon

Table 4: State frequency, switching and transition probability matrices (from January 2016 to February 2017)

Year	State frequency matrices	State switching strategy matrices	Transition probability matrices
January 2016	$\begin{bmatrix} 10 & 0 & 22 \\ 0 & 0 & 0 \\ 18 & 0 & 6 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.31 & 0 & 0.69 \\ 0 & 0 & 0 \\ 0.75 & 0 & 0.25 \end{bmatrix}$
February 2016	$\begin{bmatrix} 8 & 0 & 18 \\ 0 & 0 & 0 \\ 20 & 0 & 7 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.31 & 0 & 0.69 \\ 0 & 0 & 0 \\ 0.74 & 0 & 0.26 \end{bmatrix}$
March 2016	$\begin{bmatrix} 11 & 2 & 14 \\ 0 & 2 & 2 \\ 12 & 0 & 8 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.41 & 0.07 & 0.52 \\ 0 & 0.5 & 0.5 \\ 0.4 & 0 & 0.27 \end{bmatrix}$
April 2016	$\begin{bmatrix} 6 & 0 & 12 \\ 0 & 0 & 2 \\ 14 & 2 & 19 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.33 & 0 & 0.67 \\ 0 & 0 & 1 \\ 0.4 & 0.57 & 0.54 \end{bmatrix}$
May 2016	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.38 & 0.14 & 0.48 \\ 1 & 0 & 0 \\ 0.69 & 0.08 & 0.23 \end{bmatrix}$
June 2016	$\begin{bmatrix} 13 & 4 & 14 \\ 4 & 0 & 0 \\ 12 & 0 & 8 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.42 & 0.13 & 0.45 \\ 1 & 0 & 0 \\ 0.4 & 0 & 0.27 \end{bmatrix}$
July 2016	$\begin{bmatrix} 6 & 0 & 24 \\ 0 & 0 & 0 \\ 22 & 0 & 8 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.2 & 0 & 0.8 \\ 0 & 0 & 0 \\ 0.73 & 0 & 0.27 \end{bmatrix}$
August 2016	$\begin{bmatrix} 7 & 2 & 18 \\ 0 & 0 & 2 \\ 18 & 0 & 9 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.2 & 0 & 0.8 \\ 0 & 0 & 0 \\ 0.73 & 0 & 0.27 \end{bmatrix}$
September 2016	$\begin{bmatrix} 13 & 0 & 20 \\ 0 & 0 & 0 \\ 20 & 0 & 3 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.26 & 0.07 & 0.67 \\ 0 & 0 & 1 \\ 0.67 & 0 & 0.33 \end{bmatrix}$
October 2016	$\begin{bmatrix} 14 & 4 & 12 \\ 2 & 4 & 4 \\ 12 & 0 & 5 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.47 & 0.13 & 0.4 \\ 0.2 & 0.4 & 0.4 \\ 0.71 & 0 & 0.29 \end{bmatrix}$

(Contd...)

Table 4: ***(Continued)***

Year	State frequency matrices	State switching strategy matrices	Transition probability matrices
November 2016	$\begin{bmatrix} 13 & 4 & 12 \\ 2 & 3 & 2 \\ 12 & 2 & 9 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.45 & 0.14 & 0.41 \\ 0.29 & 0.43 & 0.29 \\ 0.52 & 0.09 & 0.39 \end{bmatrix}$
December 2016	$\begin{bmatrix} 13 & 4 & 12 \\ 2 & 3 & 2 \\ 12 & 2 & 9 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.52 & 0.24 & 0.24 \\ 0.13 & 0.47 & 0.4 \\ 0.5 & 0 & 0.5 \end{bmatrix}$
January 2017	$\begin{bmatrix} 15 & 4 & 12 \\ 0 & 5 & 2 \\ 14 & 0 & 3 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.48 & 0.13 & 0.39 \\ 0 & 0.71 & 0.29 \\ 0.82 & 0 & 0.18 \end{bmatrix}$
February 2017	$\begin{bmatrix} 9 & 0 & 10 \\ 2 & 2 & 0 \\ 10 & 0 & 6 \end{bmatrix}$	$\begin{bmatrix} BB & BH & BS \\ HB & HH & HS \\ SB & SH & SS \end{bmatrix}$	$\begin{bmatrix} 0.47 & 0 & 0.53 \\ 0.5 & 0.5 & 0 \\ 0.63 & 0 & 0.38 \end{bmatrix}$

probability value of 0.57 for the April 2016. From October 2016, the switch from Hoard to Hoard states was experienced again after that of March 2016, with a probability value of 0.4 which was relatively lower than what was achieved in March 2016. In November 2016, the B-H-S strategies were fully used and this could be as a result of the Christmas festive preparation around the corner. In a summary, it can be seen that the sell to buy states of the Bitcoin exchange rate had high probability values, people were mainly in the habit of buying and buying of Bitcoins irrespective of its volatile prices. The hoard state was a more difficult state to enter but most easy to leave once it is entered but in January 2017, a probability value of 0.71 was achieved for the hoard to hoard states which could be as a result of people trying to hoard or keep their Bitcoins so as to better understand how the Bitcoin system would work for the beginning of the year 2017.

The MST which is also the expected length, that is, the number of days or hours or time it would take each of the strategy whether B or H or S to return to a particular strategy or state after leaving that state or strategy.

Table 5 shows the individual MST for the different strategy.

Table 5: The MST for the B-H-S strategies

	Buy	Hoard	Sell
MST/expected length	1.6	1.6	1.5

MST: Mean sojourn time

From the Table 5, it can be seen that the buy strategy of the Bitcoin exchange rate price will take approximately 2 days to return to the buy state from the hoard and sell states respectively. It would also take approximately 2 days to return to hoard state from the buy and sell states respectively and 2 days approximately to return to the sell state from the buy and hoard states respectively. It is interesting to note that it takes the Bitcoin exchange rate approximately five days to switch amongst the three strategies. This implies that on an average it takes almost same time to return to the sell, the buy and the hoard states since the difference in the timing is infinitesimal, that is, 0.6, 0.6, and 0.5 respectively.

The steady state probabilities for the buy, hoard and sell strategies are given as: 0.49, 0.08, and 0.43 respectively. The stationary values or steady state values imply that on a long run, it would take the buy strategy 49% to achieve its steady state, 8% for the hoard state and 43% for the sell state. This implies that in the long run, the probability of getting into the buy state of the Bitcoin exchange rate would be 0.49, that is 49%, that is to say that people would prefer buying more Bitcoins than hoarding Bitcoins, people would also prefer selling Bitcoins and getting a fast turnover than hoarding since the market for Bitcoin exchange is highly characterized by speculative bubbles and thus highly volatile.

The mean return time for the buy-hoard-sell strategies of the Bitcoin exchange rate price (Bitcoin versus Dollar) is 2.0 for the buy, 13.2 for the hoard and 2.3 for the sell (Table 6). This result goes to justify the steady state values obtained above. It takes approximately 2 days to return to the buy state from other states immediately it leaves the buy state and this also applicable to the sell states eventually in the case of the hoard state, it is a different scenario. This is because from the steady state values obtained above in the long run, people would prefer to just do the buy-sell strategy alone and totally exclude the hoard strategy. From the value of 13.2, one can vividly see that it takes a longer time to get into the hoard state even though the mean sojourn time tells us that it approximately takes two days to leave the state. The mean return time tells us that it takes it 13.2 days to fully come back to the hoard state it left for another.

5. CONCLUSION AND RECOMMENDATION

The B-H-S strategies of the Bitcoin exchange rate presented in this work is of the three-state MC approach but with special emphasis on the mean return and mean sojourn times. A total of 14 months was looked into but on a daily basis and it was discovered that the hoard states was the most difficult state to enter since most

Table 6: The mean return time for the B-H-S strategies

	Buy	Hoard	Sell
MRT	2.0	13.2	2.3

MRT: Mean recurrence/return time

people would prefer to buy Bitcoin and sell at whatever the prevailing prices were. In other words, the hoarding strategy wasn't preferred for the Bitcoin versus the Dollar exchange rate prices. It was also discovered that the hoard state was entered during periods of festivity, may be because most people prefer to hoard or keep whatever they possess so as to watch how things unravel in the market for Bitcoin. The hypothesis for independence or memoryless were tested via the WS test statistic and the asymptotic Chi-square test statistic and the results obtained showed that the property of memoryless was significant. This implies that the current Bitcoin exchange price depends on just the immediate past price and not all other past prices. Applications from this study would help players or individuals in future planning as regards investing in Bitcoin or not and if one is to invest, the best strategy or strategies to adopt.

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