The International Journal of Engineering and Science (IJES)
|| Volume || 6 || Issue || 11 || Pages || PP 39-48 || 2017 ||
ISSN (e): 2319 – 1813 ISSN (p): 2319 – 1805

# High Volatility Detection Method Using Statistical Process Control for Cryptocurrency Exchange Rate: A Case Study of Bitcoin

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**ABSTRACT**
*Cryptocurrency is a digital currency designed to work as a medium of exchange using cryptography to secure the transactions, to control the creation of additional units, and to verify the transfer of assets. The objective of this study is to evaluate the volatility condition for cryptocurrency (Bitcoin) exchange rate and return. Volatility calculated as standard deviation of logarithmic returns. This study performed normality test using Shapiro-Wilk method. Then, the high volatility detection performed using box-whisker plot and statistical process control chart. In descriptive statistical analysis, the mean for Bitcoin return is 0.006 and the deviation is 0.04458. The standard error indicates the volatility for Bitcoin is 4.458 %. This value is considered as high value of volatility. High value of volatility indicates the investment in Bitcoin is categorical as high risk investment. The important of this study is to assist investors to develop better investment portfolio in targeting better profit and lowering the loss.*

***Keywords:*** *Bitcoin, Investment, Return, Volatility, Statistical Process Control*

Date of Submission: 06-11-2017 Date of Publication: 17-11-2017

## I. INTRODUCTION

The development of internet technologies is dramatically changing the structure and nature of financial institutions. Internet technologies are enabling financial institutions to provide a products and services more effectively to customers. The technology changes with widening access give more advantage to customer by make a transaction more easily and practically. Emerging technology also give more advantage in the banking and financial area such as technology have changed the banking industry from paper and branch based banks to digitized and networked banking services by using an internet system. Therefore, new technology system was introduced many financial technologies product and service. One of the current new technologies introduced is a digital currency known as bitcoin.

Bitcoin is a worldwide cryptocurrency and digital payment system. The system is peer-to-peer and the transactions take place between users directly without any financial intermediaries. These transactions are verified by network nodes and recorded in a public distributed ledger called a blockchain. The blockchain is a public ledger that records bitcoin transactions. A novel solution accomplishes this without any trusted central authority. The maintenance of the blockchain is performing by a network of communicating nodes running bitcoin software. While the transactions of the form payer X sends Y bitcoins to payee Z are broadcast to this network using readily available software applications. A blockchain is an open, distributed ledger that can record transactions between two parties efficiently and in a verifiable and permanent way (Reid and Harrigan, 2013).

The security of cryptocurrency ledgers is based on the assumption that the majority of miners are honestly trying to maintain the ledger, having financial incentive to do so. Most cryptocurrencies are designed to gradually decrease production of currency, placing an ultimate cap on the total amount of currency that will ever be in circulation, mimicking precious metals (Barber, et al., 2012).
Since the bitcoin cryptocurrency was developed the price raised an average of US$6,415.28 across global exchanges. Therefore, users in bitcoin network were aggressively invested in bitcoin cryptocurrency transaction. This situation affected high speculations among the user of bitcoin cryptocurrency network. In a corporate risk management framework, speculation is the extent to which financial positions are established based upon the firm's own view or forecast of future market prices (Aabo et al., 2012). Thus, high technology development can create many digital products such as bitcoin. However, since rapid accelerating of technology was growth, most

of speculators are try to predict the bitcoin cryptocurrency because bitcoin cryptocurrency are involved with high volatility. Thus, it is important to evaluate the volatility condition for bitcoin cryptocurrency exchange rate and return. In the empirical analysis on the forecasting performance of future volatility, this study fills the following gaps that have not been resolved by previous research that is evaluating the volatility condition for cryptocurrency (Bitcoin) exchange rate and return.

## II. LITERATURE REVIEW

Global economy, growing importance of innovations as well as wide use of technologies has changed the financial system worldwide (Romānova and Kudinska, 2016). The new technology was affected the investment decisions among the key issues that exchanges throughout the world face (Slimane, 2012). Among the new technology, bitcoin cryptocurrency become one of the new digital currencies. This transaction gives high impact on the digital currency trasactions.

Bitcoin is a crypto-currency based on open-source software and protocols that operates in peer-to-peer networks as a private irreversible payment mechanism. The protocol allows cross-border payments, for large and small items, with little or no transactional costs. The bitcoin transactional system is often described as an anonymous system, although it might be more accurate to describe the system as one in which users can invoke privacy. The ledger of account for all bitcoin transactions is public and distributed (Simser, 2015).

The ability of cryptocurrencies is to enable anonymous transactions allows users to trade virtual currency regardless of their geographic location, without revealing either the real-world source of their income or their own identity. According to Christopher (2014) bitcoin operates via a peer-to-peer (P2P) network. P2P networks are created when multiple individuals run the necessary software on their individual computers and connect to each other; P2P networks do not have a centralized website, server, or organizer. Many other online entities operate from a centralized location; Google, for instance, is a publicly traded company with a management team and computer servers that store information on behalf of the users. Bitcoin currency is a monetary value that is accepted for payment purposes by persons other than the issuer, with the unit of account matching that of the physical currency (Ram, et al., 2016; Bal, 2013).

The high demand and speculation in bitcoin transaction encouraged more users to participate in bitcoin transaction. This situation was associated with high volatility. Volatility is a statistical measure of the dispersion of returns for investment. An accurate forecast of future volatility delivers important information to market participants and, consequently, there is an option to essentially bet on volatility (Kongsilp and Mateus, 2017). There are many study focus on the volatility of stock market, housing price and different country. Byun et al. (2011) examine whether the superiority of the implied volatility from a stochastic volatility model in Korean. They found that the forecasting performances of both implied volatilities are improved under high volatile market or low return market.

Study from Coskun and Ertugrul (2016) regarding volatility housing price in Turkey suggest several points. First, city/country-level house price return volatility series display volatility clustering pattern and therefore volatilities in house price returns are time varying. Second, it seems that there were high (excess) and stable volatility periods during observation term. Third, a significant economic event may change country/city-level volatilities. Fourth, house price return volatilities differ across geographic areas, volatility series may show some co-movement pattern.

Messis and Zapranis (2014) investigate the existence of herding in the Athens Stock Exchange over the 1995-2010 periods and examine the effects on market volatility. They found that the large differences are observed among the portfolios regarding the herding periods. The results confirm a linear effect of herding on all volatility measures considered. Stocks exhibiting higher levels of herding or adverse herding will also present higher volatility, and from this point of view, herding can be regarded as an additional risk factor.

## III. RESEARCH METHODOLOGY

This section describes the statistical methodology that implemented in determining volatility for Bitcoin. In finance, volatility (symbol $\sigma$) is the degree of variation of a trading price series over time as measured by the standard deviation of logarithmic returns. The statistical tests that involved in this study are Shapiro-Wilk normality test, box-whisker plot and statistical process control chart.

**3.1 Data selection**
In this study, daily closing exchange rate values for Bitcoin are selected from 1st January 2017 until 31st October 2017. There are 304 observations involved in this analysis. These data are collected from *http://www.coindesk.com*.

**3.2 Volatility calculation as standard deviation of logarithmic returns**
This section describes the mathematical derivation to compute volatility for Bitcoin exchange rate. In this study, volatility is measured using standard deviation. In statistics, the standard deviation ( $\sigma$ ) is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values.

Therefore, this study calculated standard deviation (volatility) using below procedure:

Step 1: Firstly, this study calculated continuously compounded return of each period. Equation (1) shows the calculation for logarithmic return.

$$R_i = \ln\left(\frac{C_i}{C_{i-1}}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$R_i$ : Logarithmic return for observation period *i*

$C_i$ : Closing price of Bitcoin exchange rate at observation period *i*

$C_{i-1}$ : Closing price of Bitcoin exchange rate at observation period *i*-1

Step 2: The average logarithmic return is calculated using Equation (2).

$$R_{average} = \frac{\sum_{i=1}^{n} R_i}{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. (2)$$

$R_{average}$ : Average logarithmic return for observation periods (*i* =1, 2,…, n)

$R_i$ : Logarithmic return for observation period *i*

$n$ : Total of observation periods

Step 3: Calculate the squared deviation from the average for each of the returns using Equation (3).

$$\Delta R_i^2 = \left(R_i - R_{average}\right)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$\Delta R_i^2$ : The squared deviation from average for period *i*

Step 4: Variance of the sample is calculated using Equation (4).

$$\sigma^2 = \frac{\sum_{i=1}^{n} \Delta R_i^2}{n-1} = \frac{\sum_{i=1}^{n} \left(R_i - R_{average}\right)^2}{n-1} \quad \ldots\ldots\ldots\ldots.. (4)$$

Step 5: Standard deviation or volatility is derived using Equation (5).

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}\left(R_i - R_{average}\right)^2}{n-1}} \quad \text{.............. (5)}$$

**3.3 Statistical normality test using Shapiro-Wilk method**

The null-hypothesis of Shapiro-Wilk normality test is that the population is normally distributed. Thus, if the p-value is less than the chosen alpha level, then the null hypothesis is rejected and there is evidence that the data tested are not from a normally distributed population. On the opposite side, if the p-value is greater than the chosen alpha level, then the null hypothesis that the data came from a normally distributed population cannot be rejected.

The Shapiro-Wilk test is a way to tell if a random sample comes from a normal distribution. The test gives you a W value. The W value larger than chosen alpha (0.05), will concludes the distribution of data follows normal distribution. The, if the data shows small values of W, it is indicate your sample is not normally distributed. The formula for the W value is:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} \quad \text{.................................................. (6)}$$

where:

$x_i$ is the value in the sample $\left(x_1, x_2, x_3, ..., x_n\right)$ ;

$x_{(i)}$ is the ordered sample values ( $x_{(1)}$ is the smallest value in the sample);

$\bar{x} = \dfrac{\left(x_1 + x_2 + .... + x_n\right)}{n}$ is the sample mean;

$a_i$ is constants that derived generated from the means, variances and covariances of the order statistics of a sample of size *n* from a normal distribution. The calculation of $a_i$ is described in below equation.

$$\left(a_1, a_2, a_3, ..., a_n\right) = \frac{m^{\mathrm{T}} V^{-1}}{\left(m^{\mathrm{T}} V^{-1} V^{-1} m\right)^{1/2}} \quad \text{...................... .(7)}$$

where:

$V$ is the covariance matrix of those order statistics;

$$m = \left(m_1, m_2, m_3, ..., m_n\right)^{\mathrm{T}} \quad \text{.............................................................................. (8)}$$

Element in Equation (8) is represented as:

$m_1, m_2, m_3, ..., m_n$ are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution

**3.4 Outliers detection method using Box-whisker plot**

The box plot is a standardized way of displaying the distribution of data based on the five number summary: minimum (Lower extreme value limit), first quartile, median, third quartile, and maximum (upper extreme value limit). Figure 1 shows the box-plot diagram with outliers detection range. Meanwhile, Figure 2 shows the correlation between box-plot and normal distribution curve.

There are five important elements in Box-and-whisker plots:

(i) Q1 – quartile 1, the median of the lower half of the data set
(ii) Q2 – quartile 2, the median of the entire data set
(ii) Q3 – quartile 3, the median of the upper half of the data set
(iv) IQR – interquartile range, the difference from Q3 to Q1
(v) Extreme Values – the smallest and largest values in a data set

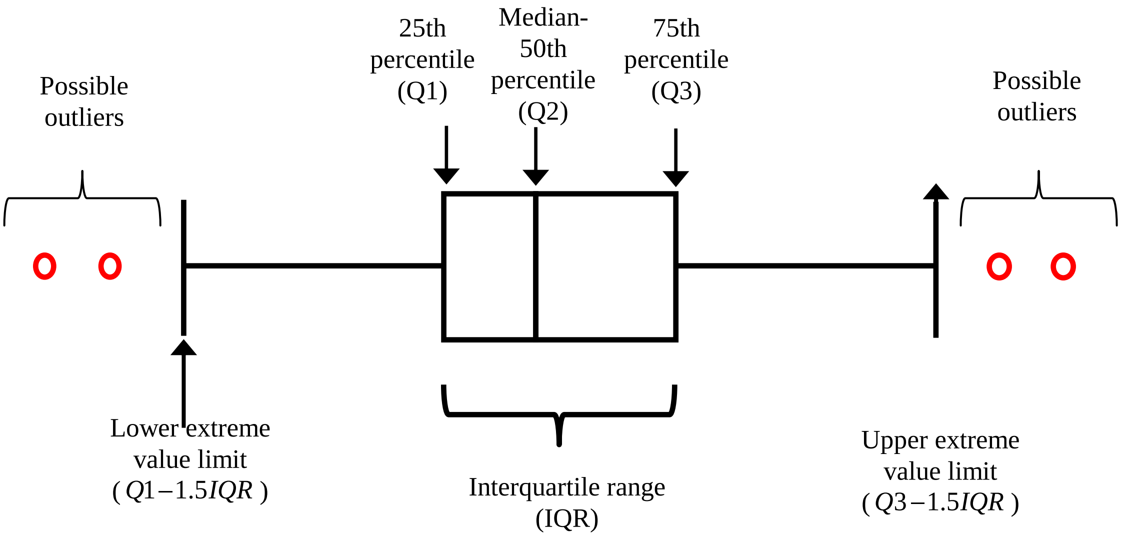


**Figure 1:** Box plot with outliers detection range

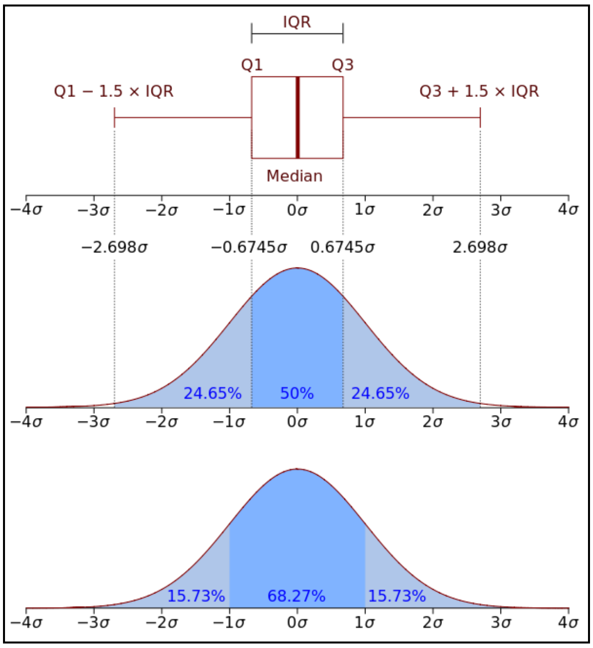

**Figure 2:** Box plot correlation with normal curve

### 3.5 High volatility detection using Statistical process control

The control chart is a graph used to study how a process changes over time. Data are plotted in time order. A control chart always has a central line for the average, an upper line for the upper control limit and a lower line for the lower control limit. These lines are determined from historical data.

Three-sigma limits (3-sigma limits) are used to set the upper and lower control limits in statistical quality control charts. Control charts are used to establish limits for a manufacturing or business process that is in a state of statistical control. The empirical rule states that 99.7% of data will fall within the first three standard deviations of the distribution's average.

Equations for statistical process control chart are described as follow:

Mean, $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$ ………………………………………. …………... (9)

where:

$x_i$ : random variable at *i*-period
$n$ : total number of observation

Upper control limit, $UCL = \bar{x} + 3\sigma_x$ …………………………………. (10)

where:

$\sigma_x$ : standard deviation of x variable

Lower control limit, $LCL = \bar{x} - 3\sigma_x$ …………………………………… (11)

Statistical process control chart in finance is to monitor the dynamic behavior of closing price. In this study, statistical process control chart is implemented to monitor the volatility of Bitcoin return. Figure 3 shows sample of statistical process control chart. Any value that larger than upper control limit (UCL) or less than lower control limit (LCL) is considered as outliers. The existence of outliers indicates the data distribution is very volatile.

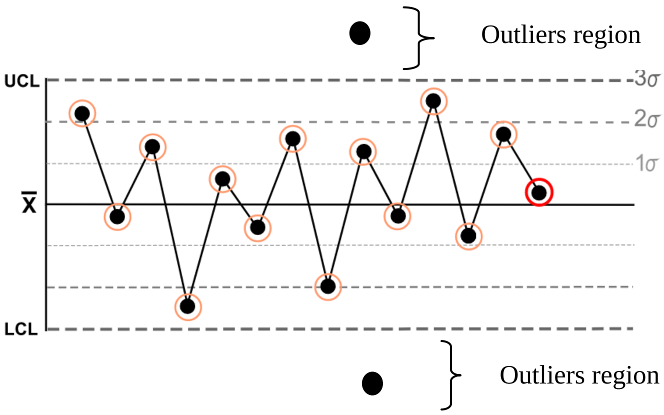


**Figure 3:** Statistical process control chart

## IV. RESULT AND DISCUSSIONS

This section describes the normality data analysis, including volatility calculation for Bitcoin dynamic behavior of exchange rate data. The outliers and statistical process control are introduced to validate the volatility of the data.

### 4.1 Exchange rate data analysis

Figure 4 shows the dynamic behavior of exchange rate for 1 Bitcoin to United States Dollar (USD). The observation starts from 1st January 2017 until 31st October 2017 (304 observations). The value of Bitcoin exchange rate on 1st January 2017 is 997.69, meanwhile on 31st October 2017 is 6142.46. There is increment of 515.7%.

Then, this study validated the normality of data distribution for Bitcoin exchange rate. Figure 5 shows the normal probability plot of Bitcoin exchange rate. Graphical test shows the distribution of data is deviate from normal distribution. Table 1 shows the numerical test of normality using Shapiro-Wilk test. Table 1 shows the probability value (p-value) is 0.000.Therefore, the data distribution follows a non-normal distribution.

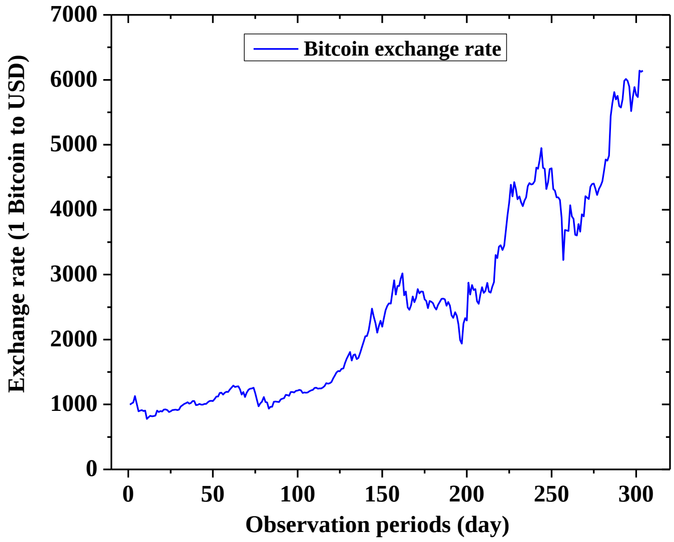


**Figure 4:** Dynamic behavior of exchange rate (1 Bitcoin to USD)

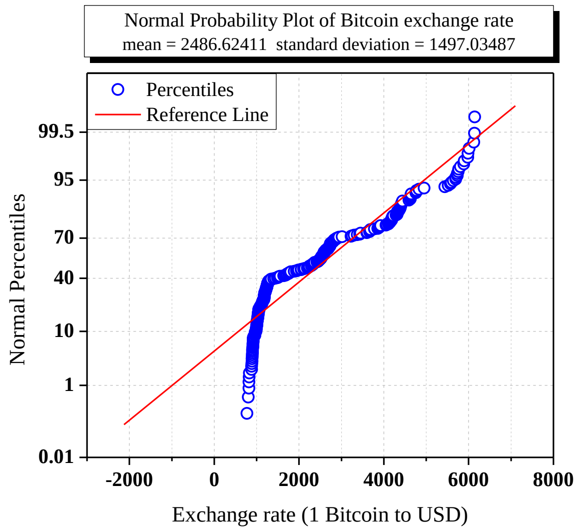


**Figure 5:** Normal probability plot of Bitcoin exchange rate

**Table 1:** Normality test for exchange

| | Shapiro-Wilk | | |
|---|---|---|---|
| | Statistic | Degree of freedom | p-value |
| Exchange Rate (1 Bitcoin to USD) | .883 | 304 | .000 |

**4.2 Evaluation method for rate of return using statistical method**

This section describes the statistical process for evaluating the characteristics of data for Bitcoin return. Figure 6 shows the dynamic behavior of Bitcoin return. The maximum return is 0.226412 on 20$^{th}$ July 2017. This value indicates there is 22.64% of increment compared to 19$^{th}$ July 2017. Then, the minimum return is -0.18298 on 14th September 2017. This value indicates 18.3% of Bitcoin return is lower compared to previous day, 13$^{th}$ September 2017. In descriptive statistical analysis, the mean for this data is 0.006 and the standard deviation is 0.04458. The standard error indicates the volatility for Bitcoin is 4.458 %. This value is considered as high value of volatility. High value of volatility indicates the investment in Bitcoin is categorical as high risk investment.

Then, this study performed normality test to analyze the distribution of return data for Bitcoin. Graphical test is performed using histogram (Figure 7) and normal probability plot (Figure 8). Numerical test is performed using Shapiro-Wilk normality test. The probability value (p-value) is 0.000. Therefore, we reject null hypothesis of Shapiro-Wilk test. Graphical test and numerical test concludes the distribution of Bitcoin return is deviated from normal distribution.

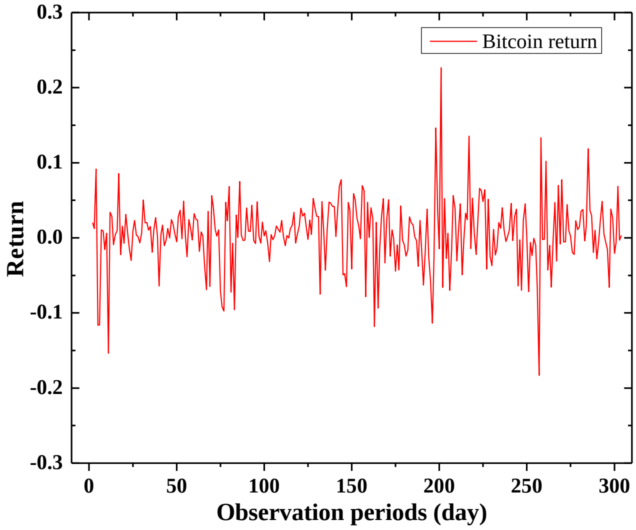


**Figure 6:** Bitcoin return analysis

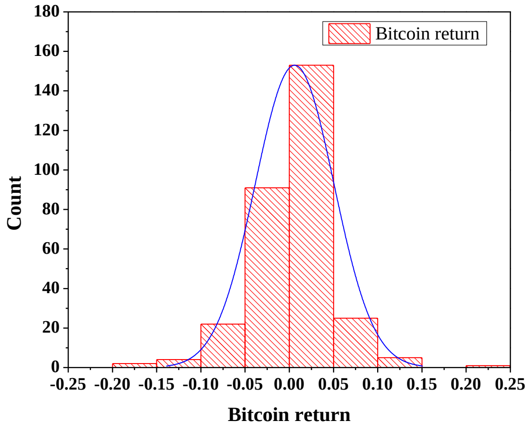


**Figure 7:** Histogram of Bitcoin return

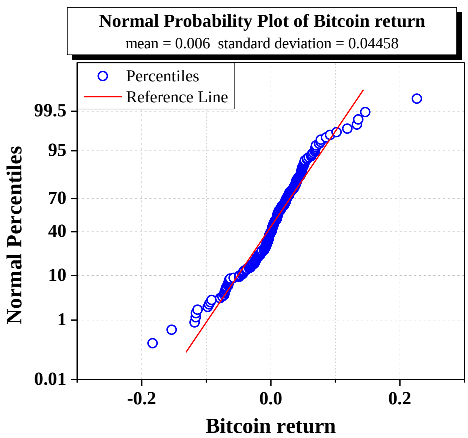


**Figure 8:** Normal probability plot of Bitcoin return

**Table 2:** Test of normality for Bitcoin return

| | Shapiro-Wilk | | |
|---|---|---|---|
| | Statistic | Degree of freedom | p-value |
| return | .942 | 303 | .000 |

**4.3 High volatility data detection method using box-whisker plot and statistical process control chart.**

This section describes the volatility detection method using box plot and statistical process control chart. Figure 9 shows the box-whisker plot analysis in detecting outliers from data of Bitcoin return. Result indicates there are 18 outliers in the data. These outliers contribute to high volatility in Bitcoin return data.

Then, this study performed the statistical process control chart. Figure 10 shows the statistical process control chart for data of Bitcoin return. There is one data point that larger than upper control limit (UCL). Next, there are two data point that lower than lower control limit (LCL). Figure 10 also shows the dispersion of data is deviate from mean. The data dispersion characteristics indicate the distribution of Bitcoin return data is highly volatile.

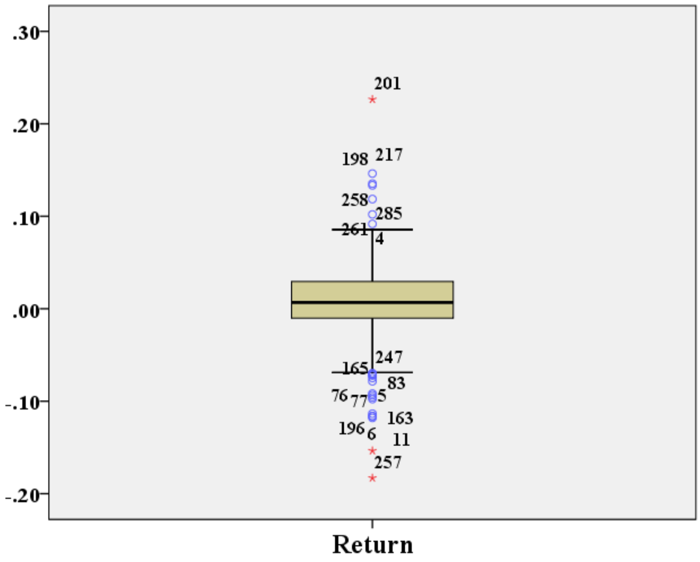


**Figure 9:** Box-whisker plot for Bitcoin return

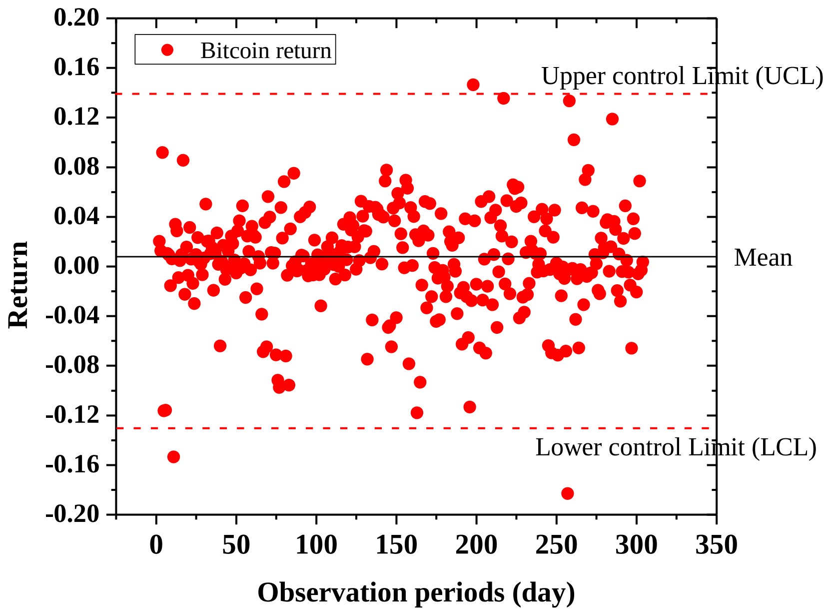


**Figure 10:** Statistical process control chart for Bitcoin return

## V. CONCLUSION

The objective of this study is to evaluate the level of volatility for Bitcoin data. This study focuses on the exchange rate for 1 Bitcoin to United States Dollar (USD). Data selected in this study is involved 304 daily closing prices for Bitcoin exchange rate starting from 1st January 2017 until 31st October 2017. Normality statistical checking is performed for data of exchange rate and rate of return for Bitcoin. Then, volatility dynamic behavior of Bitcoin return is evaluated using box-whisker plot and statistical process control. This study concluded the main findings as below:

(a) The observation of Bitcoin exchange rate selected from 1st January 2017 until 31st October 2017 (304 observations). The value of Bitcoin exchange rate on 1st January 2017 is 997.69, meanwhile on 31$^{st}$ October 2017 is 6142.46. There is increment of 515.7%.

(b) The numerical test of normality for Bitcoin exchange rate performed using Shapiro-Wilk test. Result indicates the probability value (p-value) is 0.000. Therefore, the data distribution follows a non-normal distribution.

(c) The maximum return is 0.226412 on 20th July 2017. This value indicates there is 22.64% of increment compared to 19th July 2017. In opposite, the minimum return is -0.18298 on 14th September 2017. This indicates return decline of 18.3% compared to exchange rate on previous day, 13th September 2017.
(d) In descriptive statistical analysis for Bitcoin return, the mean for this data is 0.006 and the standard deviation is 0.04458. The standard error indicates the volatility for Bitcoin is 4.458 %. This value is considered as high value of volatility. High value of volatility indicates the investment in Bitcoin is high risk.
(e) Numerical test is performed using Shapiro-Wilk normality test to evaluate the distribution data of Bitcoin return. The probability value (p-value) is 0.000. Therefore, we reject null hypothesis of Shapiro-Wilk test. Graphical test and numerical test concludes the distribution of Bitcoin return is deviate from normal distribution.
(f) This study performed outliers detection method using box-whisker plot. The box-whisker plot indicated there are 18 outliers in the data. These outliers contribute to high volatility in Bitcoin return data.
(g) Then, this study performed the statistical process control chart. Result shows one data point that larger than upper control limit (UCL). Next, there are two data point that lower than lower control limit (LCL).Data dispersion characteristics indicate the distribution of Bitcoin return data is highly volatile.

These findings are important to investors for evaluating their choice of investment selection. The investment in cryptocurrency is highly volatile. Therefore, investors need to monitor the exchange closely to gain better return and prevent loss.

## VI. FURTHER RESEARCH

This study can be extended to the factors that contribute to the value of increment and decrement of Bitcoin exchange rate. Then, the forecasting method also is one of the research opportunities that can be performed in the forecasting Bitcoin exchange rate.

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Nashirah Abu Bakar High Volatility Detection Method Using Statistical Process Control for Cryptocurrency Exchange Rate: A Case Study of Bitcoin." The International Journal of Engineering and Science (IJES), vol. 6, no. 11, 2017, pp. 39-48.