VALUE AT RISK PERFORMANCE IN CRYPTOCURRENCIES

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Abstract

Due to conclusion could not rely on only one test, in this study, we apply various approaches to verify the actuary of VaR model to find out whether VaR model, especially historical VaR and delta normal VaR model, can provide the accurate risk measurement results for cryptocurrencies risk, especially CRIX, BTC, ETH and XRP. We use Kupiec's POF test, Independence Test - Christoffersen (1998) and Joint Test that widely use for backtesting VaR model. Performance test results for risk measurement by historical VaR provide a fairly accurate over delta normal VaR when we use Kupiec's POF-test for the accuracy of VaR model. Christoffersen (1998) independence test, the exceptions (failures) of historical VaR and delta normal VaR model show independence exceptions in accordance with an only high confidence level of critical values (0.99). Otherwise, the low confidence level of critical values (0.90 and 0.95) appears dependence exceptions. For the Joint test, we combine POF-test and independence test because each model has different advantages and disadvantages. The results show that historical VaR model is suitable for measuring cryptocurrency risk over delta normal VaR only high confidence level of critical values.

Keywords: Cryptocurrency, Bitcoin, Value at Risk, Performance, POF test, Independence test, Joint test.

บทคัดย่อ

งานวิจัยนี้ได้ทำการประยุกต์ใช้แบบจำลอง VaR ในหลากหลายวิธีเพื่อทดสอบความแม่นยำในการวัดความเสี่ยงของแบบจำลอง Historical VaR และแบบจำลอง Delta Normal VaR สำหรับสกุลเงินคริปโต (Cryptocurrency) ได้แก่ CRIX BTC ETH และ XRP โดยในงานวิจัยฉบับนี้ได้ประยุกต์ใช้การทดสอบ Kupiec’s POF Test การทดสอบ Independece Test ของ Christoffersen และ การทดสอบแบบ Joint Test ที่นิยมใช้กันสำหรับการทดสอบแบบจำลอง VaR โดยผลการทดสอบแสดงว่าแบบจำลอง Historical VaR สามารถวัดความเสี่ยงได้แม่นยำกว่าแบบจำลอง Delta Normal VaR เมื่อใช้การทดสอบ Kupiec’s POF Test ในการวัดผล นอกจากนี้ยังใช้การทดสอบแบบ Joint Test ที่รวมกับทดสอบ POF Test และการทดสอบ Independence Test เข้าด้วยกันและได้ผลว่าแบบจำลอง Historical VaR สามารถความเสี่ยงสำหรับสกุลเงินคริปโตได้เหมาะสมกว่าแบบจำลอง Delta Normal VaR เฉพาะเมื่อระดับความเชื่อมั่นของค่าวิกฤตอยู่ในระดับสูง

คำสำคัญ: สกุลเงินคริปโต บิทคอยน์ Value at Risk การวัดผล การทดสอบ POF test การทดสอบ Independence test, Joint test.

1. INTRODUCTION

It is well-known fact that advances in information technology provide unprecedented context emergences of various digital currencies such as Cryptocurrency Index (CRIX), Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), etc. so-called cryptocurrency. The main advantages of such digital currencies are instantaneous transactions and borderless transfer of ownership. Many web services accept payment in the form of cryptocurrencies like Bitcoin, Ethereum, Ripple, etc. These cryptocurrencies are formed in data so you can use it for payment and trade online. Since their physical currency, most people use them with a low cost of transfer from person to person. Due to increase in demand and limited in supply, for instance, the most popular of cryptocurrency name is Bitcoin which was introduced by Nakamoto (2009) and limited number only 21 million in supply as well as no limited in demand. For these occurrences, demand side which is measured by search queries (Kristoufek, 2013) plays an important role in its volatility price over economic factors (Ciaian, et al., 2016). Furthermore, the volatility price of Bitcoin is affected by publicly announce information also (Bartos, 2015). The volatility price of cryptocurrencies is interesting for people related to this market.

There are many risk measurement techniques in finance which can be applied to determine risk level such as *beta* (volatility of systematic risk), *r-square* (value represents the correlation between the examined investment and its associated benchmark), *standard deviation* (data dispersion in regards to the mean value of the dataset), *Sharpe ratio* (performance as adjusted by the associated risks), etc. One of the most popular risk measurement techniques in finance is value at risk (VaR). VaR was proposed by J.P. Morgan in 1994 and becomes a standard measure that financial analysts use to find how much risk there are. In the past research, VaR was widely used to quantify the risk of investment for financial instrument such as stock, bond, options, futures, etc. and was studied for many different educational objectives, for instance, using VaR to estimate the extreme value theory (EVT) (Maghyereh, Aktham and Haitham, 2006), to examine movements of the stocks market indexes

(Lglesian, 2015), to investigate risk quantification for emerging and developed market equity portfolios (Dimitrakopoulos, Kavussanos, and Spyrou, 2010), to forecast VaR by model specifications using the Model Confidence Set (MCS) (Bernardi and Catania, 2016), etc.

Moreover, previous studies on VaR estimation for equity market which we mention above leave the issue for cryptocurrencies market. Regarding, cryptocurrencies is gaining rapid popularity, especially in top three cryptocurrencies (CRIX, BTC, ETH, XRP) from a total of 1,506 currencies with market cap 63.44% (as of Jan 31, 2018). In this study, we focus only on the risk measurement with VaR model, particularly historical VaR, delta normal VaR and simulation VaR to ensure that related parties are aware of the level of risk and efficiency of the tool and their performance in cryptocurrencies, particularly CRIX, BTC, ETH and XRP.

The remainder of the paper is organized as follows. Section 2 presents the knowledge about cryptocurrencies, VaR and backtesting model. Section 3 introduces materials and methods for assessing the risk of cryptocurrencies. Section 4 shows the finding results from the study. Finally, discusses and concludes of finding results.

2. LITERATURE REVIEW

2.1 Cryptocurrency

Cryptocurrency systems are purely digital and decentralized systems that use cryptographic principles to confirm transactions (Lánský, 2017). Bitcoin is the most famous cryptocurrency with the highest market cap of 33.76% followed by Ethereum 20.85% and Ripple 8.82%, respectively (coinmarketcap.com accessed Jan 31th, 2018) and also the most widespread cryptocurrency. Its exchange rate against the US dollar is 1 BTC = 9,947.75 USD (1st Feb 2018), see Coindesk.com (2018). The total maximum number of Bitcoins in circulation is fixed and amounts to 21 million, which will be achieved in 2140. The current number of Bitcoins in circulation is 16.8 million, see Coindesk.com (2018). Similarly, as dollars are divided into smaller units - cents - Bitcoins are divided into smaller units - satoshi. One Bitcoin is made of hundred million satoshi. Writing about the currency amounts expressed in Bitcoins in the article, we do not usually mean entire Bitcoins, but an amount rounded up with a precision to individual satoshi.

The cryptocurrency systems are a purely peer-to-peer version of electronic cash and would allow online payments to be sent directly from one party to another without going through a financial institution. Digital signatures provide part of the solution, but the main benefits are lost if a trusted third party is still required to prevent double-spending, solving by using a peer-to-peer network. The network timestamps transactions by hashing them into an ongoing chain of hash-based proof-of-work, forming a record that cannot be changed without redoing the proof-of-work. The longest chain not only serves as proof of the sequence of events witnessed but proof that it came from the largest pool of CPU power. As long as a majority of CPU power is controlled by nodes that are not cooperating to attack the network, they'll generate the longest chain and outpace attackers. The network itself requires minimal structure. Messages are broadcast on a best effort basis, and nodes can leave and rejoin the network at will, accepting the longest proof-of-work chain as proof of what happened while they were gone (Nakamoto, 2008). The structure of Bitcoin system users can be based on a systemic approach identified with basic concepts: Bitcoin user, propagator, developer, merchandizer, exchange, customer, miner and investor (Figure 1).

Bitcoin user, Bitcoin user can be distinguished by roles they assume in the Bitcoin system; one user can hold multiple roles. Individual roles are usually held by several thousand users, of which several dozens have a major say in the given role. Two roles that in their unification include almost all Bitcoin users are an exception. For individual groups estimates of the number of users are given. If data is missing for a given source, it was created by the authors of this article based on their own experience gained from many years of newsgroups and community websites studying.

Propagators, Propagators expand awareness of the Bitcoin system and its advantages compared to fiat currencies. By its effect on the general population, the Bitcoin system obtains additional users. There are tens of propagators at the global level.

Developers, developers create software that is used by other users for their activities in the Bitcoin system. The most influential group is 15 Bitcoin Core Developers (2017), which is the most widespread software for operating a full node. Additional thousands of developers create software for lightweight wallets, group mining and various commercial applications using Bitcoin.

Merchandisers, merchandisers offer their customers the option to pay for goods and services using Bitcoin, or possibly they offer their employees the opportunity to receive payments in Bitcoin.

Exchanges intermediate, exchanges intermediate an exchange of Bitcoin for fiat currency or other cryptocurrencies. There are approximately 100 online exchanges that everyday trade Bitcoins worth hundreds of millions of dollars. In the biggest exchange Bitfinex about 20% of the volume of all transactions is conducted.

Customers, customers use Bitcoins for purchasing goods and services or possibly obtain Bitcoins as a reward for their work. Most Bitcoin customers use Bitcoins as a supplement and carry out the vast majority of payment transactions in fiat currencies.

Miners, miners utilize a computing power of its specialized hardware devices to create new network blocks and as a reward, they receive rewards in the form of coins newly put into circulation and transaction fees.

Investors, investors hope that the price of Bitcoin against fiat currencies will rise and, to this end, they will keep a part of their savings in Bitcoin. The number of investors is the same as the number of customers, that is millions. A large number of customers are primarily investors who occasionally become customers.

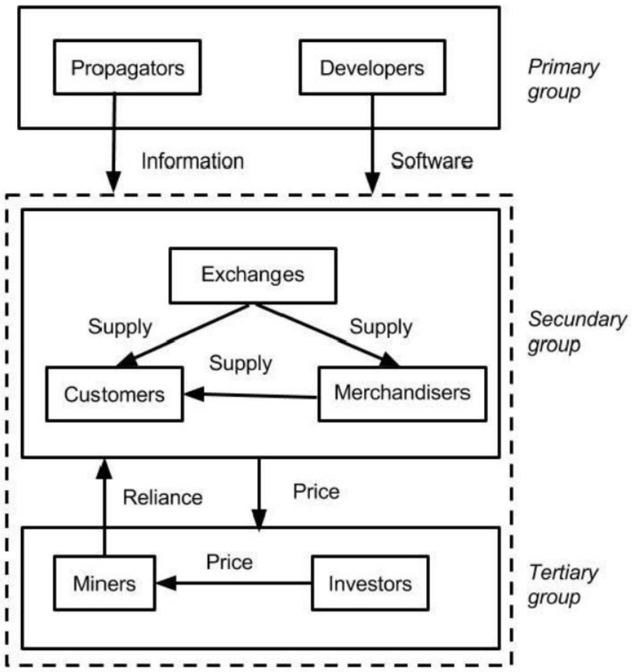

Figure 1. Users of the Bitcoin system.
Source: (Nakamoto, 2008)

All related parties are affected by price movements of cryptocurrencies. One of the most important things is that volatility of price movements results in a loss of profit. Price movements in the past year of CRIX, BTC, ETH and XRP were range between -23.84% to 19.85%, -20.75% to 22.51%, -31.55% to 29.01% and -61.63% to 102.74% respectively (Figure 2 to 5). In this study, Risk of cryptocurrencies is measured by VaR to ensure that related parties are aware of the level of risk and efficiency of the tool.

2.2 Value at Risk (VaR)

VaR describes the probability distribution for the value (earnings or losses) of an investment (firm, portfolio, etc.). Its origin in RiskMetrics, that was developed by JP Morgan (1996). Moreover, VaR became a very important measure of risk since the Basel Committee on banking supervision declared that banks should be able to cover losses in their portfolios for horizons of 10 days with a confidence level of 99 percent. There are two distinct VaR measures, one dealing with the unconditional distribution and one with the conditional distribution. In this study, we offer to measure VaR including historical VaR and delta normal VaR

2.3 Historical Simulation VaR :

Historical Simulation VaR or HS-VaR method is the simple way to measure the risk of the single or portfolio assets. This technique is nonparametric and does not require any distributional assumptions. In this concept, HS-VaR comprises a full valuation method which exploits a historical window of the last n-days. The 100(1-α)% VaR can be derived by calculating the empirical α-quantile of the sequence of past returns:

$$VaR_{t+1}^{1-\alpha} = Q^{\alpha}(\{r_t\}_{t=1}^{n}) \tag{1}$$

Where Q^{α} denotes the α-quantile. In HS-VaR, HS-VaR are valued under a number of different historical time windows such as range from 6 months to 5 years. The historical simulation based models make use of the sliding window technique to derive recursive VaR forecasts. It is worth noting that the sliding window technique is used by all of the employed VaR models and updates the estimation sample regularly by incorporating new information reflected in each sample of the return series. It can therefore be argued that this technique takes into account implicitly structural changes, such as mean and volatility shifts or changes in the distributional properties of the examined markets. The limitation of the historical simulation lies in its independent and identically distributed (i.i.d.) assumption of returns. From empirical evidence, it is known that asset returns are clearly not independent as they exhibit certain patterns such as volatility clustering. Because historical simulation does not take into account such patterns, so parametric model like delta normal and monte carlo simulation method may dominate such method (Kondapaneni, 2005), (Dimitrakopoulos, Manolis and Spyros, 2010).

2.4 Delta Normal VaR

The Delta-normal VaR or Variance-Covariance method is the best method to compute VaR for portfolios with linear positions and whose distributions are close to the normal probability density function. Historical data is used to calculate main parameters: mean, standard deviation, correlation. This method calculates VaR by assuming some theoretical distribution of asset returns. Usually, the normal distribution is used. This assumption allows volatility to be described in terms of standard deviations (SD). Another advantage of a normal distribution is that it can be described by its first two moments: mean, and standard deviation (Živković, 2005). This distribution is symmetrical so skewness is 0 and kurtosis 3. If we want to find $VaR_{1-\alpha}$ in a normal distribution we use standard value of variable Z (Z-score), so $VaR_{1-\alpha}$ for delta normal can be find with following formula:

$$VaR_{1-\alpha} = \mu + Z_{1-\alpha}\sigma \tag{2}$$

Where Z (standard value variable) is simply calculated as Z = $\frac{X-\mu}{\sigma}$, μ denotes as mean, σ denotes as standard deviation (SD). In this way, VaR can be calculated as multiple of standard deviation from eq.3.

2.5 Performance Measurement of VaR

We use backtesting techniques to measure the performance of each VaR model that whether each VaR model can measure the risk of cryptocurrency or not. The simple applying way to measure the performance of each VaR model is adopting the concepts proposed by Kupiec (1995) and Christoffersen (1998) that widely used in past research.

2.6 Kupiec's POF-test

The test proposed by Kupiec (1995), also known as the proportion of failure (POF), is one of the most popular tests. The POF approach tests the unconditional coverage property. Using this test we validate (backtest) the accuracy of the VaR model by recording the failure rate. In the backtesting method, the range for x will be calculated and thus the VaR model can be accepted or rejected (Campbell, 2005). Under the null hypothesis, the POF-test statistic given by equation (5) follows a x^2 (Chi-squared) distribution with x^2 (Chi-square) one degree of freedom. If the value of the LR_{POF} falls below the critical value compared with x^2 (Chi-squared) distribution, the model passes the backtest. Higher values above the critical region signal an inaccurate model and should lead to a rejection of the model.

The likelihood ratio (LR) test statistic for the unconditional coverage test follows a x^2 (Chi-square) distribution with one degree of freedom. In this paper, we use unconditional coverage test of Paul Kupiec (1995) that we are mention above. This test is known as POF-test and examines how many times a Value-at-Risk is exceeded over a given time interval. The test statistic is conducted as a likelihood ratio (LR) as follows:

$$LR_{POF} = -2ln\left(\frac{(1-p)^{n-x}p^x}{\left(1-\frac{x}{n}\right)^{n-x}\left(\frac{x}{n}\right)^x}\right) \tag{3}$$

Where x is number of exceptions, n is total number of observations, p is probability of failure.

2.7 Independence Test (Christoffersen, 1998)

Because unconditional coverage property, especially the POF-test, has two disadvantage, statistically weak for small sample sizes and examining testing only the failure rate and not the succession of occurrence, therefore, it may fail to reject a model that produces serially dependent violations. One of the most widely known tests of conditional coverage which examines the independence property, or exception clustering, is the independence test (or Markov test), suggested by Christoffersen (1998). By this method, if the likelihood of a VaR exception increased on a day proceeding a previous VaR exception, then this would point towards a need to raise VaR level estimates, as successive losses would imply higher risk exposure. The test is proposed by the condition as follows:

$$\text{Indicator } (I_t) = \begin{cases} 0\ if\ VaR\ is\ not\ breached, \\ 1\ otherwise \end{cases}$$

Thus we have a sequence It of 0s and 1s. For any two consecutive days, there will only be four outcomes; 00, 01, 10 and 11. The test statistic of independence test (or Markov test) is

$$LR_M = -2ln\left(\frac{(1-\pi)^{n_{00}+n_{10}}\pi^{n_{01}+n_{11}}}{(1-\pi_0)^{n_{00}}\pi_0^{n_{01}}(1-\pi_1)^{n_{10}}\pi_1^{n_{11}}}\right) \tag{4}$$

Where n_{00} is the number of days that the previous day's indicator is 0 and the subsequent day's indicator is 0, n_{01} is the number of days that the previous day's indicator is 0 and the subsequent day's indicator is 1, n_{10} is the number of days that the previous day's indicator is 1 and the subsequent day's indicator is 0 and n_{11} is the number of days that the previous day's indicator is 1 and the subsequent day's indicator is 1 (Jorion, 2007). In addition, define π as the probability of having an exception conditional on state i in the previous day. For instance, π_0 be the conditional probability of 01 occurring if the previous day is 0 and π_1 be the conditional probability of 11 occurring if the previous day is 1 (Chatfield, 2001). The π_0, π_1 and π can be calculated as follows:

$$\pi_0 = \frac{n_{01}}{n_{00}+n_{01}},\ \pi_1 = \frac{n_{11}}{n_{10}+n_{11}},\ \pi = \frac{n_{01}+n_{11}}{n_{00}+n_{01}+n_{10}+n_{11}} \tag{5}$$

Under the null hypothesis, the test statistic LR_M follows x^2(Chi-square) distribution with one degree of freedom, exceptions are independent across days, then the probabilities should be equal ($\pi = \pi_0 = \pi_1$). That is, the chance of an exception occurring after a day of no exception is the same as occurring after a day of an exception (Campbell, 2005). The disadvantage of this method is its limited power against clustering. Because it mainly tests for independence of exceptions on two consecutive days. Then jointly examine the unconditional coverage (POF-test) and independence properties (Markov test) provide an opportunity to detect VaR measures which are deficient in one way or another.

2.8 Join test of VaR

Due to the limitation of POF-test (unconditional coverage tests) and Markov test (conditional coverage tests), Join test of VaR is applied by combining coverage tests and independence tests together which are given better results. The combined test statistic for Join test of VaR is

$$LR_{CC} = LR_{POF} + LR_M \tag{6}$$

Where LR_{CC} is Join test of VaR and LR_{CC} statistic given by equation (8) follows a x^2 (Chi-squared) distribution with 2-degrees of freedom.

3. DATA AND METHODOLOGY

3.1 Data

We use the daily price of cryptocurrencies total of 1,097 observations for CRIX, BTC and XRP from 31 December 2014 to 31 December 2017, whereas ETH we use daily price total of 878 observations because of limitation of providing historical ETH price data only from 7 August 2015 to 31 December 2017 from coinmarketcap.com. For risk measurement method, firstly, we calculate the return of each cryptocurrency by using log return conducted as follows:

$$R_{pt} = \ln\left(\frac{p_t}{p_{t-1}}\right) \tag{7}$$

Where R_{pt} is log daily return of cryptocurrency at time t, p_t is daily price of cryptocurrency at time t and p_{t-1} is daily price of cryptocurrency at previous time. Secondly, we calculate each VaR model that we mention above as follows:

Historical VaR calculation procedure:

1. Calculating returns of each cryptocurrency (CRIX, BTC, ETH and XRP) by using eq.(7)
2. Putting them in order from worst to best returns.
3. Finding the historical VaR for each cryptocurrency that corresponds to the desired confidence level for a period of one year.
4. Using rolling window technique to calculate historical VaR. For instance, we calculate historical VaR at 0.99, 0.95 and 0.90 confidence level from the year 2016 to the year 2017 using 365 day returns previous year for each rolling windows from 1 Jan 2015 to 31 Dec 2017. In this step, we get total results of historical VaR for

each cryptocurrency of 730 days from 1 Jan 2016 to 31 Dec 2017. Exception for ETH, we get total results of historical VaR only 510 days due to the limitation of its historical price data. The results show from Figure 3 to Figure 5.

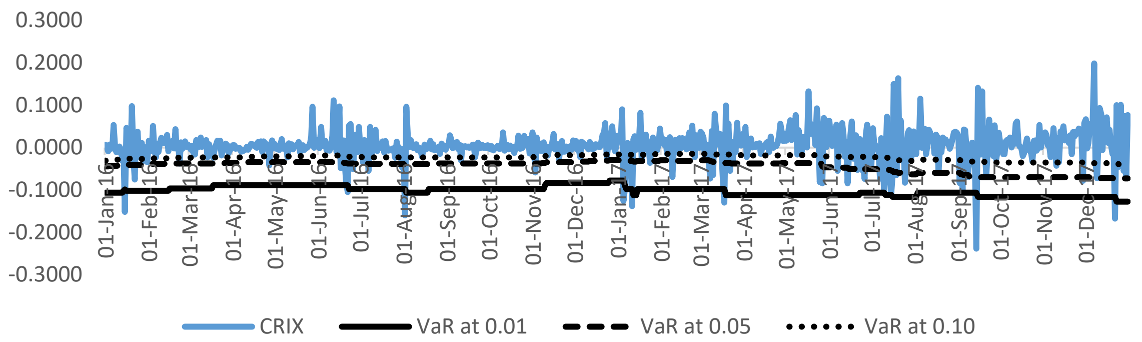

Figure 2. Historical VaR of CRIX
at the confidential level of 99%, 95% and 90%, respectively.

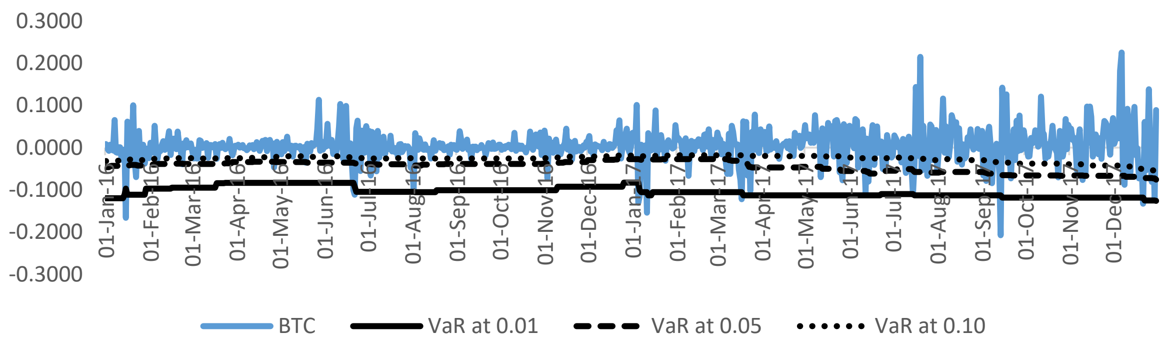

Figure 3. Historical VaR of BTC
at the confidential level of 99%, 95% and 90%, respectively.

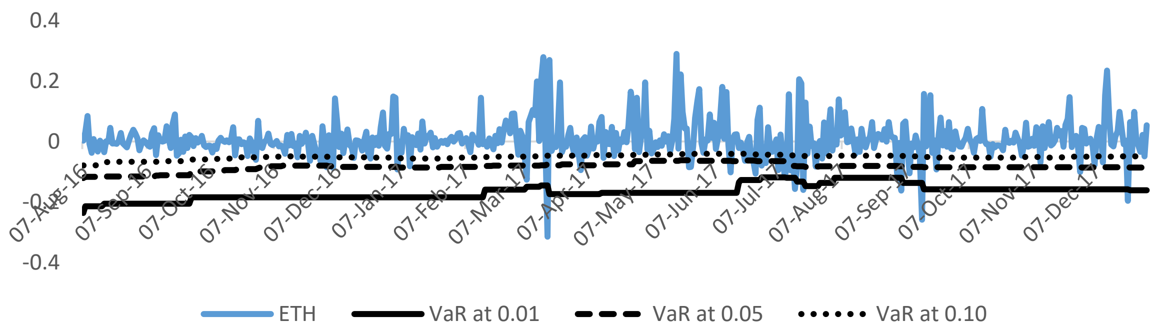

Figure 4. Historical VaR of ETH
at the confidential level of 99%, 95% and 90%, respectively.

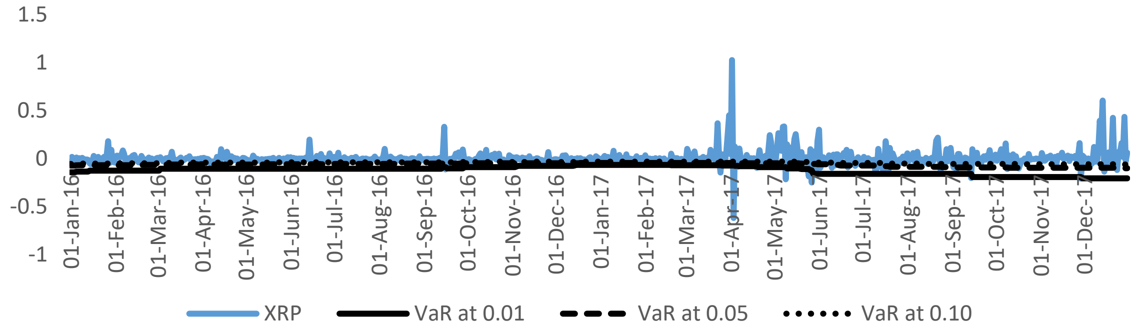

Figure 5. Historical VaR of XRP
at the confidential level of 99%, 95% and 90% respectively.

Delta normal VaR calculation procedure :

1. Calculating returns of each cryptocurrency (CRIX, BTC, ETH and XRP) by using eq.(7)
2. Calculating delta normal VaR for each cryptocurrency with eq.(2) that corresponds to the desired confidence level for period of two years from
3. From step 2, using rolling window technique to calculate delta normal VaR. For instance, we calculate delta normal VaR at 0.99, 0.95 and 0.90 confidence level from the year 2016 to the year 2017 using 365 day returns previous year for each rolling windows from 1 Jan 2015 to 31 Dec 2017. In this step, we get total results of delta normal VaR for each cryptocurrency of 730 days from 1 Jan 2016 to 31 Dec 2017. Exception for ETH, we get total results of delta normal VaR only 510 days due to the limitation of its historical price data. The results show from Figure 6 to Figure 9.

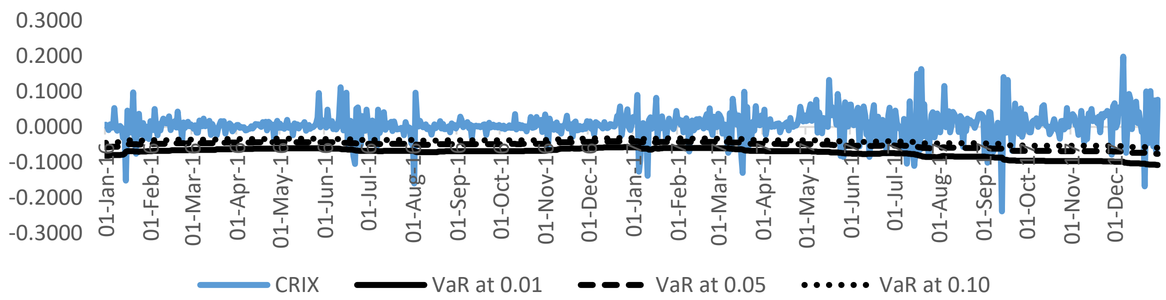

Figure 6. Delta normal VaR for CRIX
at the confidential level of 99%, 95% and 90% respectively.

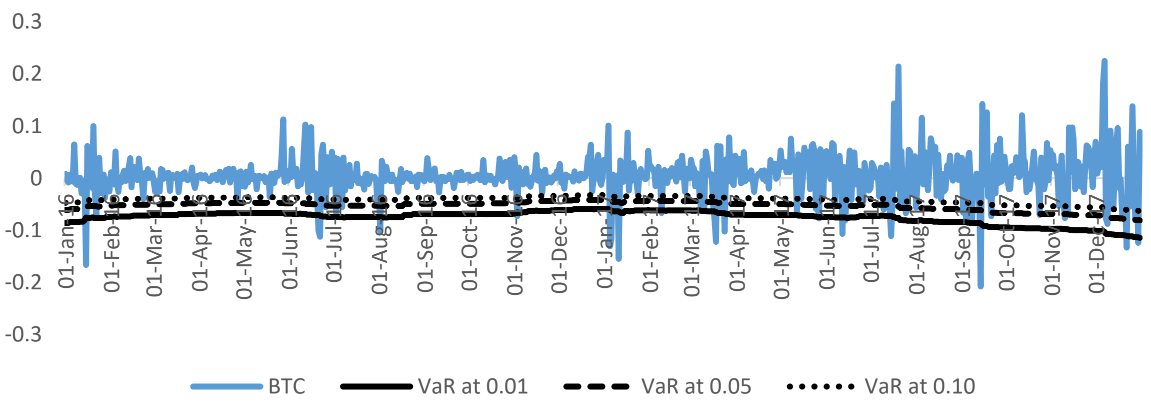

Figure 7. Delta normal VaR
for BTC at the confidential level of 99%, 95% and 90% respectively.

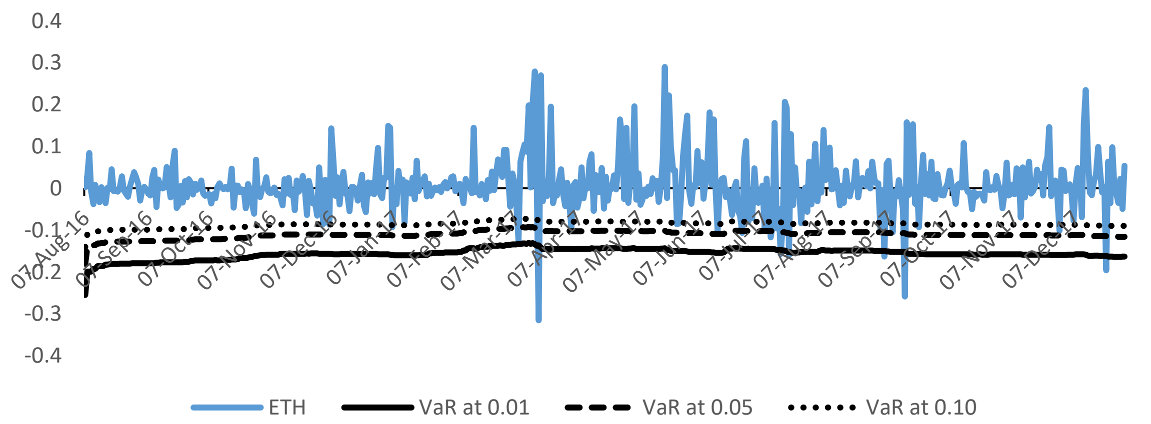

Figure 8. Delta normal VaR
for ETH at the confidential level of 99%, 95% and 90% respectively.

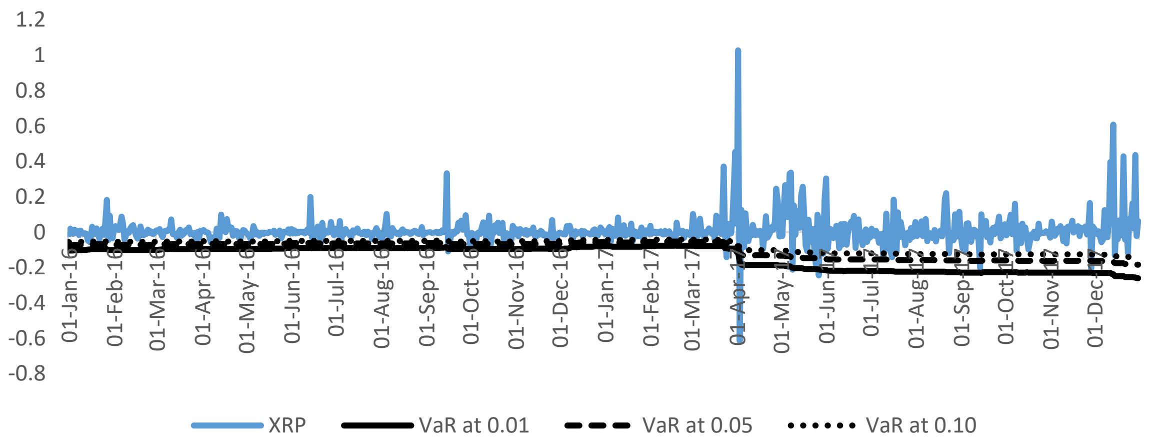

Figure 9. Delta normal VaR
for XRP at the confidential level of 99%, 95% and 90% respectively.

4. STUDY RESULTS

Information in Table 1 shows a total of descriptive statistics of cryptocurrency returns 730 observations for CRIX, BTC and XRP, whereas ETH shows a total of its returns only 510 observations because of limitation of providing historical data. We found that XRP presents the highest return of 102.74%, followed by ETH, BTC and CRIX with a return of 29.10%, 22.51% and 19.85%, respectively. The volatility of their returns has ranged from 3.73% to 8.34%. XRP presents the highest volatility of 8.34%, followed by ETH, BTC and CRIX with a volatility of 6.24%, 3.92% and 3.73%, respectively. According to Jarque-Bera, all cryptocurrencies appear non-normal distributions.

Table 1
Descriptive Statistics

	CRIX	BTC	XRP	ETH
Mean	0.0058	0.0048	0.0082	0.0083
Median	0.0044	0.0033	-0.0030	0.0018
Maximum	0.1985	0.2251	1.0274	0.2901
Minimum	-0.2384	-0.2075	-0.6163	-0.3155
Std. Dev.	0.0373	0.0392	0.0834	0.0624
Skewness	-0.4627	0.0595	3.6998	0.6640
Kurtosis	9.6732	8.9243	45.2210	8.0039
Jarque-Bera	1380.5620	1067.9835	55886.7054	569.5563
Probability	0.0000	0.0000	0.0000	0.0000
Number of observations	730	730	730	510

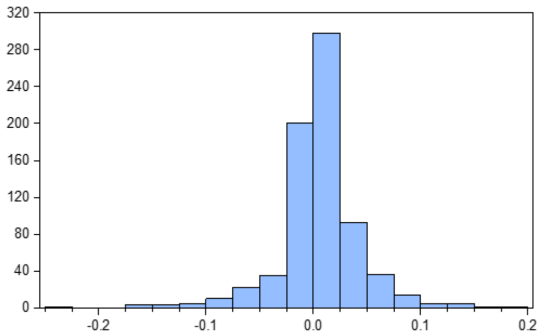

Figure 10. Histogram of CRIX Returns

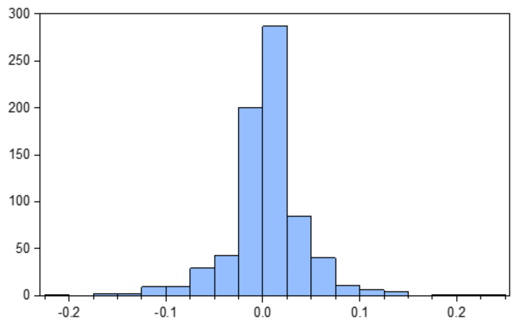

Figure 11. Histogram of BTC Returns

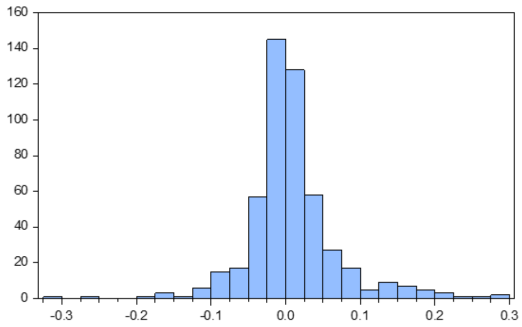

Figure 12. Histogram of ETH Returns

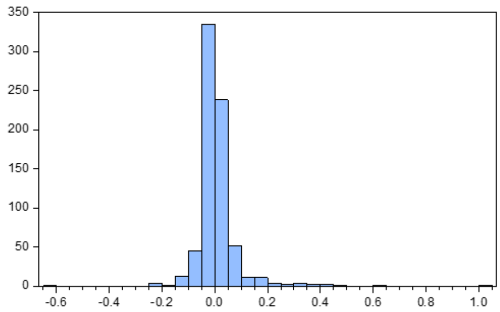

Figure 13. Histogram of XRP Returns

A number of failures for each confidence level are the count of black lines (solid and dash) that exceed the estimated VaR (Figure 2 to 9). These counts are summarized in Table 2 to 7. The expected numbers are counted by Kupiec's POF test, Independence Test - Christoffersen (1998) and Joint Test

Kupiec's POF-Test in this study is used to test the accuracy in estimating the proportion of exceptions by inspection the number of exceptions (number of failures) that is measured by too large in statistical terms. The POF-test statistic is computed by using eq.3 and compared to critical value χ^2 (0.99,0.95 and 0.90) with one degree of freedom. Criteria for selecting, accepting and rejecting, is the value of test statistic presented by LR_{POF} statistic whether higher than critical value (χ^2), we can reject the VaR model. Otherwise, the VaR model is accepted. The testing results of POF-test are in Table 2 and Table 3 by historical VaR and delta normal VaR method, respectively. Historical VaR model (Table 2), we can see all statistics not exceed the test statistic then the historical VaR model shows accuracy for measuring the risk of all cryptocurrencies (CRIX, BTC, ETH and XRP), and historical VaR is accuracy in accordance with confident level of critical values, high confidence values providing high accuracy. Delta normal VaR model, test results give a different view. Delta normal VaR shows inaccuracy to measure cryptocurrencies risk because a number of rejection appears more than a number of acception in all confident level of critical values. In other words, the number of realized exceptions (failure) exceed the number of expected exceptions. For instance, Delta normal VaR of BTC with 0.95 confidence level calculated by 730 observations, we then get the number of expected exceptions of 37 exceptions (730 delta normal VaR observations x 0.95 confidence level).

Table 2
Kupiec's POF-Test Results of Historical VaR

Cryptocurrency	Confidence Level	Test Statistic LR_{POF}	Critical Value χ^2 (Chi-square) (1;0.99)		Critical Value χ^2 (Chi-square) (1;0.95)		Critical Value χ^2 (Chi-square) (1;0.90)	
			χ^2	Test Result	χ^2	Test Result	χ^2	Test Result
CRIX	0.99	0.3723	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	1.9461	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	1.1905	6.6349	Accept	3.8415	Accept	2.7055	Accept
BTC	0.99	0.9043	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	3.4851	6.6349	Accept	3.8415	Accept	2.7055	Reject
	0.90	4.1268	6.6349	Accept	3.8415	Reject	2.7055	Reject
ETH	0.99	0.1518	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	0.0912	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	0.3570	6.6349	Accept	3.8415	Accept	2.7055	Accept
XRP	0.99	1.6394	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	4.0885	6.6349	Accept	3.8415	Reject	2.7055	Reject
	0.90	0.3731	6.6349	Accept	3.8415	Accept	2.7055	Accept

	(1;0.99)	(1;0.95)	(1;0.90)
Number of Acceptions	12	10	9
Number of Rejections	0	2	3

Table 3
Kupiec's POF-Test Results of Delta Normal VaR

Cryptocurrency	Confidence Level	Test Statistic LR_{POF}	Critical Value χ^2 (Chi-square) (1;0.99)		Critical Value χ^2 (Chi-square) (1;0.95)		Critical Value χ^2 (Chi-square) (1;0.90)	
			χ^2	Test Result	χ^2	Test Result	χ^2	Test Result
CRIX	0.99	17.2406	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.95	0.1765	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	8.1479	6.6349	Reject	3.8415	Reject	2.7055	Reject
BTC	0.99	15.1388	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.95	1.1555	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	3.1714	6.6349	Accept	3.8415	Accept	2.7055	Reject
ETH	0.99	0.1518	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	14.8095	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.90	21.0431	6.6349	Reject	3.8415	Reject	2.7055	Reject
XRP	0.99	0.8229	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	20.9460	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.90	41.4384	6.6349	Reject	3.8415	Reject	2.7055	Reject

	(1;0.99)	(1;0.95)	(1;0.90)
Number of Acceptions	5	5	4
Number of Rejections	7	7	8

Independence Test - Christoffersen (1998), this test starts with the count numbers n_{00}, n_{01}, n_{10} and n_{11} and calculates probabilities π_0, π_1 and π by using eq.5. Results of independence tests are in Table 4 and 5 by historical VaR and delta normal VaR method, respectively. Considering number of acceptions and rejections, because number of acceptions shows number of acceptions over number of rejection then we can not reject for historical VaR model. In other words, the failures are independence and this model could be accurate in accordance with only high confidence level (0.95 and 0.99), and could be inaccurate with low a confidence level (0.90). The test results of delta normal VaR model show similar to the results of the historical VaR model.

Table 4

Independence Test - Christoffersen (1998) of Historical VaR

Independence Test								
Cryptocurrency	**Confidence Level**	**Test Statistic** LR_M	**Critical Value** χ^2 **(Chi-square) (1;0.99)**		**Critical Value** χ^2 **(Chi-square) (1;0.95)**		**Critical Value** χ^2 **(Chi-square) (1;0.90)**	
			χ^2	**Test Result**	χ^2	**Test Result**	χ^2	**Test Result**
CRIX	0.99	2.8043	6.6349	Accept	3.8415	Accept	2.7055	Reject
	0.95	10.7266	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.90	10.8609	6.6349	Reject	3.8415	Reject	2.7055	Reject
BTC	0.99	7.7558	6.6349	Reject	3.8415	Reject	2.7055	Reject
	0.95	4.1658	6.6349	Accept	3.8415	Reject	2.7055	Reject
	0.90	9.7568	6.6349	Reject	3.8415	Reject	2.7055	Reject
ETH	0.99	0.1429	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	1.5093	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	4.9396	6.6349	Accept	3.8415	Reject	2.7055	Reject
XRP	0.99	0.3674	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	2.0038	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	1.7149	6.6349	Accept	3.8415	Accept	2.7055	Accept

	(1;0.99)	(1;0.95)	(1;0.90)
Number of Acceptions	8	6	5
Number of Rejections	4	6	7

Due to the shortcoming of the Kupiec's POF-test and independence test, joint test (unconditional coverage tests and conditional coverage tests) is applied by a combination of these two approaches (test for both the frequency of exceptions (number of failures) as well as the independence of exceptions). In this method, we can combine the advantages and disadvantages of both that we mention above, calculate by using eq.6, and compare test statistics (LR_M) to critical values (x^2) with two degrees of freedom at confident level 0.99, 0.95 and 0.90, respectively. Results of the joint test are presented in Table 6 and 7. Results of this model, historical VaR model, because of number of acceptions over number of rejections in accordance with only high confidence level (0.99), so we can conclude that historical VaR model is accuracy to measure cryptocurrencies risk only high confidence level. However, when we consider delta normal VaR that show different results to historical VaR because number of rejections appears more than number of acceptions in all confidence level of critical values.

Table 5
Independence Test - Christoffersen (1998) of Delta Normal VaR

Independence Test								
Cryptocurrency	**Confidence Level**	**Test Statistic LR_M**	**Critical Value χ^2 (Chi-square)**		**Critical Value χ^2 (Chi-square)**		**Critical Value χ^2 (Chi-square)**	
			χ^2	**Test Result**	**χ^2**	**Test Result**	**χ^2**	**Test Result**
CRIX	0.99	5.4185	6.6349	Accept	3.8415	Reject	2.7055	Reject
	0.95	3.4071	6.6349	Accept	3.8415	Accept	2.7055	Reject
	0.90	9.6628	6.6349	Reject	3.8415	Reject	2.7055	Reject
BTC	0.99	5.9517	6.6349	Accept	3.8415	Reject	2.7055	Reject
	0.95	6.3530	6.6349	Accept	3.8415	Reject	2.7055	Reject
	0.90	7.4791	6.6349	Reject	3.8415	Reject	2.7055	Reject
ETH	0.99	0.1429	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	0.3234	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	2.8167	6.6349	Accept	3.8415	Accept	2.7055	Reject
XRP	0.99	0.0828	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.95	0.5081	6.6349	Accept	3.8415	Accept	2.7055	Accept
	0.90	0.7764	6.6349	Accept	3.8415	Accept	2.7055	Accept

Number of Acceptions	10	7	5
Number of Rejections	2	5	7

Table 6
Joint Test - Christoffersen's Interval Forecast Test (1998) of Historical VaR

Joint Test								
Cryptocurrency	**Confidence Level**	**Test Statistic LR_{CC}**	**Critical Value χ^2 (Chi-square) (2;0.99)**		**Critical Value χ^2 (Chi-square) (2;0.95)**		**Critical Value χ^2 (Chi-square) (2;0.90)**	
			χ^2	**Test Result**	**χ^2**	**Test Result**	**χ^2**	**Test Result**
CRIX	0.99	3.1766	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.95	12.6727	9.2103	Reject	5.9915	Reject	4.6052	Reject
	0.90	12.0514	9.2103	Reject	5.9915	Reject	4.6052	Reject
BTC	0.99	8.6601	9.2103	Accept	5.9915	Reject	4.6052	Reject
	0.95	7.6509	9.2103	Accept	5.9915	Reject	4.6052	Reject
	0.90	13.8836	9.2103	Reject	5.9915	Reject	4.6052	Reject
ETH	0.99	0.2947	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.95	1.6005	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.90	5.2966	9.2103	Accept	5.9915	Accept	4.6052	Reject
XRP	0.99	2.0069	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.95	6.0923	9.2103	Accept	5.9915	Reject	4.6052	Reject
	0.90	2.0879	9.2103	Accept	5.9915	Accept	4.6052	Accept

Number of Acceptions	9	6	5
Number of Rejections	3	6	7

Table 7
Joint Test - Christoffersen's Interval Forecast Test (1998) of Delta Normal VaR

Joint Test								
Cryptocurrency	**Confidence Level**	**Test Statistic** LR_{CC}	**Critical Value** χ^2 **(Chi-square)**		**Critical Value** χ^2 **(Chi-square)**		**Critical Value** χ^2 **(Chi-square)**	
			χ^2	**Test Result**	χ^2	**Test Result**	χ^2	**Test Result**
CRIX	0.99	22.6591	9.2103	Reject	5.9915	Reject	4.6052	Reject
	0.95	3.5836	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.90	17.8107	9.2103	Reject	5.9915	Reject	4.6052	Reject
BTC	0.99	21.0905	9.2103	Reject	5.9915	Reject	4.6052	Reject
	0.95	7.5085	9.2103	Accept	5.9915	Reject	4.6052	Reject
	0.90	10.6505	9.2103	Reject	5.9915	Reject	4.6052	Reject
ETH	0.99	0.2947	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.95	15.1328	9.2103	Reject	5.9915	Reject	4.6052	Reject
	0.90	23.8598	9.2103	Reject	5.9915	Reject	4.6052	Reject
XRP	0.99	0.9058	9.2103	Accept	5.9915	Accept	4.6052	Accept
	0.95	21.4541	9.2103	Reject	5.9915	Reject	4.6052	Reject
	0.90	42.2148	9.2103	Reject	5.9915	Reject	4.6052	Reject

Number of Acceptions	4	3	3
Number of Rejections	8	9	9

5. CONCLUSION

Due to conclusion could not rely on only one test, in this study, we apply various approaches to verify the actuary of VaR model to find out whether VaR model, especially historical VaR and delta normal VaR model, can provide the accurate risk measurement results. We use Kupiec's POF test, Independence Test - Christoffersen (1998) and Joint Test that widely use for backtesting VaR model. For instance, Mirtes, 2016 applied these methods to test VaR and CVaR, Katsenga, 2014 used these methods to verify the accuracy of risk measuring of the South African market portfolio with VaR model, Nieppola, 2009 studied performance of these backtesting model, and so on.

Performance test results for risk measurement by historical VaR provide a fairly accurate over delta normal VaR when we use Kupiec's POF-test for the accuracy of VaR model. Considering Christoffersen (1998) independence test, the exceptions (failures) of historical VaR and delta normal VaR model show independence exceptions in accordance with an only high confidence level of critical values (0.99). Otherwise, the low confidence level of critical values (0.90 and 0.95) appears dependence exceptions. For the Joint test, we combine POF-test and independence test because each model has different advantages and disadvantages. The results show that historical VaR model is suitable for measuring cryptocurrency risk over delta normal VaR only high confidence level of critical values. One important reason is the calculation of the delta normal VaR based on normal distribution assumption. Otherwise, calculation of historical VaR is not based on such assumption. From Table 1 and Figure 10 to Figure 13, because all returns of cryptocurrencies CRIX, BTC, ETH and XRP show no normal distribution properties, so historical VaR is appropriate to measure cryptocurrency risk that we mention the reason above. Furthermore, the observations of historical and delta normal VaR model are adequate to the conclusion of the results because we have historical and delta normal VaR sample size larger than 500 observations (Mirtes,2016), so the probability of type I error is not occurring.

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