WHAT DRIVES CRYPTOCURRENCY BUBBLE?

BY

MR. NUTHAKAMOL PANJAROJANAKUL

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL
FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF SCIENCE
PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)
FACULTY OF COMMERCE AND ACCOUNTANCY
THAMMASAT UNIVERSITY
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ABSTRACT

This study intends to do the study on relationship between cryptocurrency. We find that there are both relationship that cryptocurrency drive each other's bubble and help each other's to reduce the inefficient. The data that is used is between 01 December 2017 and 28 February 2018. The interesting incident that occurs between these periods is the expiration of the first Bitcoin futures contract from CBOE market. Therefore, we segment the data into two periods, prior the expiration and post the expiration. We found that the relationship among cryptocurrency is diminished and substituted by momentum effect. Driving to bubble relationship and increasing in efficient relationship are also observed.

Keywords: Cryptocurrency, State Space Model, Kalman Filter, Bitcoin Futures

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Mr.Nuthakamol Panjarojanakul

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Symbols/Abbreviations	Terms
CBOE	The Chicago Board Options Exchange
BTC	Bitcoin
ETH	Ethereum
XRP	Ripple
BCH	Bitcoin Cash
LTC	Litecoin
M(t)	Permanent component
S(t)	Transitory component

CHAPTER 1
INTRODUCTION

Introduction

This paper investigates the relationship between return of main cryptocurrency. The assumption of relationship is based on triangular currency. Surprisingly, the with modern trading platform, less market boundary and less regulation is easily to observe the discrepancy in price. We find from our study that there is a relationship between cryptocurrency; however, the relationship diminishes after the first Bitcoin futures expire. There is also the observe of arbitrage. We also find evidence that there is a driving to bubble state relationship between Bitcoin and alternative currencies. Furthermore, there is also a relationship that drive to market efficiency in digital money market.

Cryptocurrency, digital currency, is one of latest asset class that is most discussed in these recent year. In 2009, Bitcoin, the first cryptocurrency, was created by anonymous, Satoshi Nakamoto 2009. Unlike fiat money, the belief of Bitcoin is based on decentralize system rather than centralize which requires third party. Not only new asset class, cryptocurrency, was invented by Satoshi Nakamoto, he also introduced the system name Blockchain which being called as “The next big thing after the internet”. Since the popularization of Bitcoin, The Blockchain technology caught all attention on business world to apply and benefit from it. In this study, we focus on trading application.

There are many cryptocurrencies that were created basing on foundation from Bitcoin technology in these following year. The increasing in popularity of Bitcoin comes together with the popularity in cryptocurrency. According to Coinmarketcap, the cryptocurrency’s market capitalization has been grown from 1.3 billion in 2013 to 600 billion in 2017. The market composition at the end of 2017 are Bitcoin(BTC) 38%, Ripple(XRP) 14%, Ethereum(ETH) 11%, Bitcoin Cash(BCH) 7% and others alternative coin 30%.

Discrepancy in cryptocurrency price was documented in several studies. Yermack(2014) documented the evidence that bitcoin price discrepancy for various dominated currencies. Aloosh (2017) also confirmed the discrepancy and even three times from Yermack(2014). Not only documented in literatures, the author also witnesses the discrepancy in cryptocurrencies' price from coin's price that quoted in Thailand exchange, BX, which higher comparing to global average price from Coinmarketcap.

We test the hypothesis on the first five ranked coin at the date of 14 April 2018. These coins represent the capitalization of the market for 70%.

CHAPTER 2
REVIEW OF LITERATURE

Alosh (2017) found that discrepancy price of bitcoin reached its peak at 27% by comparing the quote of bitcoin to major currencies (Euro, Dollar, Sterling). Unlike common commodities, Bitcoin is not priced globally. If the most liquid and highest composition of cryptocurrencies market has price discrepancy, alternative coins should face the same issue. Therefore, we would like to figure that can we take advantage from the price discrepancy by applying the concept from market microstructure.

As mentioned, we believed that price of asset can be decomposed into efficiency price, which represents fundamental of asset, and transitory price, which represent the noise from market friction. Roll (1984) introduced the model, State Space Model, to do the study on permanent component, efficient price, and transitory component, noise. The study applied the model to do study on multiple market listed stocks. They found that there was an information sharing between markets. They also introduced how to use State Space Model with dual price together with cointegration method.

Menkveld et al (2007) applied the State Space Model with dual price for multiple listed stock. Different from previous studies, they attempted to do study on overlapping trading period. Moreover, they used Kalman Filter technique instead of cointegration like Hasbrouck et al (1995). They mentioned the benefit of Kalman Filter by giving these following reasons. The Kalman Filter technique allows them the deal with (i) simultaneous quotes on overlapping period, (ii) dealing missing observations on non-overlapping period and (iii) transient price changes due to "microstructure" effects. They found that price in overlapping period played an important role for price discovery process.

Hendershott and Menkveld (2013) also did the study on price determinant process. They researched on price discovery with risks that intermediaries need to bear. The authors concluded that the intermediaries' risks affected the price discovery process of securities.

Brogaard et al (2014) did the study on high frequency trading with price discovery. They tested whether HFT increase price discovery. SSM and Kalman filter technique were used to decompose price movements into permanent and temporary components and to relate changes in both to HFTs and non-HFTs. Brogaard et al (2014) discovered that high frequency trading help to reduce the transitory component. Therefore, they concluded that high frequency trading helped price discovery process.

Our study would like to apply the SSM and Kalman filter technique to do the study of relationship between cryptocurrency. This methodology would allow us to see the inside of price component which are permanent component and transitory component.

CHAPTER 3
THEORETICAL FRAMEWORK

3.1 Price discovery model

As standard statistical model, we assume that price of securities move follows random walk process. If market friction, obstacle for trading, is absent, assets should be traded at efficient price.

$$m_j = m_{j-1} + w_t$$

The efficient price, as known as permanent component, can be characterized as martingale process. According to martingale property, sequence of efficient price, stochastic variable, is determined by present observed value even given knowledge of all prior observed values. Unfortunately, market friction exists.

By believing that there is an efficient price, observed price can be decomposed into two component which are permanent component and transitory component.

$$p_{i,j} = m_{jt} + s_{ij}$$

However, permanent component and transitory component are unobservable. State Space Model and Kalman Factor technique are used to quantify these two latent components by constructing the structure of permanent component as random walk while autoregressive process for transitory component. The permanent component is the conditioning information is a public information, the conditional expectation is sometimes called the fundamental value or the efficient price of the security. The transitory component is the deviation from expectation of the market. This may represent the speculation part of the asset's movement.

Intuitively, the permanent component of price is constructed on random walk is basing on market efficient hypothesis which mean that we cannot predict the price by using a historical data. On the opposite, the transitory component is constructed on AR(1) process which represent the imperfection of the market. Investors could use historical data to predict the price of the currency.

3.2 State Space Model

State Space Model(SSM) is the model that incorporate the Markov property. The Morkov property states that the future is determined by its past given on the present system state. Thus, state space model is based on belief that current time contains all the past information that is required to predict the future. The model consists of two equations. First, state equation. Second, observation equation.

<u>State equation</u>

$$X_t = \boldsymbol{A}_t \boldsymbol{X}_{t-1} + \boldsymbol{G}\boldsymbol{a}_t$$

<u>Observation equation</u>

$$y_t = \boldsymbol{h}_t' \boldsymbol{X}_t + \varepsilon_t$$

Each matrix helps us to construct the structure of each state variable basing on our theoretical frame work. In this study case, autoregressive process and random walk process.

$\boldsymbol{h}_t$ is a output matrix which determine the relationship between state variables and observed variables. $\boldsymbol{A}_t, transition\ matricx, and\ \boldsymbol{G}_t, volatility\ matrix$ are known matrixes that contain structure of the state system, while $\boldsymbol{a}_t$ and $\boldsymbol{\varepsilon}_t$ represents the process noise. SSM model is one of powerful framework for the analysis of dynamical systems. Unlike model which use exogenous variables to explain variation likes regression, SSM relies on the dynamics of the state variables and the linkage between the observed variables and state variables to draw statistical inference about the unobserved states. The statistical inference technique that we interested is Kalman Filter.

3.3 Kalman Filter

Kalman filter estimation is used together with state space model to estimate the values of a latent, linear, stochastic, dynamic process based on possibly observations. Assuming the distribution of each process, maximum likelihood is used for an estimation. Kalman Filter explore the relationship by using forward filtering, updates the estimation every time a new observation is available, and backward filtering, using complete observation to adjust the estimation.

CHAPTER 4
RESEARCH METHODOLOGY

4.1 Theoretical Model

The assumption of relationship between Bitcoin and alternative coins is based on triangular currency. With these relationship, we would like to test the existence of triangular arbitrage to reduce price discrepancy, the relationship that lead to bubble or more efficient in price.

We separate price into two components as this following equation.

$$P_{i,t} = M_{i,t} + S_{i,t}$$
$$M_{i,t} = M_{i,t-1} + \varepsilon_{i,t}$$
$$S_{i,t} = \emptyset S_{i,t-1} + \emptyset Volume24hrs_{i,t} + \varepsilon_{i,t}$$

$m_{i,t}$ represents permanent component. $s_{i,t}$ represent transitory component. We could notice that function of permanent component is random walk and transitory component is autoregressive. The reason why we put the volume of trading into transitory component as control variable is because it is a liquidity representative. Matching between buyers and sellers is one proxy of asymmetry information. Trading price of asset at some part is determined by asymmetry information. At the same price, informed and uninformed are willing to trade at different amount. Therefore, the volume of trading is one composition of transitory components.

To study an unobserved effect, we apply State Space Model(SSM) and Kalman Filter technique to do the study. We applied the fundamental pricing structure of price discovery process as a framework to form the SSM model

4.2 Scope of Study

We do the study on the first five main coins in cryptocurrency market. These five currencies represent more than 70% of the digital currency market. We apply the relationship of triangular currency arbitrage to do the study.

i. BTC/USD - ETH/USD - ETH/BTC
ii. BTC/USD - XRP/USD – XRP/BTC

iii. BTC/USD - BCH/USD – BCH/BTC

iv. BTC/USD – LTC/USD – LTC/BTC

4.3 Scope of Data

4.3.1 Available Data

The data that we could do at this moment are contain with these fields.

i. Currency
ii. Quoted price term of USD
iii. Quoted price term of BTC
iv. Time Stamp
v. Volume USD 24h
vi. Percent change 1h
vii. Percent change 24h
viii. Percent change 7d

The data was from Coinmarketcap by scraping from its API in every ten minutes.

4.4 Data Segmentation

There was a huge drop in cryptocurrency market in the middle of January 2018. Our observations are based on December 2017 – February 2018. Surprisingly, the drop of the price is the same period as the expiration date of the first futures contract on Bitcoin which provided by CBOE market. Therefore, we would separate the data into three set. According to CBOE Bitcoin futures fact sheet, trading hour of settlement date of contracts is closed at 14:45:00 basing on Chicago time.

1. December 2017 – 17 January 2018 14:45:00 (6,845 observations)
2. 17 January 2018 14:45:00 – February 2018 (6,094 observations)

We are doing this to see is there a relationship change in cryptocurrency market pre and post huge drop in price.

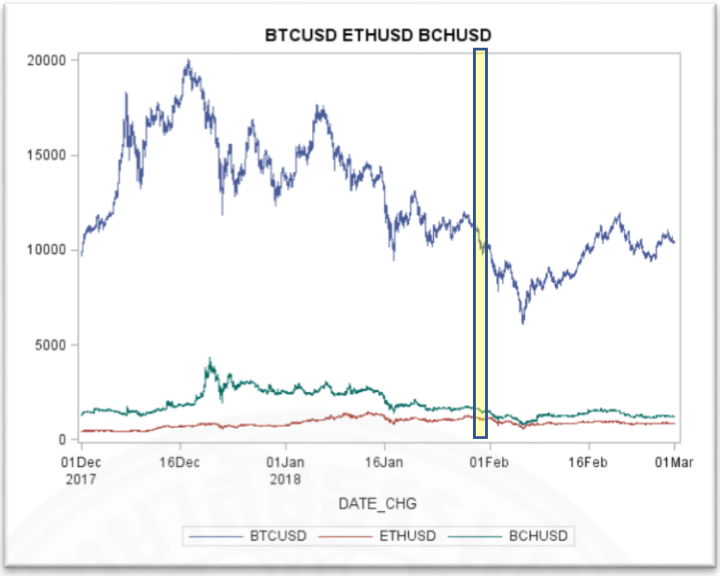

Figure 4.1 Time series of BTC/USD – ETH/USD - BCHUSD

4.5 Data Transformation

Due to dealing with time series data, all the variable that are used need to be stationary. Thus, the price of each cryptocurrency would be changed into log return and volume24hours will be transformed by using I (1) process. Unfortunately, we could not obtain the volume of altcoin with BTC quote at the time. So, we use the volume of BTC/USD as a proxy instead.

4.6 State Space Model Structure and hypothesis

Our ideal model is the model that estimate every relationship at the same time. However, there is a limitation on calculation capacity with maximum likelihood method that cannot deal with that much relationship. Therefore, we separate our calculation into 4 parts first.

Model 1: Permanent component affects Permanent component

```
Currency 1 = M1(t) + S1(t)
M1(t) = M1(t-1)+c(7)M2(t-1) + c(8)M3(t-1) + e
S1(t) = c(1)S1(t-1) + c(2)Q1 + e
```

```
Currency 2 = M2(t) + S2(t)
M2(t) = M2(t-1)+c(9)M1(t-1) + c(10)M3(t-1) + e
S2(t) = c(3)S2(t-1) + c(4)Q2+ e
```

```
Currency 3 = M3(t) + S3(t)
M3(t) = M3(t-1)+c(11)M1(t-1) + c(12)M2(t-1) + e
S3(t) = c(5)S3(t-1) + c(6)Q3 + e
```

Model 2: Permanent component affects Transitory component

```
Currency 1 = M1(t) + S1(t)
M1(t) = M1(t-1) + e
S1(t) = c(1)S1(t-1) + c(2)Q1 +c(7)M2(t-1) + c(8)M3(t-1) + e
```

```
Currency 2 = M2(t) + S2(t)
M2(t) = M2(t-1) + e
S2(t) = c(3)S2(t-1) + c(4)Q2 +c(9)M1(M9t-1) + c(10)M3(t-1) + e
```

```
Currency 3 = M3(t) + S3(t)
M3(t) = M3(t-1) + e
S3(t) = c(5)S3(t-1) + c(6)Q3 +c(11)M1(t-1) + c(12)M2(t-1) + e
```

Model 3: Transitory component affects Permanent component

```
Currency 1 = M1(t) + S1(t)
M1(t) = M1(t-1)+c(7)S2(t-1) + c(8)S3(t-1) + e
S1(t) = c(1)*S1(t-1) + c(2)Q1 + e
```

```
Currency 2 = M2(t) + S2(t)
M2(t) = M2(t-1)+c(9)S1(t-1) + c(10)S3(t-1) + e
S2(t) = c(3)S2(t-1) + c(4)Q2+ e
```

```
Currency 3 = M3(t) + S3(t)
M3(t) = M3(t-1)+c(11)S1(t-1) + c(12)S2(t-1) + e
S3(t) = c(5)S3(t-1) + c(6)Q3 + e
```

Model 4: Transitory component affects Transitory component

```
Currency 1 = M1(t) + S1(t)
M1(t) = M1(t-1) + e
S1(t) = c(1)S1(t-1) + c(2)Q1 +c(7)S2(t-1) + c(8)S3(t-1) + e
```
```
Currency 2 = M2(t) + S2(t)
M2(t) = M2(t-1) + e
S2(t) = c(3)S2(t-1) + c(4)Q2 +c(9)S1(t-1) + c(10)S3(t-1) + e
```
```
Currency 3 = M3(t) + S3(t)
M3(t) = M3(t-1) + e
S3(t) = c(5)S3(t-1) + c(6)Q3 +c(11)S1(t-1) + c(12)S2(t-1) + e
```

Hypothesis Testing

- **i.** Is there any relationship in triangular currency form?
- **ii.** Is there any relationship that increae market efficient in tri-currency relationship?
- **iii.** Is there any relationship that provoke the bubble form tri-currency relationship?
- **iv.** Is there any evidence on arbitrage relationship among tri-currency relationship?

After calculation of 4 previous element, we will keep only relationship that statistically significant above than 85%. Then we will estimate the leftover relationship again to confirm and avoid multicollinearity relationship.

With this framework, there are 10 calculation times per each pair of triangular currencies

4.7 Measurements

4.7.1 Arbitrage Relationship

According to our assumption, the relationship of our tri-currency is based on triangular relationship between BTC/USD, Alternative Coin(ALT)/USD and ALT /BTC. We would interpret that there is an arbitrage, if there are a structure following these relationships. There are three cases of opportunity to do an arbitrage.

Arbitrage is a thing that help asset to discover their fundamental value. Thus, the arbitrage should be caused by the relationship between permanent component, which represent fundamental value.

4.7.1.1 Arbitrage between ALT/BTC to BTC/USD

If permanent component of ALT/BTC affects to permanent component of BTC/USD with positive relationship, there may be an arbitrage between ALT/BTC and BTC/USD.

$$S_{ALT/BTC}\ has\ a\ positive\ relationship\ to\ S_{BTC/USD}$$

4.7.1.2 Arbitrage between ALT/BTC to ALT/USD

If permanent component of ALT/BTC affects to permanent component of ALT /USD with negative relationship, there may be an arbitrage between ALT /BTC and ALT /USD.

$$S_{ALT/BTC}\ has\ a\ negative\ relationship\ to\ S_{ALT/USD}$$

4.7.1.3 Arbitrage between ALT/USD to ALT/BTC

If permanent component of ALT/USD affects to permanent component of ALT /BTC with negative relationship, there may be an arbitrage between ALT /USD and ALT /BTC.

$$S_{ALT/USD}\ has\ a\ negative\ relationship\ to\ S_{ALT/BTC}$$

4.7.2 Relationship Interpretation

4.7.2.1 Permanent component affects Permanent component

The function of BTC, XRP, ETH, BCH and LTC should not share the same fundamental due to differences in the objective. However, there may be the relationship between permanent component which caused by these following scenarios.

- Arbitrage Cases

As mentioned, if there any relationship consistent with the above cases, we would be able to imply that there maybe an arbitrage relationship which drive to efficient market state.

- Adoption Case

If there is a positive relationship above the framework of arbitrage cases, there would be a sign that investors adopt this new asset class. This may cause by the adoption in the new payment system through the blockchain technology.

4.7.2.2 Permanent component affects Transitory component

The relationship could drive into the both scenario, driving to bubble or increasing of efficient in price

- Positive relationship

Increasing in X's permanent component drive the speculation in Y. On the contrary, decreasing in X's permanent component reduce the price discrepancy in Y.

- Negative relationship

Rising in X's permanent component reduce the speculation in Y. However, decreasing in X's permanent component increasing the price discrepancy in Y.

4.7.2.3 Transitory component affects Transitory component

The relationship could drive into the both scenario, driving to bubble or increasing of efficient in price

- Positive relationship

Increasing in X's transitory component drive the speculation in Y. On the contrary, decreasing in X's transitory component reduce the price discrepancy in Y.

- Negative relationship

Rising in X's transitory component reduce the speculation in Y. However, decreasing in X's transitory component increasing the price discrepancy in Y.

4.7.2.4 Transitory component affects Permanent component

This relationship represents bias in investors' pricing. Investors should not incorporate the transitory component which represent the inefficient price into permanent component. Moreover, transitory component should disappear rapidly. This relationship may cause the speculation or underprice in the cryptocurrency

CHAPTER 5
RESULTS

From the first five ranked coins, we observe the relationship between cryptocurrency in both term, driving to bubble and increasing in efficiency. However, the relationship of triangular currency seems to diminish after the first futures contract expires. Bitcoin has less influence on alternative coins less than the prior period. Momentum of each currency plays more role after a huge drop of Bitcoin.

5.1 BTC/USD-ETH/USD-ETH/BTC

The key difference between ETH and BTC is that ETH attract a real demand of coins user. ETH is designed to allow the others coin to use its blockchain and charge gas (Unit of ETH) as a fee. This application allows many coin issuers to do an ICO (Initial coin offering) with ETH's blockchain which creates a real demand for an ETH.

Previous the futures expire, BTC/USD and ETH/USD have a negative relationship on transitory component of each other's. Either increasing in bubble or reducing price discrepancy is based on the speculation of another. Moreover, the permanent component of ETH/USD and ETH/BTC also have a negative relationship to transitory component of each other's. The more positive in permanent component, the less speculation of these two pair currencies.

After the futures expire, the relationship between these three currencies diminish. Momentum gains more influence. However, the relationship is still observed. ETH/USD's transitory component has a negative effect to BTC/USD's which represents the bias in term of underpricing in case that transitory returns of ETH/USD is positive. The more speculation on ETH/USD leads to underprice in BTC/USD's permanent component.

Table 5.1 This table shows the structure of state space model of BTC/USD-ETH/USD-BTC/BTC and statistic measurements in the period before the expiration of BITCOIN futures.

Before 17JAN2018
BTC ETH
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 + C(8)S2(t-1) + e
LnR2(t)[ETH/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 +C(9)S1(t-1) + C(10)M3(t-1) e
LnR3(t)[ETH/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(11)S1(t-1) + C(12)M2(t-1)+ e

Parameters	Value	STD	T Stat	P Value	Significant
C(1)	0.8283	0.0348	23.8031	0.0000	****
C(2)	0.4727	0.0276	17.1117	0.0000	****
C(3)	0.7337	0.0402	18.2632	0.0000	****
C(4)	0.5862	0.0347	16.8843	0.0000	****
C(5)	0.9338	0.0456	20.4977	0.0000	****
C(6)	-0.2811	0.0285	-9.8643	0.0000	****
C(7)	0.0001	0.0039	0.0295	0.9764	
C(8)	-0.1655	0.0461	-3.5915	0.0003	****
C(9)	-0.1985	0.0574	-3.4582	0.0005	****
C(10)	-0.0887	0.0540	-1.6428	0.1004	*
C(11)	0.0473	0.0456	1.0372	0.2996	
C(12)	-0.1014	0.0462	-2.1964	0.0281	***

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

Table 5.2 This table shows the structure of state space model of BTC/USD-ETH/USD-ETH/BTC and statistic measurements in the period after the expiration of BITCOIN futures.

AF 17JAN
BTC ETH
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 + e
LnR2(t)[ETH/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 + e
LnR3(t)[ETH/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + e S3(t) = C(5)S3(t-1) - C(6)Q3 + e

Parameters	**Value**	**STD**	**T Stat**	**P Value**	**Significant**
C(1)	0.99997	0.0029	341.8965	0.0000	****
C(2)	0.34263	0.0474	7.2364	0.0000	****
C(3)	0.83813	0.0280	29.9574	0.0000	****
C(4)	0.53228	0.0357	14.8989	0.0000	****
C(5)	0.99991	0.0101	99.0379	0.0000	****
C(6)	-0.13194	0.0325	-4.0559	0.0001	****
C(7)	-0.06656	0.0337	-1.9768	0.0481	***

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

5.2 BTC/USD-XRP/USD-XRP/BTC

BTC and XRP are different in the way they were invented. The main different is that XRP is created by private company which may be the majority holder of XRP in the market. BTC use Blockchain technology, while XRP use an internal ledger.

Prior the futures expire, the arbitrage between these three currencies is noticed. Permanent component of XRP/BTC and XRP/USD have a negative relationship to each other's. Moreover, XRP/BTC's permanent component is positive to BTC/USD's permanent component. These relationships represent an occurrence of arbitrage. There are relationships that drive to discrepancy in price or lead to efficient in price according to transitory component affects transitory component and permanent component affects transitory component. The biases from transitory component affects permanent component is also observed. These biases lead to bubble and underprice between this three-digital money.

After the futures expire, the diminishing in relationship is also observed. Momentum gains more influence. In this period, the arbitrage is disappeared. Not only diminishing in relationship, the structure of relationship is also change as well. The permanent component of XRP/USD and XRP/BTC have a negative relationship to transitory component of each other's. The increasing in permanent component leads to decreasing in transitory component. The pair of XRP/USD-XRP/USD and XRP/BTC-XRP/USD have a negative relationship on transitory component of each other's. Increasing in bubble or reducing in price discrepancy is determined by the speculation of another.

Table 5.3 This table shows the structure of state space model of BTC/USD-XRP/USD-XRP/BTC and statistic measurements in the period before the expiration of BITCOIN futures.

Before 17JAN2018
BTC XRP
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + C(8)M3(t-1) + C(9)S3(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 + C(10)M3(t-1) + C(11)S3(t-1) + e
LnR2(t)[XRP/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + C(12)M3(t-1) + C(13)S3(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 + C(14)S1(t-1) + C(15)M3(t-1)+ C(16)S3(t-1) + e
LnR3(t)[XRP/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(17)M2(t-1) + C(18)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(19)M1(t-1) + C(20)S1(t-1)+ C(21)M2(t-1)+C(22)S2(t-1) + e

Parameters	Value	STD	T Stat	P Value	Significant
C(1)	0.9056	0.0257	35.2298	0.00%	****
C(2)	0.4370	0.0275	15.8701	0.00%	****
C(3)	0.4638	0.0394	11.7622	0.00%	****
C(4)	1.2910	0.0293	44.1320	0.00%	****
C(5)	0.2609	0.0303	8.6058	0.00%	****
C(6)	-0.1750	0.0234	-7.4711	0.00%	****
C(7)	-0.1439	0.0379	-3.8003	0.01%	****
C(8)	1.0171	0.5557	1.8302	6.72%	**
C(9)	0.6989	0.4464	1.5657	11.74%	*
C(10)	-0.7969	0.5438	-1.4655	14.28%	*
C(11)	-0.4881	0.4361	-1.1193	26.30%	
C(12)	-0.8260	0.1894	-4.3602	0.00%	****
C(13)	-0.8280	0.1901	-4.3550	0.00%	****
C(14)	-0.2317	0.0631	-3.6740	0.02%	****
C(15)	0.5079	0.1889	2.6888	0.72%	****
C(16)	0.0771	0.1856	0.4153	67.79%	
C(17)	-0.1950	0.0283	-6.8898	0.00%	****
C(18)	-0.1951	0.0284	-6.8799	0.00%	****
C(19)	0.4213	0.0416	10.1352	0.00%	****
C(20)	0.3237	0.0301	10.7561	0.00%	****
C(21)	0.0298	0.0538	0.5548	57.90%	
C(22)	-0.4458	0.0349	-12.7826	0.00%	****

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

Table 5.4 This table shows the structure of state space model of BTC/USD-XRP/USD-XRP/BTC and statistic measurements in the period after the expiration of BITCOIN futures.

After 17JAN2018
BTC XRP
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) +C(2)Q1 + C(8)S2(t-1) + e
LnR2(t)[XRP/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + C(9)M3(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 +C(10)S1(t-1) + C(11)M3(t-1) + C(12)S3(t-1) + e
LnR3(t)[XRP/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(13)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(14)M2(t-1) +C(15)S2(t-1)+

Parameters	**Value**	**STD**	**T Stat**	**P Value**	**Significant**
C(1)	0.9162	0.0293	31.3062	0.00%	****
C(2)	0.4130	0.0455	9.0737	0.00%	****
C(3)	0.7171	0.0451	15.8940	0.00%	****
C(4)	0.9510	0.0302	31.5326	0.00%	****
C(5)	0.9941	0.0062	161.3488	0.00%	****
C(6)	-0.0050	0.0229	-0.2181	82.74%	
C(7)	0.0016	0.0043	0.3662	71.42%	
C(8)	-0.1172	0.0327	-3.5798	0.03%	****
C(9)	0.0011	0.0032	0.3430	73.16%	
C(10)	-0.1971	0.0612	-3.2228	0.13%	****
C(11)	-0.5491	0.0451	-12.1829	0.00%	****
C(12)	-0.5369	0.0442	-12.1468	0.00%	****
C(13)	-0.0012	0.0048	-0.2404	81.00%	
C(14)	-0.7531	0.0225	-33.4066	0.00%	****
C(15)	-0.7459	0.0199	-37.4028	0.00%	****

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

5.3 BTC/USD-BCH/USD-BCH/BTC

BCH was built by hard fork from BTC. The objective of BCH is to create the digital currency same as BTC but with faster on transferring speed.

Similar to the above two cases, the relationship between this tri-currencies set is reduced after the huge drop in BTC. Momentum effect also increase the influence among currencies.

Before the huge drop in BTC, the arbitrage occurs from BCH/BTC to BCH/USD according to negative relationship from BCH/BTC's permanent component to BCH/USD's permanent component. Biases from transitory component affects permanent component are also spectated. BCH/BTC's transitory component has a negative influence on BCH/USD's permanent component. The more rising in speculation of BCH/BTC leads to the more underpricing in BCH/USD. Moreover, the relationships of transitory component on transitory component and permanent component on transitory component are also exist among three currencies. This could drive either increasing in efficiency or leading to bubble.

After the huge drop in BTC, the relationship is disappeared. Only the negative relationship between BTC/USD's transitory component and BCH/USD's transitory component is left. Either increasing in bubble or reducing price discrepancy is based on the speculation of another.

Table 5.5 This table shows the structure of state space model and statistic measurements of BTC/USD-BCH/USD-BCH/BTC in the period before the expiration of BITCOIN futures.

Before 17JAN2018
BTC BCH
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + C(8)S3(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 +C(9)S2(t-1) + C(10)M3(t-1) + C(1)*S3(t-1) + e
LnR2(t)[BCH/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + C(12)S3(t-1) + C(13)M3(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 +C(14)S1(t-1) + C(15)M3(t-1) + C(16)S3(t-1) + e
LnR3(t)[BCH/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(17)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(18)M1(t-1) + C(19)S1(t-1) + C(20)M2(t-1) + C(21)S2(t-1) + e

Parameters	Value	STD	T Stat	P Value	Significant
C(1)	0.8537	0.0272	31.3427	0.00%	****
C(2)	0.4642	0.0272	17.0500	0.00%	****
C(3)	0.5757	0.0362	15.9168	0.00%	****
C(4)	1.1143	0.0253	44.0476	0.00%	****
C(5)	0.9919	0.0130	76.1747	0.00%	****
C(6)	-0.1561	0.0208	-7.5160	0.00%	****
C(7)	-0.0394	0.2989	-0.1317	89.52%	
C(8)	0.0012	0.0093	0.1268	89.91%	
C(9)	-0.1575	0.2994	-0.5262	59.88%	
C(10)	0.2273	0.0373	6.0961	0.00%	****
C(11)	0.1956	0.0387	5.0490	0.00%	****
C(12)	-0.3626	0.0732	-4.9530	0.00%	****
C(13)	-0.3635	0.0736	-4.9377	0.00%	****
C(14)	-0.2607	0.0540	-4.8270	0.00%	****
C(15)	-0.1652	0.1045	-1.5815	11.38%	*
C(16)	-0.2184	0.0339	-6.4463	0.00%	****
C(17)	0.1789	1.4163	0.1263	89.95%	
C(18)	0.4669	0.0265	17.6458	0.00%	****
C(19)	0.4290	0.0241	17.8006	0.00%	****
C(20)	-0.5668	0.0196	-28.8814	0.00%	****
C(21)	-0.8002	1.4164	-0.5649	57.21%	

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

Table 5.6 This table shows the structure of state space model and statistic measurements of BTC/USD-BCH/USD-BCH/BTC in the period after the expiration of BITCOIN futures.

After 17JAN2018
BTC BCH
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(6)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 +C(7)S2(t-1) + e
LnR2(t)[BCH/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 +C(8)S1(t-1) + e
LnR3(t)[BCH/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + e S3(t) = C(5)S3(t-1) + e

Parameters	**Value**	**STD**	**T Stat**	**P Value**	**Significant**
C(1)	0.9068	0.0419	21.6456	0.00%	****
C(2)	0.3766	0.0466	8.0751	0.00%	****
C(3)	0.7335	0.0536	13.6731	0.00%	****
C(4)	0.5350	0.0291	18.3623	0.00%	****
C(5)	0.9999	0.0937	10.6727	0.00%	****
C(6)	0.0003	0.0083	0.0327	97.39%	
C(7)	-0.1507	0.0669	-2.2505	2.44%	***
C(8)	-0.1650	0.0923	-1.7877	7.38%	**

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

5.4 BTC/USD-LTC/USD-LTC/BTC

The major difference between LTC and BTC is that the speed of transferring the coin through its blockchain. Like the above cases, the relationship between this tri-currency set is reduced after the first futures expire and the influence from BTC is diminished.

Previous the futures expire, we observed the relationship only transitory component to transitory component and permanent component to transitory component. The inefficient component of BTC/USD, LTC/USD and LTC/BTC are driven by each other's speculation and fundamental information. These could lead either to bubble or efficient in individual currency depending on the price component of others.

The structure of relationship prior and post the futures expire are almost the same. However, the relationship between transitory component of BTC/USD and LTC/USD disappear. Moreover, as mentioned, the momentum gains more influence after the expiration. Bitcoin's influence also diminishes in the period after 17 January 2018 according to the AR(1) coefficient of LTC/BTC is equal to 1. After changing the control variable to volume of LTC/USD, the coefficient of AR(1) process is reduced

Table 5.7 This table shows the structure of state space model and statistic measurements of BTC/USD-LTC/USD- LTC /BTC in the period before the expiration of BITCOIN futures.

Before 17JAN2018
BTC LTC
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 +C(8)S2(t-1) + C(9)S3(t-1) + e
LnR2(t)[LTC/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 +C(10)S1(t-1) + C(11)M3(t-1) + C(12)S3(t-1) + e
LnR3(t)[LTC/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(13)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(14)S1(t-1) + C(15)M2(t-1) + C(16)S2(t-1) + e

Parameters	**Value**	**STD**	**T Stat**	**P Value**	**Significant**
C(1)	0.7420	0.0336	22.0578	0.00%	****
C(2)	0.4950	0.0271	18.2581	0.00%	****
C(3)	0.6590	0.0368	17.9311	0.00%	****
C(4)	1.2690	0.0321	39.5505	0.00%	****
C(5)	0.8558	0.0294	29.1336	0.00%	****
C(6)	-0.2050	0.0249	-8.2249	0.00%	****
C(7)	0.0025	0.0105	0.2350	81.43%	
C(8)	-0.1549	0.0413	-3.7531	0.02%	****
C(9)	0.1800	0.0472	3.8130	0.01%	****
C(10)	-0.2521	0.0565	-4.4655	0.00%	****
C(11)	-0.5329	0.0451	-11.8146	0.00%	****
C(12)	-0.3792	0.0470	-8.0595	0.00%	****
C(13)	0.0033	0.0143	0.2285	81.92%	
C(14)	0.2048	0.0383	5.3490	0.00%	****
C(15)	-0.5601	0.0326	-17.1764	0.00%	****
C(16)	-0.4539	0.0271	-16.7600	0.00%	****

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

Table 5.8 This table shows the structure of state space model and statistic measurements of BTC/USD-LTC/USD- LTC /BTC in the period after the expiration of BITCOIN futures.

After 17JAN2018
BTC LTC
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 + C(8)S2(t-1) + e
LnR2(t)[LTC/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)Q2 + C(9)S1(t-1) + C(10)M3(t-1) + C(11)S3(t-1) + e
LnR3(t)[LTC/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(12)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(13)S1(t-1) + C(14)M2(t-1) + C(15)S2(t-1) + e

Parameters	Value	STD	T Stat	P Value	Significant
C(1)	0.9169	0.0359	25.5224	0.00%	****
C(2)	0.4010	0.0481	8.3355	0.00%	****
C(3)	0.6790	0.0559	12.1371	0.00%	****
C(4)	0.7810	0.0373	20.9344	0.00%	****
C(5)	1.0000	0.0007	1347.9906	0.00%	****
C(6)	-0.0630	0.0303	-2.0797	3.76%	***
C(7)	0.0003	0.0093	0.0345	97.25%	
C(8)	-0.1379	0.0451	-3.0596	0.22%	****
C(9)	-0.1929	0.0824	-2.3416	1.92%	***
C(10)	-0.4010	0.0708	-5.6632	0.00%	****
C(11)	-0.4010	0.0675	-5.9389	0.00%	****
C(12)	-0.0100	3.4607	-0.0029	99.77%	
C(13)	0.0140	0.0194	0.7184	47.25%	
C(14)	-0.4630	0.0446	-10.3843	0.00%	****
C(15)	-0.4300	3.4568	-0.1244	90.10%	

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

Table 5.9 This table shows the structure of state space model and statistic measurements of BTC/USD-LTC/USD- LTC /BTC in the period after the expiration of BITCOIN futures with changing Q3 to volume of LTC/USD.

After 17JAN2018
BTC LTC
LnR1(t)[BTC/USD] = M1(t) + S1(t) M1(t) = M1(t-1) + C(7)S2(t-1) + e S1(t) = C(1)S1(t-1) + C(2)Q1 + C(8)S2(t-1) + e
LnR2(t)[LTC/USD] = M2(t) + S2(t) M2(t) = M2(t-1) + e S2(t) = C(3)S2(t-1) + C(4)*Q2 + C(9)S1(t-1) + C(10)M3(t-1) + C(11)S3(t-1) + e
LnR3(t)[LTC/BTC] = M3(t) + S3(t) M3(t) = M3(t-1) + C(12)S2(t-1) + e S3(t) = C(5)S3(t-1) + C(6)Q3 + C(13)S1(t-1) + C(14)M2(t-1) + C(15)S2(t-1) + e

Parameters	**Value**	**STD**	**T Stat**	**P Value**	**Significant**
C(1)	0.9130	0.0396	23.0501	0.00%	****
C(2)	0.3990	0.0483	8.2657	0.00%	****
C(3)	0.6760	0.0561	12.0455	0.00%	****
C(4)	0.7870	0.0373	21.1155	0.00%	****
C(5)	0.9896	0.0171	57.8273	0.00%	****
C(6)	0.2220	0.0337	6.5905	0.00%	****
C(7)	0.0003	0.0099	0.0312	97.51%	
C(8)	-0.1352	0.0481	-2.8098	0.50%	****
C(9)	-0.1811	0.0827	-2.1884	2.86%	***
C(10)	-0.3913	0.0735	-5.3281	0.00%	****
C(11)	-0.4137	0.0719	-5.7502	0.00%	****
C(12)	0.0005	0.0083	0.0561	95.52%	
C(13)	-0.0059	0.0263	-0.2257	82.14%	
C(14)	-0.4527	0.0492	-9.1947	0.00%	****
C(15)	-0.4824	0.0364	-13.2475	0.00%	****

Note: **** = 99% significant, *** = 95% significant, ** = 90% significant, * = 85% significant

CHAPTER 6
CONCLUSIONS

The study provides the inside of relationship between cryptocurrency by seeing into detail of permanent component which represents fundamental and transitory which represents speculation. Moreover, we also trying to see the shifting of relationship structure by comparing the relationship before and after the huge drop in Bitcoin's price by using the expiration date of the first Bitcoin futures from CBOE market.

All our hypothesis can be observed. The relationship is observed in all 4 observed data set. We found that there are sign of arbitrage in pair of tri-currency. There is also a sign that increasing in fundamental value could decrease the speculation in cryptocurrency. We should present more fundamental information to reduce the speculation in cryptocurrency. The relationship between currencies diminish after the first CBOE's future expire. This may cause by the increasing in power in each currency momentum effect.

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