A modelling of bitcoin price dynamics by the artificial market algorithm*

Yasufumi Shimada

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Abstract

A famous crypto-currency "Bitcoin" was invented in 2009. Since then, we have observed dramatic fluctuation of its price due to the nature of crypto-currency. In other words, the level of the fluctuation seems totally different from the ordinary financial assets like equities, interest rates and foreign exchange rates. Therefore it is afraid that the well-known framework of PDE used for those financial assets, is not suitable to express Bitcoin's dynamics. In this article, an algorithm of artificial market simulation model, so called "150 Agents Model" is proposed to express the fluctuation of Bitcoin price. The model is composed of two types of agents, Traders and Non-Traders, who trade Bitcoin through "itayose" method. The aim of the model is not pricing Bitcoin exactly for trading . Rather it could visualize the structure implied behind the price actions. By calibrating the model to actual price fluctuation of Bitcoin, we are able to see the overall market picture composed of agents to recognize their target prices and price sensitivities as the driver of the price dynamics, to predict the range of next big fluctuation and to recognize how the change of agent's target price and its sensitivity to the price change, affect the landscape of the price range. This model is versatile and flexible. We could add new agents, take new issued amount into consideration, express flash crush and also simulate fluctuation of ordinary financial assets like foreign exchange rates by applying a moderate range of the parameters, which could produce a kind of Elliot Wave dynamics.

Keywords : Bitcoin, crypto-currency, artificial market model, Elliot Wave, flash crush

1 Introduction

Although no one knows the truth of the history that the beginning of money was a stone, in fact it was said that a big stone actually played the role of money in Yap Island. It would not be meaningless to imagine the transition of money from there. It is a stone in the prairie. It has to be as big as a landmark even from a distance, and it is so heavy that people could not move easily. The person A might receive the value for selling the cattle to the person B by the stone. That is, the price of the cattle is the value of the stone in a system that proves that the owner of the stone has changed from the person B to the person A, as the village elders become witnesses.

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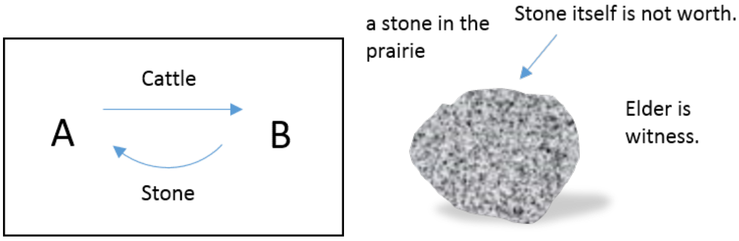
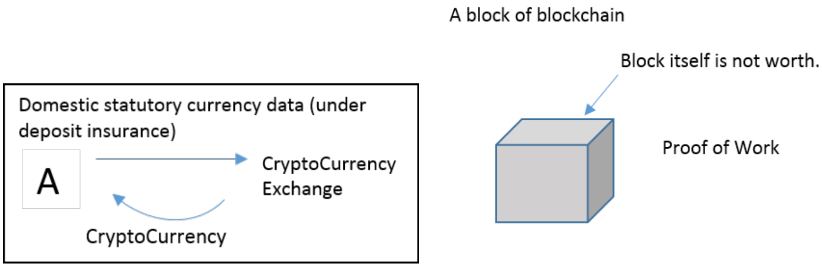


Stone itself is not worth. But the authority of elders guaranteed the stone to be equivalent to the cattle's value based on the thought of the elders. However, the cattle's value (market price) fluctuates with the passage of time due to supply and demand, etc. Therefore, a general geometric Brownian motion might be assumed for the stochastic process. Moreover, if the authority of the elder is somewhat damaged due to political events, etc., it is possible to become worthless. Therefore the value of the stone (V) is the expected value conditional upon the authority as below.

$$V_{stone(t)} = E^{elder}[V_{cattle(t)}|Elder\ has\ Authority]$$
$$SDE\ of\ CattlePrice \quad \frac{dV_{cattle(t)}}{V_{cattle(t)}} = \mu dt + \sigma dB_t$$
$$dB : standard\ brownian\ motion,\ \sigma : volatility \tag{1.1}$$

Time flows. In modern times..

The country might financially collapse. The creditworthiness of deposit insurance is concerned. The risk that deposit tax will finally take place is also increased. So the person A has changed his on-lined deposit to crypto-currency through the crypto-currency exchange. The transaction was recorded in a block of the blockchain.



The crypto-currency itself has no underlying value. As a viewpoint, crypto-currency transactions are triggered by the motivation based on market participants' market views and book prices. And transactions are done at the price where the aggregated amount of supply matches the aggregated amount of demand. (Itayose method) The market view mainly consists of the target price and the sensitivity to price change. Those two factors are assumed to trigger transactions. For each market participant, the trigger point at which new action of trading occurs is unique. However, assuming Itayose method, the price is not determined until the quantity market participants want to buy and the quantity other market participants want to sell matches.

$$V_{bitcoin(t)} = f(Target\ Prices, Price\ Sensitivities, Trigger\ points(bookprices))$$

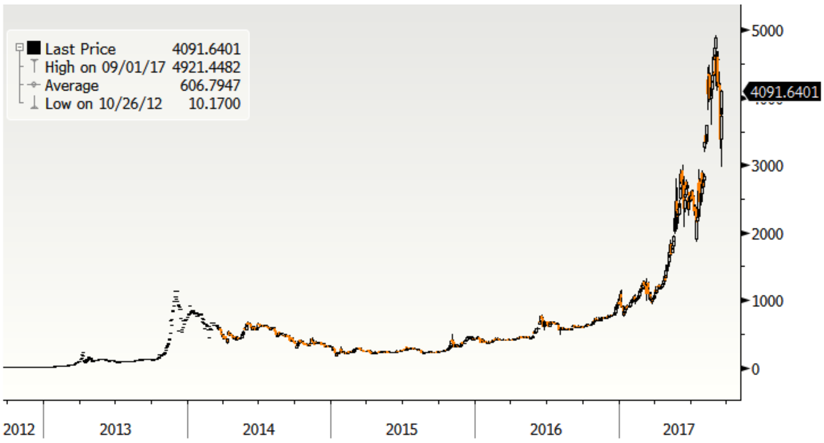


Figure 1: Bitcoin price (US$)（2012/09/12～2017/09/18)（source：Bloomberg)

The above-mentioned formulation of crypto-currency is so abstract that an artificial market simulation model (tentatively called “150 Agents Model”) is proposed here. By this model, specific price fluctuations of a representative crypto-currency, “Bitcoin” is able to be expressed.

2 Bitcoin

Since the most famous crypto-currency “Bitcoin” is invented in 2009, we have observed dramatic fluctuation of its price due to the nature of crypto-currency. In other words, the level of the fluctuation seems totally different from the other financial assets like equities, interest rates and foreign exchange rates. (see Figure1) Because the value of crypto-currency is based on the market participant's market view and behavioral pattern, not underlying asset nor legal authority.

3 An Artificial Market Simulation Model - 150 Agents Model

What is an artificial market simulation model?

Market prices of crypto-currencies are formed from market participants' market views and behavioral patterns as there is no underlying asset or governmental credibility. In such a case, an artificial market simulation model is one of choices. It defines the trade algorithm of each agent to simulate trades automatically among them. As a result, trading algorithm of participants (agents) influence the price movements. For the crypto-currency represented by Bitcoin, an artificial market simulation model is applied to reproduce the past abrupt price movements.

First of all, the mechanism of trading such as preconditions and agents' trading algorithms are specified in the model.

3.1 Preconditions

· **No Short Selling**

Futures market “ Lightning Futures ” for Bitcoin has been opened by bitFyer since April 2017 [1]. It might be better to segregate the observation period into the era without futures market (～March 2017) and the one with futures market where short selling is available (April 2017～). Even though Bitcoin price action after April 2017 is also simulated later in this paper, the model originally focuses on the price before the futures market is open (before April 2017). Therefore the premise here is that the crypto-currency can not be short sold. It is assumed that there are three ways of action ," buy "," stay "(do nothing),"sell " with the two ways of status, “long” (holding position) or "flat" (no position) ".

・Itayose methods

So in the pre-futures market era, the position of agent is “ long ” or “ flat ”. The action is either of “ buy ”, “ stay ” or “ sell ”. (In the post-futures era, the position of agent should be either of “ long ”, “ flat ” or “ short ”.)

It is synonymous with a type whose price is determined by so-called “Itayose”. Issued Bitcoin amount (= The aggregated position amount of all agents) does not change at certain amount. In other words, the aggregated position amount of all agents must be same as the amount at the previous equilibrium where the last price was determined. In this paper, the aggregated position amount is constant at 100.

Although the price is determined in an equilibrium state, a new event or news affecting the price occurs, and the process of shifting to next equilibrium state (Period) is triggered. The model simulates it according to each agent’s algorithm. Events and news affecting the crypto-currency market are, for example, the government’s control to restrict the exchange between domestic currencies and foreign currencies or to strengthen monitoring of the account holders of crypto- currency, listings of ETFs denominated in crypto-currencies, system failures and hacking accidents in exchanges of crypto-currencies, and so on.

・New issuance of Bitcoin

For simplicity, new issuance due to “proof of work” is not considered. (As the extension of the model, it could be applied.)

・No transaction cost

Assume no transaction cost for simplicity.

・Two type of Agents

There are only two types of agents. One is “ Traders ” who take/close position towards his own proprietary target price. The other is “ Non-Traders ” who take/close position by following the market momentum.

Number of each agent: 50 Traders, 100 Non-Traders (Therefore “ 150 Agents Model ”)

Although the number of agents can be arbitrarily determined, the combination of 50 Traders and 100 Non-Traders are proposed in the model as “150 Agents Model”. In real market, relatively small number of traders trade relatively large amounts and dominate the market. The model imitates it. The combination of Traders and Non-Traders could be 100:200, 500:1000, so on. However as shown later in this paper, the ratio of 50:100 seems easy to handle and reasonably enough to express the market fluctuation.

[1] If you use this service, you can buy and sell Bitcoin based on the settlement of value difference. That is to say short sale is possible.

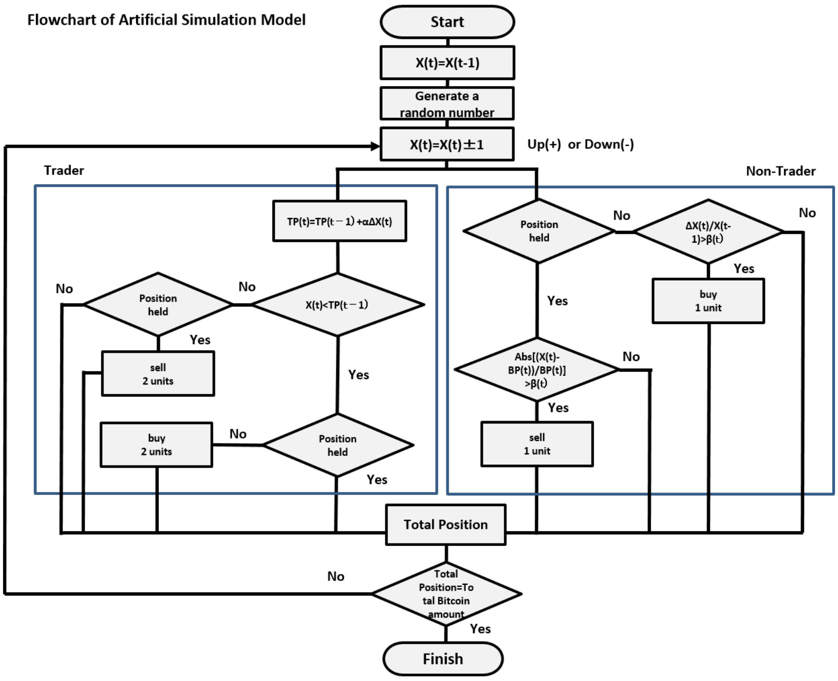


Figure 2:

3.2 Agent's Trade Algorithm

Trader has his own market view (Target Price, Sensitivity) on crypto-currency. On the other hand, those who do not have Target Prices are Non-Traders. The trade algorithm of each agent is specified as follows;

Trader : Each trader has a market view (Target Price (TP), Sensitivity) on Bitcoin. Target Price changes in conjunction with the increase / decrease of Bitcoin price X (t). α_i (i=1,⋯,50) represents $Trader_i$'s price sensitivity. tr_posi_i represents Bitcoin amount held by $Trader_i$.

$$Trader_i's\ Price\ Sensitivity : \alpha_i$$
$$Trader_i's\ TargetPrice : TP_{i(t)} = TP_{i(t-1)} + \alpha_i(X_{(t)} - X_{(t-1)})$$
$$Trader_i'sPositionAmount : tr\_posi_{i(t)} = g(Target\ Price, Price\ Sensitivity) \in 0, 2$$

If the market price is lower than Target Price, Trader makes a purchase of Bitcoin (if there is already a position, Trader does nothing). If the market price is higher than Target Price, Trader makes profit-taking (if there is no position, he does nothing). If Target Price falls below the market price, Trader closes the position. In case, he also cut off the loss depending on the book price. However, it is difficult for loss cut to occur because with the sensitivity below 1, the change of Target Price tends to be smaller than the change of market price.

For simplicity Trader always buys and sells 2 units of crypto-currency.（+ 2：long position, 0：no position）

In summary,

Target Price>$X_{(t)}$： Buy 2 unit if no position is held, otherwise no change

Target Price≤$X_{(t)}$: Sell 2 unit if long position is held, otherwise no change

Non-Trader : Non-Trader buys and sells crypto-currency without his own market view. Non-Trader is going to follow market trend and momentum made by the traders' quotes. In the case that he has a long position, if the market price go away by a certain change or more from his book price (BP), he makes either of profit taking or loss cutting. In the case that he has no position, if market price makes more than a certain change from the equilibrium price of the previous period, he buys a unit. The ratio β_j j= 1, ..., 100 of 1 to 100% is assigned to 100 Non-Traders at 1% increments. It means that if price rises by β or more of previous price , Non-Trader follows the market to make a long, and if price rises further by β from his BP, he makes profit-taking, and if it falls by β or more, he avoids further loss to do so. β represents Non-Trader's risk tolerance. Those with small β have low risk tolerance and those with large β represent those with high risk tolerance. It is assumed that Non-Trader always buys and sells one unit of crypto-currency. This one unit of amount is corresponding to 2 units of Trader's. Usually Non-Trader can not be a price maker like Trader, reflecting the relatively small transaction volume.

Price change $\Delta X_{(t)}$ = $X_{(t)}$-$X_{(t-1)}$

Position held ＋1 : 1 unit long、0 : square

Table 1: Non-Trader's Action

Price move	Position held	Condition(%)	Action
UP	0	$\Delta X_{(t)}/X_{(t-1)} > \beta$	Buy
UP	0	$\Delta X_{(t)}/X_{(t-1)} \leq \beta$	Hold
UP	+1	$(X_{(t-1)} + \Delta X_{(t)})/BP_{(t-1)}$ -1 $\geq \beta$	Sell
UP	+1	$(X_{(t-1)} + \Delta X_{(t)})/BP_{(t-1)}$ -1 $< \beta$	Hold
DOWN	0	$\Delta X_{(t)}/X_{(t-1)} \geq -\beta$	Hold
DOWN	0	$\Delta X_{(t)}/X_{(t-1)} < -\beta$	Hold
DOWN	+1	$(X_{(t-1)} + \Delta X_{(t)})/BP_{(t-1)}$ -1 $\geq -\beta$	Hold
DOWN	+ 1	$(X_{(t-1)} + \Delta X_{(t)})/BP_{(t-1)}$ -1 $< -\beta$	Sell

It is a market-tracking model in which market view of each agent fluctuates in conjunction with market price changes. Trader reflects the tendency in the real market, where the position held per Trader (= volume of transaction) is larger than the one held per Non-trader and the number of Traders is also smaller. Each agent may be interpreted as each group of same type market participants, although they are expressed like individual person in this paper. People who are not entirely interested in crypto-currencies and who own crypto-currency but do not like doing trades in the market are presumed to be out of the market.

The condition under which the new equilibrium price of the crypto-currency is determined is that the sum of the positions held by the market participants must be always same equal to the sum of the market participants' position held at the previous equilibrium price. If there is a deficiency in the overall market position, the unreasonableness that a crypto-currency that someone should have sold is not sold, or that the crypto-currency that should have been bought is not bought take places. It is not in equilibrium.

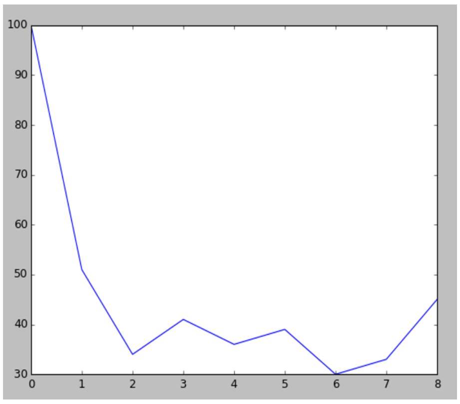


Figure 3: A sample path In the case where all the Target Prices are below 200.

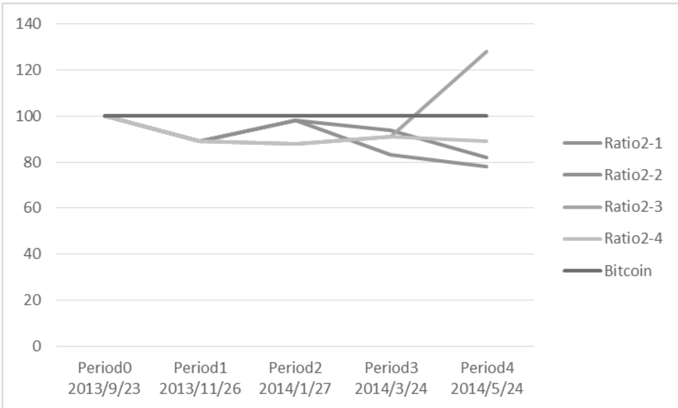


Figure 4: Four paths of highest target price=200、maximum target price sensitivity=0.6 Moderate Trader's Market Views change the equilibrium prices in narrow range.

・Trader: tr_i i=1,⋯,50
・Non Trader: ntr_j j=1,⋯,100
・Non Trader j'sThreshold Price for Action: ntr_sens_j j=1,⋯,100
・Trader's Position Amount: tr_posi_i i=1,⋯,50
・Non Trader's Position Amount: ntr_posi_j
・Issued outstanding held by Traders and Non-traders at a certain point of time (t)
(if we assume that the issued Bitcoin amounts $= \Sigma\ tr\_posi + \Sigma\ ntr\_posi$, it is the entire Bitcoin amounts): all_posi_t
・Bitcoin price at time t ：$X_{(t)}$

Trader's Target Price has become a driver for pricing. In the simulation of crypto-currency, set the initial highestTarget price to 1,500 while the value of the initial crypto-currency is set to 100 in accordance with the actual movement. For example, if you replace this 1,500 by some smaller number, the range of the equilibrium price goes down. For example, assumed that all traders with Target Price below 200, Bitcoin price simulated by the model is 100 or less. Some of the simulated results on Python program are shown in Figure 3 or Figure 4. The price range predicted is low compared to Figure 6. Conversely, if the number is larger than 1,500, the range of the equilibrium

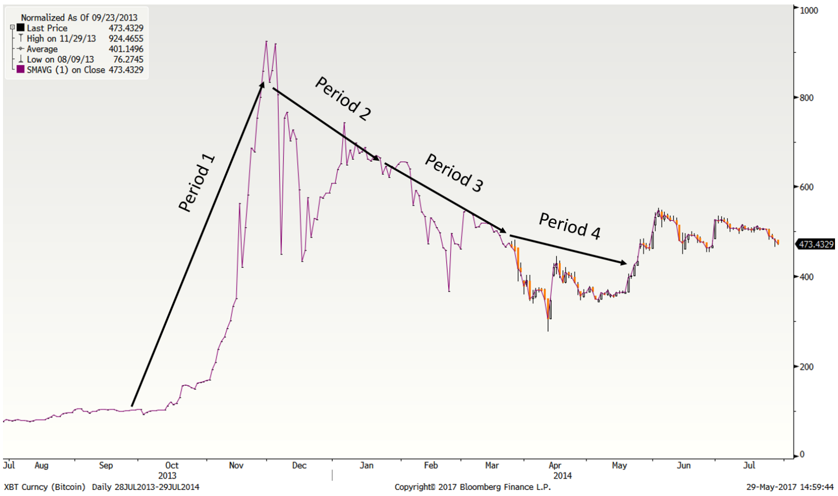


Figure 5: Case 1 - Bitcoin price chart （2013/09/23=100)（source：Bloomberg, Normalized as of 2017/09/23, The author adds the period counts.)

price goes up.

Trader and Non-Trader algorithms are summarized as shown in the chart of Figure2. The chart uses a standard normal random number instead of news on the crypto-currency market. If positive, the price increases, and vice versa. The indicative price changes one by one. In reality, the price jumps with a big news. Instead of moving the indicative price one by one, It might be an choice to let the next price jump depending on the value of random number in the program.

The features of this model are summarized below.

(1) The Target Price of Trader is a driver of equilibrium price. If Traders change their Target Price upward, the equilibrium price would be higher. Conversely, if Traders change their Target Prices downward, the equilibrium price would be lower.

(2) It is a path-dependent model. A branching takes place from the equilibrium price to the next equilibrium price. A branching means that there are multiple equilibrium pries both in upside and downside. (However, it is not guaranteed that a branching occurs always and that the equilibrium occurs always with no parameter change.)

(3) The movement of the equilibrium price can be expressed by calibrating two kinds of parameters: maximum target price sensitivity and highest target price without changing the basic structure of the model. In other words, if the model price tends to be in line with the actual prices movement without recalibrating the parameters every time, the market structure is deemed stable.

3.3 Calibration to the actual markets

Let the model to express actual Bitcoin price movements in 3 cases.

3.3.1 Case 1 - Greek Crisis from September 2013 to September 2014

First significant price fluctuation occurred from September 2013 to September 2014 due to the Greek crisis. The government was going to set the limit of drawdown amount of EURO from the bank account and to replace EURO to new Drachma. People in Greek seemed trying to evacuate their EURO out of regulation in the form of crypto-currency.

The model is set as follows;

Standardize initial price to 100.

Initial setting for each agent's position amount and its book price as follows;

Number of Traders who hold position : 25 (50%)

Number of Non-Trader who hold position : 50 (50%)

The aggregated amount is successfully set as 100 (= 25 x 2 + 50 x 1). The 1:2 ratio of Traders/Non-Traders are related to the ratio of Trader/Non-Trader's position size.

Initial Target price of 50 Traders: [1500, ⋯ ,30] (decreased by 30)

Sensitivities of Target Price for 50 Traders: [0.60, 0.59, ⋯ , 0.11] (decreased by 0.01)

Initial Book Prices of 25 Traders who hold position: [100, 98, ⋯ ,54, 52] (decreased by 2)

Initial Book Prices of 50 Non-Trader who hold position: [100, ⋯ , 52, 51](decreased by 1)

(The author implemented the model both in Python and Spread Sheets.)

Implications One of the key driver is target price of Traders. Higher the target price, the higher Bitcoin price, vice versa. It is not always but sometimes that the model shows multiple equilibrium points on price. In other words, both of upward and downward shift of the market are able to reach to new price. (See graph 7)

A big movement incurred by big news might be the case of large step beyond nearest equilibrium points.

4 equilibrium prices are observed by the model in 8 months. Period 1, 2, 3, 4 represent every two months transition starting at Period 0 (September 23, 2013) with price 100 which is adjusted base from actual price of 123.58 dollars. (Figure 6, Table 2) Ratio 2 - 4 in the Figure 6 is a sampled pass which is comparatively close to actual price movements. Given the up / down shock to the starting price, the model equilibrium price imitates 8 times rise from 100% (actual price of 123.58 US dollars) to 793 (actual price 979.45 US dollars) with the parameters for Period 1. So the initial parameters of maximum target price sensitivity(0.6)、highest target price(1,500) are set to achieve the price equilibrated in the vicinity of US $793 for Period 1. And no more change is added for Period 2 〜 Period 4. Ratio2-1 is set with maximum target price sensitivity=0.5. Ratio2-2 and Ratio2-4 are set with maximum target price sensitivity=0.6. Ratio2-3 is set with maximum target price sensitivity=0.65. Highest target price is common at 1,500.

Table 2: **The equilibrium prices produced by 150 Agents model**

	Period0 2013/9/23	Period1 2013/11/26	Period2 2014/1/27	Period3 2014/3/24	Period4 2014/5/24	max. target price sens.
Ratio2-1	100	870	585	1304	1435	0.5
Ratio2-2	100	750	825	548	1356	0.6
Ratio2-3	100	750	825	548	79	0.65
Ratio2-4	100	750	825	548	581	0.6
Bitcoin	**100**	**793**	**681**	**426**	**481**	

The figure 7 is a view of the case of Ratio 2-3 where the equilibrium price exists in each Period. The vertical axis shows the outstanding balance (the total of the market positions) The horizontal

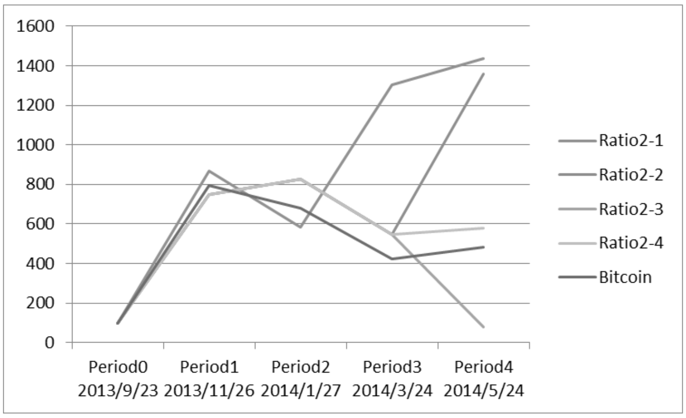


Figure 6: Case 1 - The equilibrium prices by 150 Agents model.

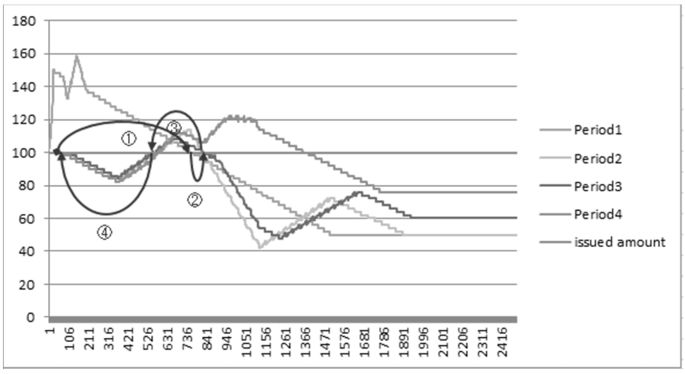


Figure 7: The equilibrium price movement of Ratio2-3 (x-axis：price、y-axis：Outstanding amount of Bitcoin)

axis is the price. Every time the balance is equal to100, the price is fixed as the equilibrium. For example, the equilibrium price starts from 100, 1 in Period 1 → 2 in Period 2 → 3 in Period 3 → 4 in Period 4, From 2 to 3 it can be seen that there are multiple equilibrium points (equilibrium prices) where the outstanding balance is 100 at both points where the price rises and goes down. In some case, they will not converge unless the parameters has to be adjusted. Because there is no guarantee that the model will surely have the equilibrium points (equilibrium prices) on both sides of ascent and descent, . If the model does not converge to the equilibrium price or the actual price, it is necessary to adjust or fit the parameters for each Period. It is difficult to assume that the market view of participants does not change at all in the actual market as well The model is flexibility to express the change in market view.

3.3.2 Case2 - The booming beyond USD 2,000 from January to May 2017

The analysis about what happened to Bitcoin market where the price was skyrocketing from January to May 2017 (see Figure 8) by 150 Agents Model is following. Because Bitcoin's price (USD 1,010) on February 2 divided by 10 is close to 100, the initial price is set as100 in the model. From now on, simply set both Bitcoin and the model prices on 10 USD units base and trace the prices every month (Period 1, 2, 3, 4) during 4 months.

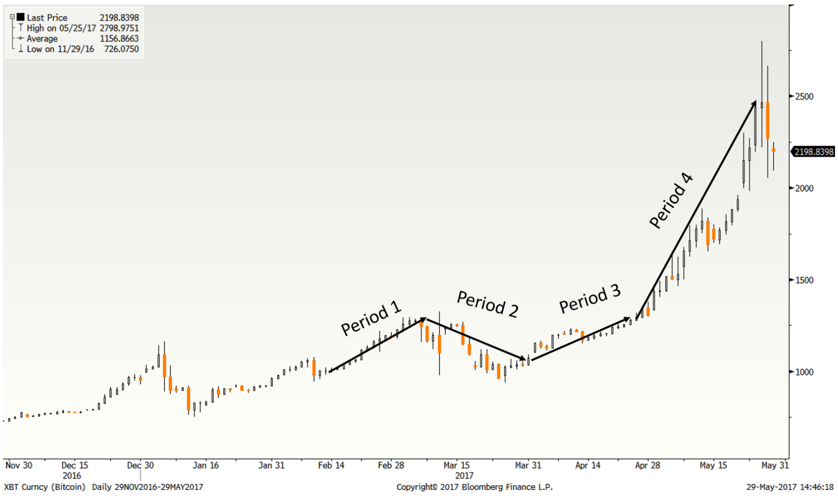


Figure 8: Case 2 - Bitcoin price chart （Source：Bloomberg, The author adds the period counts.)

The result is shown in Table 3. The highest amount of Trader's Target Price is up to 232 (USD 2,320) so that the equilibrium price in the market upward direction rises to 1.25 times from the actual Bitcoin price 101 (USD 1,010) to 125 (USD 1,257) in Period 1. After this modification, equilibrium points were formed at the actual price levels without any major change of parameters for Period 2 and 3. For Non-Trader, it was done to adjust slight deviation (±1) as for the total amount of Bitcoin by fine-tuning the upper limit of sensitivity rate from 1 to 1.02. Regarding large price change from Period 3 to 246 (USD 2,465) of Period 4, it was not formed without additional modification to Target Price after equilibrium of Period 3. So it is possible to recognize on the model that the price view of the market clearly shifted upward. If the Target Price increase is applied uniformly, +130, that is, +USD 1,300 is the value to be added. In this model the target prices of 50 Traders gradually diminish. It is enought to add +250 dollars on the highest Target Price. The interpretation is that the most bullish Trader's market view has risen to 500 (equivalent to USD 5,000).

Table 3: Fitting Model to actual Bitcoin Prices in Case 2 from February 2017 to May 2017 (unit: 10US$）

	Period0 2017/2/2	Period1 2017/3/2	Period2 2017/3/31	Period3 2017/4/28	Period4 2017/5/25	max. target price sens.
Model	100	125	109	125	250	0.6
Bitcoin	**101**	**125**	**107**	**130**	**247**	

3.3.3 Case3 - Reaching to USD 5,000 from May to September 2017

It is also tried to analyze what happened to Bitcoin which reached to USD 5,000 in September 2017 (see Figure 9) by 150 Agents Model. The same parameters are carried over from Case 2. As of February 2 Bitcoin's price (1,010 dollar) divided by 10 is close to the starting point price 100 of the model. So simply set it on USD10 units base to run for Period 1, 2, 3, 4 for 4 months.

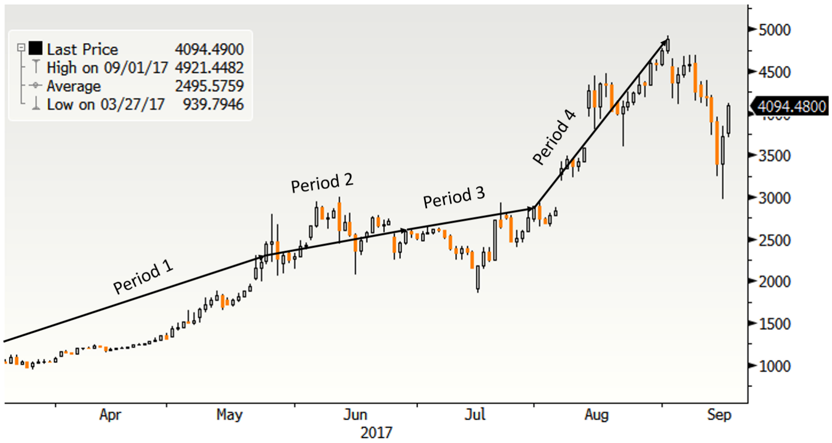


Figure 9: Bitcoin price chart in Case 3（Source：Bloomberg, The author adds the period counts.)

The results are shown in Table 4. Equilibrium points were formed at the level that matched the practicality almost without changing for Period 2 and 3. (For Non-Trader, it was possible to adjust slight deviation (±1) as for the total amount of encryption currency by fine-tuning the upper limit of follow rate from 1.02 to 1.03.) However, regarding the price change from 274 of Period 2 to 491 of Period 3, it was not formed without additional modification to Target Price after equilibrium of Period 3. So it is possible to recognize on the model that the market view of the market clearly shifted upward. As usual, adjustment of the market price of 50 Traders gradually diminishes. If you add +1,360 to the upper limit of Target Price, it equilibrated. The interpretation is that the most bullish Trader's market view has risen to 2,000 around (equivalent to USD 20,000).

Table 4: Fitting Model to actual Bitcoin Prices in Case 3 from May 2017 to September 2017 (unit: 10 USD）

	Period0 2017/2/2	Period1 2017/5/25	Period2 2017/7/3	Period3 2017/8/1	Period4 2017/9/1	max. target price sens.
Model	100	247	256	274	491	0.6
Bitcoin	**101**	**247**	**256**	**274**	**491**	

3.4 Elliot Wave

In addition, it is possible to express Elliott Wave (five waves price action) which is often observed in charts such as foreign exchange rates, stock price indices, commodities etc in this model. (However, it does not take the golden section of strict Elliott Wave theory into consideration at this time.)

Figure 10 is a graph in which the actual USDJPY exchange rate transition is normalized to the exchange rate of 100 at 03/30/2012. By the Elliott Wave method, the main trend is composed of five waves of I, II, III, IV, V, while the correction trend is composed of three waves of a, b, c. As for Elliott Wave, Frost and Prechter's "Elliott Wave Principle" [1] are detailed.

Figure 11 is an example of Elliott Wave-like expression by 150 Agents Model. The setting is moderate to target an exchange rate or stock price index rather than crypto-currency. Imagine the

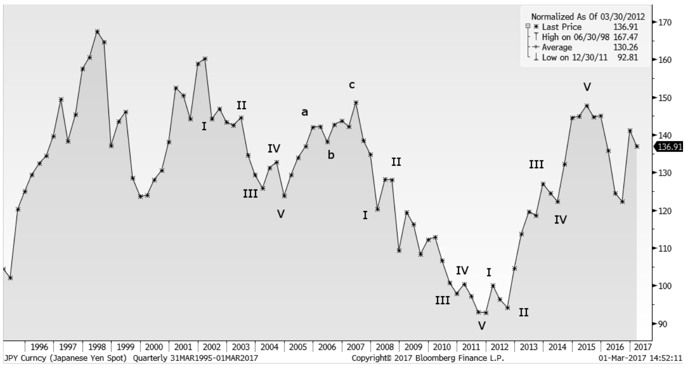


Figure 10: USDJPY Exchange Rate 2012/03/30 is a standardized graph of 100 (Source: Bloomberg, the author added Elliott Wave count on the graph.)

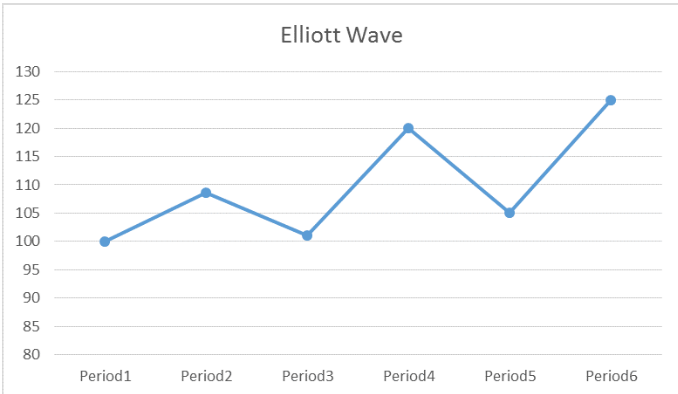


Figure 11: **Elliott Wave-like expression by 150 Agents Model**

exchange rate. Normally, the price moves in a narrow range compared to the encryption currency. It is not expected that two digit percentage change occurs in the price of 100 yen/1USD overnight or in a few days. Therefore, it is set the asset price at 100, set the highest of Trader's Target Price to 120 and the lowest limit to 95.5, reduced by 0.5 step. Also, since the range of fluctuation is small, Sensitivities of Trader's market view are in the range from 100% to 51% with 1% decrement. Non-Trader's Sensitivity decreased from the top of 10% to bottom of 0.1% with decrements of 0.1%. Regarding the initial position holders, Trader side sets the top 25 agents in terms of the market view (Sensitivity is also the same.), Non-Trader side sets the top 50 agents. Trader's book prices are decreased by 0.5 from 100. Because there are 100 Non-Traders, it's book price is reduces by 0.25 each time. This is the only setting. Similarly to the crypto-currency, it is asked for equilibrium prices whose market volume does not change for each period, and extracted patterns that express Elliott Wave's five waves.

3.5 Conclusions

This kind of artificial market model seems useful to simulate dynamics of crypto-currecies because it is not backed by any underlying assets, governmental authorities or other power body. It purely rely on the expectation among the market participants. Even though "150 Agents Model" might

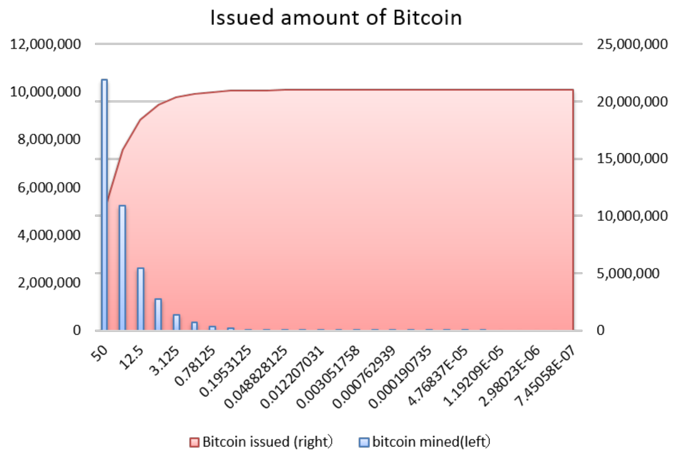


Figure 12:

be one of simplest model in this area, it could succeed to express the dynamics of historical prices and simulate the impact caused by the shift of market views which are defined in the form of target prices and its sensitivities of market participants (Trader, Non-trader) to some extent.

In this way, it is possible to fit the model to the actual price movement by calibrating the parameters. The model is able to tell us where the equilibrium price will be settled next, no matter which direction (upwards or downwards) the next market direction comes out. However real price mechanism seems more complicated. Therefore it is reasonable use cases of the model to estimate Trader's Target Price and Sensitivity as a proxy that are implied in the market and simulate the price with some proxy value changes. The model is able to express the vulnerability of the market like flash crush, where the price can be plummeted from 1,000 USD level to one digit or double digit USD level. It is not the case of Bitcoin. But it is said in the news that on 21 June, 2017 Ethereum briefly plunged in a flash crash from 317.64 dollars to 10 cents before rebounding on Coinbase's GDAX exchange due to the margin call or large stop loss order.

As an extension of this model,
(1) Set the loss limit for each Trader.
(2) Extension of Target Price to Price Range.
(3) Change distribution of uniformly distributed Target Price.
(4) Make it possible to short sell more than the futures market has been made.
(5) It increases outstanding according to the new issue by pow.
etc.
are also possible. Supplementary to the last point (5), Bitcoin is newly issued for pow's reward[2]. However the reward will decrease by half every 210,000 blocks from the original 50 BTC. There is an upper limit because the payment would not be paid if the reward reaches minimum unit 0.00000001 (= 1 satoshi) BTC. See Figure 12 for the image of the issued amount.

In that case, you may increase the number of Traders. It is necessary to set the market view of new Trader to be added. It may be considered to adopt the average value of existing traders as one

[2]Bitcoin experienced several hard folks (Bitcoin Cash, Bitcoin Gold) in 2017.

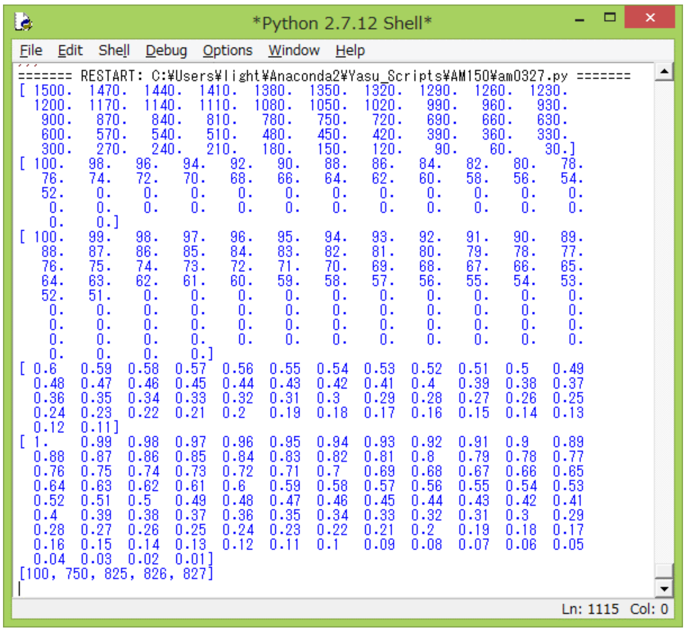


Figure 13: **Output by150 Agents Model on Python Shell.**

option.

The setting of initial book prices is one of the challenges. The model would be improved further in this point.

Figure 13 shows Python shell screen of this model. From top to bottom, Trader's Target Price、Trader's Book Price、Non-Trader's Book Price、Trader's Sensitivity、 Non-Trader's Sensitivity(Threshold)、 Simulated Bitcoin prices for 4 Periods. [3]

References

[1] A.J. Frost and Robert Prechter. *Elliott Wave Principle: Key To Market Behavior*. New Classics Library, 2005.

[2] Y. Shimada, et al. FinTech イノベーション入門 (in Japanese). Asakura Publishing, 2017.

[3]The detail of Python code for this model is shown in Shimada, et al. [2].