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Original Paper

Bitcoin vs. Gold: Who is the Better Choice for Trading?

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Abstract

Venture capital led by Bitcoin and gold has become increasingly popular in the past several years, so the research of cryptocurrencies (such as Bitcoin) becomes deeper and deeper. Many researchers have studied the collaborative investment of bitcoin and gold, which is an expective portfolio. In this paper, the authors constructed a systematic model, achieving the combination among prediction, making strategies, solving profits, and evaluation. All the study in this paper is based on the given data and constructed model with accurate references.

In this paper, the authors selected the long short-term memory model (LSTM) as the basis, then designed two models called the ***gold price prediction model (GPPM) and the Bitcoin price prediction model (BPPM)*** *to estimate the price of both gold and Bitcoin, standing as a trader, not a "god economist". The error analysis shows a good performance of GPPM and BPPM, and it gives the authors confidence to make strategies and calculate final profits (investment worth).*

Unambiguously, the final goal of this question is to maximize the total assets (profits), so the author set up a single objective optimization model (SOOM) called the ***trading strategy model (TSM)****. The total constraint conditions are divided into six directions, including the basic trading conditions, the evaluation of financial risk, and the difference between gold and Bitcoin. Additionally, the costumers with different trading risk tolerance will acquire different assets finally, which indicates that the prudent policy generally can lead to a better result. After calculation, the asset on 2021/9/10 is about* ***1.59×10^8 USD****, a considerable number.*

The evaluation of TSM has two parts, one is the ***disturbance test****. This test randomly sets that several days' trading does not occur, then has a comparison between the original model prices and the prices after disturbance. The result proves that the strategy predicted by TSM is the best strategy. The result of the* ***sensitivity test*** *in section 4 finds the polynomial relationship between the assets and the transaction costs. Under current conditions, the final assets will* ***decrease by 4.2% if*** *the transaction costs of gold*

increase by 1%*, and will* ***increase by 2.1% if*** *the transaction costs of bitcoin* ***increase by 1%****.*

Finally, the authors wrote a memorandum for different customers & traders. We sincerely hope the memorandum can help them in the near future.

Keywords

LSTM, SOOM, Trading Strategy, Disturbance Test, Sensitivity Test

1. Introduction

1.1 Problem Background

Traders always try their best to formulate trading strategies in venture capital, aiming to gain more profits in a certain period of time. In recent years, cryptocurrencies such as Bitcoin have taken a more significant position as an investment asset in the financial markets (Klein, Hien Pham, & Walther, 2018; Baur, Dimpfl, & Kuck, 2018; Long, Pei, Tian, & Lang, 2021). Obviously, Bitcoin has more financial risks, and there is also more consideration about the geopolitical risk and the impact to macroeconomic of Bitcoin (Wu, Tong, Yang, & Derbali, 2019). However, gold is a traditional investment asset with a more stable rate of return, which was a symbol of wealth from Middle Ages (Baur, Dimpfl, & Kuck, 2018), and kept playing an important role in financial markets until now (Ye, Sun, & Miao, 2020).

Many researchers have studied the economic-inner relationship between Bitcoin and gold such as the conditional variance properties, hedging capabilities, etc. (Baur, Dimpfl, & Kuck, 2018; Long, Pei, Tian, & Lang, 2021; Wu, Tong, Yang, & Derbali, 2019; Ye, Sun, & Miao, 2020; Chkili, Ben Rejeb, & Arfaoui, 2021; Guesmi, Saadi, Abid, & Ftiti, 2019), and some of the researchers found that hedging strategies involving Bitcoin will reduce the portfolio’s risk, as compared to the risk of the portfolio without Bitcoin (gold, oil, etc.) (Wu, Tong, Yang, & Derbali, 2019; Guesmi, Saadi, Abid, & Ftiti, 2019). This discovery gives us the confidence to find the best trading strategy of the portfolio made by Bitcoin and gold.

1.2 Problem Analysis

In this question, we already know the daily prices of Bitcoin and gold. However, we cannot stand at the God’s perspective, because the tomorrow’s price is unknown for the traders, which is referenced and forecasted by the asset’s performance on today (Here, you can imagine that you are the trader in the trading center, and the only reference for trading is the previous data, especially the data on today is the most trustworthy.). Due to this, it is necessary to predict the price of both Bitcoin and gold according to today’s price. Here, the first question appears: “How to predict the price of both Bitcoin and gold?”

For the prediction, the team selected long short-term memory (LSTM) model, a popular model that can have deep learning spontaneously by giving financial time-series data (Wang, Wang, Tang, Kumar, & Hsu, 2021; Livieris, Kiriakidou, Stavroyiannis, & Pintelas, 2021; Alkhodhairi, Aljalhami, Rusayni, Alshobaili, Al-Shargabi, & Alabdulatif, 2021; Li, Arab, Liu, Liu, & Han, 2019). Additionally, the conventional model is advanced by the team, and it is evaluated by the daily data from 2016/9/11 to 2021/9/10. The improved model is called gold/Bitcoin price prediction model (**GPPM & BPPM**, will be introduced in section 2). The data used in this model such as mean squared error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) is further discussed with more details in section 2.

If the prediction data is available, we can set up an objective programming model (trading strategy) with specific objective function and a series of constraint conditions. Here, we set up a new model called trading strategy model **(TSM)**. The objective function of TSM is easy to define: the maximum value of profit. There may be some problems to find accurate constraint conditions of TSM. For instance, how to stipulate the date of trading (for Bitcoin, there is no limitation, but for gold, weekend is not allowable.) and how to justify the proportion of Bitcoin and gold (could the proportion change every day or that value maintains a constant in a period?) are the regions that are difficult to define. The questions will be further considered in section 3.

After that, the model will be evaluated by testing the sensitivity of strategy in section 4. Finally, all the model and strategies are concluded in a memorandum. The memorandum is the conclusion of the model we have set up, the strategies we have made up, and the result analyzed by GPPM, BPPM, and TSM.

1.3 Problem Assumption

In section 1.2, it is known that we have two main models: GPPM & BPPM and TSM. In TSM, the assumption is about the type of price of the given data:

- The data is the closing price on each day.
- The unknown data on workdays is dealing with the average price of the day before and after that day (Here, we ignore special days such as holiday). (More details will be shown in section 2.1)
- The strategy is based on the given data of today, and the predictive data given by GPPM & BPPM in section 2.
- The types of traders are based on their ability to assess risk turbulence, we ignore other conditions.

1.4 Notation

Notation	Meaning
$(Pb)_t$	Prediction of Bitcoin price on day t
$(Pg)_t$	Prediction of gold price on day t
G_t	Gold price on day t
B_t	Bitcoin price on day t
$tanh$	Hyperbolic tangent function feedforward network layer
σ	Sigmoid function feedforward network layer
$f_t, W_f, b_f, \widetilde{C}_t, i_t, O_t$	Intermediate quantities in LSTM
n	Total days
y_i	Prediction value on day i
$\hat{y}_i$	Real value on day i

Z	Daily total assets
x_1	The amount of cash (unit: dollar)
x_2	The amount of gold (unit: troy ounce)
x_3	The amount of bitcoin (unit: bitcoin)
C	Bank rate
α_b	Transaction cost of bitcoin
α_g	Transaction cost of gold
Pt	Transaction cost
Pp	The loss to be avoided or gain of each trade
Rg	Risk value of gold
Rb	Risk value of bitcoin
S	Sensitivity

1.5 Problem Framework

The work we have finished is shown in Figure 1. The graph also shows the dispersion of questions and sections of this paper.

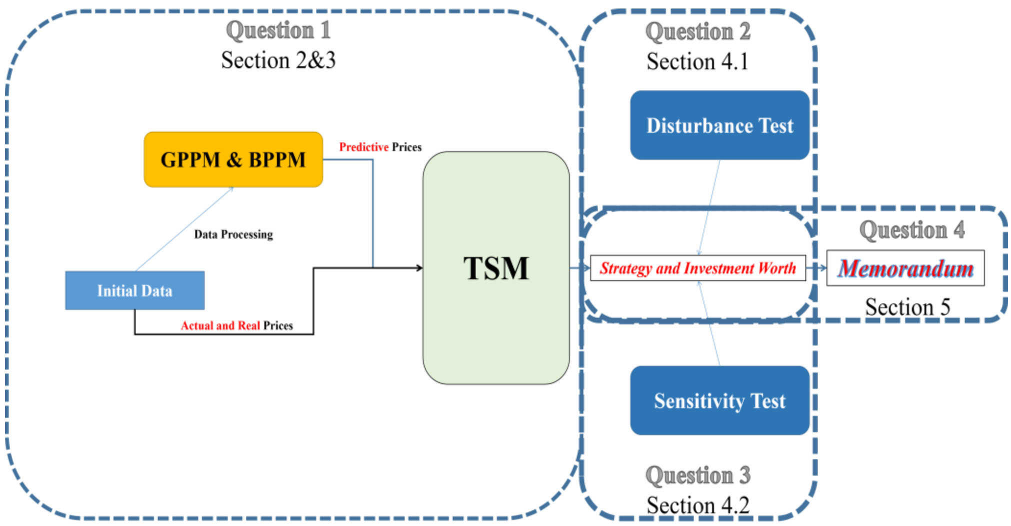


Figure 1. The Framework of This Paper

2. Model for Data Prediction

2.1 Data Processing

As for the data in “LBMA-GOLD.csv”, there are many empty regions in the table. Considering that the dates are workdays, the price of gold must exist, so we use the average value of prices on the days before and after “empty day” to instead of the empty region. For example, on 2020/12/24, the value of price is nothing, we use the average value 1874.65 USD of prices on 2020/12/23 (1875 USD) and 2020/12/29 (1874.3 USD) to instead of the empty region.

The number of empty regions is over 200, so the modification of it makes the data more continuous and reasonable.

2.2 Gold Price Prediction Model (GPPM)

As analyzed in section 1.2, LSTM is the basis of GPPM, and GPPM has all the general structure of LSTM (Livieris, Kiriakidou, Stavroyiannis, & Pintelas, 2021). The most special characteristic of LSTM is shown in Figure 2, whose structure consists of three gates: input gate, output gate, and forget gate, and the cell state (Wang, Wang, Tang, Kumar, & Hsu, 2021). Input gate is used to receive the data, and output gate will export the data (Wang, Wang, Tang, Kumar, & Hsu, 2021). Both two gates can modify and fix the parameters (Wang, Wang, Tang, Kumar, & Hsu, 2021). Additionally, the forget door could determine the state information before reservation, which controls how much historical information be remembered (Wang, Wang, Tang, Kumar, & Hsu, 2021). Three gates can help the model study through the experience to handle and predict the delay time sequence, and it is the most specific property of GPPM.

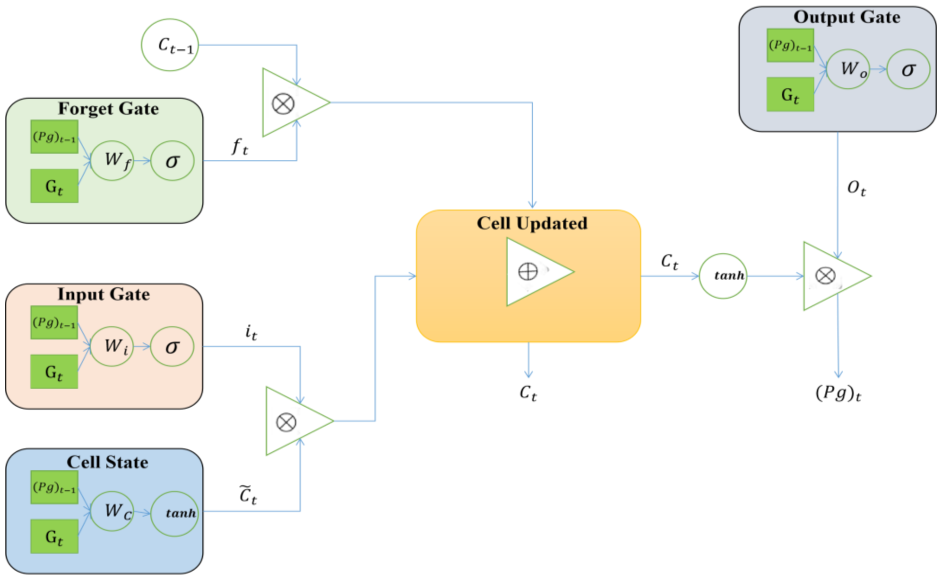


Figure 2. Flow Chart of GPPM

There are four parts to gain the predictive prices of gold, and each part has one or two steps. Here, σ is excitement function, and it decides the proportion of output information (the value of σ is from 0 to 1, if $\sigma = 1$, all the information will be output; if $\sigma = 0$, there is not any information can be output.). The values of $G_t, (Pg)_{t-1}$ are given.

Step 1: Calculation of excitement value f_t for forget gate when the time is t.

The excitement value called f_t defines how much information will be delated or forgotten according to the state of cell in equation (1).

$$f_t = \sigma\left(W_f \circledast (G_t, (Pg)_{t-1}) + b_f\right) \quad (1)$$

Here, W_f and b_f are the weights and offset values for the forget gate.

Step 2: Calculation of excitement value i_t for input gate, and the candidate status $\widetilde{C_t}$ for input cell.

Firstly, the candidate status of input cell is controlled by function $tanh$, and the value of $\widetilde{C_t}$ determines the details of updated information through equation (2):

$$\widetilde{C_t} = tanh(W_C \circledast (G_t, (Pg)_{t-1}) + b_C) \tag{2}$$

Here, W_c and b_c are the weights and offset values for the cell state.

Secondly, the excitement value called i_t defines how much information will be updated and added according to the state of cell in equation (3).

$$i_t = \sigma(W_i \circledast (G_t, (Pg)_{t-1}) + b_i) \tag{3}$$

Here, W_i and b_i are the weights and offset values for the input gate, to make sure the proportion of remaining information.

Step 3: Calculation of updated state C_t of input cell.

The updated state is related to both the input gate and forget gate, the remaining information from the old cell and the new information from input gate updates the cell through equation (4).

$$C_t = f_t \circledast C_{t-1} + i_t \circledast \widetilde{C_t} \tag{4}$$

Step 4: Calculation of the final output value h_t.

Firstly, the proportion of output information O_t is defined by equation (5):

$$O_t = \sigma(W_O \circledast (G_t, (Pg)_{t-1}) + b_O) \tag{5}$$

Secondly, the final output value $(Pg)_t$ is determined by equation (6):

$$(Pg)_t = O_t \circledast \tanh(C_t) \tag{6}$$

2.3 Bitcoin Price Prediction Model (BPPM)

BPPM is quite similar to GPPM, all the principles are same, and the process is clearly shown in Figure 3.

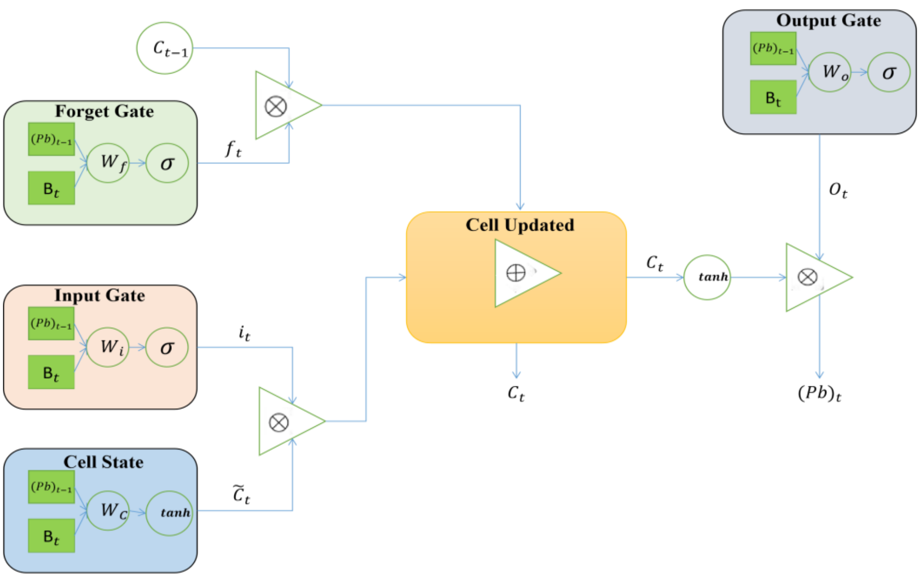


Figure 3. Flow Chart of BPPM

There are also four steps to gain the predictive prices of Bitcoin, and the values of $B_t, (Pb)_{t-1}$ are given, too. All the equations for BPPM are listed as follows:

The excitement value $f_t{}'$ for the forget gate:

$$f_t{}' = \sigma'\left(W_f{}' \circledast (B_t, (Pb)_{t-1}) + b_f{}'\right) \tag{7}$$

The candidate status $\widetilde{C_t}{}'$ for input cell, and the excitement value $i_t{}'$:

$$\widetilde{C_t}{}' = tanh(W_C{}' \circledast (B_t, (Pb)_{t-1}) + b_C{}') \tag{8}$$

$$i_t{}' = \sigma'(W_i{}' \circledast (B_t, (Pb)_{t-1}) + b_i{}') \tag{9}$$

The updated state $C_t{}'$of input cell

$$C_t{}' = f_t{}' \circledast C_{t-1}{}' + i_t{}' \circledast \widetilde{C_t}{}' \tag{10}$$

The proportion of output information $O_t{}'$ and the final output value $(Pb)_t{}'$

$$O_t{}' = \sigma'(W_O{}' \circledast (B_t, (Pb)_{t-1}) + b_O{}') \tag{11}$$

$$(Pb)_t{}' = O_t{}' \circledast \tanh(C_t{}') \tag{12}$$

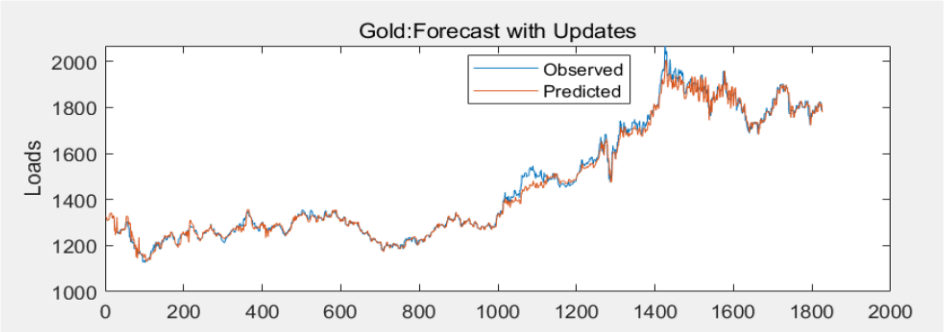
2.4 Prediction Result

Initially, we consider that the traders need several days to observe and justify the markets of gold and Bitcoin. Therefore, we assume that the price of gold from 2016/9/10 to 2016/9/23 and that of Bitcoin from 2016/9/10 to 2016/9/23 are known to predict the following prices.

By applying GPPM, the forecast value of gold's price is shown in Figure 4(a), where the blue line reflects the observed price in the given data, and the orange line shows the predictive prices. Furthermore, it is necessary to determine the error of the prediction, and we selected root mean squared error (RMSE) by equation (13), and the result of error analysis is shown in Figure 4(b).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

(a)



(b)

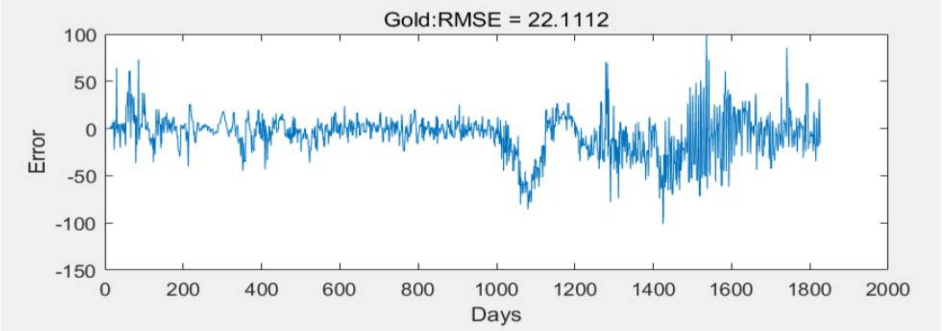


Figure 4. (a) The Forecast Prices of Gold (in Orange) with the Initial Data (in Blue); (b) The RMSE Result of Gold

The result in Figure 4 shows that gold is a stable asset, indicates that the prediction of gold's price is accurate, because the mean RMSE is only 22.11. It also shows that the prediction maybe not correct if the market is unnormal and unnatural.

Similarly, the price of Bitcoin is predicted by applying BPPM that is shown in Figure 5(a), and the error analysis by RMSE is shown in Figure 5(b).

(a)

(b)

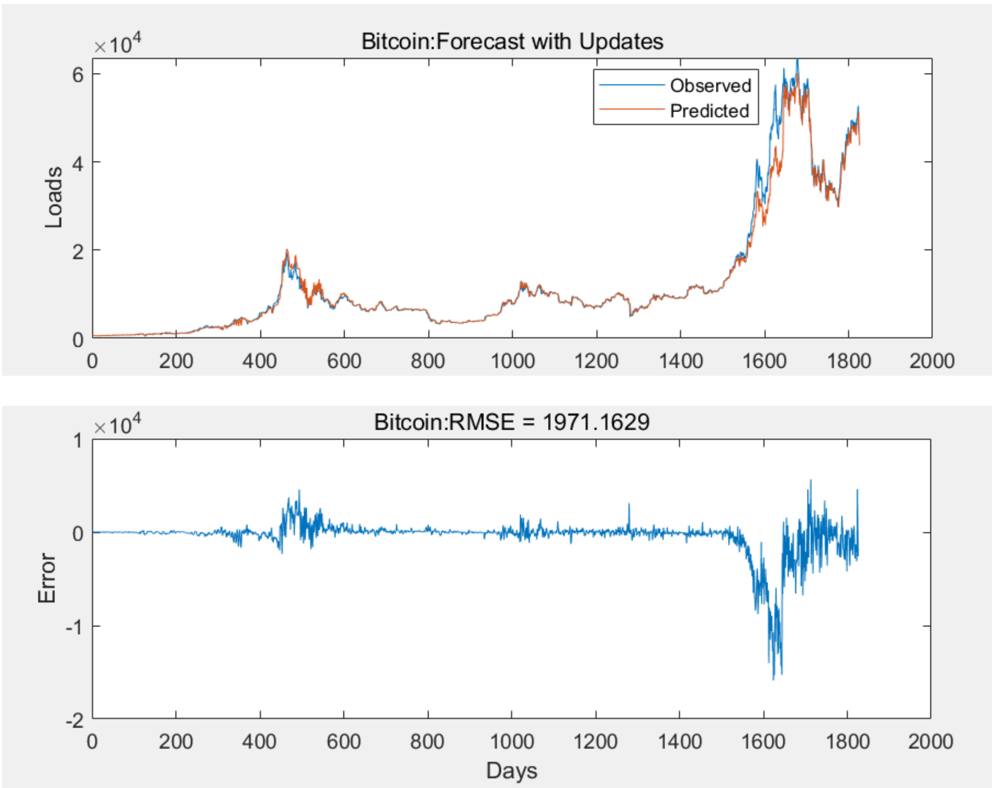


Figure 5. (a) The Forecast Prices of Bitcoin (in Orange) with the Initial Data (in Blue); (b) The RMSE Result of Bitcoin

The result in Figure 5(a) clearly reflects that Bitcoin is an asset with higher risk than gold, especially the trend in 2020, the price of Bitcoin increased about 5~6 times than the initial one. This kind of trend is difficult to predict accurately, which is deeply impacted by the bubble economy (Alkhodhairi, Aljalhami, Rusayni, Alshobaili, Al-Shargabi, & Alabdulatif, 2021). The unstable trend is also proved by RMSE result in Figure 5(b), the great influence caused by the bubble and inflation makes a large average RMSE: 1971.16, about 90 times higher than that of gold. However, the adjustment ability of GPPM & BPPM is strong, so that the model can give an approximately approached price after the series increasing or dropping of the market.

3. Model for Trading Strategy

3.1 Introduction to Trading Strategy Model (TSM)

We have already known that the final goal of the trading strategy is the maximum of profit that is set as the objective function. Distinctly, we set a single objective optimization model (SOOM) called trading strategy model (TSM) to find the maximum value of profit (Fang, Zou, Tang, Wu, Zhang, Jiang, Wang, & Chen; Liu, Yu, Zhu, & Wu; Fan, Yuan, & Cheng; Zhang, Wang, Liu, Zhao, & Pei; Saye, Lutenegger, Brown, & Kumm, 2016; Gil-Alana, 2004).

The interest rate of dollar (USD), the actual gold and Bitcoin's prices of the day before that day, and the forecast gold and Bitcoin's prices on that day are applied to construct TSM. Particularly, the decision variables are the dollar, gold and Bitcoin held on that day. Also, the constraint conditions include "The profit on that day must be greater than the transaction costs", "The amount of certain product purchased on that day is greater than 0", "The maximum transaction amount is the total price of assets on that day", and etc. All the constraint conditions will be further discussed in section 3.2.

3.2 Model Analysis

Firstly, we consider the objective function that is shown in equation (14), and it maximizes daily total assets:

$$max\ Z = x_1(n)(1+C) + x_2(n)Pg(n)\left(1-\alpha_g\right) + x_3(n)Pb(n)(1-\alpha_b) \tag{14}$$

Secondly, we think about the constraint conditions from six directions:

(1) The loss to be avoided or gain of each trade are more than the commission for each transaction that is shown from equation (15) to equation (17):

$$Pt = |x_2(n) - x_2(n-1)|Pg(n-1)\alpha_g + |x_3(n) - x_3(n-1)|Pb(n-1)\alpha_b \tag{15}$$

$$Pp = \left|\begin{matrix}[x_1(n) - x_1(n-1)] + [x_2(n)Pg(n) - x_2(n-1)Pg(n-1)] + \\ [x_3(n)Pb(n) - x_3(n-1)Pb(n-1)]\end{matrix}\right| \tag{16}$$

$$Pt \le Pp \tag{17}$$

(2) The amount of a product on one day shall not be less than 0, and shall not be more than the amount of the product purchased by all the assets held on the day before that day, which is shown from equation (18) to equation (20):

$$0 \le x_1(n) \le x_1(n-1) + x_2(n-1)Pg(n-1)\left(1-\alpha_g\right) + x_3(n-1)Pb(n-1)(1-\alpha_b) \tag{18}$$

$$0 \le x_2(n) \le x_2(n-1) + \frac{x_1(n-1) + x_3(n-1)Pb(n-1)(1-\alpha_b)}{Pb(n)} \tag{19}$$

$$0 \le x_3(n) \le x_3(n-1) + \frac{x_1(n-1) + x_2(n-1)Pg(n-1)\left(1-\alpha_g\right)}{Pg(n)} \tag{20}$$

(3) The amount of money left over from one day should be equal to the amount left over from the day before that day plus the amount of money taken out after that day that is reflected by equation (21):

$$x_1(n) = x_1(n-1) - \left(x_2(n) - x_2(n-1)\right)Pg(n)\left(1-\alpha_g\right) - \left(x_3(n) - x_3(n-1)\right)Pb(n)(1-\alpha_b) \tag{21}$$

(4) Also, there is no trade of gold on weekends:

$$x_2(n) - x_2(n-1) = 0, n = 7m+1\ or\ n = 7m+7\ (m \in N) \tag{22}$$

$$Pg(n) = Pg(n-1), n = 7m + 7\ (m \in N) \tag{23}$$

$$Pg(n) = Pg(n-2), n = 7m + 1\ (m \in N) \tag{24}$$

(5) The risk evaluation for both gold trading and Bitcoin trading:

As for gold trading, the standard deviation σ_g, the accuracy of prediction r_g, and the final trading risk Rg are defined by equation (25) to equation (27):

$$\sigma_g = \sqrt{\sum [Pg(n-1) - G(n-1)]^2} \tag{25}$$

$$r_g = 1 - \frac{Pg(n-1) - G(n-1)}{G(n-1)} \tag{26}$$

$$Rg = \frac{\sigma_g}{r_g} \tag{27}$$

Similarly, for Bitcoin trading: the standard deviation σ_b, the accuracy of prediction r_b, and the final trading risk Rb are defined by equation (28) to equation (30):

$$\sigma_b = \sqrt{\sum [Pb(n-1) - B(n-1)]^2} \tag{28}$$

$$r_b = 1 - \frac{Pb(n-1) - B(n-1)}{B(n-1)} \tag{29}$$

$$Rb = \frac{\sigma_b}{r_b} \tag{30}$$

Rg and Rb are normalized.

(6) We consider that the risk for traders with different trading risk tolerance (risk capacity), and we divide the customers into three teams:

<1> Balance traders (R_1): There is a certain amount of risk of product, and the return (profit) fluctuates to some extent. When the normalized risk is greater than 0.02, the transaction will not occur:

$$x_2(n) - x_2(n-1) = 0, Rg > 0.02 \tag{31}$$

$$x_2(n) - x_3(n-1) = 0, Rb > 0.02 \tag{32}$$

<2> Advanced traders (R_2): The risk for advanced customers is larger than that of R_1, when the normalized risk is greater than 0.04, the transaction will not occur:

$$x_2(n) - x_2(n-1) = 0, Rg > 0.04 \tag{33}$$

$$x_2(n) - x_3(n-1) = 0, Rb > 0.04 \tag{34}$$

<3> Brave traders (R_3): This term of customers will ignore the financial risk, so there is no limitation for their transaction.

Comprehensively considering the conditions listed from six directions, we selected (R_1) customers as an example to show the set of constraint conditions in equation (35):

$$
s.t.\begin{cases}
Pt \le Pp \\
0 \le x_1(n) \le x_1(n-1) + x_2(n-1)Pg(n-1)\left(1-\alpha_g\right) + x_3(n-1)Pb(n-1)(1-\alpha_b) \\
0 \le x_2(n) \le x_2(n-1) + \dfrac{x_1(n-1) + x_3(n-1)Pb(n-1)(1-\alpha_b)}{Pb(n)} \\
0 \le x_3(n) \le x_3(n-1) + \dfrac{x_1(n-1) + x_2(n-1)Pg(n-1)\left(1-\alpha_g\right)}{Pg(n)} \\
x_1(n) = x_1(n-1) - \left(x_2(n) - x_2(n-1)\right)Pg(n)\left(1-\alpha_g\right) - \left(x_3(n) - x_3(n-1)\right)Pb(n)(1-\alpha_b) \\
x_2(n) - x_2(n-1) = 0, n = 7m+1 \ or \ n = 7m+7 \\
Pg(n) = Pg(n-1), n = 7m+7 \\
Pg(n) = Pg(n-2), n = 7m+1 \\
x_2(n) - x_2(n-1) = 0, Rg > 0.02 \\
x_2(n) - x_3(n-1) = 0, Rb > 0.02
\end{cases} \tag{35}
$$

Combining with equation (14), TSM is constructed successfully.

3.3 Result and Further Discussion

Through equation (14) and equation (35), the initial 1000$ investment worth Z_{R_1} on 2021/9/10 is:

$$Z_{R_1} = 1.59 \times 10^8 \ (USD) \tag{36}$$

Here, we reset TSM with the changing of trader teams to have a further discussion about the impacted caused by the strategy to financial risk.

As for the traders without considering risk, the initial 1000$ investment worth Z_{R_3} on 2021/9/10 is:

$$Z_{R_3} = 1.02 \times 10^8 \ (USD) \tag{37}$$

Additionally, we deeply discussed the variation of total assets for different teams of traders in Figure 6. R_1 traders have the best assets finally, and the team without considering risk will gain about two thirds assets than R_1's. The result also indicates that the prudent policy generally can lead a better result. We will have a further discussion about the strategy in section 5. For more specific strategies, please see Appendix B.

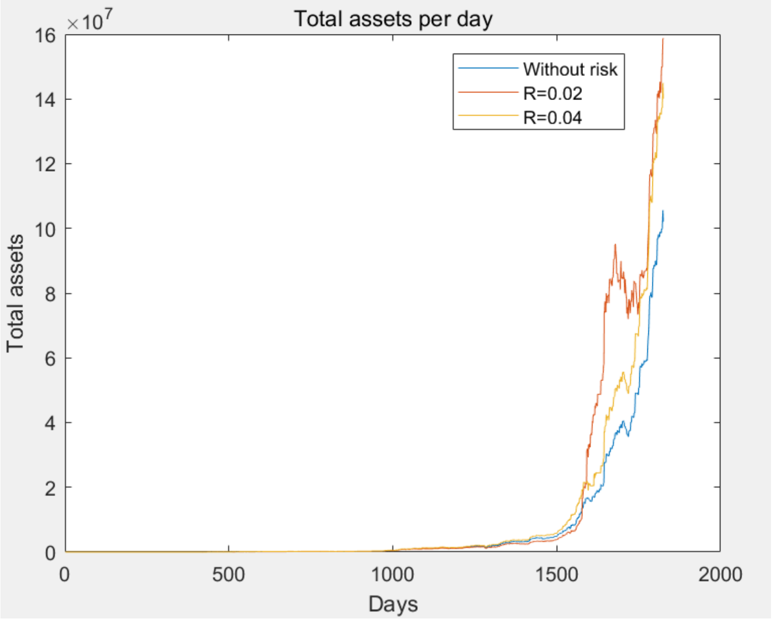


Figure 6. The Total Assets Variation with Different Teams

4. Model Evaluation

4.1 Disturbance Test

The result in section 3 is local optimum strategy on each day. This phenomenon is normal because nearly nobody can make a specific strategy that is instructive and useful in five years, the true strategy is changing as time goes by, and it is also the policy we have followed in the previous study. To prove the strategy we have gained is the best one, the team used disturbance test. The principle of disturbance test is that: firstly, we randomly select a day with a trading with Bitcoin and gold, after that, we cancel the trading, finally, we predict the assets of several days after the selected day and have a comparison between the assets with trading and that without trading (Saye, Lutenegger, Brown, & Kumm, 2016; Gil-Alana, 2004).

How does the disturbance test work? In this section, the decision of trading is made by TSM, whose goal is to gain a higher asset. Here, we simulate that if the trader queries with the strategy defined by TSM, and he & she decides to cancel the trading on that day, then we can estimate the assets after that day by TSM. If the assets after that day are not impacted by the trader's decision, or the assets are higher than the prediction, TSM is failed to achieve its initial goal. However, if the situation is opposite, this phenomenon proves that TSM finishes its task and gives the trader a better strategy to gain more assets.

In Figure 7, the team randomly selected 4 days, and cancelled these days' trading. The lines in blue are the total assets with trading on the random days, and the values of total assets are greater or equal to the assets on the days without trading (lines in orange). The result proves that the strategy of trading is correct, which can make the assets higher.

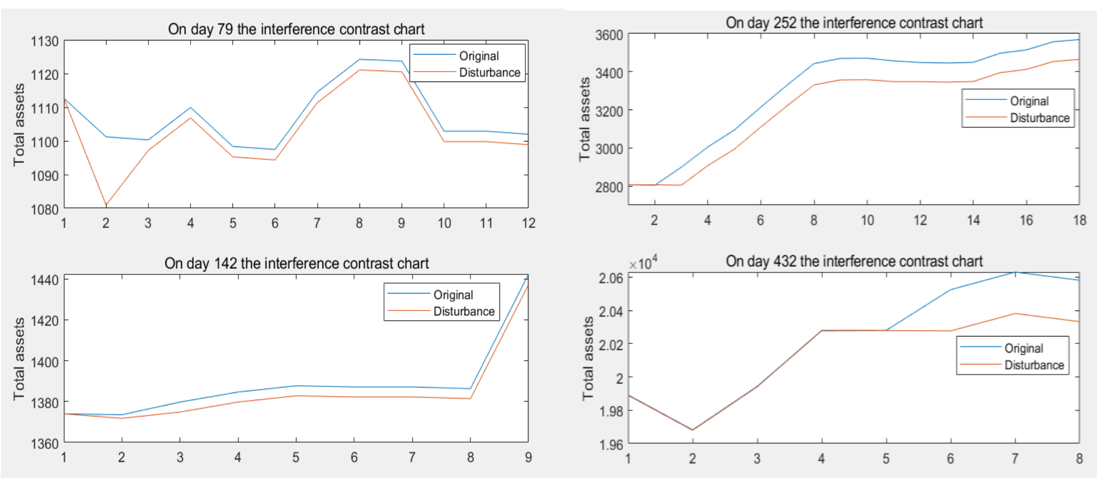


Figure 7. The Disturbance Test on (a) Day 79; (b) Day 142; (c) Day 252; (d) Day 432

4.2 Sensitivity Test by Transaction Costs

To determine how sensitive the strategy is to transaction costs, we discuss the transaction costs of gold and bitcoin separately. The change of strategy can be indicated by the change of total assets. Therefore, sensitivity coefficient refers to the degree to which changes of transaction cost bring changes to the total assets value under the condition that other conditions remain unchanged. Low sensitivity indicates good stability of the model. According to constraint conditions, the loss to be avoided or gain of each trade are more than the commission for each transaction, which indicates that the change of transaction costs can change the number of transactions in the strategy. The larger transaction costs, the smaller number of transactions.

Sensitivity of the strategy to transaction costs of gold

We choose several different α_g around 1% and calculate corresponding assets, so that we can get the sensitivity relation between Z and α_g. Polynomial curve is used to fit the points.

$$Z(\alpha_b) = p_0{\alpha_b}^k + p_1{\alpha_b}^{k-1} + p_2{\alpha_b}^{k-2} + \cdots + p_k \tag{38}$$

$$R^2 = 1 - \frac{S_e}{S_t} \tag{39}$$

The change of strategy can be indicated by the change of total assets. Therefore, sensitivity coefficient refers to the degree to which changes of transaction cost bring changes to the total assets value under the condition that other conditions remain unchanged.

$$S(Z, \alpha_g) = \frac{dZ/Z}{d\alpha_g/\alpha_g} = \frac{dZ}{d\alpha_g} \cdot \frac{\alpha_g}{Z} \tag{40}$$

Sensitivity of the strategy to transaction costs of Bitcoin

We choose several different α_b around 2% and calculated corresponding assets, so that we can get the sensitivity relation between Z' and α_b. Polynomial curve is used to fit the points.

$$Z'^{(\alpha_b)} = {p'}_0{\alpha_b}^{k'} + {p'}_1{\alpha_b}^{k'-1} + {p'}_2{\alpha_b}^{k'-2} + \cdots + {p'}_{k'} \tag{41}$$

$$R'^2 = 1 - \frac{{S'}_e}{{S'}_t} \tag{42}$$

The change of strategy can be indicated by the change of total assets. Therefore, sensitivity coefficient refers to the degree to which changes of transaction cost bring changes to the total assets value under the condition that other conditions remain unchanged.

$$S'^{(Z', \alpha_b)} = \frac{dZ'/Z'}{d\alpha_b/\alpha_b} = \frac{dZ'}{d\alpha_b} \cdot \frac{\alpha_b}{Z'} \tag{43}$$

Sensitivity of the strategy to transaction costs of gold

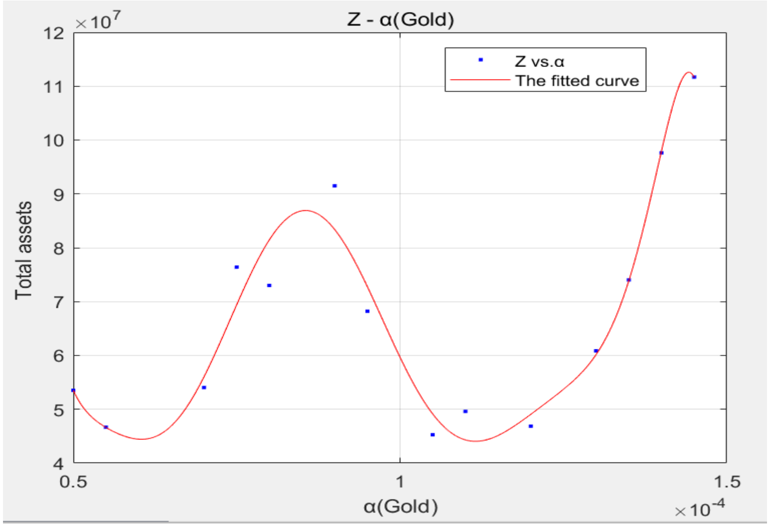


Figure 8. The Polynomial Fitting to Transaction Costs of Gold

Therefore, the sensitivity of the strategy to transaction costs of gold is given by: For equation (X), $=9$, $p_0 = -6.0 \times 10^{47}$, $p_1 = 5.1 \times 10^{44}$, $p_2 = -1.9 \times 10^{41}$, $p_3 = 4.1 \times 10^{37}$, $p_4 = -5.5 \times 10^{33}$, $p_5 = 4.8 \times 10^{29}$, $p_6 = -2.7 \times 10^{25}$, $p_7 = 9.9 \times 10^{20}$, $p_8 = -2.0 \times 10^{16}$, $p_9 = 1.8 \times 10^{11}$. $RMSE = 8.0 \times 10^6$ and $R^2 = 0.9544$, which show the fitting is significant.

Therefore, the sensitivity of the strategy to transaction costs of gold is given by:

$$S(Z, \alpha_g) = \frac{dZ}{d\alpha_g} \cdot \frac{\alpha_g}{Z} \tag{44}$$

For $Z = 1.59 \times 10^8$ and $\alpha_g = 0.0001$, $S(1.59 \times 10^8, 0.0001) = -4.2$, which indicates that for the current model, if α_g increases by 1%, Z decreases by 4.2%. When the transaction cost of gold changes, the change of the result is small, which means the model is stable.

Sensitivity of the strategy to transaction costs of Bitcoin

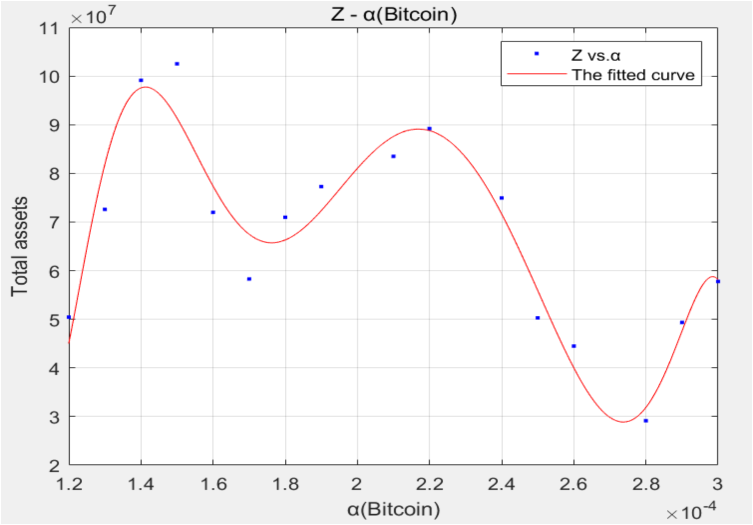


Figure 9. The Polynomial Fitting to Transaction Costs of Bitcoin

For equation (X), $' = 9$, $p'_0 = -1.1 \times 10^{45}$, $p'_1 = 2.2 \times 10^{42}$, $p'_2 = -1.8 \times 10^{39}$, $p'_3 = 8.9 \times 10^{35}$, $p'_4 = -2.8 \times 10^{32}$, $p'_5 = 5.6 \times 10^{28}$, $p'_6 = -7.6 \times 10^{24}$, $p'_7 = 6.5 \times 10^{20}$, $p'_8 = -3.2 \times 10^{16}$, $p'_9 = 6.7 \times 10^{11}$. $RMSE' = 8.388 \times 10^6$ and $R'^2 = 0.9293$, which show the fitting is significant.

Therefore, the sensitivity of the strategy to transaction costs of Bitcoin is given by:

$$S'(Z', \alpha_b) = \frac{dZ'}{d\alpha_b} \cdot \frac{\alpha_b}{Z'} \tag{45}$$

For $Z' = 1.59 \times 10^8$ and $\alpha_b = 0.0002$, $S'(1.59 \times 10^8, 0.0002) = 2.1$, which indicates that for the current model, if α_b increases by 1%, Z'increases by 2.1%. When the transaction cost of Bitcoin changes, the change of the result is small, which means the model is stable.

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