Strategies to "Bitcoin-Gold" Trading

Decoupling the Qualitative Decision and the Quantitative Investment

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Abstract: As investment fever rises, investment strategy is a critical choice for investors. In this paper, based on the price data of gold and bitcoin from 9/11/2016 to 9/10/2021, the corresponding mathematical models are established by the LSTM, evaluation model, and single-objective optimization model in an attempt to obtain the optimal investment strategy. Firstly, the price is predicted by the LSTM model after data cleaning. The evaluation system is constructed from three perspectives: market trading intention, price stability and market environment trend. Based on the scores and thresholds of the evaluation system, the trading directions (buy, sell, hold) are obtained qualitatively. Then, based on the corrected predicted price, a single-objective optimization is established for maximizing total assets, obtaining the final investment strategy, where an initial $1,000 asset is able to reach a final total asset of $134,226 after five years. Secondly, we establish the evaluation system of investment strategies and establish three evaluation indexes of Sharpe Value, Max Drawdown, and Interest Rate in terms of both return and risk. We construct four new investment strategies with different types of investment product and model selection. Comparing the five investment strategies, we can find that our investment strategy has the highest Interest Rate, higher Sharpe Value, and smaller Max Drawdown compared with other investment strategies. Thirdly, we test the impact of transaction costs on the model and learn that the model is more sensitive to the change of bitcoin transaction costs and not sensitive to the change of gold transaction cost.

Keywords: LSTM, two-stage evaluation model, single objective optimization model

1 Introduction

1.1 Background

As the world economy grows and people's assets increase, investing in the market has become an increasingly popular way for people to raise their income. The use of mathematical modeling to analyze investment cases and find patterns to outline specific investment strategies have become a hot topic these years.

Gold and Bitcoin, as two typical investment currencies, can be paired with each other for risk hedging purposes. Gold has always been a highly recognized international hard currency, while Bitcoin, as a young investment with high yield, high volatility and tax-free features, can

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complement gold. Therefore, it is important and relevant to explore the relationship between bitcoin and gold and the asset allocation.

1.2 Literature Review

Extensive methods and indexes have been proposed for evaluating the investment strategies of "Bitcoin-Gold" Trading [1]. The Noise Accumulation index [2] was proposed to describe the overall market trend. Izabela et al. used the Max Drawdown [3] to indicate the investment risk and the maximum loss that a trader may face during his trading. Zhou et al. adopted the Sharpe value [4] as an evaluation indicator of risk and return. Besides, the Relative Strength Index Indicator (RSI) [5] [6] was proposed to describe the willingness of both trading sides of the market.

Howerver, almost all of the methods and indexes are based on the predicted price of Bitcoin and Gold and it's hard to predicted these prices pricisely. The issue of predicting the price of Bitcoin and Gold has attracted numerous researchers' attention. The statistical based models and the deep learning based models are two principal methods for price prediction. The statistical based models include ARCH model [7], ARIMA model [8], logistic regression model [9] and so on.

Recently, the deep learning based models are really popular methods to predict the price of Bitcoin and Gold [10] [11] (Lee Kamwoo, Ulkuatam Sinan, Beling Peter, Scherer William, 2018). Moreover, Ding et al. adopted the LSTM [12] which is an classical artificial neural network that has good memorability to predict the prices.

2 Materials and methods

2.1 Model for Part One

As shown in Fig1, firstly, a price prediction model is built based on the historical price data of gold and bitcoin given in the Appendix. First of all, the data are cleaned and the blank invalid data segments are deleted. Second, according to the different stability of the price of gold and bitcoin, time windows of different lengths are defined and the data are time-series predicted using an LSTM prediction model.

Secondly, an evaluation model of market trends is established for the decision of whether to buy or sell. The evaluation indexes are constructed from three perspectives: the willingness of both sides of the market to trade, the price stability of the investment product, and the general trend of the market environment. And the corresponding three evaluation indexes are as follows: the relative strength index (RSI), the price stability index, and the noise accumulation index. The higher the comprehensive evaluation score based on the three indexes above, the higher the probability of buying; conversely, the lower the score, the higher the probability of selling. Based on the tendency score and the given threshold value, the operational direction for the investment strategy can be determined.

Thirdly, a single-objective optimization model is developed to determine the trading volume for each operation. Given that there are deviations in the predicted prices as well as investors' investment styles (aggressive or conservative), the output price of the prediction model will be corrected by the given threshold value in part 2 firstly. Then, a single-objective planning with

maximization of the next day's assets is established to obtain the decision results for the daily trading volume.

With the qualitative operation direction in the second part and the quantitative trading volume in the third part, we can obtain the daily trading decisions that can be helpful to investors.

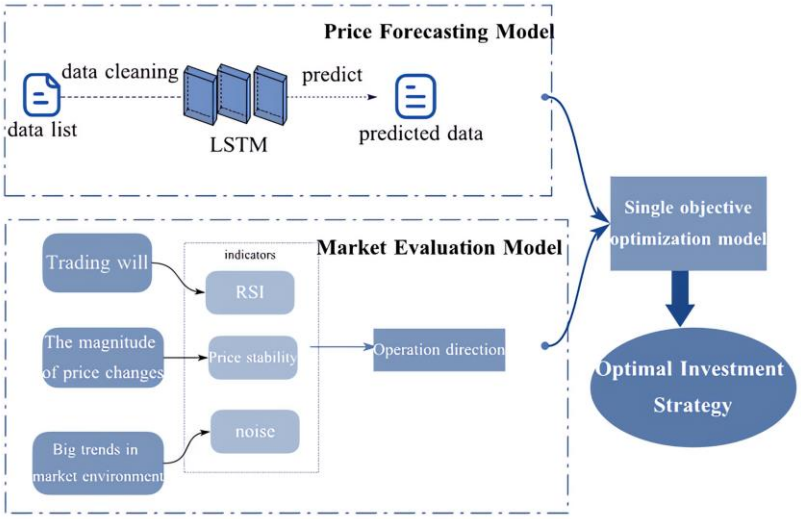

Figure 1: Part I Flow Chart

LSTM-based time series prediction

- **Data pre-processing**

By observing and analyzing the given data in gold and bitcoin, it has been found that there exist invalid data, such as irrelevant blank or zero. So, the data was cleaned and ready for the following analysis and calculation.

- **Long short-term memory (LSTM) prediction**

The LSTM [12] is an artificial neural network that has good memorability and can use longer data series to build a self-learning model (often for time series prediction). We take the time series data m as input vector for LSTM. However, while the gold price is more stable, the bitcoin price tends to be uncertain and stochastic. Many researches have been proposed to predict the price of bitcoin [13] and its market trend [14]. In our model, we use different time window for gold and bitcoin to relieve the problem. Actually, we define five days as the time window for gold and ten days as the time window for bitcoin. The window length is the same as the length of the input vector, and the price data up to that day are loaded into it.

We purposed the network with 4 LSTM layers, with 96 hidden layers contained in each of them, and one fully-connected network for output. We defined the learning rate to 0.005 and decays to half after 50% of the training. The first 80% of the historical data was labelled as training

dataset and we trained 250 epochs, and the latter 20% was labelled as testing dataset. (The non-trading days of gold are erased in previous).

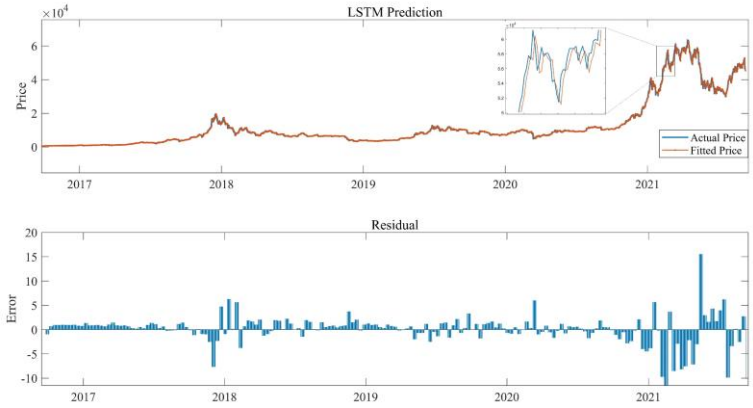

Figure 2: Prediction in gold price and overall residual

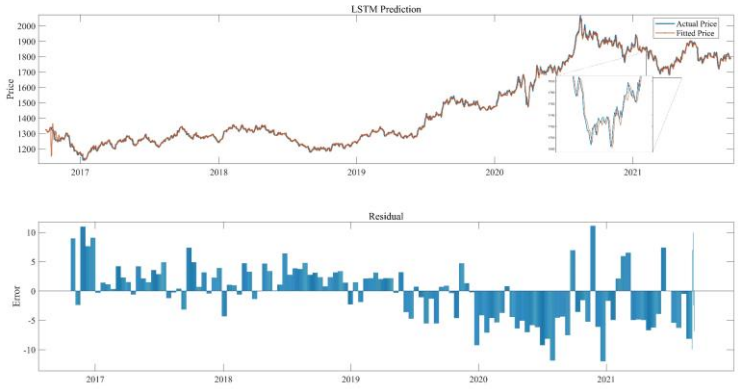

Figure 3: Prediction in bitcoin price and overall residual

- **The prediction results**

The results of gold and bitcoin price prediction are shown in Fig2 and Fig3. It was found that the LSTM model prediction was accurate and matches well with the real price data. The average residual of gold prediction is 145.74 and of bitcoin prediction was 810.36. The LSTM model is more accurate in predicting gold price than predicting bitcoin, which also indicates that gold is easier to be predicted compared to bitcoin.

Investment strategy based on market evaluating system: For an investment strategy, the method of investment is a vital decision, which includes buying, selling or holding, and it determines the trading.

In order to determine the specific investment strategy, we established a market evaluating system. We construct the evaluation in three perspectives: **the willingness of both sides of the trading market, the stability of the market price, and the trend of the market**. Then, a tendency score for each day can be calculated. After that, the given threshold R can be used to decide to choose the daily decision (whether to buy or not).

- **Criterion for the system**

(1) Relative strength index (RSI_i)

The Relative Strength Index Indicator (RSI) [5] was used to describe the willingness of both trading sides of the market. It represents the market strength within a time period. When the RSI is high, the ratio of price growth is also rapid, which also indicates that the buyer's market is strengthening and surpassing the seller's market [15], actually, an improved version of RSI has also been proposed these years

In this part, within a time window (gold time window $T=10$, bitcoin $T=5$), the change in price magnitude between two days $mar_{\mathrm{i}}=m_{\mathrm{i}+1}-m_{\mathrm{i}}$ is first calculated, and then sum up the positive magnitude of the price change:

$$a_m=\sum_{t=0}^{T-1} mar_{i+t} \quad (sign(mar_{i+t})>0) \tag{1}$$

And the sum of the negative magnitude of the price change

$$b_m=\sum_{t=0}^{T-1} mar_{i+t} \quad (sign(mar_{i+t})<0) \tag{2}$$

The formula for the RSI is expressed as:

$$RSI_i=\frac{a_m}{a_m+b_m} \tag{3}$$

(2) Price stability index sta_i

The price stability index is used to describe the price stability of specific trading. It is the ratio of the number of days of price growth to the sum of the number of days of growth and the number of days of decline within a time window. When the price stability index is high, it indicates that the investment product tends to grow and tend to be stable.

In the calculation, through counting the change in price magnitude mar_{i} the number of positive

$$a_d = \sum_{t=0}^{T-1} sign(mar_{i+t}) \quad (sign(mar_{i+t}) > 0) \tag{4}$$

and the number of negative

$$b_d = \sum_{t=0}^{T-1} sign(mar_{i+t}) \quad (sign(mar_{i+t}) < 0) \tag{5}$$

within a time window can be obtained. Eventually, the formula for the price stability index sta is expressed as:

$$sta_i = \frac{a_d}{a_d + b_d} \tag{6}$$

(3) Noise Accumulation Index ($noise_i$)

The Noise Accumulation index [2] is mainly used to describe the overall market trend. When the market goes up, the price will also respond to its upward trend. We use a moving average to represent the baseline for noise accumulation, and $noise_i$ is the difference between the current price and the moving average. Using three days as an evaluation window, the moving average $\widetilde{P}_i$ and noise ε_i can be calculated with the equation:

$$\widetilde{P}_i = \frac{1}{3} \sum_{t=0}^{2} m_{i+t} \tag{7}$$

$$\varepsilon_i = m_i - \widetilde{P}_i \tag{8}$$

The noise accumulation in the time series window can be calculated by the value of the noise as $S_{Ti} = \sum_{t=0}^{T-1} \varepsilon_{i+t}$, the shifted standard deviation is also calculated as:

$$\sigma_i = \sqrt{\sum_{t=0}^{2} \frac{\left(m_{i-t} - \widetilde{P}_i\right)^2}{2}} \tag{9}$$

and its overall equation for noise accumulation is shown below:

$$noise_i = \frac{S_{Ti}}{\sqrt{\sum_{t=0}^{T-1} \sigma_{i-t}^2}} \tag{10}$$

- **Tendency index**

Based on the three evaluation indexes, they can be integrated through the following procedures.

First, scale the RSI index, Price Stability index, and Noise Accumulation index into $[0, 1]$. Specifically, the noise accumulation is transformed using the sigmoid function:

$$noise_i' = \frac{1}{1 + e^{-noise_i}} \tag{11}$$

We used geometric mean of the three-scaled-index as the final tendency score:

$$p_i = \sqrt[3]{RSI_i \times sta_i \times noise_i'} \tag{12}$$

- **Determine the trading direction**

As long as the tendency score p_i is fixed between $[0, 1]$, we defined the thresholds R and $1 - R$ for the score. We set up three intervals $[0, R]$ $(R, 1 - R)$ $[1 - R, 1]$ representing sell, hold and buy respectively. When the tendency score is in the corresponding range, the corresponding trading direction is determined. The discrete decision variables r_i follow:

$$r_i = \begin{cases} -1, & p_i \in [0, R] \\ 0, & p_i \in (R, 1 - R) \\ 1, & p_i \in [1 - R, 1] \end{cases} \tag{13}$$

If decision variables r_i is -1, it indicates that we will sell (or hold) the trade in the day. Vice versa, when r_i is 1, we might buy in or hold the trade.

Single-Objective-Optimization model for trading volume: In order to determine the trading volume for each investment, a single objective optimization model is developed with the goal to maximize the next day's general assets.

- **Price Correction**

Due to the deviation in the forecasted prices (up to that day) and the subjective willingness of the trader, the price prediction is given by the previous LSTM model should be corrected. The threshold value reflects the subjective intention of different traders, so the forecast price is corrected by the price correction factor:

$$c_i = \left(\frac{m_i}{m_{i-1}} - 1\right)\left(1 - e^{-(1-(1-2p_i))}\right) \tag{14}$$

New forecast price corrected by price correction factor m_i' as follows:

$$m_i' = m_i(c_i + 1) \tag{15}$$

- **Target function**

By calculating the total assets of the next day based on the predicted price, it is suited as the target function. We set the gold trading volume of the day as x_1, bitcoin trading volume x_2 as the decision variable. Total assets are the sum of the value of the next day's gold holdings e_1, the value of the next day's bitcoin holdings e_2, and the next day's cash e_3. The formula is as follows:

$$\max\ Z(x_1, x_2) = e_1 + e_2 + e_3 \tag{16}$$

(1) the value of the tomorrow's gold holdings e_1

Tomorrow's gold holding value equals the amount of tomorrow's gold holdings multiplied by tomorrow's gold price and minus the commission. The next day's gold holdings amount is the same with today's gold holdings amount z_1 plus today's trading volume $r_1 x_1$.The commission of gold is 1%, so the value of tomorrow's gold holdings is:

$$e_1 = (1 - 1\%)m_1'(z_1 + r_1 x_1) \tag{17}$$

(2) the value of the tomorrow's bitcoin holdings e_2

The value of tomorrow's bitcoin holdings is identical to that of gold; however, they differ in the commission as the fee is 2% for bitcoin. So, the value of bitcoin holdings tomorrow should be:

$$e_2 = (1 - 2\%)m_2'(z_2 + r_2 x_2) \tag{18}$$

(3) Tomorrow's cash amount e_3

The amount of cash on the next day should be all cash in possession on that day minus all the spending that day. The expenses include the gold commission for $1\%x_1$ and the bitcoin commission for $2\%x_2$, as well as the gold purchase fee $m_1' r_1 x_1$ and the bitcoin purchase fee $m_2' r_2 x_2$, which the equation as follows:

$$e_3 = z_0 - 1\%x_1 - 2\%x_2 - m_1' r_1 x_1 - m_2' r_2 x_2 \tag{19}$$

- **Constraints**

Constraint 1 Decision variable is non-negative.

The daily trading volume x_1, x_2 are non-negative because of the defined trading direction r_i represents the operation of selling or buying, x_1, x_2 are only the amount for it:

$$x_1, x_2 \geqslant 0 \tag{20}$$

Constraint 2 Holdings are non-negative.

Gold, bitcoin and cash holdings cannot be negative, so three non-negative constraints are defined:

$$z_1 + r_1 x_1 \geqslant 0 \tag{21}$$

$$z_2 + r_2 x_2 \geqslant 0 \tag{22}$$

$$z_0 - 1\%x_1 - 2\%x_2 - m_1' r_1 x_1 - m_2' r_2 x_2 \geqslant 0 \tag{23}$$

- **Single-objective optimization model**

Inconclusion, the entire optimization model can be treated as a linear programming system:

$$\max\ Z(x_1, x_2) = e_1 + e_2 + e_3$$

$$s.t. \begin{cases} e_1 = (1-1\%)m_1'(z_1 + r_1 x_1) \\ e_2 = (1-2\%)m_2'(z_2 + r_2 x_2) \\ e_3 = z_0 - 1\%x_1 - 2\%x_2 - m_1' r_1 x_1 - m_2' r_2 x_2 \\ x_1, x_2 \geqslant 0 \\ z_1 + r_1 x_1 \geqslant 0 \\ z_2 + r_2 x_2 \geqslant 0 \\ z_0 - 1\%x_1 - 2\%x_2 - m_1' r_1 x_1 - m_2' r_2 x_2 \geqslant 0 \end{cases} \tag{24}$$

2.2 Model for Part Two

In the second part, we developed an evaluation system to evaluate the merits and demerits of a trading strategy and thus prove that our model serves the best one.

To demonstrate that the model provides the best trade strategy, four new investment strategies are constructed and analyzed in comparison with the original investment strategy in terms of the necessity of different parts in the model and the choice of investment products.

The first comparison strategy is to invest using only the scores brought by the market trend evaluation model; the second comparison strategy is to invest using only the single-objective planning with the largest assets; the third comparison strategy is to buy only bitcoin, and the fourth comparison strategy is to buy only gold.

To better evaluate the advantages of a trading strategy, we establish an investment strategy evaluation model. Firstly, we construct an evaluation system to evaluate the five strategies from three perspectives: maximum retracement risk, total capital profit ratio, and Sharpe Value. Then, we also build an investment strategy radar chart based on the scores of the three perspectives above and judge the advantages of an investment strategy in an all-around way.

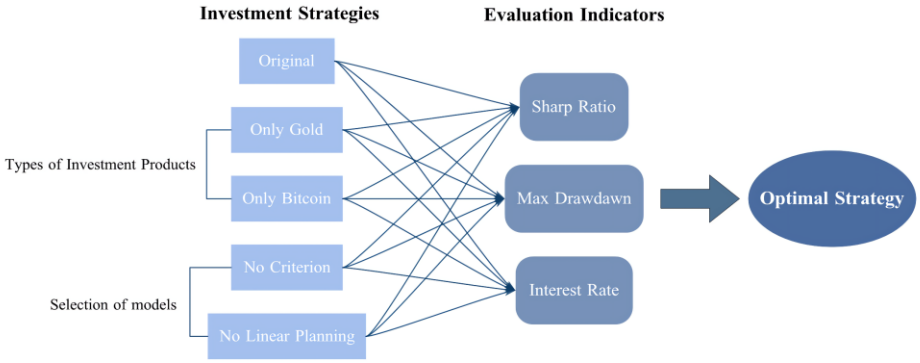

Figure 4: Part II Flow Chart

Strategy evaluation system establishment: In order to better evaluate the goodness of the investment strategy, we selected three evaluation indicators: Max Drawdown, Interest Rate, and Sharpe Value. And we constructed a comprehensive evaluation system as shown in Fig 4.

- **Max Drawdown** Dra

Max Drawdown [3] is an important indicator of investment risk and indicates the maximum loss that a trader may face during his trading. It represents the maximum value of the decline from any highest return point to the lowest subsequent return point or the maximum loss. The lower the value of the Max Drawdown, the lower the possible risk. It can be calculated with the equation follows:

$$Dra = \max\{Z_i - \min(Z_j)\} \tag{25}$$

- **Interest Rate** Y

Interest Rate is an important indicator of profit, as all traders seek the chance to enhance it. Therefore, the higher the Interest Rate, the better the investment strategy. The Interest Rate is the ratio of total assets to costs on the last day and then minus 1, as shown in the formula below:

$$Y = \frac{Z_{\max(i)} - C}{C} \tag{26}$$

- **Sharpe Value** $Sharp$

Sharpe value [4] is an evaluation indicator of risk and return. It indicates the level of return per unit of risk and can be used to evaluate the merits of asset portfolio strategies. Since our model contains investment of gold and bitcoin and they are both risky, it is suitable to consider the Sharp Value into the model. The Sharpe value is the ratio of the expected return to the standard deviation of the return. Each daily return are differenced by the previous day. And we get

$$y_i = \frac{Z_i - Z_{i-1}}{C} \tag{27}$$

for which the mean and standard deviation are calculated and divided to obtain the Sharpe value.

$$\bar{y} = \frac{\sum_{t=1}^{N} y_i}{N} \tag{28}$$

$$Sharp = \frac{\bar{y}}{\sqrt{\frac{\sum_{t=1}^{N} (y_i - \bar{y})^2}{N-1}}} \tag{29}$$

Building a comparison strategy: To better prove that our investment strategies are optimal, we construct four new investment strategies in terms of the necessity of steps and the choice of investment products. And we analyze them in comparison with the original investment strategies.

Strategy 1: Trade gold only.

This strategy only considers the result of gold trading, and it gives up trading bitcoin. It only uses the mathematical model of evaluating system (4.1.2) and linear programming in gold.

Strategy 2: Trade Bitcoin only.

Almost the same as Strategy 1 but replace gold with bitcoin.

Strategy 3: No evaluating system or criterion.

Without the evaluating system, there is no need to correct the predicted prices. The absence of the transaction direction r_i gives the decision of it to the optimization system. The single-objective planning with an objective function of maximum total assets is shown below:

$$\max\ Z(x_1,x_2)=e_1+e_2+e_3$$

$$s.t.\begin{cases} e_1=(1-1\%)m_1(z_1+x_1) \\ e_2=(1-2\%)m_2(z_2+x_2) \\ e_3=z_0-1\%x_1-2\%x_2-m_1x_1-m_2x_2 \\ z_1+x_1\geqslant 0 \\ z_2+x_2\geqslant 0 \\ z_0-1\%|x_1|-2\%|x_2|-m_1x_1-m_2x_2\geqslant 0 \end{cases} \tag{30}$$

Strategy 4: No linear planning.

Without using a single-objective optimization model. Use only the tendency score p_i of the evaluation model to make a trading strategy. Transform the tendency scores so that they can be defined in the interval $[-1,1]$:

$$p_i'=\begin{cases} p_i-1 \ , & p_i\in[0,R] \\ 0 \ , & p_i\in(R,1-R) \\ p_i \ , & p_i\in[1-R,1] \end{cases} \tag{31}$$

The tendency score of gold p_{i1}' and bitcoin p_{i2}' can be obtained. If the transaction direction is purchased $(p_i'>0)$, the purchasing volume is equal to the product of cash e_3 and the tendency score. If the direction of the transaction is selling $(p_i'<0)$, then the selling volume is equal to the product of the amount of the product held $m_jz_j(j=1,2)$ and the tendency score. Weighted allocation to cash if both gold and bitcoin need to be bought. In summary, the formula for calculating transaction volume is shown below:

$$\begin{cases} x_j=\dfrac{p_j}{p_1+p_2}e_3\cdot p_{ij}' & ,p_{i1}'\geqslant 0,p_{i2}'\geqslant 0 \\ x_j=p_{ij}'e_3 & ,p_{ij}'\geqslant 0 \\ x_j=p_{ij}'m_jz_j & ,p_{ij}'<0 \end{cases} \qquad j=(1,2) \tag{32}$$

3 Results and discussion

3.1 Result analysis

Trading strategy solving and result analysis: Solving the given optimization model with the attached data, it yields the following table 1 of daily trading strategies. The initial cash of $1,000 in assets can eventually reach $134,226 in total assets after five years of trading.

Table 1: Trade Strategy Partial Data

Date	Gold Trading	Bitcoin Trading
2021-3-1	0	1.256557
2021-3-4	0	-1.25656
2021-3-8	36.4803	0
2021-3-25	-36.4803	0
2021-3-26	0	1.196384829
2021-3-31	0	-1.19638
2021-4-26	0	1.3756
2021-4-27	0	0
2021-4-28	0	-1.3756
……	……	……

Based on the graph Fig5 of gold and bitcoin transactions over time, we can see that gold is significantly less frequently traded than bitcoin, and the overall holding time of both investment products is shorter, with bitcoin being held for a shorter period of time than gold, and it suits with the more unpredictable property of bitcoin.

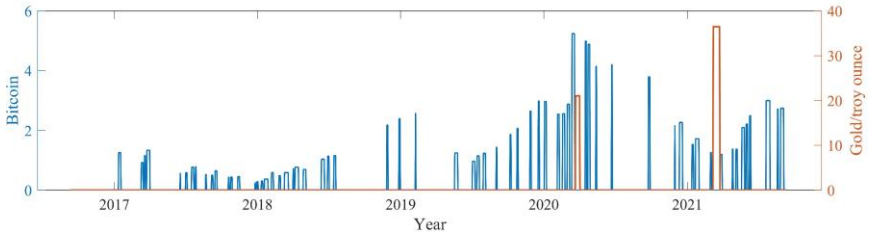

Figure 5: The graph of gold and bitcoin transactions over time

According to the graph Fig6 of cash holdings and total assets over time, it can be witnessed that the total assets own a steady upward trend over time, with time passes it increased rapidly and less volatility. This indicates that our model's returns are increasing and the risk is low.

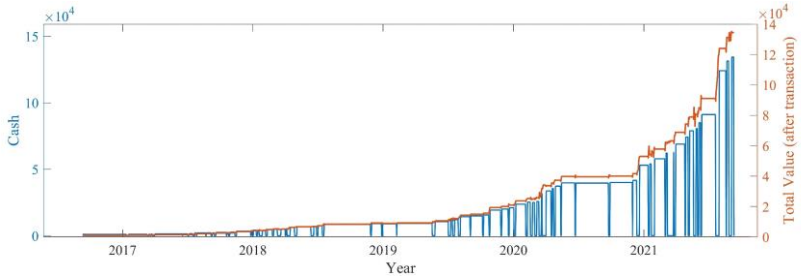

Figure 6: The graph of cash holdings and total assets over time

Comparative analysis: Based on our investment strategies and the four newly constructed trading strategies. The Sharp Value, Max Drawdown and, Interest Rate of each strategy can be calculated and the scores of the corresponding indexes are shown in the following table 2:

Table 2: Scoring table of indicators for different strategies

Strategies	Sharp Value	Max Drawdown	Interest Rate
Original	1.5062	0.0934	133.2267
Only gold	1.514	0.0647	1.8309
Only Bitcoin	0.9179	0.2317	19.4099
No Criterion	-0.0069	0.47	0.9898
No Linear Planning	1.1563	0.1411	16.7365

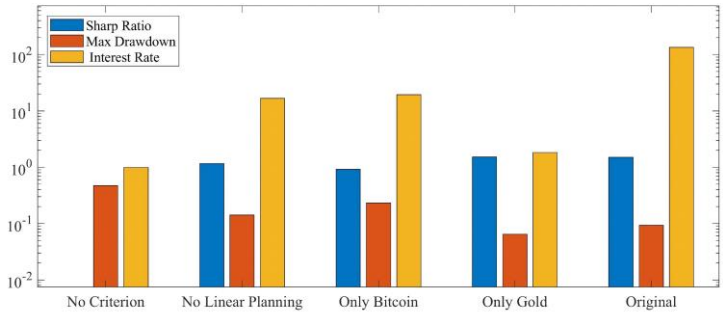

Figure 7: Metrics scoring chart for different strategies

As it can be seen from the graph Figure 7, our investment strategy differs greatly from other investment strategies in terms of Interest Rate. Our investment strategy has the highest Interest Rate, higher Sharp Value, and smaller Max Drawdown, which means that the return is high and the risk is low.

When we buy only gold, Sharp Value holds the maximum, and Max Drawdown holds the minimum, but Interest Rate is really low. This investment strategy is very solid and suitable for extremely conservative investors, with little risk but also very little return.

When we buy only Bitcoin, the Sharp Value is low, the Max Drawdown is large, and the Interest Rate is high. This investment strategy is very risky and still has a much lower Interest Rate than our investment strategy.

When we use only the evaluating system for our trading strategy, there is some loss of money and the risk is so enormous that it is not suitable to be used alone.

When we use only the model of the optimization part to determine the investment strategy, Sharp Value is larger, Max Drawdown is larger as well. But the Interest Rate is smaller, and all evaluation indicators are worse than our own investment strategy.

As can be seen above, each part of our investment strategy has optimal performance and each part is very important and relevant to the goal. The model of evaluating system and its tendency score corrects the predicted prices for the model in the third part and narrows the optimization range, reducing the computational effort. The model of the third part provides more accurate trading volume for the second part, which gives the model superior performance.

3.2 Sensitivity test

Transaction cost: In this part we studied the sensitivity of the transaction cost to the model, the original data in this paper is 1% of the transaction price for gold and 2% of the transaction price for bitcoin. In this paper we change the transaction cost into 0%, 1%, 2%, 5%, 10%. The combinations of gold transaction costs and bitcoin transaction costs result in 25 transaction cost scenarios that are substituted into our model to generate the corresponding investment strategies.

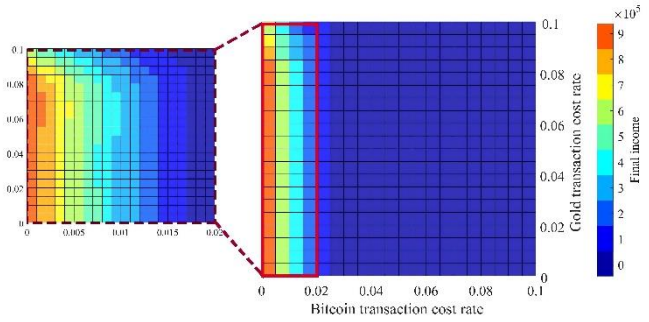

Figure 8: Transaction cost sensitivity test chart

As shown in Fig8, the sensitivity test shows that the transaction cost of bitcoin has a greater impact on the total return of the investment strategy and that of bitcoin holds the inferior, i.e., the investment strategy is insensitive to the transaction cost of gold and more sensitive to the transaction cost of bitcoin.

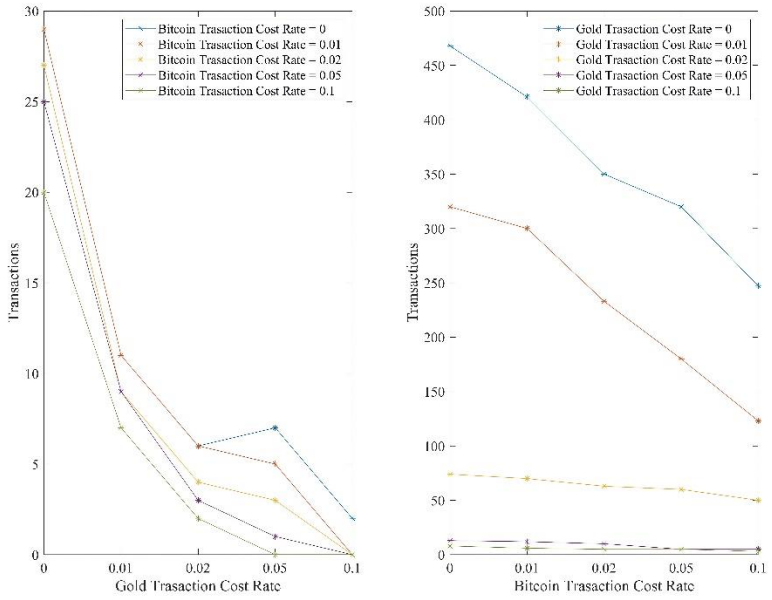

Figure 9: Diagram of the effect of transaction costs on trading strategies

In order to explore the impact of different transaction costs on the investment strategy, the difference between the number of transactions of gold and bitcoin with different transaction costs is calculated. As shown in the Figure 9, the higher the transaction cost, the lower the overall trend in the number of transactions. As the price of transaction costs rises, the impact on the number of gold trades becomes progressively smaller, while the impact on the number of bitcoin trades is largely consistent. In the lower transaction cost region, the change in the number of gold transactions is sharp.

Thresholds: In the model of this paper, the thresholds are influenced by human subjective factors. Therefore, the impact of different thresholds on the model is explored to test the stability of the model. Different thresholds are selected, and the graphs of final total assets with threshold values are obtained as shown below.

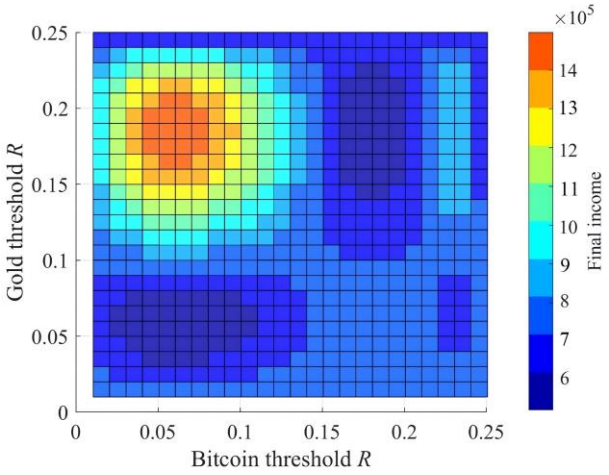

Figure 10: Sensitivity of Threshold

As shown in Fig10, we can learn that the maximum total assets can reach about 130,000 under different threshold picks, while most of the thresholds can reach about 70,000 total assets. It proves that the model still has good stability and can produce better investment results under different threshold values of picking.

4 Further discussion

- Our model can be widely used in other scenarios, for example, stocks, futures goods, funds.
- More relevant factors and advanced trading strategies should be taken into consideration, for example, the influence of economic policies and hedging between gold and bitcoin duo.
- The model currently relies more on the accuracy of forecasts, and more efforts can be made to reduce the reliance on forecasts in the future.
- Modeling the subjective intentions of investors is simple and can be considered to categorize investors according to their investment psychology, thus generating more precise and personalized investment strategies.

- Adaptive adjustment factors can be set to adjust the next trading strategy and aggressiveness based on historical trading returns and risks.

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