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Trading Strategy Formulation Based on the Dynamic Linear Programming Model

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Abstract

The word "buying and selling" can be traced back to primitive human society. At all times, people want to maximize returns. This paper mainly predicts the price of gold and bitcoin by establishing a mathematical model and formulating a trading strategy to maximize profits. The research on this issue can guide for investors to maximize benefits and minimize risks. Based only on price data of gold and bitcoin up to that day, the paper is asked to determine the trading strategy for maximizing returns. Essentially, this is a single-objective multi-variable programming problem with the dynamic linear restrict condition. First, we use a Time Sequence Model to predict the missing price. Then, the risk score was obtained by the Entropy Weight Method and the TOPSIS model. Finally, we use the Dynamic Linear Programming Model to simulate the trading strategy. Among them, we performed a Double Sample Z-Test on the data, which was obtained under different constraints, and the original data to judge the validity of the model. Upon examination, we learned that the model is effective and optimized by nearly 30% compared with the planning results under other conditions. What's more, we conduct Sensitivity Analysis on the model of Task Ⅰ In this paper, the transaction cost ratio R of gold and bitcoin is changed to 5%: 1%, 2%: 1%, 1%: 1%, and 1%: 5% respectively, and detailed analysis is conducted. When the transaction cost in the model changes, the final asset changes are 90.53%, 115.35%, 98.73%, and 113.90%. Therefore, the final asset value obtained by this model is relatively insensitive to the change of transaction cost. Last but not least, we conclude the results of our model.

Keywords

Time Sequence Model; Dynamic Linear Programming Model; Double Sample Z-Test; Trading Strategy Formulation Model; Sensitivity Analysis.

1. INTRODUCTION

To indicate the origin of Trading Strategies, the following background is worth mentioning. With the continuous development of the financial industry and the continuous innovation of financial products, the development of modern money presents diversification and virtualization [1]. Now, gold, an old and stable financial asset, and bitcoin, a new financial asset, are popular with the population [2].

But as bitcoin has risen and fallen repeatedly, more and more investors have begun to weigh in on cryptocurrency and gold. The question is mainly about the price prediction, risk assessment, and quantitative investment of gold and bitcoin. In recent years, the research on quantitative investment of financial products by domestic and foreign scholars has become a hot topic, especially bitcoin. Among them, mainly include bitcoin price forecast and portfolio optimization [3].

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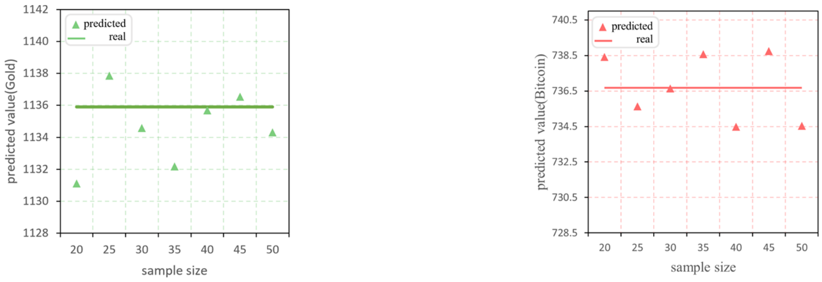
2. TRADING STRATEGY MAKING

2.1. Time Sequence Model

Time series, also known as dynamic series, is a sequence of different values at different times arranged in chronological order [4]Time series can be divided into three parts, namely, describing the past, analyzing laws, and predicting the future. It mainly includes three models: seasonal decomposition, exponential smoothing, and ARIMA. We imported the two groups of data into the expert modeler in SPSS, and the optimal model was the ARIMA model.

2.1.1 Comparison of Prediction Data of Different Samples

Since the prediction results of different numbers of initial samples are different [5]. We need to determine the sample size of bitcoin and gold that best fits their predictions over different time series. Therefore, we chose 1135.9 and 736.57 as the true values of gold and bitcoin respectively. The data of 20, 25, 30, 35, 40, 45, and 50 days before the date were selected for ARIMA prediction. The results are shown in the Figure below:



(a) Gold (b) Bitcoin

Figure 1. Comparison between predicted value and real value in different periods

We calculate the error rate of each sample prediction by using the following formula for the real value and predicted value:

$$ER = \frac{P_p - P_r}{P_r} \times 100\% \tag{1}$$

$(ER\ is\ error\ rate,\ P_p\ is\ the\ predicted\ value,\ P_r\ is\ the\ real\ value)$

Table 1. Comparison of predicted value, real value and error rate in different periods

sample size	real value	predicted value	error value
20	1135.9	1131.11	0.42%
25	1135.9	1137.86	-0.17%
30	1135.9	1134.59	0.12%
35	1135.9	1132.18	0.33%
40	1135.9	1135.68	0.02%
45	1135.9	1136.55	-0.06%
50	1135.9	1134.32	0.14%

(a) Gold

sample size	real value	predicted value	error value
20	736.67	738.41	0.24%
25	736.67	735.64	-0.14%
30	736.67	736.64	0.00%
35	736.67	738.57	0.26%
40	736.67	734.48	-0.30%
45	736.67	738.74	0.28%
50	736.67	734.53	-0.29%

(b) Bitcoin

As can be seen from the above figures, in the time series of the gold price, it is most accurate to take the data of the first 40 days of the forecast day for prediction. For bitcoin, it's the current 30 days.

2.1.2 Model construction and solution

Step I Make a time series diagram, determine the variation, and decompose

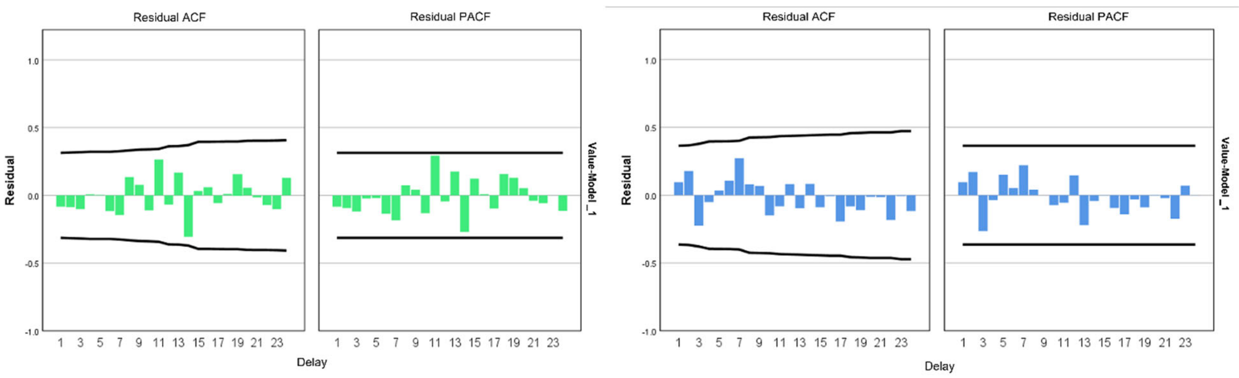
The price of bitcoin has an upward trend and irregular fluctuation, while the price of gold has a downward trend and irregular fluctuation, to make a time series diagram, judge the changing components, and decompose them.

Step II Through Model recognition, we use the ARIMA model to obtain relevant parameters, and the results are shown in the Table 1 above.

Step III Predicted results

$$
\begin{aligned}
&\textit{because}\ \left(1-\sum_{i=1}^{p}\alpha_i L^i\right)(1-L)^d y_t=\alpha_0+\left(1+\sum_{i=1}^{q}\beta_i L^i\right)\varepsilon_t\\
&\textit{than}\ ARIMA(0,1,0):\ (1-L)y_t=\alpha_0+\varepsilon_t\\
&\Rightarrow y_t-y_{t-1}=\alpha_0+\varepsilon_t \Rightarrow y_t=\alpha_0+y_{t-1}+\varepsilon_t\\
&\Rightarrow \hat{y}_{(1/9)}=\textit{estimated constant}+y_{(31/8)}+E_{\varepsilon_{(1/9)}}\\
&\Rightarrow \hat{y}_{(10/9)}=596.018+\hat{y}_{(9/9)}+E_{\varepsilon_{(10/9)}}\\
&\textit{because}\ \{\varepsilon_t\}\ \textit{is the White Noise Sequence},\ E(\varepsilon_t)=0
\end{aligned}
\tag{2}
$$

Step IV To test whether the model is completely recognized, the residual test of white noise is carried out below, and the results are shown in the Figure below.



(a) The most likely location of fishes (b) The location of fishes (std)

Figure 2. White noise residual testWhite noise residual test

As can be seen from the ACF and PACF diagrams of residuals, there is no significant difference between autocorrelation coefficient, partial correlation coefficient, and 0 of all lag orders

Table 2. Yang boxs Q test

Model Description

			Model Type
Model ID	Value	Model_1	ARIMA(0,1, 0)

ARIMA Model Parameters

					E	SE	t	p
Value-Model_1	Value	Don't convert	Constant		596.018	269.334	2.213	0.035
			Difference		1			

Model	predicted variable number	Goodness of Fit	Yang-Box Q(18)			outlier
		R2	statistics	DF	p	
Value-Model_1	0	-2.22E-16	13.753	18	0.745	0

Model	predicted variable number	Goodness of Fit	Yang-Box Q(18)			outlier
		R2	statistics	DF	p	
Value-Model_1	0	6.84E-01	17.263	18	0.505	3

(a) The most likely location of fishes (b) The location of fishes (std)

As can be seen from the above two figures, the P values of residual of bitcoin price and gold price are 0.745 and 0.505 respectively after Q test of residual, that is, we cannot reject the null

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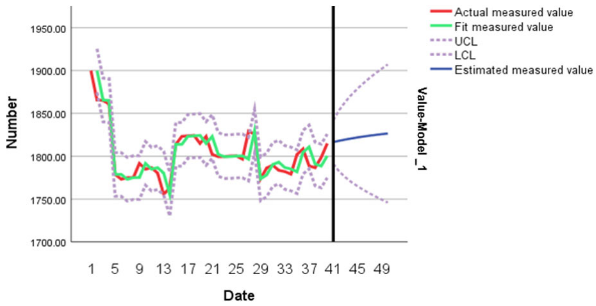
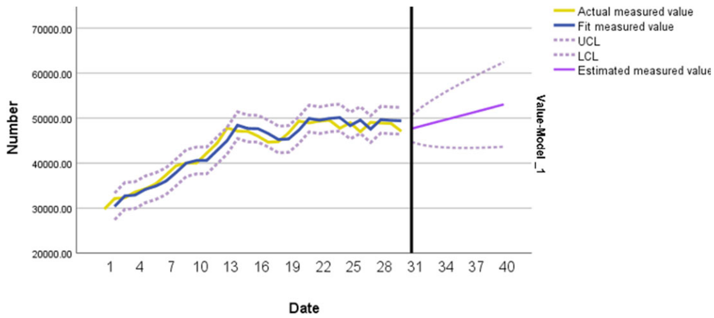
hypothesis and believe that residual is a white noise sequence, so ARIMA model can well identify the price data in this case

Step V Predictive effect graph

After the prediction of the ARIMA model, we can get the following results Figure .



(a) The most likely location of fishes



(b) The location of fishes (std)

Figure 3. Predicted effect graph

It can be seen from the above two figures that there is little difference between the real data of gold and bitcoin and the time sequence diagram of the fitted data, which indicates that ARIMA has a good fitting of the original data

3. DYNAMIC LINEAR PROGRAMMING MODEL

Linear programming model, in business management, is often used to solve the problem of reasonable allocation and utilization of limited resources [6]. Dynamic programming is a systematic technique for solving multi-stage decision problems. The multi-stage decision-making problem is transformed into a series of interconnected single-stage problems, and then solved one by one. The "optimization principle" for solving such problems is proposed [7].

3.1. The Superiority of the Optimization Principle

Optimization principle A uses the dynamic programming model to solve a simple linear programming problem and generalize it[8]. It can be concluded that dynamic programming to solve the linear programming problem reflects the scarcity of resources and the dynamics of resource allocation, and takes into account the benefits of resources in each link, which has certain advantages.

3.2. Solution and Result

Step I The linear programming decision variables are constructed and the equations are established.

Suppose the existing asset L, the amount of cash available is C, the trading volume of gold on that day is X, the trading volume of bitcoin on that day is Y, the price of gold on that day is gP_n,

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the price of bitcoin on that day is bP_n, the price of gold tomorrow is gP_t, and the price of bitcoin tomorrow is bP_n. The existing gold quantity is G, and the existing bitcoin quantity is B. The planning model that maximizes the profit gained from investment is obtained, and the objective function is:

$$L = C - gP\_n \times (0.01|x| + x) - bP\_n(0.02|y| + y) + (g + x) \times gP\_t + (b + y) \times bP\_t \tag{3}$$

Step II Establishment of constraint conditions

This question assumes that the investment will not occur, C < 0, so:

$$L = C - gP\_n \times (0.01|x| + x) - bP\_n(0.02|y| + y) + (g + x) \times gP\_t + (b + y) \times bP\_t > 0 \tag{4}$$

According to the title, gold is distinguished by trading day and non-trading day, so the constraint conditions can be divided into the following two categories :

(introducing Risk coefficient, Risk coefficient conversion rate, and last round asset L')

(1) When gold is tradable:

$$\begin{aligned} &\max\ L \\ &s.t.\begin{cases} x \geqslant -g \\ y \geqslant -b \\ x \times gP\_n \leqslant C \times Risk \\ y \times bP\_n \leqslant C \times Risk \\ x \times gP\_n + y \times bP\_n \leqslant C \times RiskRate \\ 0.01|x \times gP\_n + 0.02|y| \times bP\_n > C * RiskRate - (x \times gP\_n + y \times bP\_n) \\ L > L' \end{cases} \end{aligned} \tag{5}$$

(2) When gold is not tradeable

$$\begin{aligned} &\max\ L \\ &s.t.\begin{cases} y \geqslant -b \\ 0.02 \times |y| \times bP\_n > C \times RiskRate - y \times bP\_n \\ L > L' \end{cases} \end{aligned} \tag{6}$$

Step III Solution method for model

Dynamic linear programming is carried out according to the above constraints, and the following Figure4 are obtained:

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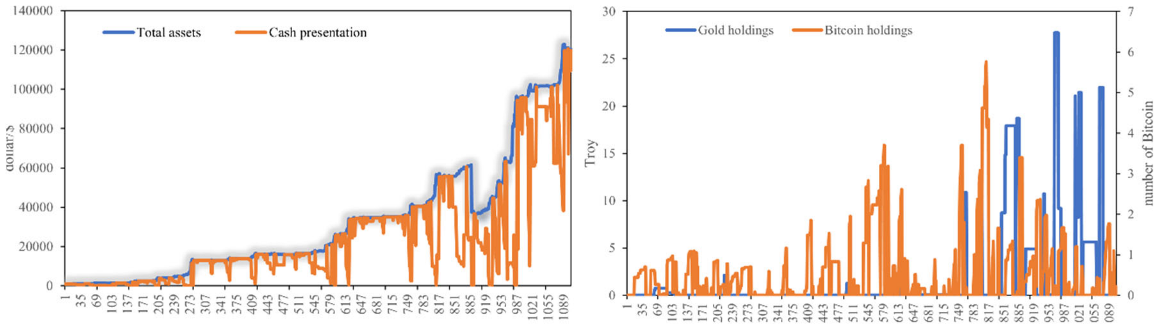

(a) Total assets vs. Cash (b) Gold holdings vs Bitcoin Holdings

Figure 4. Comparison of holdings by currency

Therefore, it can be seen that the maximum final income on 9/10/2021 is 114074.5 dollars.

4. OPTIMAL STRATEGY ANALYSIS

4.1. A Brief Introduction to the Double Sample Z-Test

Sample Z test is generally used to test the difference between the mean values of large samples (i.e., sample size greater than 30). It is to use standard normal distribution theory to infer the probability of the occurrence of differences, to compare the difference between two means is significant.

4.1.1 Step Description of the Double Sample Z-Test

Step I The nihilistic hypothesis is established, that is, the two mean values are not significantly different, which is represented by.

Step II Calculates the statistic Z value according to the formula. For the two-sample comparison, the Z value is calculated by the formula below.

$$Z=\frac{\overline{X}_1-\overline{X}_2}{\sqrt{\frac{S_1^{\,2}}{n_1}+\frac{S_2^{\,2}}{n_2}}}\quad (\overline{X}_{1,2}\ \textit{is the average of sample}1,2;\ S_{1,2}\ \textit{is the standard deviation of sample}1,2;\ n_{1,2}\ \textit{is the volume sample}1,2) \tag{4}$$

The calculated z-value and the theoretical Z-value were compared to infer the probability of occurrence, and the judgment was made according to the z-value and significance relationship table. The results are shown in the Table below

Table 3. Significance judgment basis

|Z|	P	Difference degree
≥2.58	≤0.01	Significant
≥1.96	≤0.05	General
<1.96	>0.05	Non- Significant

4.1.2 Analysis Results of the Two-sample Z Test

The left table shows that we assume that the relationship between the non-de-risk forecast Cashflow and the Optimal prediction asset is less than. According to the significance P-value of 1.000, there is no sign at the level, so the null hypothesis cannot be rejected. It indicates that there is no significant difference between the mean difference of the two fields and the test

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comparison difference of 0.000, and the relationship is less than that, indicating that the result of Optimal Prediction Asset is better than the non-de-risk forecast Cashflow, and the model established in Task 1 is better than the non-de-risk model.

The right table shows that we assume that the relationship between considering only Bitcoin Assets and the Optimal prediction asset is less than, and according to the significance P-value is 1.000, there is no significance at the level and the null hypothesis cannot be rejected. It indicates that there is no significant difference between the mean difference of the two fields and the test comparison difference of 0.000, and the relationship is smaller than 0.000, indicating that the result of the Optimal Prediction Asset is superior to Consider only Bitcoin Assets, and the model established is superior to the non-risk elimination model.

Table 4. Z-test results under different conditions

Difference compared: 0		
Hypothesis: Less		
	Non-de-risk forecast asset	Optimal prediction asset
Size	1105	1105
Min	1000	950.08
Median	12948.4	54551
Max	102958	115825.3
Mode	1000	54446.9
Average	19472.081	52881.365
SD	22393.289	31052.585
SE	673.654	934.15
Mean difference	33409.283	
Z	-29.008	
p	1	

(a) The relationship between non de risk forecast cashflow and optimal prediction asset is less than

Difference compared: 0		
Hypothesis: Less		
	Consider only bitcoin asset	Optimal prediction asset
Size	1105	1105
Min	957.561	950.08
Median	20299.1	54551
Max	160685	115825.3
Mode	4953.56	54446.9
Average	30161.518	52881.365
SD	34686.473	31052.585
SE	1043.468	934.15
Mean difference	22719.846	
Z	-16.222	
p	1	

(b)The relationship between non de risk forecast cashflow and optimal prediction asset is greater than

optimal strategy.

5. SENSITIVITY ANALYSIS

5.1. Sensitivity Analysis Procedure

Step I Consider the impossibility of data accuracy

When we buy or sell bitcoin and gold, the price of the next day is predicted by the previous data, so we need to consider the possibility of inaccurate data.

Step II Set the ratio of gold and bitcoin transaction fees to R

When we predict the currency price of the next day, the currency price and trend of the previous period are certain but may be affected by some special circumstances, such as national policies, current issues, and other factors, so we do not accurately predict the possible abrupt changes in the data of the next day. Now suppose that the ratio of the gold transaction fee to the bitcoin transaction fee is different, set as R, and repeat the previous solution process for several different R values, we will have an idea of how sensitive the solution of the problem is is to the transaction cost.

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Step III Calculate different transaction costs to get the final value

In the objective function, the COINS and gold poundage of different numerical may affect the transaction costs, thus affecting the current maximum of total assets, so we choose the current total assets, the current cash, the current has gold value, currently has the currency value, study the effect of R values for different results, choose R ratio of 5%: 1%, 2%, 1%, 1%: 1%, 1%: 5%.

As can be seen from the left figure, when transaction costs in the model change, the final asset changes are 90.53%, 115.35%, 98.73%, and 113.90%. By comparing the final value of assets under five circumstances, the final value of assets obtained by this model is relatively insensitive to the change of transaction cost. Meanwhile, it can be seen intuitively that the change of gold transaction ratio has a greater impact on the model than bitcoin.

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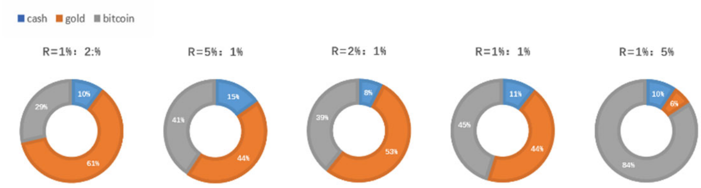

Figure 5. Comparison of currency holdings at different transaction costs

6. CONCLUSION

Anyway, in this paper, we do a lot of data processing. To solve the problem of maximizing investment value, we need to use a variety of techniques in the field of statistics and computer science, and according to the law of value of the financial market, through time series analysis, entropy weight TOSPSIS evaluation method, dynamic linear programming, two-sample Z-test method to extract the characteristics of short-term financial products.

Based on these characteristics, the trading strategy based on a dynamic linear programming model is developed under the condition of stable political and trading factors in the objective market environment.

According to the sensitivity analysis, the paper finds that the final value of assets is relatively insensitive to the change of transaction cost, and bitcoin is more sensitive to the change of transaction ratio compared to gold, which makes us further identify the place that can make our model more powerful.

Unconsciously, the model has high overall sensitivity and can react flexibly to the market, effectively controlling risks and avoiding losses caused by blind investment. Trade strategies continue to present interesting ways for humans to think about and develop mathematical tools to solve. We try to get into this question closely following this narrative, to illustrate and validate the importance of applying theory and curiosity to explore.

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