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A Quantitative Trading Strategy Based on A Position Management Model

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Abstract: With the rapid development of economic globalization, various financial products have appeared in the domestic and foreign financial markets. How to adopt ideal trading strategies to meet the demands of market traders for high returns and low risks has become the focus of investors and the research goal of scholars. In order to solve this problem, this paper establishes a quantitative trading strategy based on the position management model.First, we performed price forecasting for gold and bitcoin based on the Time-series ARIMA method. A differential autoregressive moving average model was developed for the price data of gold and bitcoin at different cycle times, respectively, and used to predict the price of the next trading day. Error analysis was performed with the actual prices, and it was found that the prediction error was the smallest when the data was 60 days, and the relative error of the average prediction value (APV) could be controlled at 0.003016.Then, we establish a quantitative trading strategy based on the position management model. We use the Apriori algorithm of Association rules to study the rising and falling rules of gold and bitcoin assets. According to the rule of " High throw bargain - hunting" in the investment market, we established a position management model and achieved dynamic and stable returns. After the model is established, we continue to introduce the evaluation indexes of the investment value of financial assets, among which the first-class indexes are profitability and safety. We use the Analytic Hierarchy Process (AHP) to determine the weight of each evaluation index, and allocate the daily trading investment through the ratio of two asset evaluation indexes. This quantitative trading strategy, based on the position management model of AHP, can not only stabilize the income but also avoid risks, reaching a quantitative trading strategy with an annualized rate of return of 25%. On September 10th, 2021, the accumulated income could reach 223,640.58 USD.Further, we evaluate the profitability and risk resistance of the strategy using Principal component analysis. Model validation was performed by varying the parameter values and selecting the parameters that yielded a locally optimal solution, which was found to be consistent with our initial parameters and was proof of the optimal solution of the model.Finally, we conducted a sensitivity analysis of the model. The two variable parameters of initial commission fluctuation and investment principal of gold and bitcoin are varied up and down respectively, and the results show that as the initial commission increases or the principal decreases, the number of trades under this strategy gradually decreases and the trading return gradually decreases, and the sensitivity curve shows that the model is sensitive and meets expectations.

Keywords: Time-series Analysis, ARIMA, Position management model, Quantitative trading.

1. Introduction

With the rapid development of economic globalization, financial markets, at home and abroad, have been improving, and a variety of financial products appear. On January 3, 2009, Bitcoin, an online virtual currency, was created. Subsequently, more and more virtual currencies, Wright Currency (LTC) for instance, appear in the mainstream media; and promote the development of financial markets remarkably. As traders make decisions by choosing stocks, bonds, and currencies in financial markets, they find those traditional schemes for market analysis, investment and prediction fail to meet their urgent demand for investment. [1]

Market traders need to make decisions in an extremely complex market, where both profit and risk are uncontrollable factors. [2]How to allocate capital in these financial products to meet market traders' requirements for high returns and low risks has become the focus of market traders and the target of scholars' research.

1.1. Problem Background

1.2. Restatement of the Problem

In financial markets, market traders often buy and sell assets whose value fluctuates greatly to achieve the goal of maximizing total returns. Our team needed to use two pricing data files to build a model to determine whether traders should buy, hold, or sell their portfolios each day to give the optimal daily trading strategy. From September 11, 2016, to September 11, 2021, we will start at $1,000 for a total of five years of trading. Traders' portfolios will include cash, gold, and bitcoin. Given that the initial state is [1000,0,0]; Gold and Bitcoin are paid 1% and 2% of each transaction, respectively.

Problem 1 Build a model based on the price data up to the day, which can give the best daily trading strategy. Using the model and strategy, what is the investment value of the initial $1,000 on September 10, 2021?

Problem 2 Provides data to prove that the model established in the first question provides the optimal strategy.

Problem 3 Prove the sensitivity of our strategy to the transaction price and ask how our strategy and results are affected by the transaction price.

Problem 4 Send our strategy, model, and results to the trader in a memo of no more than two pages.

1.3. Our Work

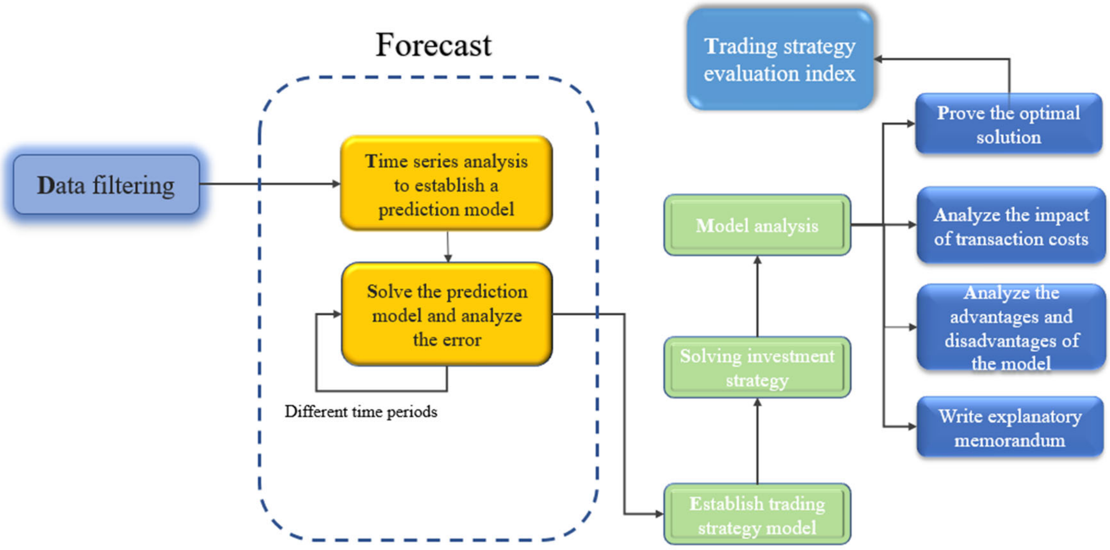

Figure 1. The Flow Chart in This Paper

First, according to the market emotional theory, it is better to use less data for short-term prediction. Therefore we selected 100 days of price data.

Next, we established an ARIMA prediction model using time series analysis. Predict the rise and fall of the next trading day. Since the period of the data has a greater impact on the forecast results, we further analyze the forecast results of different periods and achieve an average. After inspection, the average prediction result is smaller. We finally got an accurate predictive model solution.

Further, on the basis of a more accurate prediction, based on the investment law of the financial market, it is sold when the price of financial products has increased, and it is bought when the price of financial products fell. After analyzing the routine of Bitcoin and gold, we have established a trading strategy model for position management.

Secondly, we have established an evaluation index of the extent of the trading strategy, and the hierarchical analysis is used to make a simple evaluation, which proves that our trading strategy model is the local optimal solution. We analyze how the transaction strategy model is sensitive to transaction costs and how transaction costs affect strategies.

Finally, we analyzed the advantages and disadvantages of the model and wrote a memorandum to deal with our strategy, model, and results.

2. Assumptions and Justifications

1.Assume that the price data of Bitcoin and the price is not affected by the banker control of the dealer.

The banker can take advantage of huge trading volumes and capital control over investment transactions.[3]Because of human subjective initiative, we cannot predict the operation of bankers to compare bitcoin and gold. So we assume that the man is a rational investor, and assume that there is no malicious control.

2. Suppose we have a certain risk of risk during the investment process.

Investors' personality determines their ability to accept risks, and at the same time, investors have certain limits to accept risks.

3. Suppose our transaction operation is fully based on model planning.

Investment traders are prone to various factors such a s market sentiment in the transaction. In reality, the tra der's mentality cannot be ignored, but we assume that t he trader fully follows the trading strategy model to ver ify the model.

4. Suppose the Trading strategies cannot achieve the absolute optimal value.

In addition to the operation of the bankers, we still can't fully accurately predict market activities. In fact, our best trading strategy should only be able to achieve the relative optimal value.

3. Notations

The key mathematical notations used in this paper are listed in Table 1.

Table 1. Notations used in this paper

Symbol	Description
Av	Actual value
Pv	Predicted value
h	Number of consecutive increases
k	Number of consecutive declines
APv	Average predicted value
P	Position amount

4. A Quantitative Trading Strategy Based on A Position Management Model

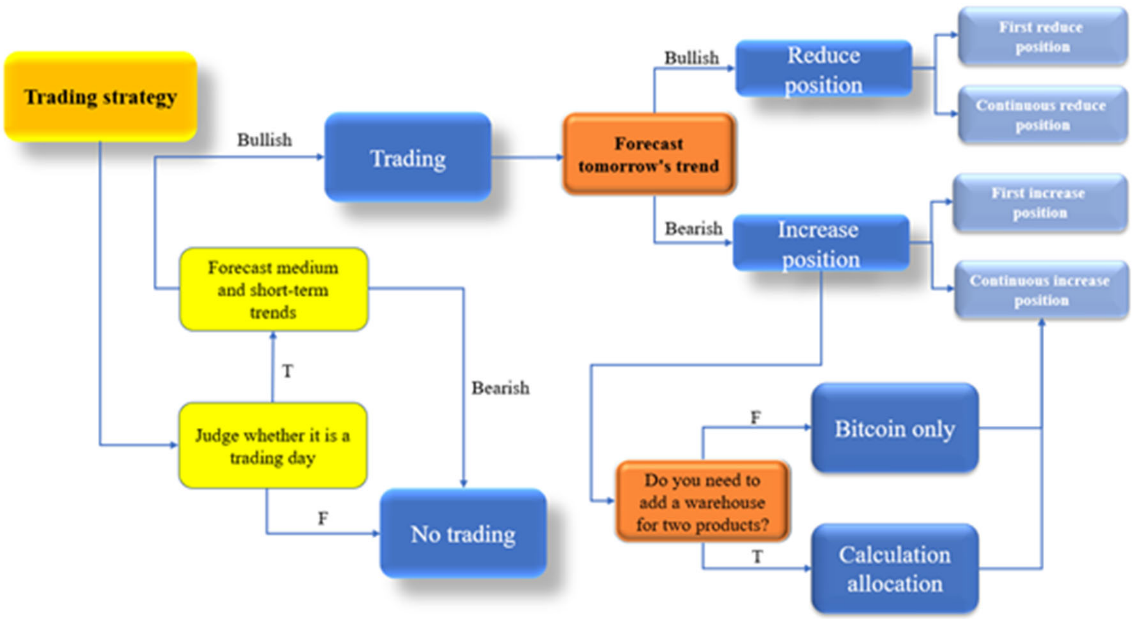

Figure 2. Trading strategy flow chart

For problem 1, the best daily trading strategy is given based only on the price data up to that date and the value is found on 2021.9.10. We first pre-process the existing data and build an ARIMA model based on it to forecast the price of the financial product for the next trading day. Based on the forecast data, we build a trading strategy model based on position management planning and develop a trading strategy for that day based on the principle of buying low and selling high.

4.1. Data Description

Taking Bitcoin as an example, we select the first 100 days of Bitcoin price data from the database given in the question, exclude other data to get the following data, and plot a line graph of Bitcoin price change over 100 days. We can see that the price of bitcoin is trending upward. At the same time, there is some volatility as the price of bitcoin continues to rise.

Table 2. One-day price of Bitcoin in 100 days

Date	Value	Date	Value	Date	Value	Date	Value
9/11/16	621.65	10/6/16	612.08	10/31/16	702	11/25/16	735.64
9/12/16	609.67	10/7/16	617.21	11/1/16	697.01	11/26/16	733.67
9/13/16	610.92	10/8/16	614.74	11/2/16	733.33	11/27/16	727.96
9/14/16	608.82	10/9/16	615.65	11/3/16	686.17	11/28/16	727.31
9/15/16	610.38	10/10/16	617.54	11/4/16	683.69	11/29/16	732.71
9/16/16	609.11	10/11/16	614.77	11/5/16	704.79	11/30/16	742.69
9/17/16	607.04	10/12/16	635.01	11/6/16	712	12/1/16	742.05
9/18/16	611.58	10/13/16	635.96	11/7/16	709.96	12/2/16	772.43
9/19/16	610.19	10/14/16	634.02	11/8/16	708.97	12/3/16	764.33
9/20/16	608.66	10/15/16	637.94	11/9/16	720.93	12/4/16	762.97
9/21/16	598.88	10/16/16	641.42	11/10/16	721.5	12/5/16	754.63
9/22/16	597.42	10/17/16	638.97	11/11/16	715.45	12/6/16	756.62
9/23/16	594.08	10/18/16	636.29	11/12/16	703.71	12/7/16	758.99
9/24/16	603.88	10/19/16	629.25	11/13/16	702.28	12/8/16	769.72
9/25/16	601.74	10/20/16	627.72	11/14/16	706.46	12/9/16	770.02
9/26/16	598.98	10/21/16	631.92	11/15/16	710.91	12/10/16	769.08
9/27/16	605.96	10/22/16	655.48	11/16/16	711.73	12/11/16	777
9/28/16	605.67	10/23/16	653.25	11/17/16	736.96	12/12/16	777
9/29/16	603.85	10/24/16	651.39	11/18/16	747.52	12/13/16	777.99
9/30/16	609.39	10/25/16	655.31	11/19/16	748.98	12/14/16	774.89
10/1/16	614.82	10/26/16	651.45	11/20/16	729.06	12/15/16	776.75
10/2/16	612.98	10/27/16	682.22	11/21/16	738.53	12/16/16	775.88
10/3/16	611.85	10/28/16	687.68	11/22/16	736.97	12/17/16	788.7
10/4/16	609.62	10/29/16	685.91	11/23/16	741.63	12/18/16	788.4
10/5/16	607.18	10/30/16	698	11/24/16	737.45	12/19/16	788.67

Figure 3. Bitcoin price changes in 100 days

4.2. Short-term Price Forecasting Based on Time Series ARIMA Model

Time series, also known as dynamic series, is a series of values of indicators of a phenomenon arranged in time order. ARIMA (Autoregressive Integrated Moving Average Model) is one of the most commonly used forecasting methods for time series. Because ARIMA models are very capable of capturing information from linear data and require only endogenous variables without resorting to other exogenous variables, they are particularly successful in statistical and forecasting stock price changes and are commonly used in financial forecasting. In this paper, we build a differential autoregressive moving average model ARIMA(p,d,q) with 100 days of Bitcoin price change data based on the theory related to time series analysis.

$$y'_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y'_{t-i} + \varepsilon_t + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i} \quad (1)$$

and $y'_t = \Delta^d y_t = (1-L)^d y_t$.

$$\left(1 - \sum_{i=1}^{p} \alpha_i L^i\right)(1-L)^d y_t = \alpha_0 + \left(1 + \sum_{i=1}^{q} \beta_i L^i\right)\varepsilon_t \quad (2)$$

where p is the number of autoregressive terms; d denotes the order of the difference; and q is the number of sliding average terms.

4.2.1. Checking the Smoothness of the Time Series

For the ARIMA model, it is required that the time series data satisfy smoothness. View the results of the ADF test to determine whether it can significantly reject the hypothesis that the series is not smooth (p<0.05 or 0.01), based on the analyzed t-values.

Table 3. ADF test

ADF test							
variable	Order of difference	t	p	AIC	critical value		
					1%	5%	10%
Value	0	0.988	0.994	369.969	-3.5	-2.892	-2.583
	1	-7.693	0.000***	360.538	-3.5	-2.892	-2.583
	2	-7.306	0.000***	364.595	-3.507	-2.895	-2.585

Note: * * *, * * and * represent the significance levels of 1%, 5% and 10% respectively

At the difference of order 0, the significance P-value is 0.971, which does not present significance at the level, and the original hypothesis cannot be rejected, and the series is an unsteady time series.

At the 1st order of difference, the significance P-value is 0.000***, which is significant at the level and the original hypothesis is rejected, and the series is a smooth time series.

At the difference of order 2, the significance P-value is 0.000***, which presents significance at the level, and the original hypothesis is rejected, and the series is a smooth time series.

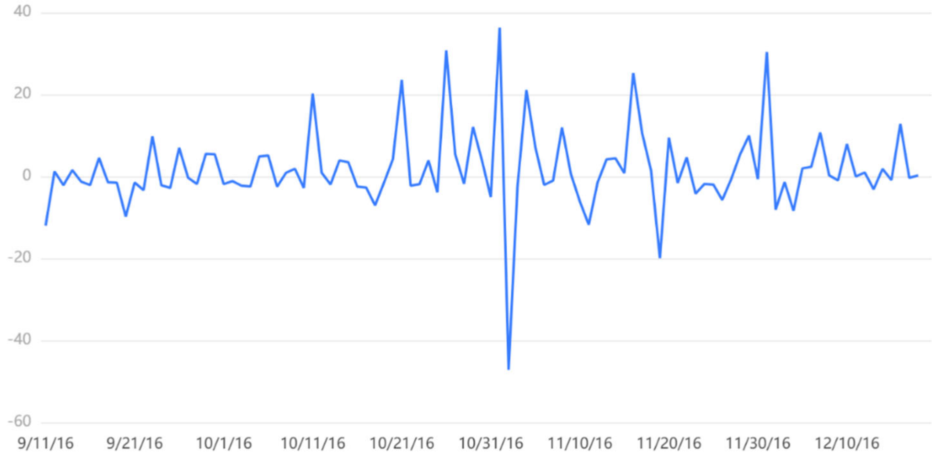

Figure 4. Optimal difference sequence diagram

The original data do not fluctuate much up and down after first-order differencing, and the series satisfies smoothness.

4.2.2. Selected Order

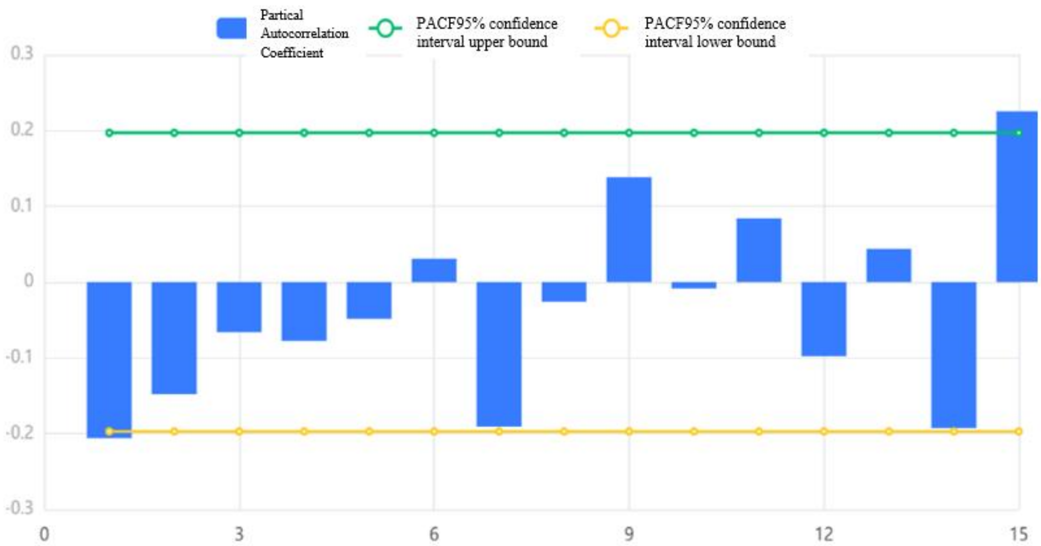

Figure 5. Partial Autocorrelation Function (PACF)

Figure 6. Autocorrelation Function (ACF)

Within the confidence interval, ACF or PACF fluctuates around 0. Both autocorrelation and partial autocorrelation plots dragged the tails, and the most significant order (minimum) in the combined PACF and ACF plots estimated p and q values of 1.

Table 4. Model parameters table

Model parameters table						
	Coefficient	Standard deviation	t	p>|t|	0.025	0.975
Constants	1.773	0.509	3.482	0	0.775	2.771
ar.L1.D.Value	0.445	0.222	2.002	0.045	0.009	0.881
ma.L1.D.Vale	-0.713	0.176	-4.049	0	-1.058	-0.368

The results of the model are the ARIMA model (1,1,1) test table and based on 1 difference data, the model formula is as follows:

$$y(t) = 1.773 + 0.445 \times y(t-1) - 0.713 \times \varepsilon(t-1) \quad (3)$$

4.2.3. Test of the Model

Table 5. Q Statistics

Q Statistics	Q6(P-value)	0.002(0.963)
	Q12(P-value)	0.296(1.000)
	Q18(P-value)	7.648(0.812)
	Q24(P-value)	16.309(0.571)
	Q30(P-value)	20.066(0.693)

From the analysis of the Q-statistic results, it can be obtained that Q6 does not present significance at the level and the hypothesis that the residuals of the model are white noise series cannot be rejected.

$$R^2 = 1 - \frac{ES}{TS} = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y_i})^2}{\sum_{i=1}^{n}(y_i-\bar{y_i})^2} \quad (4)$$

The goodness-of-fit R^2 of the model is 0.977, the model performs well, and the model basically meets the requirements.
(2)

4.2.4. Solving of the Mode

Select the first 100 days, 60 days, 30 days, and 10 days of price data to make the forecast respectively. Calculate the relative error of the forecast results.

Actual value(Av): 721.5.

$$RE = \frac{|Pv-Av|}{Av} \quad (5)$$

According to the error analysis, the most accurate forecast result is obtained when the chosen forecast data is 60 days:

$$RE_p = 0.003454 \quad (6)$$

Table 6. Table of relative error of forecast for different days

Relative error table	
Time	Relative Error
100 Days	0.00365
60 Days	0.00345
30 Days	0.00428
10 Days	0.01991

Table 7. Predicted value

Predicted value	
Order (time)	Predicted value
1	719.008

Because the forecast result is closely related to the period, we choose the price data solution model with different periods of 60 days. And the average value is taken to obtain a more accurate prediction result.

Table 8. Predicted value

Time Period	Separate predicted values
1	719.008
2	724.767
3	714.196

Average predicted value (Apv): 719.324 RE_a: 0.003016

$$RE_a < RE_p \quad (7)$$

Therefore, the average prediction results are more accurate.

Similarly, for gold, we choose 60 days of different time periods of price data to solve the model. And take its average value, we get a more accurate prediction result: 1174.25, the model performance is excellent and basically meets the requirements.

4.3. Position Management Model

Fund management is a very important idea in transactions. We often control the risk of transactions by controlling the use of funds and placing orders based on a fixed percentage of funds. These strategies can be realized by writing the model of adding and reducing warehouses. The model of adding and reducing positions refers to allowing continuous opening signals or continuous closing signals to add and reduce positions. For traders who need to add or subtract positions, when the strategy is implemented, they hope that the next action after opening the position can still be opening the position, or they can continue to close positions in batches. If it is a one-opening-one-leveling signal filtering model, the opening can only be the corresponding closing operation, thus the strategy of adding and reducing the positions cannot be realized. The model of adding and reducing positions allows continuous opening signals or continuous closing signals to solve this problem.

According to the time series ARIMA model above, we first forecast the future trend of the short and medium-term and judge whether to trade. Then forecast the price of any future trading day and judge the price trend of a future trading day. After that, we control the trading risk by using the plus-minus model and establish a quantitative trading strategy. Taking into account the fluctuation of the positions held before the trading day, the total invested capital is guaranteed to be in a non-loss state by adding or reducing the positions. That is, when the risk is lowest, a trading strategy with relatively stable returns is obtained. The method avoids that the transaction is at extremely high risk due to a single search for the optimal solution when the transaction yield is the highest.

4.3.1. Analysis of the Law of Rising and Fall

First of all, we analyze the fluctuation rule of historical transaction price data of gold and bitcoin respectively.

Step 1: Separately calculate the rise and fall rates of gold and bitcoin for each trading day before the trading day. The price increase rate t_n on day n is {closing price on day n–closing price on day (n-1)}/closing price on the day (n-1), i.e.

$$t_n = \frac{W_n - W_{n-1}}{W_{n-1}} \tag{8}$$

Step 2: Get the median of all the gains/losses in gold and bitcoin respectively.

Step 3: According to the association rule Apriori algorithm, count the number of subsets in the transaction data for 2 consecutive times, 3 consecutive times, 4 consecutive times and 5 consecutive times of rise/fall: up {h2,h3,h4,h5}, down {k1,k2,k3,k4,k5}.

Step 4: Obtaining that the number of consecutive times of more than 90% of the subsets in all continuously rising/falling subsets is greater than/less than u1 times.

Step 5: In the historical transaction data, for every U price, increase and decrease, get M9 of all price increases and M1 of all price decreases. Among them, M9 is the ninetieth digit in all the increased data, indicating that 90% of the data fall under M9; M1 is the first decile of all the increased data, indicating that 10% of the data falls under M1.

Based on the above statistics, it can be analyzed that under ideal conditions, if there is no significant difference between each increase and decrease when the price falls u1 times, it just falls M1. If we add positions every time the price goes down, then we will get a profit the next time the price goes up by M5.

4.3.2. Model Establishment and Solution

When making the forecast based on the ARIMA model, we found that the error between the forecast result and the actual price is the smallest when the 60-day data is used for the forecast. Therefore, our cash, gold, and bitcoin [C, G, B] allocation values for the first 60 days remain in the initial state [1000, 0, 0]. When we forecast based on the ARIMA model when trading from the 61st day, we found that when we forecast using the 60-day data, the error between the forecast result and the actual price is minimal. Therefore, our cash, gold, and bitcoin [C, G, B] allocations for the first 60 days remain in their initial state [1000,0,0] and are traded from day 61 onwards.

Table 9. Statement of loss at trade date

Trading Day	Investment amount	The previous day's trading day's increase or decrease	service charge	Actual loss
Day 1	P_1	-m	1% P_1	1% P_1
Day 2	P_2	-n	1% P_2	1%(P_1+ P_2)+ $P_1 \times$ m
Day 3	P_3	-o	1%P_3	1%(P_1+P_2+ P_3)+ P_1×m+(P_1+P_2)×n
…	…			…
Day n	P_n	-z	1%P_n	$1\% \sum_{i=1}^{n} P_i + P_1 \times m$ $+(P_1 + P_2) \times n + \cdots$ $+(P_1 + P_2 + \cdots + P_{n-1}) \times z$

Based on the above statistics, it can be analyzed that under ideal conditions, if there is no significant difference between each increase and decrease when the price falls u1 times, it just falls m1. If we add positions every time the price goes down, then we will get a profit the next time the price goes up by M_5.

Among them, the amount of the first addition is P_1;

The amount of the second addition is P_2;

The amount of the third position increase is P_3;

The amount of the nth additional position is P_n.

Countable formula:

$$P_2 \times (1-1\%) \times M_{0.5} + P_1(1-1\%) \times \left(\frac{M_{0.1}}{u_1}\right) M_{0.5} \geq 0 \tag{9}$$

$$P_3(1-1\%) \times M_0 5 + P_2(1-P_2)\left(\frac{M_{0.1}}{u_1}\right) M_{0,5} + P_1\left(\frac{M_{0,1}}{u_1}\right)^2 M_{0.5} \geq 0 \tag{10}$$

By analogy, the conditions to be satisfied for the n-th addition are:

$$(1-1\%)\left[P_n \times M_{0.5} + P_{n-1}\left(\frac{M_{0.1}}{u_1}\right) M_{0.5} + \cdots P_1\left(\frac{M_{0.1}}{u_1}\right)^{n-1} M_{0.5}\right] \geq 0 \tag{11}$$

Among them, n also indicates our ability to increase positions, which is related to the maximum number of ups and downs we counted. That is, if the maximum number of falls calculated for more than 90% on that day is 4, this means that the probability will only fall 4 times in a row. We will ensure that we have the ability to add positions 5 times to determine the number of positions for the first time.

For example, when we were working on the 300-day bitcoin position on the same day, we knew that the 299-day bitcoin fell by -0.0455. We first counted the number and frequency of consecutive decreases in the first 299 days, as shown in the following table:

Table 10. The number and frequency of consecutive declines in the previous 299 days

K	Frequency	Probability
K2	27	58.70%
K3	11	23.91%
K4	6	13.04%
K5	2	4.35%

From the data in the table:

$$P(K2)+ P(K3)+ P(K4)=95.65\% \tag{12}$$

We calculated that the maximum number of consecutive falls of more than 90% is 4, i.e. only 4.35% is likely to have more than 4 consecutive falls.

Calculated by MATLAB, the median decrease is M5: -0.0047593, and the decile decrease is M1:-0.056583. At this point, we get the required parameters.

At this time, we only need to consider that we can still close the position under the condition of 4 consecutive falls. Through the above formula, we can use MATLAB polynomial to calculate and solve P1=75.4158345. P1 is the amount we added when we first fell, i.e. we should at least make up the position of bitcoin at $75.416 on the 300th day to guarantee revenue.

The above is the analysis and calculation of the position management strategy. Next, we establish an evaluation index for financial products and allocate the amount of investment in the two financial products in proportion when the second financial product needs to be added to the position simultaneously.

We use the volatility of financial products to express their safety and use the average increase and the number of days of increase to express their profitability. We then use safety and profitability to calculate the allocation of funds when both need to be placed simultaneously.

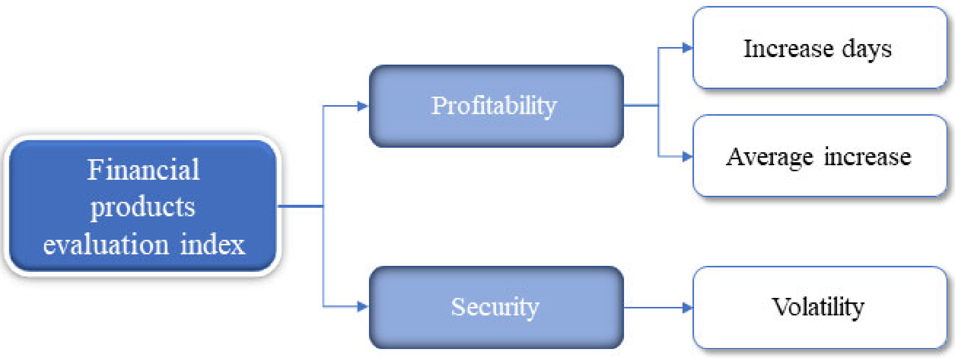

Figure 7. Evaluation Index System of Financial Products

A blank line in the chart indicates that the day is a non-trading day for gold, so there is no allocation. At the beginning of the trading period, the average increase and the number of days of increase are equal for both, so the amount of money allocated to both is equal. As bitcoin rises more, the amount invested is allocated more. But at the same time, the volatility of bitcoin becomes larger, and the maximum 60-day standard deviation of the neighboring bitcoin reaches 486.37, which makes it less safe. Therefore, the tendency of the bitcoin investment amount allocation to become larger is reduced, and this allocation strategy ensures both the safety and profitability of the fund allocation.

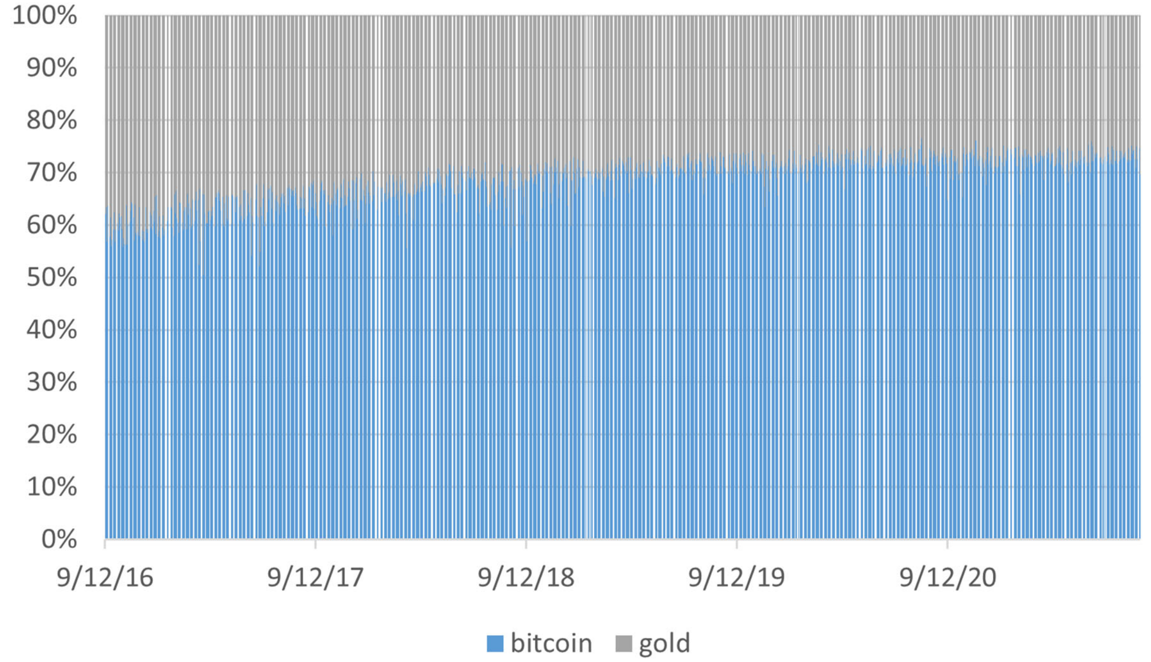

Figure 8. Investment allocation rate

The above is the analysis and calculation of the position management strategy. Next, we set up an evaluation index for financial products to allocate the investment amount in proportion. We use the volatility of financial products to express their safety and use the average increase and the number of days of increase to express their profitability. We then use safety and profitability to calculate the allocation of funds when both need to be placed simultaneously. At the beginning of the transaction, the average increase of the two companies is equal to the number of days of increase, so the allocation of funds between the two companies is equal. When the increase in bitcoin increases, the allocation of investment amount increases, but at the same time, the fluctuation degree of bitcoin increases, and the security decreases. Therefore, the trend of bitcoin investment amount allocation becoming larger decreases, and this allocation strategy ensures the safety and profitability of fund allocation.

Based on the above calculation of transaction allocation for different financial products, combined with the judgment of whether to conduct transactions and the analysis and calculation of position management strategies, we have established a complete transaction strategy model.

Based on our trading strategy model, we conduct daily trading and calculate the annualized trading rate for each trading day. The results are shown in the figure below. It can be seen that the annualized yield is generally on the rise. The annualized rate of return was negative for a few days in the beginning because the prior period was affected by the decline. With the increase in the number of transactions, the daily annualized rate of return rose rapidly in the first three months or so before the investment began, and finally stabilized at about 25%. Our trading achieved the trading objective of continuous and stable revenue and low risk.

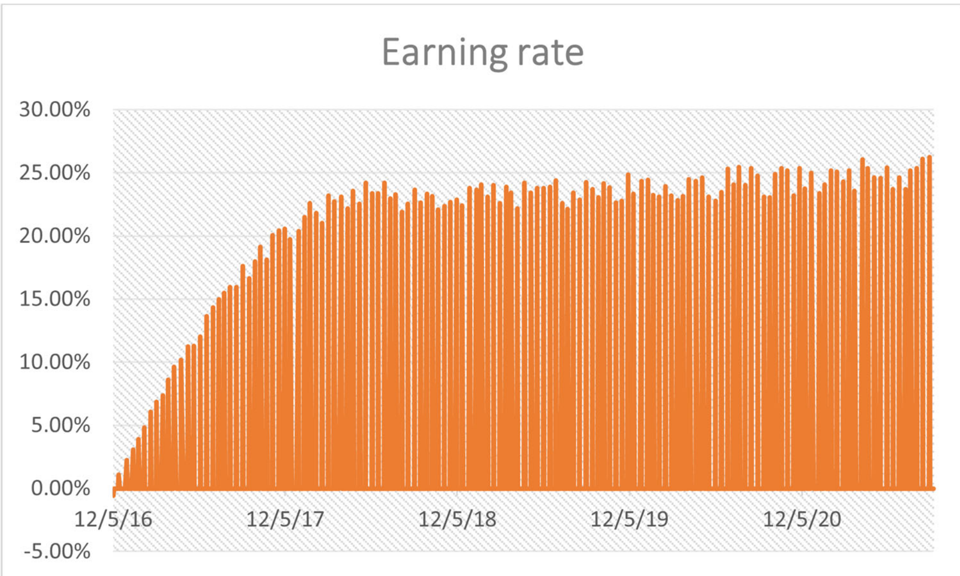

Figure 9. Earning rate

5. Proof of the Best Strategy

A quantitative trading strategy requires a continuous updating and optimization process to adapt to the increasingly complex changes in the investment market. The use of computer-aided analysis and optimization processes is obviously more efficient than manual analysis.

Through the continuous optimization of quantitative trading strategies, the operation of models, and the analysis of data, quantitative investment can better help people to manage capital, improve revenue, and control withdrawal. Through continuous optimization of trading strategies, we can guide people's trading behavior.

Yield, revenue stability, and expected revenue are all evaluation indicators to measure the feasibility of this trading strategy. The yield can be used to measure the profitability of a model. At the same time, considering the risks, the model should have the ability to resist the risks. Therefore, a trading strategy evaluation index includes the ability to return and the ability to resist risks. The evaluation index of trading strategy is used to judge whether the trading strategy of a model is good or bad. The higher the value, the better the trading strategy of the model.

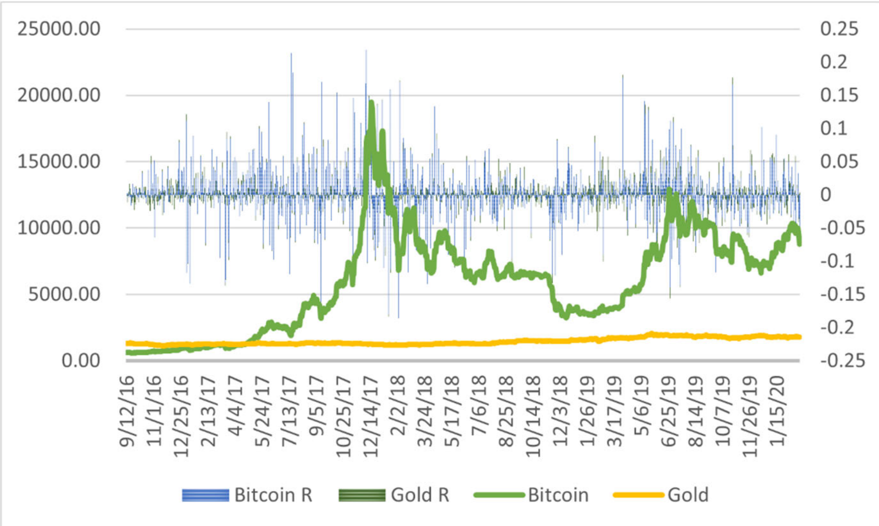

Figure 10. Bitcoin and gold daily price rises and falls

According to the test result of the trading strategy in Question 1, when using the existing data to simulate the strategy given by the model, the strategy can obtain higher revenue than buying and holding, maintain certain stability under various conditions, and obtain better revenue. Based on the trading strategy proposed above. We try our best to grasp the maximum range of each rising price trend and increase the overall yield under the premise of equal risk. Moreover, we can help investors to find statistically significant parts in highly random or non-random price fluctuations, so as to improve the security of transactions and obtain long-term stable profits. Therefore, the model in this paper gives the best strategy.

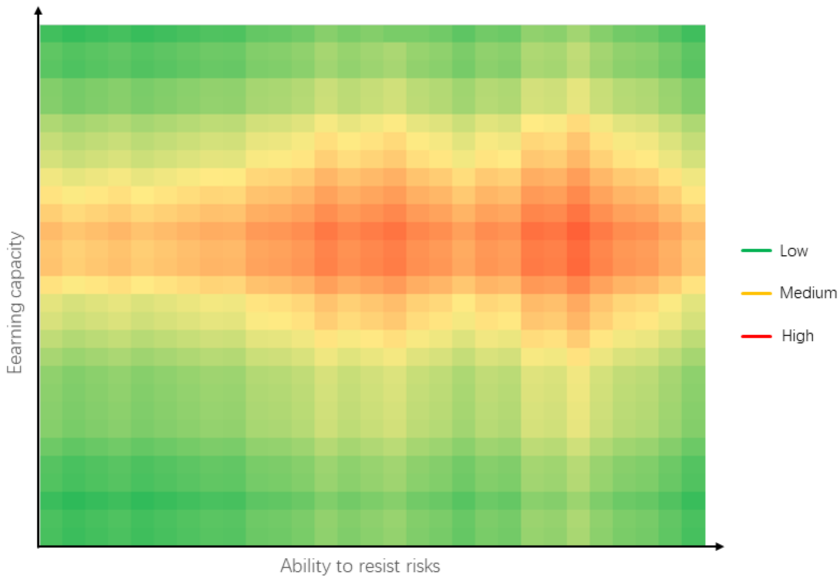

Figure 11. Strategy evaluation index thermal diagram

We change the forecast range of the trading strategy model and the starting time of trading to get the data of different situations. Evaluate their profitability and ability to resist risks by principal component analysis. And calculate the evaluation index of trading strategy when these two data are different. The red part indicates that the value of the trading strategy evaluation index is high.

6. Transaction Costs to The Sensitivity Analysis of The Strategy

To address question three, we need to determine the sensitivity of the strategy to the transaction cost. By changing the transaction cost parameters, we make the commission fluctuate from 1% and 2% for gold and bitcoin respectively when trading. Using the quantitative trading strategy established in the previous step, the following results were obtained.

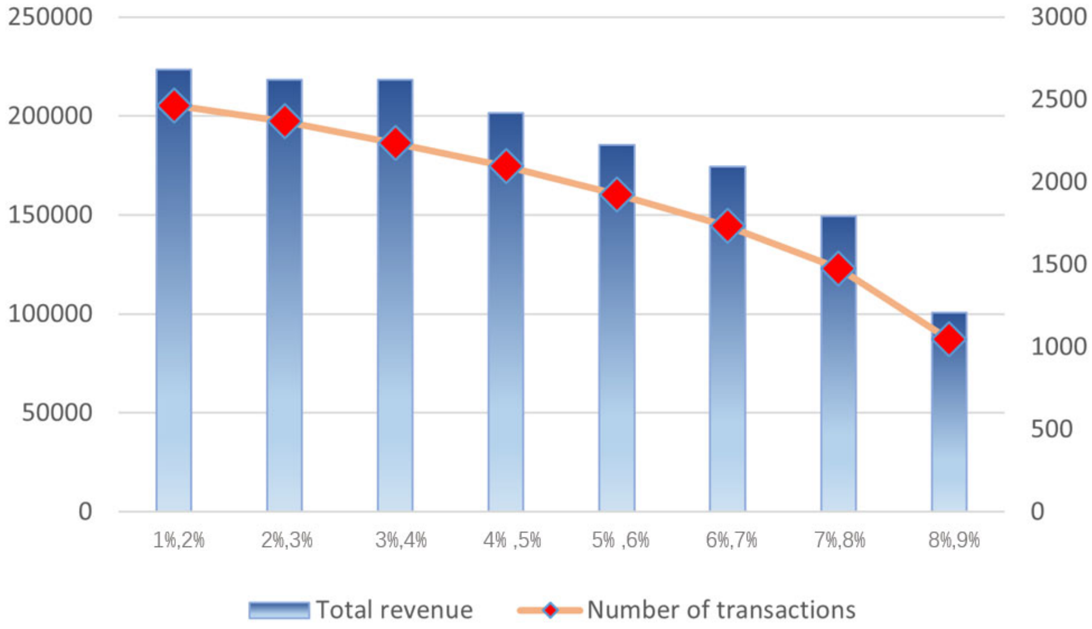

Figure 12. Number of transactions and total revenue when transaction costs fluctuate

The results show that when the trading commissions of gold and bitcoin are 1% and 2%, respectively, the total transaction income is 223,640.6 US dollars. When the trading commissions of gold and bitcoin are 2% and 3%, the total revenue of the transaction is 21,846.37 US dollars. When the trading commissions of gold and bitcoin are 3% and 4%, the total revenue of the transaction is 21,843.45 USD. When the trading commissions of gold and bitcoin are 4% and 5%, the total revenue of the transaction is 20156.89 USD. Since then, when the transaction cost becomes larger, the number of transactions gradually decreases, the decline is faster and faster, and the total income shows a downward trend. It can be seen that the quantitative trading strategy we established is highly sensitive to the transaction cost.

When the transaction cost does not change much, for example, when the trading commissions of gold and bitcoin change from 2% and 3% to 3% and 4%, there is a slight increase, because both risks and benefits are affected. Because reducing the risk of transaction avoidance is greater than the loss. However, when the transaction cost becomes too large, the number of transactions will drop significantly, and the income will also drop significantly.

7. Sensitivity Analysis

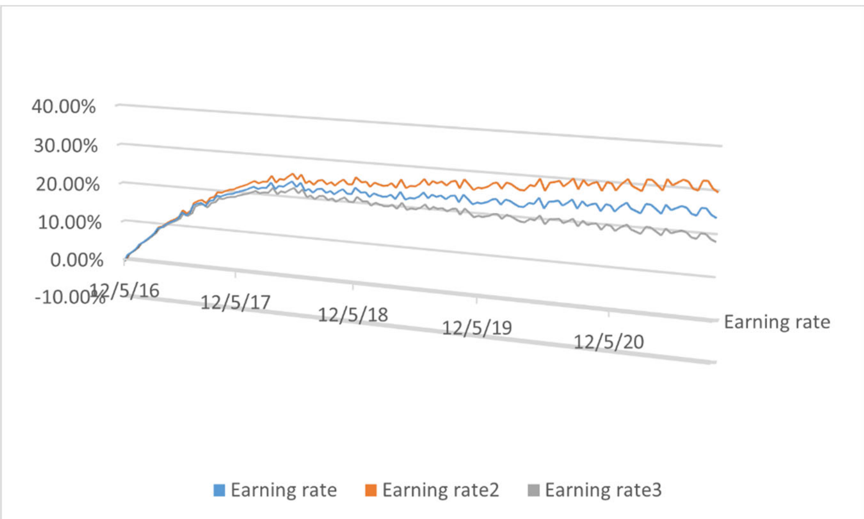

Figure 13. The rate of return when you change the principal

The results show that when the transaction cost is reduced by 10%, the annual return rate is obviously increased. However, when transaction costs increased by 10%, the annual yield decreased. This is reasonable and understandable. This is because both risks and benefits are affected. The changing trend of the curve obtained from the sensitivity test is consistent with the actual situation.

8. Model Evaluation and Further Discussion

8.1. Strengths

1. ARIMA model can be used as a short-term prediction model, and it can be seen from the fitting diagram that the fitting effect is good, which provides a certain reference for the formulation of trading strategies. The error of the result obtained by reasonable assumption is relatively small,

2. When making trading strategies, we use the Apriori algorithm in association rules to produce candidate sets, which greatly reduces the size of frequent sets and achieves good performance.

3. This strategy can achieve higher returns than buying and holding, and maintain certain stability in various situations to obtain better returns.

8.2. Weaknesses

Our model is only suitable for short-term prediction, and the prediction error of long-term results will be relatively large. If the external sound changes greatly, our model will have greatly deviated.

8.3. Further Discussion

Every strategy is formulated with certain timeliness. The trading model can bring investors excess returns in a specific time window and under a specific market situation, but it does not mean that it is a successful trading model at any time. Once it is imitated by a large number of traders in the market, the yield will inevitably decrease. A successful trading model relies on continuous optimization and improvement by using the latest data and algorithms. At the same time, in the process of trading, dynamic information should be monitored in real-time, an early warning mechanism should be established, and strategies should be stopped when problems are found, to prevent the occurrence of major events.

Most of the problems in the problem are idealized and simplified, and some information is covered up to a certain extent. Aiming at the problem, the number of idealized assumptions when the model is established can be reduced by combining with actual experiments, so that the model is more in line with the actual situation.

In the process of the practical application of the model, multi-direction efforts are also needed to realize effective control of investment risks.

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