香港中文大學
The Chinese University of Hong Kong

Time Selection Model of Risk and Return Based on CAPM

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ZHANG Xincong 1155166336
GUO Zhongyuan 1155162320
HUANG Yijing 1155164917
LIU Luyao 1155169203
MA Ziqing 1155162325
RAO Jiayi 1155164916

Content

Executive Summary

This research mainly uses the data of Hushen 300 index from 2005 to 2021 and the data of 22 citic first-level industries. Python3.8 version is used to calculate the industry β according to the capital asset pricing model (CAPM). The spearman rank correlation coefficient between industry β and industry rate of return was calculated to analyze the market performance and forecast the future trend of Hushen 300 index. Through sensitivity analysis of the data in the sample, this study selected the relatively stable spearman rank correlation coefficient threshold and the calculation range of β. When the spearman rank correlation coefficient exceeded the threshold, this model would send long or short signals to guide investors' strategies. It is found that the model has good stability in the long term and performs well under the condition of stable market. The sharp change is the main risk of this model.

1 Introduction

1.1 Research Background and Significance

1.1.1 Research Background

Finance and expectations are inherently linked.

When market participants think that the liquidity is high-level and the future is unknowable, the main purpose of market participants' investment changes. They no longer have the main purpose of discovering the true value of the investment target, but are more inclined to predict the next trend of the market, and sell their stocks to the receiver at the right time. What market participants have to predict is the future price of the stock, the general trend of the future market and the more optimistic or pessimistic expectations of the market, rather than the true value of the stock in the unknown future. This forward-looking way of thinking has brought us more thinking about the financial market. The time selection model of the financial market has also become a topic of continuous discussion and research by many people in the financial industry.

1.1.2 Research Purpose and Significance

Successfully predicting the future trend of the market is always an unrelenting goal pursued by investors. The ups and downs of the market have a significant impact on the results of investors' transactions.

Since the Capital Asset Pricing Model (CAPM) was proposed in the 1950s, CAPM has become a commonly used method in the financial industry to calculate the expected rate of return. Beta index can be used to reflect the relationship between assets and the market. We find this structure by using CAPM, and give the relationship between different industries and the value of beta through the spearman correlation test, and in turn use this structure to predict the market trend, thereby construct a CAPM-based market time selection model.

Using this model, we can determine whether it is favorable time to invest in HS300 on Hushen300 index, and which investment strategy we should choose.

1.2 Literature Review

Quantitative time selection is a strategy of making stock investment buying and selling decisions through quantitative analysis of macro and micro indicators, trying to look back on historical data, and predicting future market price trends based on historical data. This prediction can be based on technical analysis or fundamental analysis. Prospects for market or economic conditions. By reviewing domestic and foreign literature, the quantitative time selection ideas favored by investors in the current market can be summarized into the following three categories: the first category is based on macro-fundamental economic indicators for market forecast time selection, and the second category is based on market price and volume information. The time selection of trends and technical patterns, the third type of mental time selection of investment are based on the hedging of returns and risks.

In terms of literature research based on the macro-state time selection strategy, foreign scholars have a long history of starting research on this. The world's first quantitative investment product is the passive index fund issued by Wells Fargo Bank, which was issued in 1971. Since then, with the continuous development and advancement of the capital market and the continuous development and improvement of quantitative finance, quantitative investment has been favored by investors due to its unique advantages and has shined in foreign securities markets. In 1952, Markowitz first incorporated mathematical tools into financial research and established a mean-variance model. This was the beginning of modern quantitative investment theory research. The mean-variance model determines the return and risk of the investment portfolio in a quantitative way, and draws an important conclusion-the expected return of an asset is determined by its own risk. On the basis of this theory, Sharpe (1964) proposed the Capital Asset Pricing Model (CAPM), Treynor (1965) developed the Treyner index to measure fund performance, and Jensen (1968) proposed the use of α Indicator measurement, the richly developed CAPM model has become the theoretical basis for quantitative investment. Fama (1965) proposed the Efficient Market Hypothesis (EMH), in which rational investors will actively participate in competition in order to maximize their interests. In an efficient market, stock prices can reflect all market information, everyone can obtain all the information, and any prediction of stock prices is invalid. In 1973, Black and Litterman established the Black-Litterman model. The option pricing model has been quickly used in financial practice, making financial instruments increasingly abundant and financial innovation developing unprecedentedly.

In 2005, Sorensen, Hua and Qian proposed that the α quantification model cannot always be applicable and will never change. It needs to be continuously optimized with changes in market conditions.[1] Brooks (2017) used half a century of data (since 1970) to explore four macro-states (economic cycle, international trade, monetary policy, and risk sentiment) and four types of assets (stocks, currencies, long-term government bonds, and short-term.It is found that the long-term returns of the macro-momentum strategy are considerable and stable.[2] Domestic GuangFa Securities analyst Zhang Chao (2018) studied the application of macro factors in market time selection and selected six macro indicators from five categories: economic level, interest rate spreads, consumption and price indices, monetary and fiscal policies, and overseas markets to filter effective factors, using these six effective factors to establish a multiple regression model to predict the future trend of the Shanghai Composite Index. The empirical findings show that this time selection strategy can effectively outperform the rising composite index and can play a good protective role in the event of a large retracement.[3]

In the process of combing domestic and foreign documents, the second type of trend tracking or technical form time selection based on market price and volume information is also the main content of many scholars' research. Moskowitz et al. (2012) elaborated on a typical representative of trend-following time selection strategies-Time Series Momentum, which refers to the trend of asset prices continuing the original direction of movement, specifically if the previous price is rising Trend predicts that it will continue to rise in the future, and vice versa. [4]The third type of investment psychological time selection thinking based on return and risk hedging is an aspect that current domestic and foreign experts and scholars have been working on. It is mainly classified into two categories: α strategy and β strategy, while most of the current time selection strategies The α strategy is the main focus, and the research on the β strategy is gradually being discussed by more scholars. Ibbotson and Chen (2006) studied the relationship between α, β and cost in quantitative hedge funds, and analyzed that hedge funds aimed to pursue α income.[5] Xie Jiang, Wang Hongbing and Cao Chuanqi (2008) found that this strategy is effective in my country's stock market through the study of α strategy. Through quantitative stock selection and

1 Edward Qian, Eric H. Sorensen ,Ronald Hua. Information Horizon, Portfolio Turnover, and Optimal Alpha Models[J].The Journal of Portfolio Management Fall 2007, 34 (1)
2 Jordan Brooks,A half Century of Macro Momentum.AQR Capital Management.August 2017
3 ZhangChao, Macro-factor time selection strategy considering the relationship between lead and lag.July 2018
4 Tobias J.Moskowit, Yao HuaOoi,Lasse Heje Pedersen.Time Series Momentum[J].Journal of Financial Economics.May 2012
5 Roger G Ibbotson,Peng Chen.The A,B,Cs of hedge Funds:Alphas,Betas,and Costs[J].SSRN,June 2005

quantitative time selection using financial derivatives, α income can be obtained.[6] Qu Yunxiang and Huang Qi (2011) conducted an empirical study on quantitative investment by constructing a quantitative investment portfolio that can achieve α returns, and verified the feasibility and effectiveness of quantitative investment from an empirical point of view.[7] Ding Peng (2012) systematically discussed and analyzed common quantitative investment strategies at home and abroad, and through the analysis of domestic market data, combined with the actual description of the domestic application areas and prospects of quantitative investment. Introduced examples of trend trading strategies using Multicharts programmatic trading platform. Combined with his own work experience, he designed the D- α quantitative hedging trading system. The trading system includes quantitative stock selection, time selection, arbitrage, programmatic trading and other strategies, which has strong practicability. [8] Fu Yingbian(2012) through the study of the combination β coefficient and its stability and the CAPM empirical test on the sample data, it is concluded that the β coefficient has good stability during the sample period, and whether the expected return rate of the combination is between the β coefficient The positive linear correlation is tested, and the result shows that there is a negative correlation between the expected return of China's industry portfolio and β; the result is analyzed on the industry β coefficient, and then time series and cross-sectional tests are performed to obtain the system risk There is no positive correlation with the expected rate of return as shown in CAPM, but a negative correlation. It is concluded that non-systematic risks also have an important impact on the return of stocks. [9]

1.3 Literature Analysis

Based on the above literature review and analysis of the research results of domestic and foreign scholars for many years, the quantitative time selection ideas favored by investors in the current market can be summarized into three categories. Among them, the first type of market forecast time selection thinking based on macroeconomic fundamental economic indicators is the early traditional time selection strategy, while the second type of time selection strategy that uses stock market price and volume information to track has a more direct response to the market, and the analysis results are also Closer to the actual market phenomenon, the strategy win rate is higher. However, most of the current research on time selection strategies are carried out based

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6 Xie Jiang, Wang Hongbing and Cao Chuanqi. United Securities-Alpha Strategic Research Series ,2008.

7 Quyunxiang,Huangqi.A Study on the Quantitative Portfolio Strategy for Obtaining Alpha Returns——An Empirical Study Based on the Shanghai and Shenzhen 300 Index[J].Mordern Industry,2011

8 DingPeng,Quantitative investment——strategy and technology ,2012

9 Fu Yingbian,The Research Status of Capital Asset Pricing Model CAPM in China's Stock Market[J],Investment and cooperation,2012

on traditional methods and theories. The most common and widely used CAPM model is obviously less widely used in time selection. In addition, in the application of CAPM model, the β coefficient has always been the top priority. However, based on the previous calculation of β value to measure the expected rate of return of individual stocks or individual industries, this article uses the known β Value, the correlation between individual stocks and β value is used to reversely predict the market, in order to achieve the purpose of time selection, so as to construct a quantitative time selection strategy, and at the same time, after the effectiveness and generalization of the time selection strategy are tested to get conclusion.

2 Research Methods and Research Contents

2.1 Research Methods

According to the capital asset pricing model, assuming that the beta value of the asset is stable, when the market rises, the beta high assets should reap higher returns, but when the market falls, they will also bear more losses, so the beta value represents The size of the market risk that the asset bears. Through the capital asset pricing model, we have found a structure that exists in the market. There will be a relatively fixed correspondence between the rise and fall of different assets and the rise and fall of the market portfolio. If you use this correspondence in reverse, you will get a way of observing the market. For example, when it is found that high-beta asset returns are higher and low-beta asset returns are lower, the market is likely to be in an upward state. It is found that the high-beta asset return is low, and the low-beta asset return is high, the market may be in a downward state, so we can construct a time selection model.

2.2 Research Contents

2.2.1 Capital Asset Pricing Model (CAPM)

American scholars William Sharpe (1952), Lintner (John Lintner, 1965) and others developed CAPM on the basis of asset portfolio theory and capital market theory. It is the equilibrium theory of the selection theory of investment portfolio. Its basic idea is the market return at which people take risks when equilibrium is reached. The formula for the expected rate of return of a single asset or a portfolio of assets is derived as follows:

$$E(R_P) = R_f + \beta_P\left(R_m - R_f\right)$$

Where R_P is the rate of return of the asset or asset portfolio, R_f is the risk-free rate, R_m is the rate of return of the market portfolio, and β_P is the systemic risk beta of the asset. Beta coefficient is an important concept in the CAPM model. In the method of evaluating stock market volatility risks and investment opportunities, the beta coefficient is one of the important reference indicators for measuring structural and systemic risks. Its true meaning is a specific asset (or portfolio of assets). System risk measurement. The so-called systemic risk refers to the price fluctuations of assets that are affected by macroeconomics, market sentiment and other overall factors. In other words, it is the linkage between stocks and the market. The higher the system risk ratio, the stronger the linkage. Beta reflects the sensitivity of the price of a specific asset to the overall economic fluctuations, and reflects the degree of deviation of a certain investment object from the overall asset (market fluctuation).

The larger the absolute value, the larger the change in the return range relative to the market; the smaller the absolute value, the smaller the change in the market. If it is a negative value, it shows that the direction of change is opposite to that of the market. The β coefficient is based on investment theory.

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)}$$

β=1, which means that the risk return rate of the single asset changes in the same proportion as the average risk return rate of the market portfolio, and its risk situation is consistent with the risk situation of the market investment portfolio;

β>1, indicating the risk-return ratio of the single asset is higher than the average risk-return ratio of the market portfolio, the risk of the single asset is greater than the risk of the entire market portfolio;

β<1, indicating that the risk-return ratio of the single asset is less than the average risk-return ratio of the market portfolio, then the single asset The degree of risk of the asset is less than the risk of the entire market portfolio.

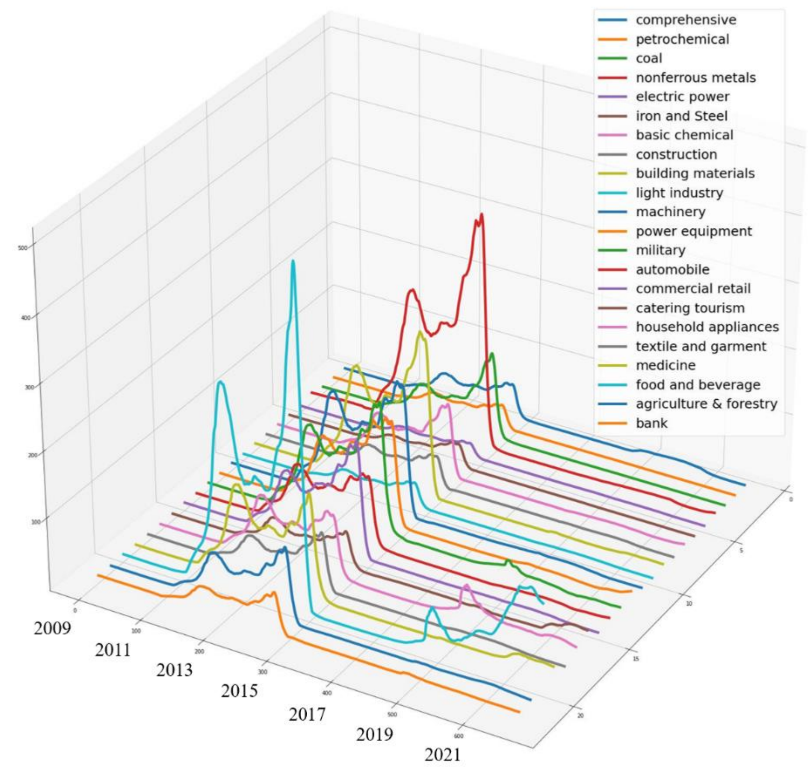
In the rate of return formula of the capital asset pricing model, if the beta is fixed, then the rate of return on capital mainly depends on the rate of return of the market. Therefore, when the market rises, high-beta industries will increase more, and if the market declines, high-beta industries will fall more. With this, we try to reversely infer the market's rise and fall. When the industry's growth rate is basically consistent with its beta state, we say that the market is rising. On the contrary, it means that the market is falling. Based on the above theory, we use the β strategy of passively tracking the market index.

2.2.2 The Cycle Characteristics of Different Industries With β

All trades and industries are affected to varying degrees by domestic and foreign macroeconomic factors, but the degree of impact is different. Industries that are highly correlated with the macroeconomic environment and show cyclical cycles are called cyclical industries. It is characterized by cyclical fluctuations in product demand and raw material prices. Typical industries are automobiles, steel, coal, etc. The performance of this type of industry is closely linked to market performance and usually has a high beta.

The opposite type of industry is called a defensive industry. The demand of this kind of industries is more stable than that of the cyclical industry, and the flexibility is relatively small. The prosperity degree of the industry is affected by macro economy. Typical industries are food, health care, public utilities, etc. This type of industry usually has a lower beta. Although the betas of different companies in each industry often differ greatly and the beta of the industry is not static, the long-term comprehensive view shows that the relationship between the characteristic attributes of each industry and its beta is basically stable. The beta value of most industries is between 0.8-1.2. The beta value tends to remain relatively stable for a period of time, but there are also transitional changes at some special moments. For example, in the mid-2015, a sharp rise in the market caused changes in the beta of many industries, and this change has continued to this day. Favoring TMT industries, the beta values of computers, media, electronics, communications, power equipment, etc. rose sharply in May and June 2015 and turned into high-beta industries, while the beta value of banking, non-banking and other industries dropped rapidly. The characteristics are closer to low beta. After that, the beta value of the industry has been in a relatively stable state for 16 years. The decline of bulk commodities from 2011 to 2014 has led to cyclical industries with high beta characteristics such as petroleum and petrochemical, coal, nonferrous metals, steel, chemical, machinery, automobiles and other industries whose beta value has been in a downward channel, but the changes have not been drastic. So in the long run, the industry beta can be regarded as a relatively stable value.

Figure 1. Beta value of 22 industries



3 Construct the Time Selection Model of Risk and Return

Market time selection refers to using specific models to judge the trend of the market. If our expectations of market are going to rise, we will take a long position; otherwise, we choose to sell and clear the position or take short position. In this way, we can obtain a rate of return that goes beyond the simple buy-and-hold strategy. Adding time selection conditions to the strategy has a good effect on improving the stability of the strategy and reducing the frequency of drawdown. We used the relationship between β of the industry and the market rate of return to construct the time-selected model.

3.1 Use Beta and Revenue to Measure Industry Consistency and Market Performance

There is a correlation between β of the assets and the range of profit changes in assets, and each industry has a relatively stable β. Based on this, we can measure the β and revenue of the industry, and then judge the situation of the market:

1. If the high-beta industry has higher returns, the market is considered to be performing well and we will take a long position.

2. If the industry with high β has lower returns, the market is considered to be underperforming and we will take a short position.

Compared with the industry and market index, this strategy is relatively stable in the long run and is suitable for making long-term market judgments. We used

Spearman's rank correlation coefficient to measure the consistency between the β of industry and the rate of return.

3.2 Introduction to Spearman's Rank Correlation Coefficient

Spearman's rank correlation coefficient is a non-parametric statistical method. It is used to measure the strength of the correlation between two variables. The calculation method is as follows:

We denote rate of return of the i-th industry as x_i, β of the i-th industry as y_i. We sort the data (x_i, y_i) in the two sets of variables (X, Y) in ascending order, and the sorted position (rank) as x_i', y_i', then we observe the rank difference of i:$d_i = x_i' - y_i'$. The Spearman rank correlation coefficient is:

$$\rho_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

where

$$n = 22,$$
$$d_i = x_i' - y_i'$$

We took the beta of 22 industries in the third week and the corresponding return of return in the fourth week as an example to show the calculation of the Spearman's rank correlation coefficient.

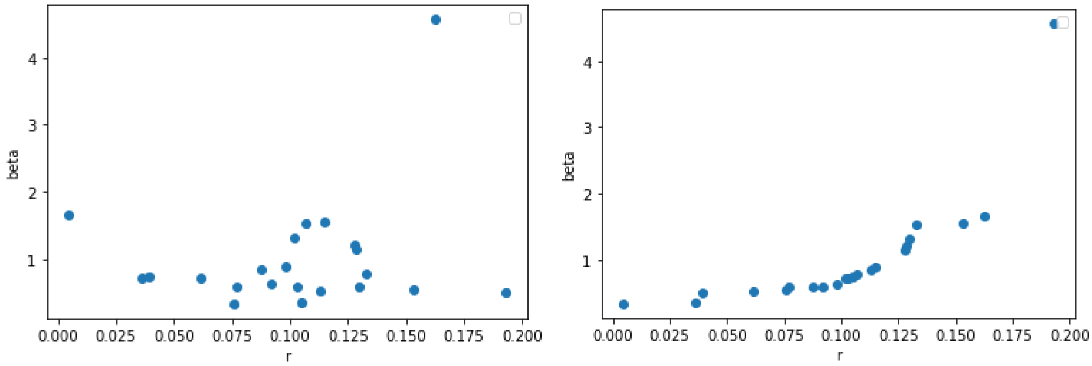
Location	x_i (R_P)	*after sorting*	*x'i*	y_i (β)	*after sorting*	*y'i*	*x'i-y'i*
1	0.1533	0.193069	3	0.550307	4.571714	18	-15
2	0.061778	0.162817	19	0.70513	1.667976	12	7
3	0.035945	0.1533	21	0.703852	1.549783	13	8
4	0.162817	0.132626	2	4.571714	1.539375	1	1
5	0.075816	0.129473	18	0.330094	1.317105	22	-4
6	0.039051	0.128283	20	0.745304	1.20983	11	9
7	0.087394	0.1279	16	0.852514	1.14065	9	7
8	0.076953	0.114756	17	0.578887	0.878665	17	0
9	0.128283	0.112732	6	1.14065	0.852514	7	-1
10	0.104871	0.106549	11	0.344755	0.786457	21	-10
11	0.10173	0.104871	13	1.317105	0.745304	5	8
12	0.097994	0.10317	14	0.878665	0.70513	8	6
13	0.1279	0.10173	7	1.20983	0.703852	6	1
14	0.132626	0.097994	4	0.786457	0.637588	10	-6
15	0.106549	0.09167	10	1.539375	0.588534	4	6
16	0.129473	0.087394	5	0.581433	0.581433	16	-11
17	0.193069	0.076953	1	0.501415	0.578887	20	-19
18	0.112732	0.075816	9	0.524022	0.550307	19	-10

19	0.10317	0.061778	12	0.588534	0.524022	15	-3
20	0.114756	0.039051	8	1.549783	0.501415	3	5
21	0.09167	0.035945	15	0.637588	0.344755	14	1
22	0.004441	0.004441	22	1.667976	0.330094	2	20

Table 1. Example of Spearman Rank Correlation Coefficient Calculation

The scatter plots below illustrate the beta and income distribution of 22 industries in the given weeks.

Figure2. Point Plot of β and rate of return



Before sorting After sorting

The value of ρ_s belongs to [-1,1]. The advantage of Spearman is that the calculated coefficient difference is more obvious, which avoids that the coefficient difference of each period is too small. It can prevent the parameters to be too sensitive. The figure below is the Spearman correlation coefficient between the β of different industries and HUSHEN 300's rate, which measures the consistency of the market as the market changes. We used the β of different industries, rate of return and Spearman's rank correlation coefficient to establish the time selection strategy.

3.3 Time selection Strategy Construction

3.3.1 Basic Data Selection

The CITIC first-level industry index is relatively stable since it launched. HUSHEN 300 is the 300 A-shares with large market capitalization and good liquidity in the Shanghai and Shenzhen securities markets, which can basically reflect the status of various industries in the market. We select these two indexes as industry benchmark data and market benchmark data, respectively. We use weekly data as the return sequence, and the data collection window is from January 03, 2005 to October 29, 2021.

We divide the data into two parts. In term1, we tested the length of historical data we need to use to calculate the beta and spearman time selection threshold. We found that when the weeks are 200 and the threshold is 0.177, the model performs best on term1, and the performance on term2 is close to that on term1. Therefore, the data from January 08, 2010 to December 06, 2013 are term1, and the data from January 08, 2016 to

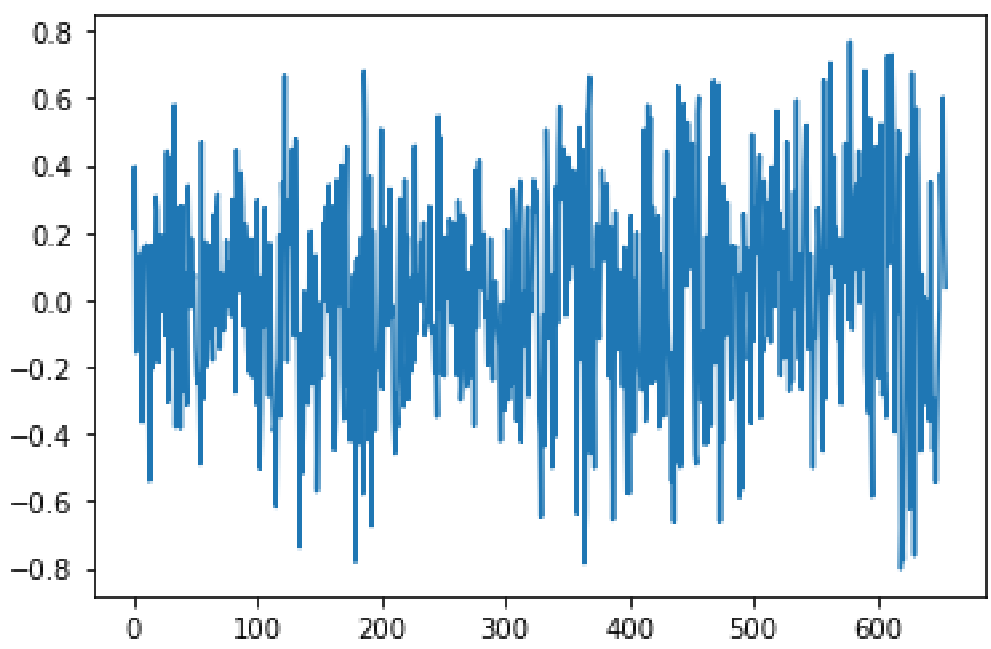
October 29, 2021 are term2. In the term1, we get the threshold of spearman, that is, 0.177. The volatility of the return rate of the two terms under the threshold of 0.177 is also similar and this threshold also has the best performance in term2.

3.3.2 Signal Generation and Time selection System Construction

We assume there are 5 trading days per week and 4 trading weeks per month. We used CITIC first-level industry index to calculate the 200-week beta of the 22 industries, and got beta of every week where $\beta_t = [\beta_{t,i1}, \beta_{t,i2}, \beta_{t,i3}, \ldots, \beta_{t,i22}]$. After getting the beta, we used HUSHEN 300 as the market index to calculate the weekly returns where $r_t = [r_{t,i1}, r_{t,i2}, r_{t,i3}, \ldots, r_{t,i22}]$. In the calculation, we assume that the beta of industry remains static in the middle of the week.

Then we used the current week's rate of return r_t of 22 industries[10] and its last week's beta β_{t-1} to calculate the Spearman's rank correlation coefficient $\rho_{s,t}$. In this way, the beta will not contain this week's information, and these two index remain relatively independent. It can prevent the deviation of beta which caused by outliers. In order to filter the noise in the correlation coefficient and obtain a more stable long-period time selection signal, we took a 4-week moving average of the rank correlation coefficient to obtain a moving average sequence $\bar{\rho}_s$.

Figure3. 4-week moving average Spearman's rank correlation coefficient



[10] These 22 industries include: general, petroleum and petrochemical, coal, non-ferrous metals, power and public utilities, iron and steel, basic chemicals, construction, building materials, light industry manufacturing, machinery, power equipment, national defense and military industry, automobiles, commerce and retail, catering and tourism, home appliances , Textiles and clothing, medicine, food and beverage, agriculture, forestry, animal husbandry and fishery, banks.

3.3.3 Long/Short Strategy and Long Strategy

Long short strategy and long strategy are two common strategies. In this project, we also used these two strategies to operate HS300. We use two different strategies:

(a)Long/short strategy: If the first signal is a long position, we buy the HS300, close the position at the short position and hold a short position. When the next signal is a long position, we close the position and hold a long position. If the first signal is short, then we short the HS300. When the next point is long, close the position and long.

(b)Long strategy: buy the HS300 at the long position point and sell the HS300 at the short position point.

Through calculation, we select 200 weeks of data to calculate beta, and the threshold of the rank correlation coefficient is 0.177. When $\bar{\rho}_S \geq 0.177$, mark it as a long position signal, and when $\bar{\rho}_S \leq -0.177$, mark it as a short position signal.

3.3.4 Back Test

We use the stock index data of HUSHEN 300 from J December 31, 2015 to October 29, 2021 to back test the model. The red point is the long position signal, and the green point is the short position signal.

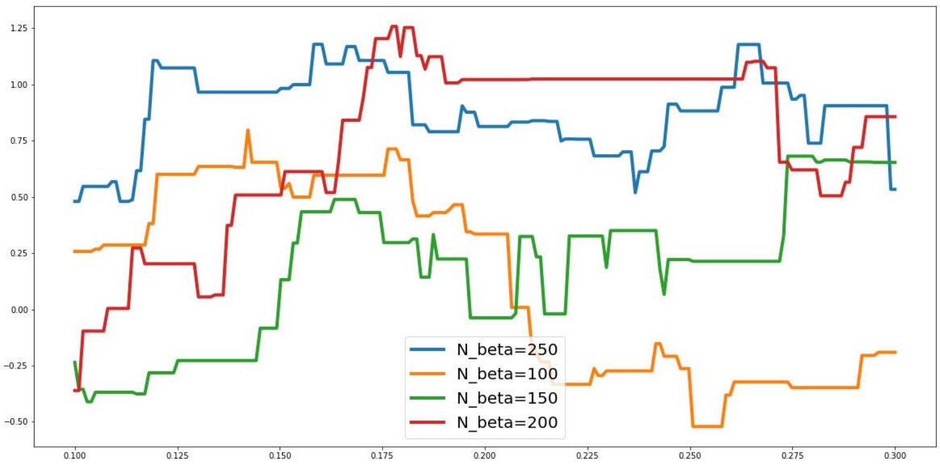
Figure 4. Long and Short Signals from 03/01/2016 to 29/10/2021

4 Sensitivity Analysis and Parameter Selection

4.1 In - sample Sensitivity Analysis and Optimization

Spearman's rank correlation coefficient is sensitive, and the rejection region needs to be accurate to three decimal places. Therefore, we need to make sensitivity analysis to find a threshold that makes the model work best. Besides, we adopt the method of in-sample optimization to select the optimal threshold. As for the in-sample data, we selected the data between 2005 and 2013 to calculate beta using 50 weeks, 100 weeks, 150 weeks and 200 weeks respectively so to get a relatively reliable threshold. The other parameter of the signal trigger threshold, 0.100-0.300 (step size 0.001) was selected for the test. Sharpe ratio was selected as the optimization target. The variation of the Sharp ratio in the sample is shown as follows:

Figure 5. Threshold Selection

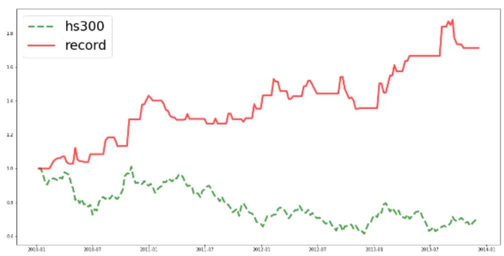


As shown in the figure above, the strategy with high Sharpe ratio generally appears in the situation where the signal trigger threshold is 0.150-0.190. The highest point is 200 weeks, and the threshold is 0.177. Therefore, the strategy parameters are 200 weeks and 0.177 of threshold.

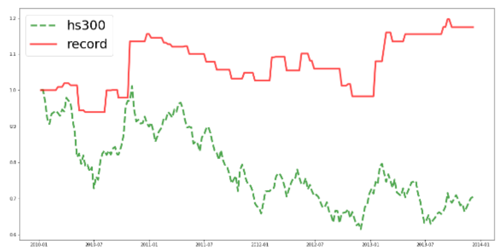
4.2 Strategy Performances of In - sample

The figures below show the in-sample performance of the two strategies. It can be seen that both strategies have increased yields to varying degrees and reduced volatility.

Figure 6. Strategy performances of in - sample



Long/Short Strategy



Long Strategy

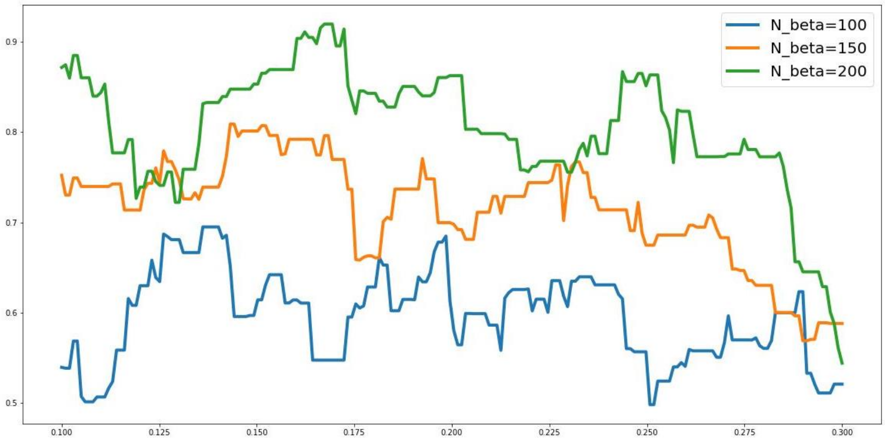
Strategy		*Rate of Return*	*Volatility*	*Max Drawdown*	*Sharpe Ratio*
HS300		1.19%	25.31%	-18.42%	-0.0636
Long	CAPM	15.90%	13.35%	-9.33%	0.9813
Long and Short	CAPM	20.05%	17.94%	-8.46%	1.1179

Table 2. Comparison of Long, Long/Short Strategies and HS300 from 2010 to 2014

4.3 Sensitivity Analysis of Full-sample

The same method as selecting parameters is used to conduct parameter sensitivity analysis on the full sample data, and the result is as shown in the figure below. In fact, there is not so much difference between the full-sample and the in-sample. Again, it works best when number of weeks equals to 200 and threshold is around 0.177. Hence parameter properties have continuity, and the strategy is relatively stable and reliable in practical application.

Figure 7. Sensitivity Analysis of Full-sample



5 Performance of Pure Long Strategy vs Long/Short Strategy

5.1 Long Strategy Performance

In practice, shorting a stock is a relatively difficult thing to do, so we change the strategy to a long strategy. It means that the stocks buying operation is performed when there is a long signal, and the position is closed when there is a short signal.

In the previous section, we have calculated the optimal threshold value of the Spearman coefficient to be 0.177. Under the threshold value of 0.177, we back tested the long strategy on the Hushen 300 index, with data selected from 08/01/2016 to 29/10/2021, and the strategy performed as follows.

Figure 8. Comparison of HS300 and Long Strategy

The starting capital is 1 million RMB, and the ending capital is about 1.77 million RMB. The annualized rate of return of the long strategy reached 10.50%, of which 22 out of 17 trades were profitable and Sharpe ratio of 1.5104.

5.2 The Long/Short Strategy Performance

The Long/Short Strategy is to buy one part of the asset and sell another part of the asset to control the risk, but here we choose Hushen 300 index futures to test the performance of the long/short strategy. That is, when there is a long signal, hold a long position in Hushen 300 index futures, and when there is a short signal, hold a short position in Hushen 300 index futures

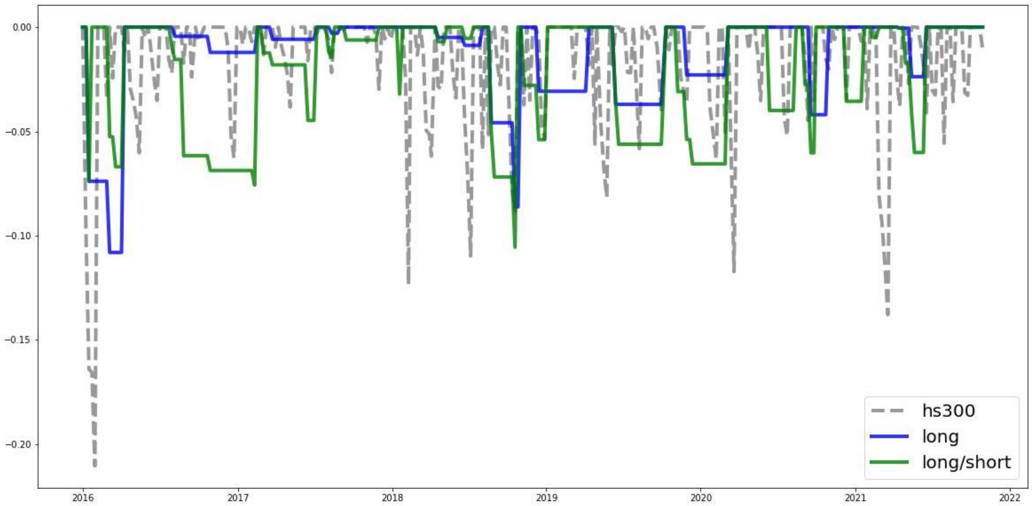
Similarly, with a threshold of 0.177, we back tested the long/short strategy on the HUSHEN 300 index, with data selected from 08/01/2016 to 29/10/2021, and the strategy performs as follows.

Figure 9. Comparison of HS300 and Long/Short Strategy

The starting capital is 1 million RMB, and the ending capital is about 2.78 million. The annualized rate of return of the long/short strategy reached 19.50%, with 43 profitable trades out of 77 trades and Sharpe ratio of 1.0291.

5.3 Model Performance Summary

Figure 10. Drawback plot of Long, Short/Long strategy and HS300 between 08/01/2016 to 29/10/2021



In a word, under the condition of stable market, this model shows a good rate of return and stability, thus this model is a stable medium - and long-term model.

Strategy		*Rate of Return*	*Volatility*	*Max Drawdown*	*Sharpe Ratio*
HS300		6.99%	25.31%	-21.04%	0.2762
Long	CAPM	10.50%	16.50%	-10.80%	0.6362
Long and Short	CAPM	19.50%	18.95%	-10.55%	1.0291

Table 3. Model Performance From 2016 to 2021 Summary

6 Key Findings and Summary

By sorting out the strategies in this research as follows, it can be found that risk-return consistent time selection model is sustainable and effective in long term. The Sharpe ratio of this model is not high, but the probability of single trading loss is small. Hence it is a stable medium- and long-term time selection model.

Strategy	*Time(Yr)*	*Rate of Return*	*Volatility*	*Max Drawdown*	*Sharpe Ratio*
HS300	16-21	6.99%	25.31%	-21.04%	0.2762
Long	16-21	10.50%	16.50%	-10.80%	0.6362
Long and Short	16-21	19.50%	18.95%	-10.55%	1.0291
HS300	10-13	1.19%	25.31%	-18.42%	-0.0636
Long	10-13	15.90%	13.35%	-9.33%	0.9813
Long and Short	10-13	20.05%	17.94%	-8.46%	1.1179
HS300	14-21	10.33%	22.43%	-27.16%	0.4606

Long	14-21	11.64%	15.18%	-8.87%	0.7668
Long and Short	14-21	5.27%	24.43%	-50.35%	0.2156

Table 4. Model Performance Summary

As shown in the table above, during the period 2016-2021, the two strategies of the model performed well, with the volatility of the return significantly reduced, the return significantly increased, and the maximum drawback also decreased.

During the period of 2014-2021, long/short strategies performed worse than 2016-2021, and the volatility of returns increased, while the long strategy could still significantly reduce volatility and improve Sharpe ratio. The main reason for the change mainly comes from the rapid decline in mid-2015, during which the beta values of various industries changed dramatically. And this change also led to the lag and deviation of the signal, which is the main risk of the model, namely, the sharp change of market style.

Changes in market style are highly disruptive to most strategies, not just to this model. Because models are always based on some inherent pattern that already exists in the market, it is difficult for them to forecast when the pattern changes rapidly. This is another example of the scarcity of long-term stable strategies.

To improve the model drawback, one way to consider is to increase the trading frequency, or even to do some operations within a day, giving up part of the return to reduce volatility and drawback. However, this is bound to bring about higher trading costs.

In short, there is no two-sided approach in the market, and risk-return consistent time selection model has been a relatively excellent medium- and long-term time selection model.

7 Reference

[1] Edward Qian, Eric H. Sorensen, Ronald Hua. Information Horizon, Portfolio Turnover, and Optimal Alpha Models[J]. The Journal of Portfolio Management Fall 2007, 34 (1)

[2] Jordan Brooks, A half Century of Macro Momentum. AQR Capital Management. August 2017

[3] Zhang Chao, Macro-factor timing strategy considering the relationship between lead and lag. July 2018

[4] Tobias J. Moskowit, Yao Huaooi, Lasse Heje Pedersen. Time Series Momentum[J]. Journal of Financial Economics. May 2012

[5] Roger G Ibbotson, Peng Chen. The A, B, Cs of hedge Funds: Alphas, Betas, and Costs[J]. SSRN, June 2005

[6] Xie Jiang, Wang Hongbing and Cao Chuanqi. United Securities-Alpha Strategic Research Series, 2008.

[7] Qu Yunxiang, Huang Qi. A Study on the Quantitative Portfolio Strategy for Obtaining Alpha Returns——An Empirical Study Based on the Shanghai and Shenzhen 300 Index[J].Modern Industry,2011
[8] Ding Peng, Quantitative investment——strategy and technology ,2012
[9] Fu Yingbian, The Research Status of Capital Asset Pricing Model CAPM in China's Stock Market[J], Investment and cooperation, 2012

Appendix

Code

https://github.com/Guozhongyuan/TimeSelectionModel-CAPM/tree/main