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Design of Pairs Trading Strategies for Brown and Green Assets with Risk Diversification

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Abstract: Pairs trading attempts to use the idea of relative pricing, that is, if two securities have similar characteristics, then the prices of both securities must be more or less the same. With the promotion of carbon neutrality, the green transformation of brown assets has become a hot topic. Through a series of steps including securities selection, co-integration coefficients calculation, mean-reverting examination, threshold parameters determination, threshold lines design and test set back-testing, a complete pairs trading is done by using brown and green stocks. Besides, a portfolio strategy containing 50 pairs with the strongest co-integration relationship is carried out for diversifying fundamental differential risk, and the result of back-testing is profitable.

1. Brief Introduction

Pairs trading attempts to use the idea of relative pricing, that is, if two securities have similar characteristics, then the prices of both securities must be more or less the same. If the prices happen to be different, it could be that one of the securities is overpriced, the other security is underpriced, or the mispricing is a combination of both. Pairs trading involves selling the higher-priced security and buying the lower-priced security with the idea that the mispricing will correct itself in the future.

2. Road Map for Strategy Design

2.1. Identify Stock Pairs that Could Potentially be Co-integrated

This process can be based on the stock fundamentals or alternately on a pure statistical approach based on historical data. The preferred approach is the combination of these two methods.

2.1.1. Fundamental Approach

According to APT, a pair of stocks with the same risk factor exposure profile satisfies the necessary conditions for co-integration. For example, stocks in the same industry can often be used for pairs trading [1-3], financial assets of the same type can be paired for trading [4-6]. Pairs trading can also be done between stocks of the same company listed separately on the AH stock market [7]. Therefore, targeted stocks can be found under the same investment theme. With the promotion of carbon neutrality, the green transformation of brown assets has become a hot topic. Some researches point out that a “carbon” beta can be obtained by regressing the returns of brown assets and green assets [8-9]. This idea can be further applied to creating investment strategies [10-12].

There exists a suitable way for choosing ideal brown assets and green assets in the stock market, that is, enterprises under the carbon-neutral concept can be divided into the “low-carbon” group (clean energy, carbon reduction technology, finance, testing, environment fathering, etc.) and the “high-carbon” group (mining, metal smelting, chemical industry, thermal power, construction, transportation, etc.) according to the relative intensity of carbon emissions of their production activities. The former can be regarded as green assets and the latter as brown assets.

2.1.2. Statistical Approach

Select stocks under the concept of carbon neutral in iFinD as the targeted stock pool, clean up those with large number of missing values, and categorize brown and green stocks by Shenwan third-level industry classification standard. The training set ranges from 2020 to 2021, and the validation set and test set are 2022 and 2023, respectively.

The statistical premise for pairs trading is that two stocks have a co-integration relationship [13-14]. Firstly, use the unit root test to examine whether the two sequences are single integral (the original sequence is not stationary, but the first-order difference sequence is stationary). Secondly, judge whether there exists a significant co-integration relationship. It is found that there are 200 pairs of brown and green stocks with significant co-integration relationship.

It is worth noting that due to brown and green stocks are in different sectors, pairs trading of only a single group carries a high fundamental differential risk. Therefore, transactions are carried out for 50 pairs of stocks with the strongest co-integration relationship (measured by t-value), so as to construct a portfolio strategy for diversifying risk.

Figure 1: Green & brown series comparison.

2.2. Determine the Co-integration Coefficient

Taking the pair of stocks with the strongest co-integration relationship as an example (Figure 1), assume that the brown stock is X and the green stock is Y. By using training set data, simple linear regressions can be performed to obtain co-integration coefficients. The equation is $lnP_{Brown} = 0.8286 * lnP_{Green} + 1.0648$, and the slope coefficient p value is 0.0000, which is significant at the 1% level. Therefore, the co-integration vector is $(1, -0.8286)$, and the co-integration coefficient is 0.8286.

2.3. Examining the Spread Time Series to Ensure that it is Stationary and Mean-reverting

One of the properties of stationary series, the property of mean reversion, is of particular importance to us. It turns out that highly mean-reverting series are also characterized by a high frequency of zero-crossings. A zero-crossing is defined as the transition of the time series across its long-run mean.

The most direct approach would be to count the number of zero crossings of the residual series and calculate the zero-crossing rate by dividing the number of crossings by the total time. A resampling technique popularly known as the bootstrap can be applied. A probability distribution is then constructed by resampling repeatedly from the existing sample.

Taking the pair of stocks with the strongest co-integration relationship for instance, use the Bootstrap method to draw 200 groups of data each time and iterate 1000 times. The average mean reversion rate of different subsamples in the validation set reaches 46.44% ≈ 50%. The 95% confidence interval is [0.3900,0.5350], which means that the average deviation once will come back, and the mean reversion effect is obvious.

2.4. Examine the Co-integrated Pairs to Determine the Delta

In an idealized situation, transaction costs are not considered. The portfolio can be bought (long Y and short X) when the time series is $k\sigma$ below the mean μ, and can be sold (sell Y and buy X) when it is $k\sigma$ above the mean. In accordance with relevant rules of the stock exchanges, if a transaction occurs at T, the profit will be realized at T+1. For simplicity, we use logarithmic prices to calculate profits, consistent with the price difference calculation formula below.

$$ln(P_1^Y) - \gamma ln(P_1^X) = \mu - k\sigma \quad (1)$$

$$ln(P_2^Y) - \gamma ln(P_2^X) = \mu + k\sigma \quad (2)$$

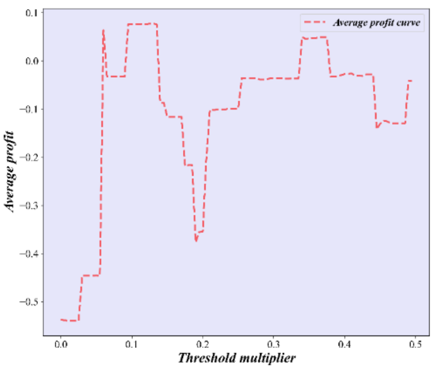

Figure 2: Average profit curve.

It is worth noting that not "the bigger the total gross profit is, the better the strategy is." Because in reality, if there are too many transactions, the transaction cost will be high and the total profit after deduction may not be the highest. Therefore, we should look for a certain k that maximize the average profit. The searching process can be realized by using a nonparametric approach.

Assume that invariant μ and σ are used to construct threshold lines. Use training set for determining μ and σ and validation set for optimization. Take the pair of stocks with the strongest co-integration relationship for instance, as shown in Figure 2, the maximum average profit is 0.0775 per share, and the optimal threshold k is 0.125.

2.5. Modification of the Threshold Lines

2.5.1. Rolling Threshold Line

Assume that the threshold lines are time-varying by using rolling mean and standard deviation, as shown in Figure 3. μ and σ of the training set are applied to the first day of the verification set, μ and σ of the period ranging from training set t=2 to verification set t=1 is applied to the second day, and so on. Therefore, all historical data are used for dynamic calculation. Take the pair of stocks with the strongest co-integration relationship for instance, the maximum average profit is 0.1316 per share, and the optimal threshold k is 0.355.

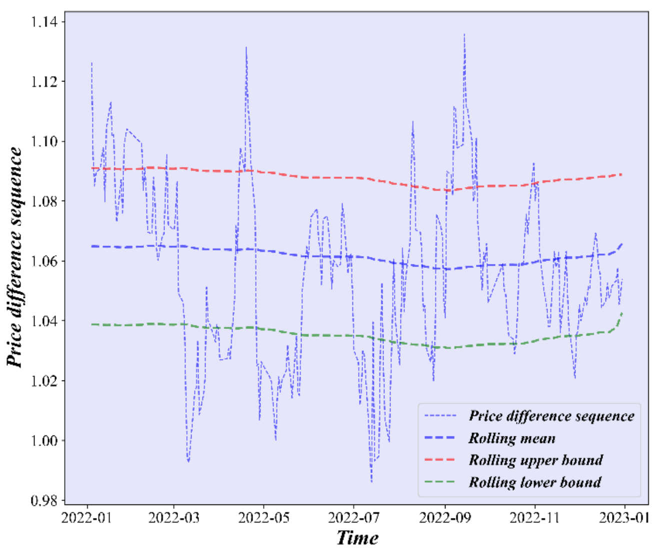

Figure 3: Rolling Strategy.

2.5.2. ARCH Threshold Line

Considering the potential agglomeration effect of price fluctuations, time-varying threshold lines can also be designed based on the ARCH effect [15-16]. Consistent with the rolling threshold lines, by fitting the ARCH model with new data and estimating forward one phase, all historical data are used for dynamic calculation. Take the pair of stocks with the strongest co-integration relationship for instance, the maximum average profit is 0.0976 per share, and the optimal threshold k is 0.03.

2.6. Back-testing

Taking both calculation difficulty and strategy reliability into consideration, the optimal threshold value obtained from the rolling strategy is substituted into the test set for back-testing.

Table 1: Performance Evaluation Indicators for the Top 50 Co-integration Pairs.

Brown code	Green code	k*	N	Retracement*	Cumulative	Average
603698.SH	600292.SH	0.355	1	1.0621	0.869	0.869
002085.SZ	300422.SZ	0.16	5	0.5249	0.5848	0.117
600989.SH	000767.SZ	0.26	1	1.2406	1.0194	1.0194
000928.SZ	000966.SZ	0.165	1	0.5062	0.243	0.243
000652.SZ	300417.SZ	0.38	4	0.2675	0.0773	0.0193
000540.SZ	000826.SZ	0.445	4	0.2377	-0.2609	-0.0652
603053.SH	000767.SZ	0.025	12	3.2418	19.2625	1.6052
603053.SH	300422.SZ	0.475	6	0.1145	-0.1021	-0.017
600871.SH	002401.SZ	0.29	0	0	0	0
000540.SZ	300422.SZ	0.245	2	0.916	-0.8009	-0.4004
000652.SZ	300800.SZ	0.36	4	0.1242	-0.1465	-0.0366
300105.SZ	300007.SZ	0.04	4	0.2197	-0.3928	-0.0982
300716.SZ	300649.SZ	0.44	2	0.5964	0.4486	0.2243
603053.SH	600292.SH	0.105	6	3.5873	10.6575	1.7762
002272.SZ	002610.SZ	0.345	3	1.574	0.1089	0.0363
001896.SZ	000767.SZ	0	4	0.6103	1.2682	0.3171
000540.SZ	300190.SZ	0	5	0.8137	1.9747	0.3949
000652.SZ	002887.SZ	0.06	2	1.0803	1.1219	0.561
000652.SZ	002063.SZ	0.36	1	0.8249	0.6868	0.6868
600968.SH	000993.SZ	0.495	1	0.6965	0.6029	0.6029
300716.SZ	002309.SZ	0	1	1.9752	-2.0673	-2.0673
600968.SH	002549.SZ	0.27	1	0.5244	0.3627	0.3627
000652.SZ	300166.SZ	0.09	1	1.0556	0.5632	0.5632
000540.SZ	600292.SH	0	4	1.1223	2.2306	0.5576
000032.SZ	600475.SH	0.49	4	1.451	0.5633	0.1408
603698.SH	300422.SZ	0.28	3	4.6645	-9.0079	-3.0026
000540.SZ	000591.SZ	0.06	4	0.927	1.9812	0.4953
002909.SZ	603359.SH	0.485	3	0.1176	-0.1878	-0.0626
002564.SZ	002309.SZ	0.045	6	0.6797	-1.7853	-0.2975
601369.SH	000826.SZ	0.075	3	3.6474	-0.0898	-0.0299
000540.SZ	603359.SH	0.27	3	0.7866	1.2691	0.423
600170.SH	002573.SZ	0	10	0.0842	0.3649	0.0365
000540.SZ	603126.SH	0	6	1.0014	3.0477	0.508
000540.SZ	603316.SH	0	4	0.3511	-0.489	-0.1222
002272.SZ	000591.SZ	0.16	7	1.244	2.4694	0.3528
603053.SH	603177.SH	0.24	2	4.0344	4.0025	2.0013
300356.SZ	300422.SZ	0	3	1.7835	3.5658	1.1886
002672.SZ	000826.SZ	0.01	6	1.116	3.3433	0.5572
000027.SZ	600292.SH	0.355	7	0.0649	0.0934	0.0133
000540.SZ	002401.SZ	0.005	0	0	0	0
002554.SZ	000993.SZ	0.31	1	0.729	-0.7294	-0.7294
000540.SZ	603177.SH	0.435	3	1.5344	-0.1536	-0.0512
603698.SH	603177.SH	0.11	1	0.5955	0.3791	0.3791
000488.SZ	300166.SZ	0.475	1	4.1711	3.5544	3.5544
000928.SZ	002658.SZ	0	8	1.6093	6.5974	0.8247
000540.SZ	000966.SZ	0	4	0.7649	1.6456	0.4114
000540.SZ	000767.SZ	0.04	4	0.9225	1.8228	0.4557
002085.SZ	600292.SH	0.485	5	2.7145	-2.4147	-0.4829
001896.SZ	600292.SH	0.155	3	1.1862	-0.0133	-0.0044
000617.SZ	300355.SZ	0.04	9	3.2083	15.4143	1.7127
Average		0.198	3.7	1.2461	1.4711	0.3109

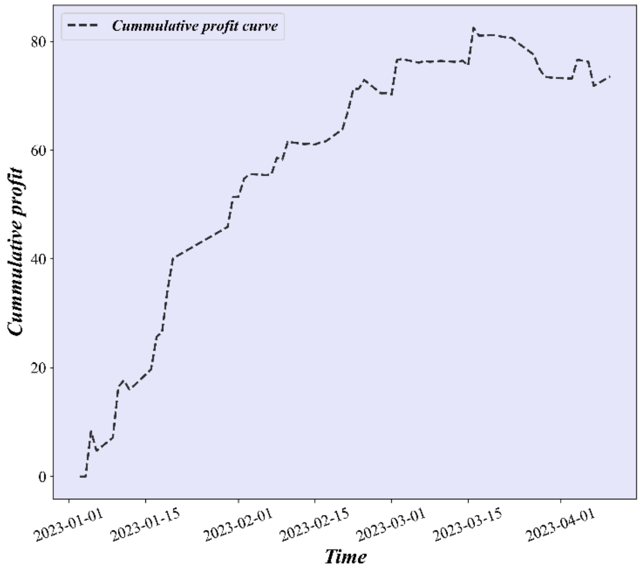

Figure 4: Portfolio Cumulative Profit.

According to Section 2.1, pairs trading is done for the top 50 pairs of stocks with the strongest co-integration relationship. Their performance evaluation indicators are also calculated, including optimal threshold k, number of transactions N, maximum profit retracement, cumulative profit and average profit, which are summarized in the Table 1.

Finally, the cumulative profits of all transactions are added up to obtain the profit curve of the portfolio strategy, as shown in Figure 4, which demonstrate both a high terminal value of 73.5548 and a historical value of 82.4891. These profitable results indicate the effectiveness of our designed strategy.

3. Limitations and Potential Risks

First, slip point refers to the difference between the order price and the actual transaction price. Under normal circumstances, the market is liquid and quotes securities continuously. However, when the market fluctuates violently, trading slips will occur. This paper takes the number of shares N=1 as an example to demonstrate the pairs trading strategy and calculate profits. However, in the real Chinese stock market, the minimum purchase volume is 100 shares. When there is a shortage of liquidity in the market, large orders are difficult to be traded, which is easy to produce a larger transaction slip point, which will have a greater impact on the profits of the strategy.

Secondly, pairs trading may involve short selling, at present, the A-share market require investors to pay a certain proportion of margin before short sales. Therefore, when market extremes occur, they may face the problem of insufficient margin caused by strategy losses.

Thirdly, the threshold parameters used in the out-of-sample test are based on in-sample calculation and optimization. When the overall out-of-sample volatility is small, the spread series may not break through the pre-established threshold line regularly (that is, fewer trading signals are generated), resulting in a long-term one-leg market of the strategy, which will lead to poor application effectiveness of the strategy.

Finally, statistical model failure and technical fault are also potential sources of strategic risks.

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