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An Empirical Study on Pairs Trading Strategy in China's A-Share Market —Taking the Liquor-Making Industry as an Example

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Abstract: Pairs trading is a quantitative arbitrage strategy that exploits financial assets with mean-reversion characteristics. It involves identifying two stocks with closely correlated price movements; when their relative price trends diverge, the undervalued stock is bought and the overvalued one is sold short. Profits are realized by closing positions when the relative price relationship reverts to normal. This paper selects suitable stock pairs for pairs trading using the cointegration test, and establishes trading thresholds through the fixed-parameter method and the GARCH model to form a complete trading strategy. Finally, the strategy is empirically tested using real data from China' s financial market to verify its effectiveness.

1. Introduction

Pairs trading is a market-neutral strategy that profits from spread fluctuations by selecting two stocks with highly correlated historical price movements. Specifically, the spread has a high probability of reverting to its mean once deviating from it; arbitrageurs buy the relatively undervalued stock and sell the relatively overvalued one, and close positions for profit when the spread reverts to the mean. Pairs trading originated in the 1920s from the “Sister Stocks” trading strategy used by Wall Street trader Jesse Lauriston Livermore. In 1985, Morgan Stanley assembled a trading team led by astrophysicist Tartagli to conduct research on quantitative trading, with pairs trading as one of the core strategies.

Although China' s stock market has a relatively short development history, the country has gradually deregulated margin trading and short selling and introduced short-selling mechanisms, significantly improving the operational efficiency and effectiveness of the capital market (Chu Jian & Fang Junxiong, 2016). The implementation of the margin trading and short selling system on March 31, 2010, marked the official launch of short-selling in China' s securities market, providing a foundation for the application of quantitative strategies such as pairs trading that pursue low risk and high expected returns (Suzuki, 2020).

As an independent sector on financial trading platforms, liquor-making stocks are affected by similar fundamentals including macroeconomic conditions, industrial policies, market demand, brand influence, and consumption upgrading trends. Therefore, this paper selects stocks from the liquor-making industry as the underlying assets. First, it tests the long-term and short-term equilibrium relationships between stock pairs to select optimal pairs and derive the spread series. Second, it adopts two methods: fixed thresholds based on constant standard deviations and dynamic thresholds based on time-varying standard deviations. Finally, it empirically compares the two approaches.

The practical significance of this study is as follows. First, the strategy design fully considers real-world margin trading, short selling, and margin requirements, making it directly applicable in practice with strong practical value. Second, the empirical results can serve as a reference for investors.

2. Literature Review

Pairs trading design consists of two core steps: stock pair selection and trading threshold determination. Existing literature mainly focuses on these two aspects.

2.1. Stock Pair Selection

Scholars have developed various methods for pair selection, including the minimum distance method (Gatev et al., 2006), cointegration method (Vidyamurthy, 2004), stochastic spread method (Zhao et al., 2023), and machine learning algorithms (Huck, 2010). The earliest systematic pairs trading framework was proposed by Gatev et al., who minimized the sum of squared deviations between normalized price series to form pairs. Wang (2021) used the Engle-Granger (E-G) two-step cointegration test to select optimal pairs for Shanghai copper futures. Chen (2024) applied cointegration equations to select agriculture-forestry sector stocks with co-moving price trends. Cai et al. (2012) introduced two stochastic spread models based on cointegration to study arbitrage opportunities between CSI 300 index futures and SSE 180 ETF. Zhao et al. (2023) characterized the mean-reversion of spreads using the Ornstein-Uhlenbeck (OU) process and screened pairs by mean-reversion speed and realized volatility. Bagci & Soylu (2024) proposed a machine learning approach to predict optimal rebalancing ranges for pairs trading.

2.2. Trading Threshold Determination

The traditional threshold-setting method is the fixed-parameter approach, which bases trading signals on the standard deviation of historical spreads. Current research covers three main streams: stochastic control (Huang et al., 2015), time-series methods (Peng, 2013), and intelligent algorithms (Yu et al., 2020). Yu and Zhou (2018) constructed an optimal threshold pairs trading strategy based on the OU process, achieving significantly positive arbitrage returns in China' s commodity futures market. Cui et al. (2023) built a time-varying coefficient cointegration statistical arbitrage strategy using the state-space model and applied it to A-share prices of five major state-owned banks. Extracting volatility clustering information via the GARCH model, they verified that time-varying thresholds effectively capture such patterns. Bi et al. (2020) integrated genetic algorithms into partial cointegration pairs trading, optimizing thresholds and monitoring partial cointegration with rolling windows.

3. Theories Related to Pairs Trading

3.1. Pairs Trading Strategy

Pairs trading is a statistical arbitrage strategy. Its core lies in identifying two financial assets with highly correlated prices but short-term divergences, conducting long-short hedging, and profiting from spread reversion. The strategy has two steps: Firstly: Identify stable stock pairs: Screen assets with high historical price correlation and verify long-term equilibrium via cointegration tests, ensuring short-term divergences will eventually revert.Secondly: Set trading thresholds and execute trades: Traditional fixed-parameter methods use fixed multiples of historical spread standard deviations for signals. The GARCH model captures time-varying volatility to set dynamic thresholds, improving adaptability to market fluctuations and risk-adjusted returns.

3.2. Cointegration Theory

Pairs trading requires identifying stock pairs with stable relationships during the formation period using certain methods. Currently, the main approaches include the minimum distance method, the correlation coefficient method, and the cointegration method. This paper employs the cointegration method to select stock pairs with long-run equilibrium relationships during the formation period for an empirical study of pairs trading.

Cointegration theory was formally proposed by Granger and R. F. Engle in 1987. Granger first put forward the conceptual idea of cointegration in 1981, and later collaborated with Engle to complete rigorous theorem proofs and a concrete operational framework.

Definition of cointegration theory: Suppose there exists a set of non-stationary time series $x_t = (x_{1t}, x_{2t}, \ldots, x_{nt})$. If each series is integrated of order d (denoted I(d)), but some linear combination of them is integrated of order $d-b$ ($0<b\leq d$), then these series are said to have a cointegration relationship.

This paper uses the Engle-Granger two-step method to test the cointegration relationship between stock pairs. The specific steps are as follows: First, conduct a stationarity test on each individual series. Only when all series are integrated of the same order can we proceed to the next step. Next, perform a regression analysis with one series as the dependent variable and the other as the independent variable, and save the regression residuals. Finally, conduct a stationarity test on the residual series. If the residual series is stationary, it indicates that a cointegration relationship exists between the two series, and they pass the cointegration test.

In economic and financial data, many variables are non-stationary, but there may be long-run stable equilibrium relationships among them. Cointegration theory can identify such relationships and help analyze the long-run interactions between variables.

3.3. Fixed-Parameter Method

In economics and finance, the fixed-parameter method is commonly used in fixed-effects models for panel data analysis. It is suitable for scenarios where individual characteristics are closely related to explanatory variables, such as studying the relationship between firm performance and corporate governance structure.The fixed-parameter method sets certain parameters as fixed values during model construction or data analysis. Its purpose is to control some variables unchanged so that the effects of other variables on outcomes can be observed more clearly. This approach has two main advantages: Firstly, it accounts for spread volatility to some extent, because the standard deviation reflects the degree of fluctuation in the spread during the formation period. Secondly, it is simple to calculate and easy to understand. However, it also has a drawback: financial time series usually exhibit volatility clustering and heteroskedasticity.

3.4. GARCH Model

Suppose there exists a conditional mean model:

$$Y_t = \beta X_t + \varepsilon_t \tag{1}$$

If the variance of the disturbance term is not a fixed constant, a quadratic function can be adopted for fitting to characterize such heteroskedasticity:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{2}$$

Its implication is that if the disturbance term in the previous period is large, the variance of the current disturbance term will be greater. This indicates that a large disturbance in the current period will lead to an even larger disturbance in the next period. In other words, large disturbances tend to be followed by other large disturbances, while small disturbances tend to be followed by other small disturbances. This is the ARCH(1) model, in which the variance of the disturbance term is characterized by a constant plus the squared disturbance term of the previous period. The ARCH(1) model can be further generalized to the ARCH(p) model:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_p \, \varepsilon_{t-1}^2 \tag{3}$$

When the order is excessively large, given the finite sample size, the number of parameters to be estimated will increase sharply, resulting in a loss of degrees of freedom and biased estimation results. To address this issue, a GARCH term can be introduced, which effectively improves the model estimation accuracy:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma \sigma_{t-1}^2 \tag{4}$$

In the formula, $\alpha_1 \varepsilon_{t-1}^2$denotes the ARCH term and $\gamma \sigma_{t-1}^2$represents the GARCH term. The equation above is the GARCH(1,1) model. Similarly, the GARCH(1,1) specification can be extended to the general GARCH(p, q) form.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_p \, \varepsilon_{t-1}^2 + \alpha_p \, \varepsilon_{t-1}^2 + \gamma_1 \sigma_{t-1}^2 + \gamma_2 \sigma_{t-p}^2 \tag{5}$$

When constructing ARCH and GARCH models, the conditional mean model serves as the foundation. ARCH and GARCH models are established on the basis of the conditional mean model. Therefore, it is necessary to first specify the conditional mean model before constructing ARCH and GARCH frameworks. Once the GARCH model is formulated, it can be applied to forecast future volatility.

4. Pairs Trading Strategy Design

4.1. Calculate Correlation Coefficients

There are three major methods for calculating correlation coefficients in statistics, namely the Pearson correlation coefficient, Spearman correlation coefficient and Kendall correlation coefficient. Taking the daily closing prices during the formation period of 24 stocks in the liquor sector among the margin trading securities listed on the Shanghai and Shenzhen stock exchanges as research data, this paper adopts the Pearson correlation coefficient formula to calculate the pairwise correlation coefficients and construct a correlation coefficient matrix for intuitive observation.

This paper first screens stock pairs with potential cointegration relationships by calculating the Pearson correlation coefficient. Then, cointegration tests are conducted on the top five stock pairs with the highest Pearson correlation coefficients. Those pairs that pass the cointegration test will be included in the subsequent empirical research.

4.2. EG two-step test for cointegration relationship

After screening out the five stock pairs with the highest Pearson correlation coefficients, this paper conducts a cointegration test on them by adopting the Engle-Granger (E-G) two-step method. The specific procedures are as follows. First, this paper tests the stationarity of stock price series of selected stock pairs during the formation period. If both series are integrated of the same order, the research proceeds to the next step. Second, regression analysis is performed on these identically integrated stock pairs to obtain the cointegration equation, and the cointegration vector and residuals are retained. Afterwards, a stationarity test is carried out on the residuals. If the residuals are stationary, it indicates a cointegration relationship between the stock pairs, which qualifies them for subsequent empirical analysis.

In the regression analysis, it is necessary to determine whether to adopt the original stock price series or the logarithmic stock price series. This paper selects the original stock price series for regression for the following reasons. The application of logarithmic stock prices in regression is generally based on two considerations: first, the first difference of logarithmic stock prices can approximately represent stock returns; second, logarithmic transformation can eliminate the heteroscedasticity of the original series. However, the research objective of this paper neither involves the calculation of individual stock returns nor requires heteroscedasticity elimination. Accordingly, using the original stock price series for regression is more concise and appropriate.

4.3. Trading Threshold Setting

This paper conducts empirical analysis by adopting two methods to set trading thresholds, namely the fixed parameter method and the GARCH model.

First, the spread of stock pairs during the formation period is derived through the cointegration equation, with the specific formula expressed as: $\mathrm{spread}_t = y_t - \beta x_t$, where spread_t denotes the spread between Stock X and Stock Y at time. y_t refers to the stock price of dependent variable Stock Y in the cointegration equation at time. x_t represents the stock price of independent variable Stock X at time. β is the slope coefficient in the cointegration equation.

After obtaining the spread series of the formation period, the mean value and standard deviation are calculated.

The spread of stock pairs in the trading period is then measured in the same way as that adopted for the formation period. Subsequently, the trading-period spread is centralized. The formula for the centralized spread series is as follows: $\mathrm{M}spread_t = spread_t - Mean(spread)$. In this formula, $\mathrm{M}spread_t$ is the value of the centralized spread at time. In the trading period, $spread_t$ stands for the spread between Stock A and Stock B at time. $Mean(spread)$ indicates the average value of the spread series during the formation period.

5. Empirical Analysis of Pairs Trading of Liquor Stocks

5.1 Correlation Coefficient

Taking June 30, 2022 to July 1, 2023 as the formation period, this paper calculates the Pearson correlation coefficients of 24 A-share listed liquor enterprises included in the margin trading list. Among the 276 pairs formed by the 24 enterprises, 3 pairs have a Pearson correlation coefficient exceeding 0.9, 193 pairs have a coefficient greater than 0, and 38 pairs have a coefficient less than 0.

The top five pairs with the highest Pearson correlation coefficients are summarized in the table below.

Table 1. Top 5 pairs with the highest Pearson correlation coefficient in the liquor industry during the formation period

Stock Pair	Pearson Correlation Coefficient
Yanjing Beer - Huiquan Beer	0.9332
Tianyoude Liquor - Jiuguijiu	0.9303
Jinhui Liquor - Tianyoude Liquor	0.9058
Luzhou Laojiao - Wuliangye	0.8916
Jinshiyuan - Yanjing Beer	0.8914

5.2 Cointegration Test

Next, the E-G two-step method is adopted to conduct cointegration tests on the 8 stocks involved in the five pairs with the highest Pearson correlation coefficients. Firstly, stationarity tests are performed on the original stock price series, and the results are summarized in the table below.

Table 2. Stationarity test results of paired stock prices

Original Series	ADF value	1% Significance Level	5% Significance Level	10% Significance Level	P value
Yanjing Beer	-1.1364	-3.4577	-2.8736	-2.5732	0.7003
Huiquan Beer	-1.7392	-3.4576	-2.8735	-2.5731	0.4110
Tianyoude Liquor	-0.9952	-3.4576	-2.8735	-2.5731	0.7550
Jiuguijiu	-0.4826	-3.4576	-2.8735	-2.5731	0.8954
Jinhui Liquor	-0.3637	-3.4576	-2.8735	-2.5731	0.9160
Luzhou Laojiao	-1.6386	-3.4576	-2.8735	-2.5731	0.4630
Wuliangye	-1.2601	-3.4576	-2.8735	-2.5731	0.6472
Jinshiyuan	-1.0429	-3.4576	-2.8735	-2.5731	0.7373

It can be seen from the above table that the ADF statistics of the stock price series of the eight stocks during the formation period are all greater than the critical value at the 5% significance level. Consequently, the null hypothesis of unit root existence cannot be rejected. Therefore, this paper proceeds to the next step and tests the stationarity of the first-order difference series of the eight stock prices. The test results are summarized in the table below.

Based on the data in the above table, the ADF statistics of the first-order difference series of stock prices for the eight stocks in the formation period are all lower than the critical value at the 1% significance level, with all p-values equal to 0. Accordingly, the null hypothesis of a unit root can be rejected, indicating that the stock price series of the eight stocks are all integrated of order one in the formation period. Next, regression analysis is conducted on the five stock pairs, and the regression equations are summarized as follows.

Table 3. Stationarity test results of first-order differences of paired stock prices

Original Series	ADF Value	1% Significance Level	5% Significance Level	10% Significance Level	P Value
Yanjing Beer	-16.9407	-3.4577	-2.8736	-2.5732	0.0000
Huiquan Beer	-15.2168	-3.4577	-2.8736	-2.5732	0.0000
Tianyoude Liquor	-16.824	-3.4577	-2.8736	-2.5732	0.0000
Jiuguijiu	-14.5912	-3.4577	-2.8736	-2.5732	0.0000
Jinhui Liquor	-14.9793	-3.4577	-2.8736	-2.5732	0.0000
Luzhou Laojiao	-7.7365	-3.4580	-2.8737	-2.5733	0.0000
Wuliangye	-16.1347	-3.4577	-2.8736	-2.5732	0.0000
Jinshiyuan	-15.8535	-3.4577	-2.8736	-2.5732	0.0000

Table 4. Regression results of pairs

Stock Pair	Regression Equation
Yanjing Beer - Huiquan Beer	$YJB_t = 3.8760 + 0.6332{*}HQB_t + e_{1t}$
Tianyoude Liquor - Jiuguijiu	$TYL_t = -88.6955 + 14.1699 * JGJ_t + e_{2t}$
Jinhui Liquor - Tianyoude Liquor	$JHL_t = 3.6266 + 0.4536 * TYD_t + e_{3t}$
Luzhou Laojiao - Wuliangye	$LZLJ_t = 9.0503 + 0.7565 * WLY_t + e_{4t}$
Jinshiyuan - Yanjing Beer	$JSY_t = 0.7527 + 0.1971 * YJB_t + e_{5t}$

In the table, YJB, HQB, JGJ, JHJ, LZLJ, WLY and JSY respectively represent the stock prices of Yanjing Beer, Huiquan Beer, Tiande Liquor, Jiugui Liquor, Jinhui Liquor, Luzhou Laojiao, Wuliangye and Jinsiyuan at time. Afterwards, the five residual series are retained and subjected to stationarity tests, and the test results are presented in the following table.

Table 5. Stationarity test results of residuals of paired regression equations

Residual	ADF Value	1% Significance Level	5% Significance Level	10% Significance Level	P Value
e_{1t}	-3.5916	-3.4576	-2.8735	-2.5731	0.0059
e_{2t}	-3.2672	-3.4577	-2.8736	-2.5732	0.0164
e_{3t}	-2.4887	-3.4581	-2.8738	-2.5733	0.1182
e_{4t}	-1.8267	-3.4576	-2.8735	-2.5731	0.3673
e_{5t}	-2.0883	-3.4577	-2.8736	-2.5732	0.2492

By observing the data in the table, it can be found that the ADF statistics of the first two residual series are both lower than the critical value at the 5% significance level, with relatively small p-values. Therefore, the null hypothesis of unit root can be rejected, indicating that the first two residual series are stationary.

5.3 Empirical Analysis of Pairs Trading

5.3.1. Empirical Analysis of Fixed-Parameter Method

For liquor enterprises, a pairs trading test under the fixed-parameter method was conducted with June 30, 2022 to July 1, 2023 as the formation period and July 2, 2023 to December 31, 2023 as the trading period. The trading thresholds were set as follows:0.5 times the standard deviation of the formation-period spread as the take-profit threshold,0.75 times the standard deviation of the formation-period spread as the opening threshold,and 2 times the standard deviation of the formation-period spread as the stop-loss threshold.

First, an intuitive understanding was obtained through the spread sequence chart during the trading period. In the chart, the green line represents the opening threshold for pairs trading, the yellow line represents the closing threshold for pairs trading, and the black line represents the stop-loss threshold for pairs trading.

Figure 1. Spread Series of Yanjing Beer–Huiquan Beer

Figure 2. Trading Spread Series of Tiande Liquor and Jiugui Liquor

Among the two paired groups of liquor enterprises, during the trading period, the spread of the Yanjing Beer–Huiquan Beer pair fluctuated around its mean value, implying the potential to obtain positive returns through pair trading. By contrast, the spread of the Tiande Liquor–Jiugui Liquor pair deviated greatly from its mean level.

The statistics on pair trading frequencies are summarized in the table below.

Table 6. Number of trades of pairs

Stock Pair	Take-Profit Times	Stop-Loss Times	Total Trading Times
Yanjing Beer - Huiquan Beer	2	5	7
Tianyoude Liquor - Jiuguijiu	1	0	1

Pairs trading earnings.

Table 7. Earnings of pairs trading

	Trading Profit/Loss (yuan)	Trading Cost (yuan)	Total Return (yuan)	Annualized Return Rate
Yanjing Beer - Huiquan Beer	-1389.6713	1400.0000	1.2703	-2.7675%
Tianyoude Liquor - Jiuguijiu	-53.8777	300.0000	246.3148	-0.1080%

By observing the data in the above table, it can be seen that the annualized returns of the five liquor stock pairs are all negative. Nevertheless, the two pairs, namely Yanjing Beer–Huiquan Beer and Tianyoude Liquor–Jiugui Liquor, are capable of covering high transaction costs, including securities borrowing interest.

5.3.2. Empirical Analysis of Pairs Trading under GARCH Model

In the previous empirical analysis adopting the fixed parameter method, the trading strategy for the stock pair of Yanjing Beer and Huiquan Beer during the trading period is further optimized. The GARCH model is applied to characterize its standard deviation, and the standard deviation predicted by the GARCH(1,1) model is taken as the trading signal to obtain the optimized trading results.A mean equation $\mathrm{Mspread}_t = c + \lambda_t$ is constructed to test the stationarity of the explained variable $\mathrm{Mspread}_t$, and the test results are presented as follows.

Table 8. Stationarity test results of Mspread series

	ADF Value	1% Significance Level	5% Significance Level	10% Significance Level	P Value
Yanjing Beer - Huiquan Beer	-0.8033	-3.4847	-2.8853	-2.5795	0.8182

The explained variable $\mathrm{Mspread}_t$ fails the unit root test, indicating that the series is non-stationary.

6. Conclusion

This paper selects 24 liquor stocks for correlation coefficient test, pairs the top 5 stock pairs by correlation coefficient, conducts an empirical study of pairs trading under the fixed-parameter method, and conducts an empirical study of pairs trading under the GARCH model on 2 liquor stock pairs. The empirical results show that if the spread during the trading period deviates from the historical spread mean during the formation period, the pairs trading strategy will cause losses. Under the fixed-parameter method, the annualized return rates of the 5 pairs are all negative. This is because the stable long-term equilibrium relationship formed during the formation period may not last until the trading period. During the trading period, the spread deviates from its historical mean, which does not conform to the core idea of the pairs trading strategy, namely mean reversion, and the basis for profiting through pairs trading disappears. In this chapter, one pair is selected from the 5 pairs under the fixed-parameter method for pairs trading test under the GARCH model, but it also fails the test. The method of using the GARCH model to optimize the pairs trading strategy is limited.

7. Suggestion

Firstly, only a small number of stocks and finalized stock pairs are selected in the pairs trading test, which may lead to unsatisfactory empirical results. Therefore, subsequent research should incorporate more liquor enterprises, and the selection of correlation-based pairs should no longer be limited to merely five groups. Secondly, further optimization of pairs trading results can be achieved by expanding the sample size, conducting data transformation, or adopting the IGARCH model. Third, only securities borrowing interest is included as the transaction cost in this study. In practice, however, additional expenses such as commissions, transfer fees and stamp duties also exist, which are not taken into account in this paper.

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