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Exploring arbitrage opportunities between China's carbon markets based on statistical arbitrage pairs trading strategy

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ABSTRACT

Pairs trading is one of the mainstream statistical arbitrage strategies in current financial market practice that can seize possible arbitrage opportunities caused by mispricing between similar assets. Based on the theory of statistical arbitrage and the similar attributes of carbon emission allowances traded in different carbon markets, this paper studies the applicability of the pairs trading strategy among different pilot markets in China. The novelty and possible contribution of this paper are as follows. Firstly, this paper extends the statistical arbitrage-based pairs trading framework to the analysis of carbon market transactions in China, which broadens the understanding of the correlation between China's carbon markets. Secondly, this study explores the arbitrage opportunities among China's regional carbon markets that have not been revealed by previous studies. Thirdly, based on the pairs trading analytical model adopted in this study, this paper further investigates the operation characteristics of China's carbon markets and the interaction between markets, as the sensitivity of strategy performance to the key parameters is also discussed. The results show that arbitrage based on pairs trading is profitable. In the baseline case, the annualized arbitrage returns between the Shanghai emission allowance and Beijing emission allowance is about 9.11%, the highest among all pairs. However, there is almost no pairing relationship between the Tianjin carbon market and other markets. By discussing the time distribution of arbitrage signals generated by the pairs trading strategy, it is found that most signals are sent out during the inactive trading period in a compliance cycle. The conclusions provide valuable insights for formulating relevant carbon market regulatory policies and investors' participation in arbitrage activities in China's carbon trading markets.

1. Introduction

The carbon trading mechanism is one of the most critical policies for reducing carbon emissions (Sun et al., 2020a). The increasingly unstable climate environment makes many scholars and policymakers more aware of the impact of climate change on economic and social development (Lin and Yang, 2022). Carbon dioxide emissions mainly come from extensive fossil fuels and other traditional energy (Lin and Jia, 2019; Liu and Sun, 2021). Today's energy price formation mechanism generally reflects the financial cost and resource scarcity in the production process of energy products. However, many external energy production and consumption costs have not yet been fully reflected in energy prices, such as environmental and ecological pollution, climate change, and intergenerational problems caused by resource depletion.

Currently, many countries and regions have started the operation, test and practice of carbon emission trading system (ETS) (Deng and Zhang, 2019; Song et al., 2021). EU is the pioneer of carbon trading market practice. In January 2005, the EU carbon trading mechanism came into effect (Dong et al., 2020). At present, the EU has the largest carbon emission trading market globally, which has been running for >15 years (Ji et al., 2018). China's economy has experienced nearly 40 years of rapid development, followed by the rapid growth of energy consumption and carbon dioxide emissions. China has become the world's largest energy consumer and carbon dioxide emitter (Lin and Tan, 2021). With the continuous development of China's economic level and the continuous improvement of its international status as a responsible developing country, China is willing to make more significant contributions to global environmental governance (Song et al., 2020). Since 2013, China has carried out carbon emission trading pilot projects in eight provinces and cities (Yi et al., 2020). These include Beijing, Shanghai, Shenzhen, Tianjin, Hubei, Guangdong, Chongqing, and Fujian (Zhao et al., 2022). Compared with the EU ETS, China's ETS is

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still in a relatively immature stage (Dong et al., 2020). Except for the Guangdong carbon market, which adopts the allowance allocation method of combining free and auction allocation, other pilot carbon markets adopt the free allocation method. These pilot markets mainly cover energy-intensive industries, including electric power, iron, steel, electrolytic aluminium, the chemical industry, non-ferrous metals, papermaking, etc. (Wang et al., 2022b). Allowance approval methods vary by market, mainly based on historical emission data, historical carbon intensity data, and benchmark values (Peng et al., 2021).

The core issue of global energy policy is to curb the further increase of greenhouse gas emissions and mitigate the negative impact of global climate change. The carbon market plays an irreplaceable role in global climate governance, whether to achieve the 1.5-degree or ambitious carbon-neutral goal. The carbon price signal is the endogenous driving force for economic entities to reduce carbon dioxide emissions under the current economic system (Zhu et al., 2018). The carbon trading mechanism can reflect the environmental externalities in energy production and consumption to a certain extent, promote the transformation of the energy structure through the force of price and market (Sun et al., 2019; Wang et al., 2022a), improve the overall emission efficiency of the energy industry (Jia, 2023), and ultimately reduce carbon dioxide emissions. At present, the carbon trading market may be the only place where reliable and continuous carbon prices can be obtained. Carbon price discovery is one of the critical functions of the carbon market. Mispricing is almost inevitable even in highly efficient markets, allowing speculators to earn risk-free returns through the spread of mispriced assets. In this process, the mispricing may also be corrected to a certain extent. If there are moderate arbitrage speculation and active trading activities in the carbon market, it is more conducive to generating accurate carbon prices.

As a lucrative arbitrage trading strategy, pairs trading is widely used in the speculative activities of hedge funds and investment banks (Gatev et al., 2006). The basic logic behind pairs trading is quite simple and intuitive. First, track the investment assets with similar historical price trends for matching. Usually, these assets have identical or similar components and may constitute a specific substitute relationship in economic meanings. After that, if the price difference between paired assets is temporarily enlarged for some reason, a paired portfolio can be constructed by buying the loser and selling the winner. When the price diversification cycle ends and the market returns to rationality, the matched underlying prices will show a specific convergence trend to make the arbitrage portfolio profitable (Jacobs and Weber, 2015). The prices of carbon emission allowances in different carbon markets usually correlate due to the homogeneity, which many scholars have investigated. But it is still unclear whether the pairs trading strategy is applicable to China's carbon markets and how much arbitrage space can be obtained.

By constructing a statistical arbitrage strategy based on two-stage correlation and co-integration, this paper studies the application of pairs trading strategy in China's carbon markets and analyses how the arbitragers in the carbon trading market can explore the correlation between carbon prices in different markets. And the time distribution characteristics of arbitrage signals and the key factors that affect arbitrage return are discussed. Based on the research results, this paper provides some valuable insights and policy implications for constructing China's carbon trading markets in the future.

The content of this paper is organized as follows. Section 2 reviews the previous relevant literature. Section 3 introduces the methods and models to be used in this study. Section 4 presents the data, and the main empirical results of this study, as the sensitivity analysis of the pairs trading strategy is reflected in the fifth chapter. Section 5 is the conclusion and policy implications.

2. Literature review

Pairs trading strategy is one of the most popular statistical arbitrage strategies, and its related research interest has dramatically surged recently. Since pairs trading was proposed, most scholars have paid attention to its performance in financial markets such as the equity market and bond market (Chiu and Wong, 2018; Sarmento and Horta, 2020; Yang et al., 2016). Pairs trading emerged as a result of long-standing Wall Street financial practices and the boom in quantitative financial technology. The earliest pairs trading systems were originally designed to replace intuitive manual trading with standardized mathematical models and trading programs to achieve more stable and sustainable arbitrage returns. In the design of a pairs trading strategy, pairs screening, position holding time, and transaction parameter optimization are the key factors affecting the strategy returns (Nath, 2003). In pairs screening, some strategies employ spread distance indicators as criteria for target screening and position opening. However, with the introduction of econometric methods, the cointegration test method is widely accepted due to its statistical reliability in pair screening (Lin et al., 2006). The early studies were based on statistical models to construct pair trading arbitrage strategies with the goal of enhancing the returns of the strategies as much as possible, and a lot of efforts were made in parameter optimization. For example, by setting the minimum profit level, the weight distribution of the portfolio, and a shorter trading cycle, it is possible to improve the strategy's returns (Broussard and Vaihekoski, 2012; Huck, 2010).

For the past few years, the focus of research has gradually expanded to commodity and emerging markets and cross-market pairs trading opportunities. In addition to the return of the pairs trading strategy, a few researchers have also discussed the mechanism of return generated by pairs trading. Most research on pairs trading confirms that the strategy yields a stable return which is not related to market risk. Since the return characteristics of pairs trading are significantly different from those of momentum trading and mean-reversion trading, there is an ongoing discussion on the return mechanism of pairs trading. Some scholars have attempted to explain the return mechanism of pairs trading in terms of market efficiency and have argued that the source of the return is due to a lack of market efficiency. According to the efficient market hypothesis, arbitrage opportunities may not exist even in weakly efficient markets because market information is already fully reflected in asset prices (Fama, 1965). Sánchez-Granero et al. (2020) examined the relationship between market effectiveness and strategy returns and confirmed that pairs trading strategy performs better in emerging markets such as Latin American stock markets compared to weakly effective markets such as the Nasdaq 100 stock pool. Therefore, the level of returns of pairs trading strategy can also reflect the market effectiveness to some extent. Based on U.S. market data, Jacobs and Weber (2015) investigated the persistent and uncommon returns from pairs trading and argued that the news that leads to discrete pairs prices, the dynamics of investors' focus, and the presence of arbitrage restrictions are important reasons for the profit generated by pairs trading strategy. Usually, investors' reactions to emerging market information tend not to be consistent. One group of investors may overreact while another group may under-react, which results in price movement of paired assets may diverge in the short term. This provides arbitrage opportunities for pairs trading. And once the market has fully digested the impact of the news shock, the price movements between the two assets will gradually synchronize. Such a convergence process can be explained by the Law of One Price, which is also confirmed by Hain et al. (2018) based on diverse economic and statistical data.

The premise of studying whether to apply the pairs trading strategy to the underlying assets is to examine whether there is a significant correlation between the two assets and whether the market price discovery is effective. Many scholars argued that the pairs trading strategy's primary method and logic are based on the Law of One Price (Alsayed and McGroarty, 2012; Gatev et al., 2006; Huck and Afawubo, 2015). Similar alternatives or those underlying assets with similar returns should also have similar pricing. As homogeneous underlying assets, carbon emission allowances of carbon trading markets may also conform to the Law of One Price. Therefore, it is possible to arbitrate in the carbon market using a pairs trading strategy.

Many scholars have made great efforts to study the correlation between carbon markets (Wang and Guo, 2018; Zhang and Sun, 2016; Zhu et al., 2020) and the effectiveness of carbon markets (Fan et al., 2019; Kanamura, 2016; Wen et al., 2022). Based on the existing literature, correlations are widely discussed and confirmed to be prevalent between spot and futures prices in carbon markets, cross-regional carbon markets, and energy commodities and carbon prices. Charles et al. (2013) examined the cointegration relationship between futures and spots in European carbon markets. Subsequently, Philip and Shi (2015) further observed that the spot market price will show stronger price leadership before the quota submission date, while the futures market price will be in the leading position after the quota submission date. It is worth mentioning that there is also asymmetric volatility spillover between European Union Allowance (EUA) market and certified emissions reduction (CER) market. According to Zeng et al. (2021), the spillover effect of the EUA market to the CER market is more significant. Due to the stricter replacement requirements of CER and EUA, the spillover effect weakened after the third stage. In addition, the dynamics of market information such as auction mechanisms, energy price fluctuations and sudden temperature changes may also affect the price correlation between carbon market prices and other related varieties Batten et al. (2021).

Some scholars have also studied the operation situation of China's carbon market, but most of these studies only focus on the price or information correlation between carbon markets, as well as the efficiency and maturity of the market. In general, the development of China's carbon market is still at an early stage compared to the European carbon market. Compared with the EU carbon market, China's carbon market has more substantial volatility and noise, lower efficiency, and is relatively immature (Liu et al., 2021; Sun et al., 2020b). Beijing and Guangdong's carbon market ranks at the top in terms of maturity, while Tianjin and Chongqing had the lowest carbon market maturity (Liu and Zhang, 2019). On the characteristics of market prices and returns, China's carbon market returns have heavy tails, and a weak autocorrelation exists between the raw and absolute returns. The yield of China's carbon market reflects strong volatility aggregation and leverage effect, but weak long-term dependence (Yan et al., 2020). Additionally, some price convergence has been observed in the pilot carbon trading markets such as Beijing, Shanghai and Guangzhou market (Lee et al., 2019). This market characteristic may indicate the feasibility of implementing pairs trading in the Chinese carbon markets.

Many researchers have interpreted the carbon market's internal and external correlation from price spillover and connectedness. By contrast, there is little research on the characteristics of carbon price correlation under the framework of pairs trading. Furthermore, in terms of ETS operation efficiency and the interaction between regional carbon markets, there are few studies on the quantitative discussion of possible arbitrage opportunity, which is expected to provide compensation for market participants to implement the Law of One Price, so as to ensure the efficiency of market price discovery. In addition, the existing literature mainly discusses the situation of the EU carbon trading mechanism, while the research on China's carbon market is still insufficient. However, as an essential carbon emission country globally, the development and research of China's carbon market should be paid more attention.

Based on the previous literature review, the novelty and possible contribution of this paper are as follows. Firstly, to our knowledge, this paper may be the first attempt to extend the statistical arbitrage-based pairs trading framework to the analysis of carbon market transactions in China, which broadens the understanding of the correlation between China's carbon markets. Secondly, this study explores the arbitrage opportunities among China's regional carbon markets that have not been revealed by previous studies. This will provide compensation for arbitragers thereby improving market operation efficiency and facilitating the price discovery of carbon markets. Thirdly, based on the pairs trading analytical model adopted in this study, this paper further investigates the operation characteristics of China's carbon markets and the interaction between markets, as the sensitivity of strategy performance to the key parameters is also discussed. Finally, from the distinct perspective of arbitrage trading, the conclusions and practical implications proposed by this study are expected to provide valuable insights for traders and policymakers involved in the carbon markets.

3. Methodology

Referring to the previous research paradigms, the pairs trading strategy adopted in this study consists of three steps. In the first step, we use a statistical method to find the underlying assets with a long-term co-integration relationship. The early matching method finds the two assets with the smallest standardized historical price distance as the portfolio (Gatev et al., 2006). But with the development of econometric theory, more complex and scientific statistical means enrich the methodology of the pairing process. Among them, the co-integration test is a widely accepted pairing method. Cointegration can be regarded as a measure of the interdependence between two or more variables. In short, if there is a linear combination between two or more groups of variables, and this combination is first-order stationary, then there is a co-integration relationship between these variables. To confirm the long-term co-integration relationship between two or more underlying assets, this study uses Engle-Granger tests (Engle and Granger, 1987) to examine the existence of co-integration.

$$Y_t^1 = a + Y_t^2 b + \varepsilon_t \tag{1}$$

Where Y_t^1 is the historical price of paired asset 1, Y_t^2 is the historical price of paired asset 2, a is the mean value of the co-integration, b is the coefficient of the co-integration, and ε_t is the residual.

The OLS method can be used to estimate parameters a and b, and then the residual will be tested for stationarity. Augmented Dickey-Fuller (ADF) test is the most commonly used stationary test method (Dickey and Fuller, 1979), which can be used to check whether the residual presents unit root:

$$\Delta y_t = \beta + \rho y_{t-1} + \gamma t + \sum_{i=1}^{p-1} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

Where p is the lag order, β is constant term, γt represents the time trend, and ε_t is an error term.

In order to test whether AR (p) has a unit root, a regression can be performed for Eq. (2) and the following tests are considered:

Null hypothesis H0: ρ=0 versus the alternative hypothesis H1: $\rho \leq 0$.

The estimated co-integration coefficient and t-statistic can be obtained through regression:

$$\text{ADF } t = \frac{\widehat{\rho}}{\sigma(\widehat{\rho})} \tag{3}$$

$$\sigma(\widehat{\rho}) = \sqrt{\frac{\sum_{i=1}^{n} (\Delta y_{ti} - \Delta \widehat{y}_t)^2}{(n-2)\sum_{i=1}^{n}\left(y_{i(t-1)} - \overline{y_{i(t-1)}}\right)^2}} \tag{4}$$

Where, $\widehat{\rho}$ is the estimate of co-integration coefficient, and $\sigma(\widehat{\rho})$ is the standard deviation of OLS.

If the t-statistic obtained from Eq. (3) is less than the critical value of ADF test, the null hypothesis is rejected, which means that AR (p) does not show a unit root, and the residual term in Eq. (1) is stationary. Finally, it can be proved that the prices of the two assets are cointegrated.

The selection of the lag order p of the ADF test may have a great impact on the test results. Therefore, the lag order should be carefully estimated before the ADF test. According to the rule of thumb proposed by Schwert (2002), the maximum value of the lag order is generally taken as:

$$p_{\max} = \left[12 \cdot (T/100)^{1/4}\right] \tag{5}$$

Where, T is the sample size, and $[\cdot]$ represents the integer operation. Information criteria can also be used to select the lag order, such as Akaike information criterion (AIC) (Akaike, 1998) and Bayesian information criterion (BIC) (Liew, 2004):

$$IC(A) = ln\left(\widehat{\sigma}_p^2\right) + 2p/T \tag{6}$$

$$IC(B) = (T-p)ln\left(\frac{T\widehat{\sigma}_p^2}{T-p}\right) + T\left[1 + ln\left(\sqrt{2\pi}\right)\right] + pln\left[\frac{\sum_{t=1}^{T}(\Delta Z_t)^2 - T\widehat{\sigma}_p^2}{p}\right] \tag{7}$$

Where, $\widehat{\sigma}_p^2$ is error variance.

$$\widehat{\sigma}_p^2 = \frac{\sum_{t=p}^{T}\widehat{\varepsilon}_t^{\,2}}{T-p-1} \tag{8}$$

Then, the lag order can be determined by the following formula:

$$p = argmin_{p \le p_{\max}}[IC(\cdot)] \tag{9}$$

A series of co-integration relations between different carbon emission allowances can be obtained through the co-integration test of carbon prices in different carbon trading pilot markets in China. The carbon emission allowance pairs which reject the null hypothesis that there is no co-integration relationship at the 5% confidence level are screened out. These pairs are the main objects for further analysis of the performance of the pairs trading strategy.

In the second step, after selecting the carbon emission allowance pairs with long-term co-integration relationships, we examine whether there is a short-term co-integration relationship between carbon allowance price pairs in a smaller time window and take it as an essential basis for guiding trading. Although there may be a long-term co-integration relationship between carbon price pairs, it does not mean that the co-integration relationship also exists in a shorter period. One of the critical assumptions of paired trading is that after confirming a co-integration relationship, it is expected that this relationship will continue for some time. Therefore, studying the co-integration relationship between carbon allowance pairs in a shorter period is necessary. The specific inspection methods are as follows. Assuming that the trading window is N days, the co-integration test is carried out in M days before every trading window. If the co-integration relationship is confirmed within M days, we can further investigate whether the carbon allowance pair triggers the trading signal during the trading window, and then a pair trading portfolio will be considered. In the process of the co-integration test, the correlation coefficient vector between different carbon allowance pairs can also be obtained. These correlation coefficients will be used to calculate the weights of paired portfolios. The specific steps of confirming the short-term co-integration relationship are shown in Fig. 1.

In the third step, we trade the best matching carbon allowance assets according to a technical index which is designed in this paper. Specifically, we first calculate the residual R of paired carbon allowance prices in the N-day trading window:

$$R = Y_t^1 - a - Y_t^2 b \tag{10}$$

Then the residual of the carbon price and its standard deviation are used to construct the trading index:

$$S_h = \begin{cases} 1, R > m + nStd \\ -1, R < m - nStd \end{cases} \tag{11}$$

Where S_h is the trading signal of the h-th trading window, m is the mean level of the residual, n is the risk preference factor, and Std is the standard deviation of the residual.

Specifically, the technical index is a price residual threshold range. The upper and lower bounds of the range are the mean level of residual plus or minus risk preference factor multiplied by the standard deviation of residual. The risk preference factor can be adjusted according to investors' risk appetite. The spread position is opened when the price residual of paired underlying assets is greater than the upper bound or less than the lower bound. The spread position is closed when the price difference reaches the mean level of the price residual. In other words, when $S_h = 1$, Y_1 price is more likely to decline in the short term, while Y_2 price is more likely to increase in the short term. Therefore, the arbitrager can short Y_1 and buy Y_2 to construct a portfolio whose combination weight is determined by the regression coefficient of Eq. (1). On the contrary, when $S_h = -1$, it indicates that the price of Y_1 is more likely to rise in the short term, and the price of Y_2 is more likely to fall. Hence, the arbitrager can buy Y_1 and short Y_2 (if short is allowed).

Within the N-day trading window, the yield of the pairs trading portfolio is:

$$r_t^{k,h} = \sum_{i=1}^{2}\left(S \cdot \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} \cdot \frac{P_{t-1}^i b_i}{\sum_{j=1}^{2} P_{t-1}^j b_j}\right) \cdot C \tag{12}$$

Where, $r_t^{k,h}$ is the yield of the kth paired carbon allowance portfolio at t time of the h-th trading window, S is the trading signal, P_t^i is the ith carbon allowance price at time t, t∈(0 , M), b_i is the weight of carbon allowance which can be determined from the regression result of Eq. (1). If the asset cannot be shorted, then the weight of the asset needed to be short in the paired portfolio equals zero.

It is assumed that the investors' funds have sufficient liquidity, that is, the unoccupied funds in the trading desks can be quickly used for redistribution. After that, the risk-adjusted return can be obtained by calculating the value-weighted average return of a pairs trading.

4. Data and results

4.1. Data description and strategy parameters setting

Based on the carbon price data of Beijing, Tianjin, Shanghai, Chongqing, Hubei, and Guangdong carbon exchanges, this paper studies the performance of convergence trading strategy in the carbon market (Yan et al., 2020). All the carbon price data were from the CSMAR database. The carbon price data of the Shenzhen carbon trading market

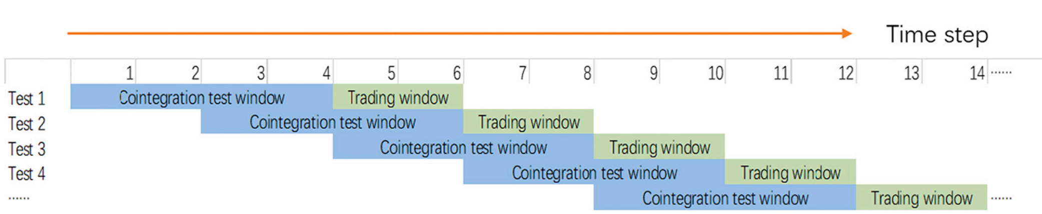

Fig. 1. Diagram of short-period co-integration tests and trading window selection.

was not considered in this study because there are multiple allowance varieties in one period, and there is no continuity between different allowance varieties. Due to the different start-up times of different pilot markets, some markets started earlier. For example, Beijing, Tianjin, and Shanghai markets already had carbon trading records in 2013. Considering that the operation time of the Fujian carbon market is too short to generate enough stable carbon trading data, there is a problem of insufficient liquidity due to its small market trading volume. Therefore, the allowance of the Fujian carbon trading market is not considered in this study. To unify the cycle of co-integration, we selected the complete listed varieties and active trading period, that is, the carbon trading data from January 9, 2017, to March 1, 2021. Table 1 records the basic statistical information of different markets.

In the benchmark case, the trading window is set to 22 days, the risk preference multiplier of spread is set to 1.5, and the co-integration test cycle is set to 66 days. The transaction cost is 0.5%.

4.2. Strategy performance

Table 2 shows the carbon emission allowance pairs that pass the Engel-Granger test in the whole cycle, which implies that a long-term co-integration relationship exists between these carbon emission allowance pairs. In addition, Table 2 also reports the relative value arbitrage return between different carbon emission allowance portfolios based on the pairs trading strategy adopted in this paper.

It can be found from Table 2 that a total of six pairs of carbon allowances have passed the ADF test and can reject the null hypothesis that there is no co-integration relationship at the significance level of 5%. These paired portfolios are SHEA& BJEA, SHEA& HBEA, HBEA& GDEA, HBEA& BJEA, CQEA& SHEA, SHEA& GDEA, respectively. Among the six pilot carbon markets allowance considered in this study, TJEA is the only carbon allowance without a long-term co-integration relationship with other carbon allowances. The SHEA launched by the Shanghai carbon market has the highest frequency in all paired portfolios, indicating a good correlation with other markets. From the performance of different allowance portfolios, it is still possible to make profits through the pairs trading strategy in China's carbon trading pilot markets. This also shows that China's current carbon trading pilot market is not completely effective. Figs. 2 to 7 shows a graphical illustration of the pairs trading strategy. Regarding the annualized return of different allowance pair strategies, the portfolio composed of SHEA and BJEA can get the highest annualized return, which is about 9.11%. The couple of SHEA& HBEA is in second place, with annualized returns of 8.83%.

From the time distribution of intensive transactions, an obvious “trading volume tide” phenomenon of China's pilot carbon markets can be observed. Specifically, before the implementation date each year, the trading volume of pilot carbon markets is significantly enlarged. After the implementation date, the trading volume decreased significantly as most of the arbitrage trading signals generated by the strategy are often sent out in the non-intensive transaction interval. This also reminds participants of the Chinese pilot carbon markets that more efforts must be made to improve the operational efficiency of the carbon markets at other times beyond the implementation period.

In addition to the internal factors of the market, the selection of transaction parameters may also have a significant impact on the return of the arbitrage strategy. The changes in key factors such as transaction cost, risk preference factor, the length of the trading window and the co-integration test window may affect the performance and applicability of the pairs trading strategy. This issue will be further analysed and discussed in the following sensitivity analysis.

Table 1
Brief description of carbon emission allowances data of different pilot markets*.

Market	Symbol	Average daily volume (ton)	Average daily price (CNY)	Highest price (CNY)	Lowest price (CNY)
Chongqing	CQEA	7896.60	14.45	44.86	1
Tianjin	TJEA	7049.94	14.70	28	8.51
Shanghai	SHEA	9204.08	37.43	49.98	24.75
Hubei	HBEA	40,548.64	24.16	53.85	11.56
Guangdong	GDEA	55,259.44	20.39	32.28	9.8
Beijing	BEA	9677.93	67.28	102.96	30

* The time span is from January 9, 2017, to March 1, 2021.

4.3. Sensitivity analysis

In this section, key parameters such as transaction cost, risk preference factor, transaction window, and co-integration test window are selected to analyse the sensitivity of arbitrage strategy performance to transaction parameters. The Sharpe ratio and annualized yield are the main indicators to measure the performance of the arbitrage strategy. Generally, the investment excess return divided by the return's standard deviation is used as the value of the Sharpe ratio (Zakamouline and Koekebakker, 2009), which can be interpreted as the ratio of risk-return. Arbitrage traders are usually institutional investors who focus on specific varieties. The overall risk is the most important factor they care about for these investors. Therefore, when assessing the performance of an arbitrage strategy, Sharpe Ratio is one of the essential indicators besides yield (Shleifer and Vishny, 1997).

4.3.1. Sensitivity of transaction cost

Fig. 8 shows the change in annualized yield and the Sharpe ratio of arbitrage strategy with different transaction cost rates. In general, the reduction of transaction cost significantly improves the return and the Sharpe Ratio of the strategy. With the increase of transaction rate from 0.1% to 0.5%, Pair 2 has the biggest change of annualized return (5.1%), while Pair 1 has the smallest change (0.9%). When the transaction cost increases from 0.1% to 0.5%, Pair 3 has the biggest change in Sharpe Ratio (0.19), while Pair 5 has the smallest change (0.06).

4.3.2. Sensitivity of risk preference factor

Fig. 9 illustrates the changes in annualized return and the Sharpe ratio of arbitrage strategy under different risk preference factor values. It can be found from the figure that the risk preference factor has a non-linear effect on the annualized return and Sharpe ratio of emission allowance pairs. For Pair 1, Pair 2, Pair 4 and Pair 5, when the risk preference factor increases from 1 to 1.7, a peak in the Sharpe ratio can be observed. The peak Sharpe ratio for Pair 1, Pair 2 and Pair 3 are all found at a risk preference factor of 1.5. While the peak Sharpe ratio for Pair 5 appears at a risk preference factor of 1.1. For Pair 3, as the risk preference factor increases, both its strategy return and Sharpe ratio increase. When the risk preference factor reaches 1.7, the strategy return turns from negative to positive. For Pair 6, on the other hand, its strategy return and Sharpe ratio decrease as the risk preference factor increases. The maximum strategy return and Sharpe ratio are obtained when the risk preference factor is 1.

4.3.3. Sensitivity of trading window and co-integration test window

Fig. 10 shows how the performance of the pairs trading strategy varies with the trading window and co-integration test window. It can be found from Fig. 10 that through the optimal setting of the trading window and co-integration test window, all six pairs can yield a positive annualized return. For Pair 1, a co-integration test window of about 60 days and a trading window of about 10 days can yield the highest returns for the arbitrage strategy. And for Pair 2, a co-integration test cycle of about 80 days and a trading cycle of about 10 days yields the best arbitrage strategy returns. Both Pair 3 and Pair 4 obtain the optimal returns of the pairs trading strategy when the co-integration test period is about 60 days and the trading period is about 30 days. However, for Pair5 and Pair6, the best pairs trading strategy returns are obtained at a co-integration test window of about 20 days. The combination of

Table 2
Pairs trading portfolios and their basic performance.

Allowance 1	Allowance 2	Coefficient	Cumulative net value	Sharpe ratio	Annualized yield
SHEA	BJEA	0.14***	1.42	0.69	9.11%
SHEA	HBEA	0.30***	1.40	0.97	8.83%
HBEA	GDEA	0.77**	1.13	0.20	3.00%
HBEA	BJEA	0.27**	1.11	0.17	2.54%
CQEA	SHEA	0.90**	1.03	0.12	0.68%
SHEA	GDEA	0.45***	0.93	0.26	−1.87%

Note: *, **, *** denote the null hypothesis was rejected at the significance level of 10%, 5%, and 1%, respectively.

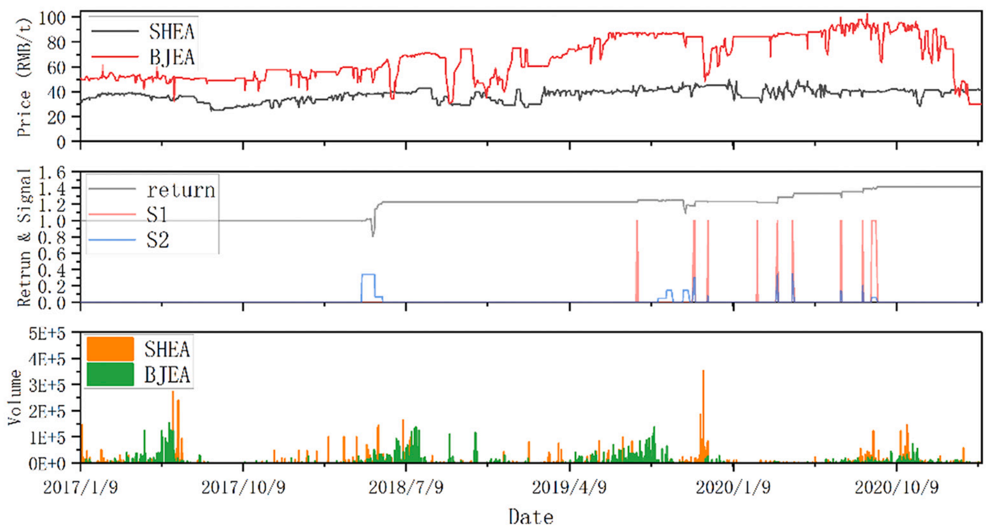

Fig. 2. Pairs trading strategy performance on SHEA and BJEA.

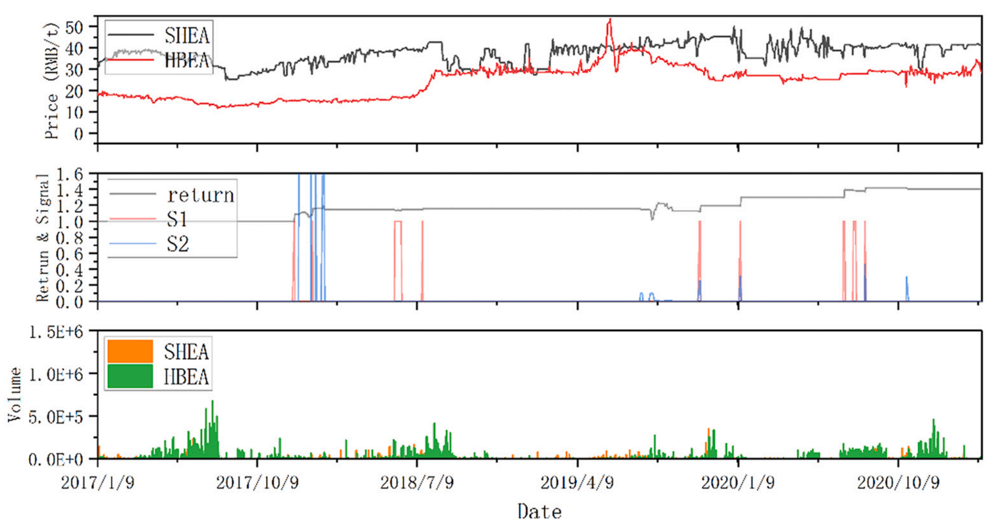

Fig. 3. Pairs trading strategy performance on SHEA and HBEA.

different trading windows and co-integration test windows will have a significant impact on the returns of the pairs trading strategy. Therefore, paying more attention to selecting these two window parameters may be necessary when carrying out transactions in these paired markets.

5. Conclusions and policy implications

This paper studies the applicability of pairs trading based on two-stage co-integration in China's carbon trading markets and provides insights into the profitability of the pairs trading strategy. In this study, the co-integration relationship between carbon allowances of different carbon trading markets is statistically tested. Based on the arbitrage framework of the pairs trading strategy adopted in this study, the carbon allowance price data of China's pilot carbon markets are used to test the strategy's performance. In the baseline case, the arbitrage return between Shanghai and Beijing exchanges ranked first with 9.11%. Among all paired emission allowances, SHEA has the highest frequency of occurrence. This may indicate good compatibility of SHEA with other carbon market varieties. No co-integration relationship exists between the Tianjin exchange and other exchanges, implying that the pairs

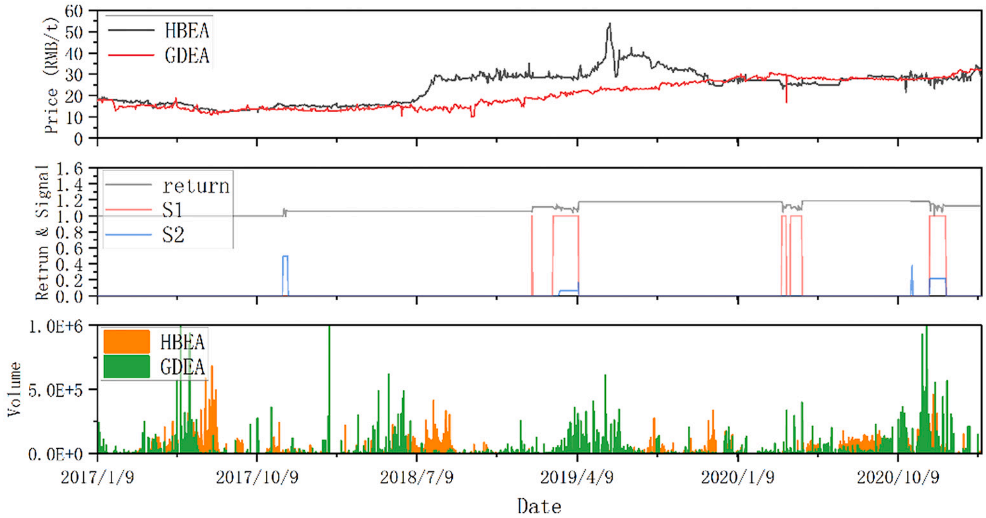

Fig. 4. Pairs trading strategy performance on HBEA and GDEA.

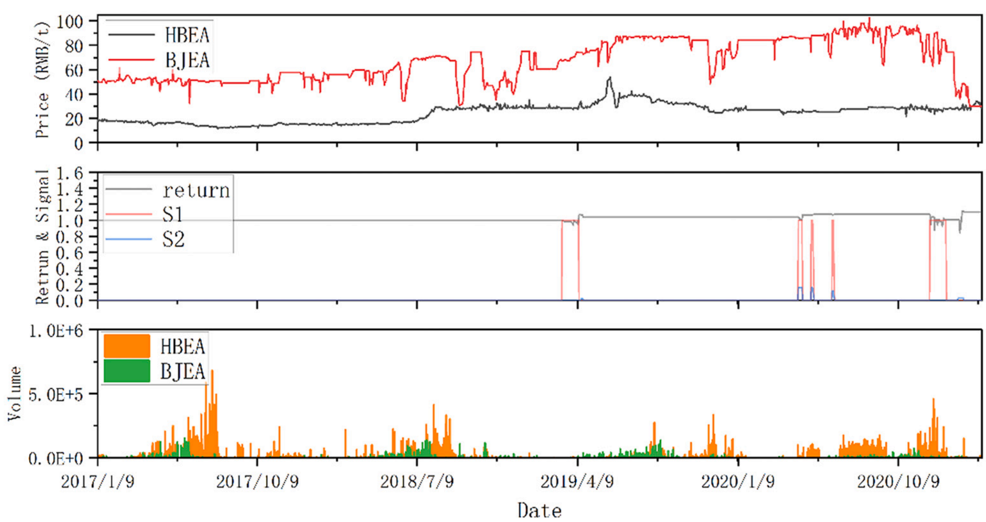

Fig. 5. Pairs trading strategy performance on HBEA and BJEA.

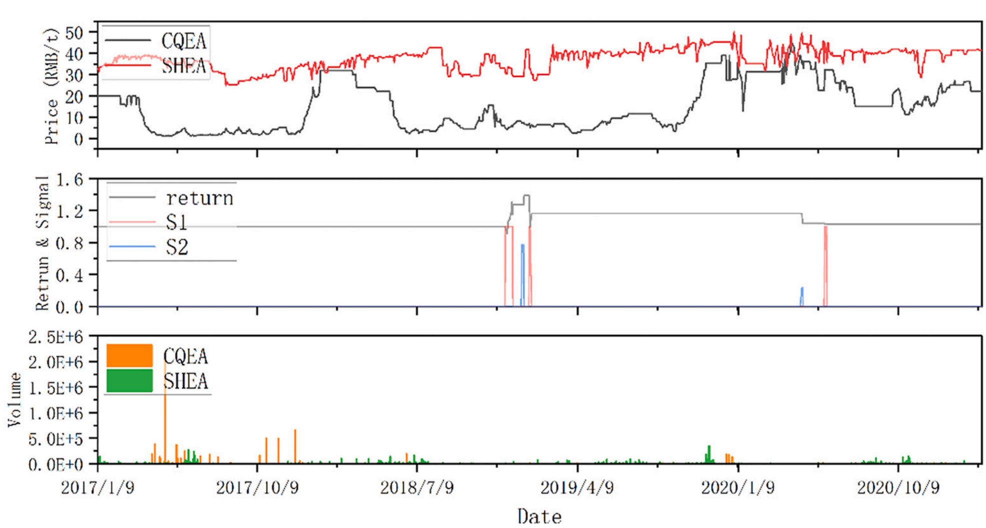

Fig. 6. Pairs trading strategy performance on CQEA and SHEA.

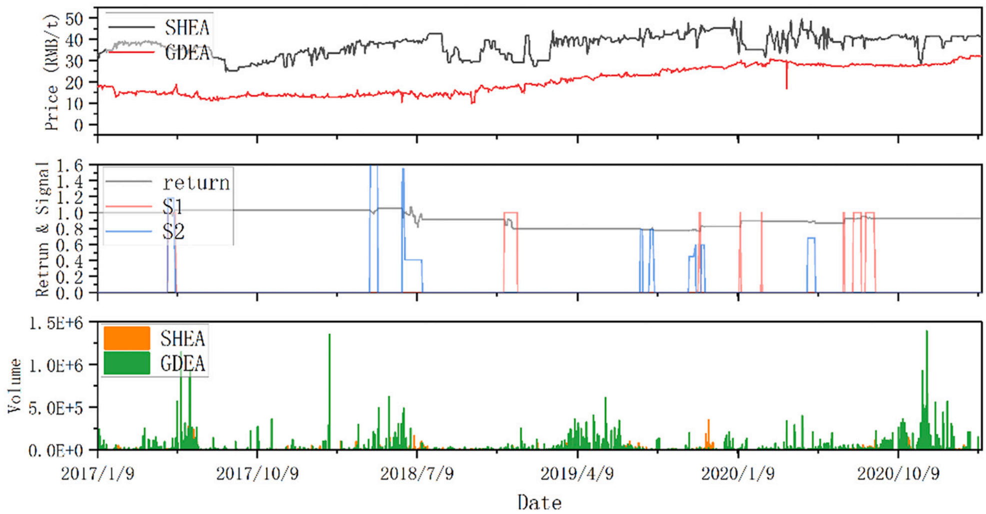

Fig. 7. Pairs trading strategy performance on SHEA and GDEA.

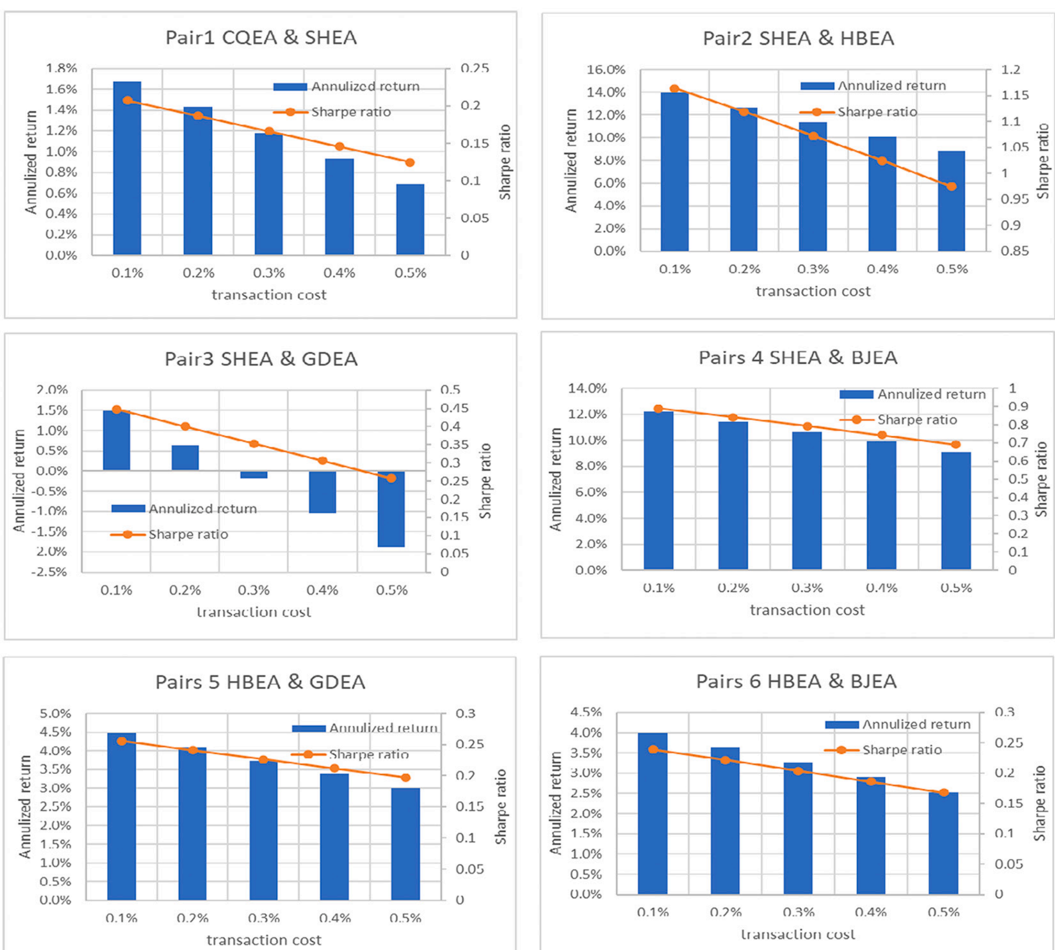

Fig. 8. The influence of transaction cost.

trading strategy is unsuitable for the Tianjin market. In terms of the distribution of trading signals generated over time, it is found that most arbitrage signals are not sent out around the end of compliance when there are usually many transactions.

Sensitivity analysis of crucial strategy parameters is also carried out to explore the impact of transaction cost, risk preference factor, transaction window, and co-integration test window on the performance of pairs trading strategy. Through sensitivity analysis, it is found that the reduction of transaction cost obviously improves each pair's return and Sharpe ratio. Risk preference factor, trading window, and co-integration test window will have a non-linear impact on the performance of the pairs trading strategy. The sensitivity analysis results also indicate that

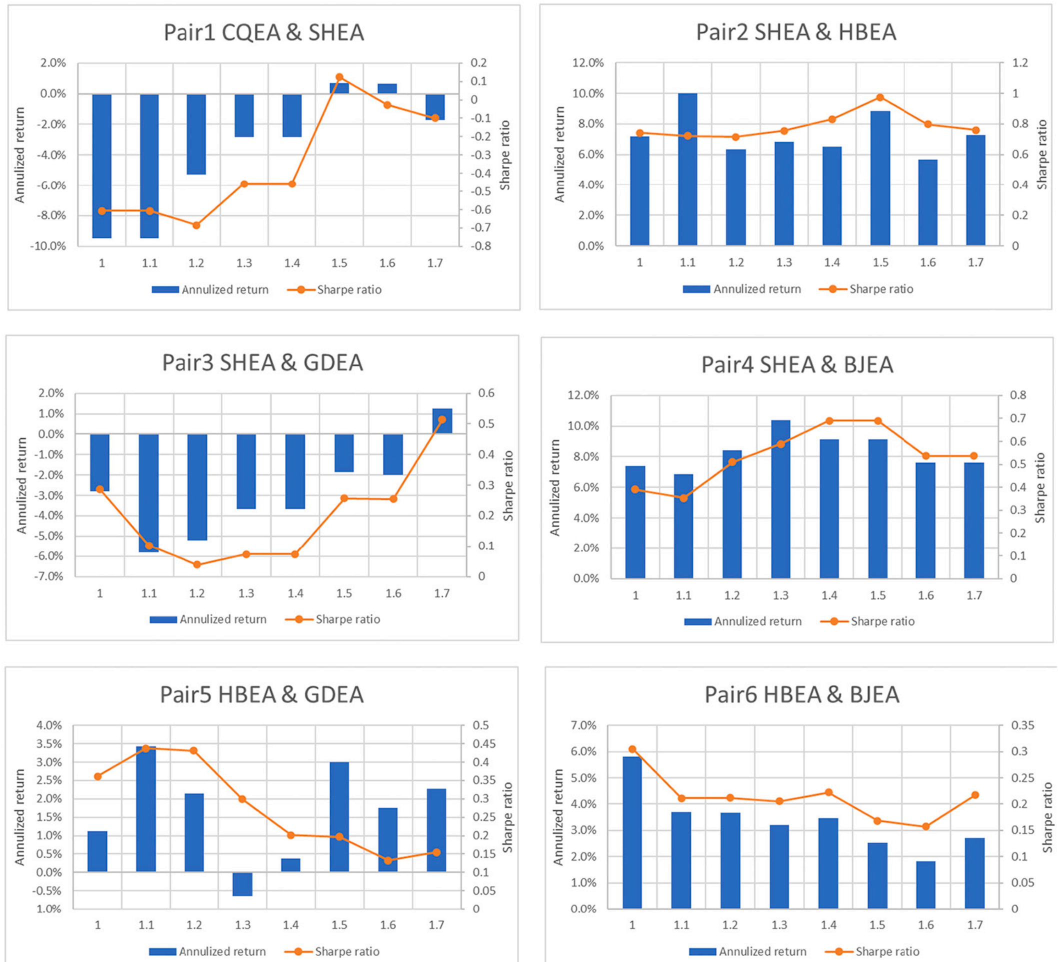

Fig. 9. The influence of the risk preference factor.

through appropriate parameter adjustment, all paired portfolios can yield positive annualized returns, which also reflects the adaptability of the pairs trading strategy in China's carbon trading market.

Based on the results of this study, some theoretical, managerial, and international implications are also put forward. First of all, in terms of theoretical implications, this study extends the pairs trading strategy to the carbon market and confirms the effectiveness and profitability of pairs trading among carbon markets. In addition, key elements that affect the pairs trading strategy, such as transaction cost, cointegration test window, trading window, and risk preference factor are proposed and tested, which enrich the theory of statistical arbitrage.

Secondly, in terms of managerial implications, by examining the time distribution of pairs trading signals, this study finds that most carbon allowance trading activity occurs at the end of the compliance period, resulting in inactive trading for the rest of the period. As a result, the operational efficiency of the carbon market may be affected to some extent. Therefore, corresponding policies should be introduced to promote trading activity in other periods beyond the end of the compliance period to eliminate arbitrage risk as much as possible. Transaction costs should be a potential policy tool for adjusting the activeness level of market trading. The transaction cost is critical in adjusting the arbitrage profits. Policymakers can adjust the market arbitrage activity to a reasonable level by changing the rate of the transaction cost.

Thirdly, in terms of international implications, as the world's largest carbon emission country, the scale and international influence of China's carbon markets are also continuously expanding. The research results and related management policy implications for China's carbon markets are also expected to provide lessons for other countries to carry out carbon market construction. In addition, the findings of the pairs trading strategy presented in this paper are also expected to provide strategic insights for international investment institutions or speculators to participate in China's carbon markets and seize trading opportunities.

Finally, when applying a pairs trading strategy to China's carbon trading markets, attention should be paid to optimizing trading parameters. Due to the compatibility shown by the Shanghai market, it is worth the efforts of arbitragers to explore the pairs trading opportunities between the Shanghai market and other markets. Especially in the context of establishing China's national carbon market, it is expected that the interaction between different regional markets will be strengthened, which will bring more arbitrage opportunities.

CRediT authorship contribution statement

Boqiang Lin: Conceptualization, Investigation, Supervision, Writing - review & editing. **Zhizhou Tan:** Methodology, Formal analysis, Software, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

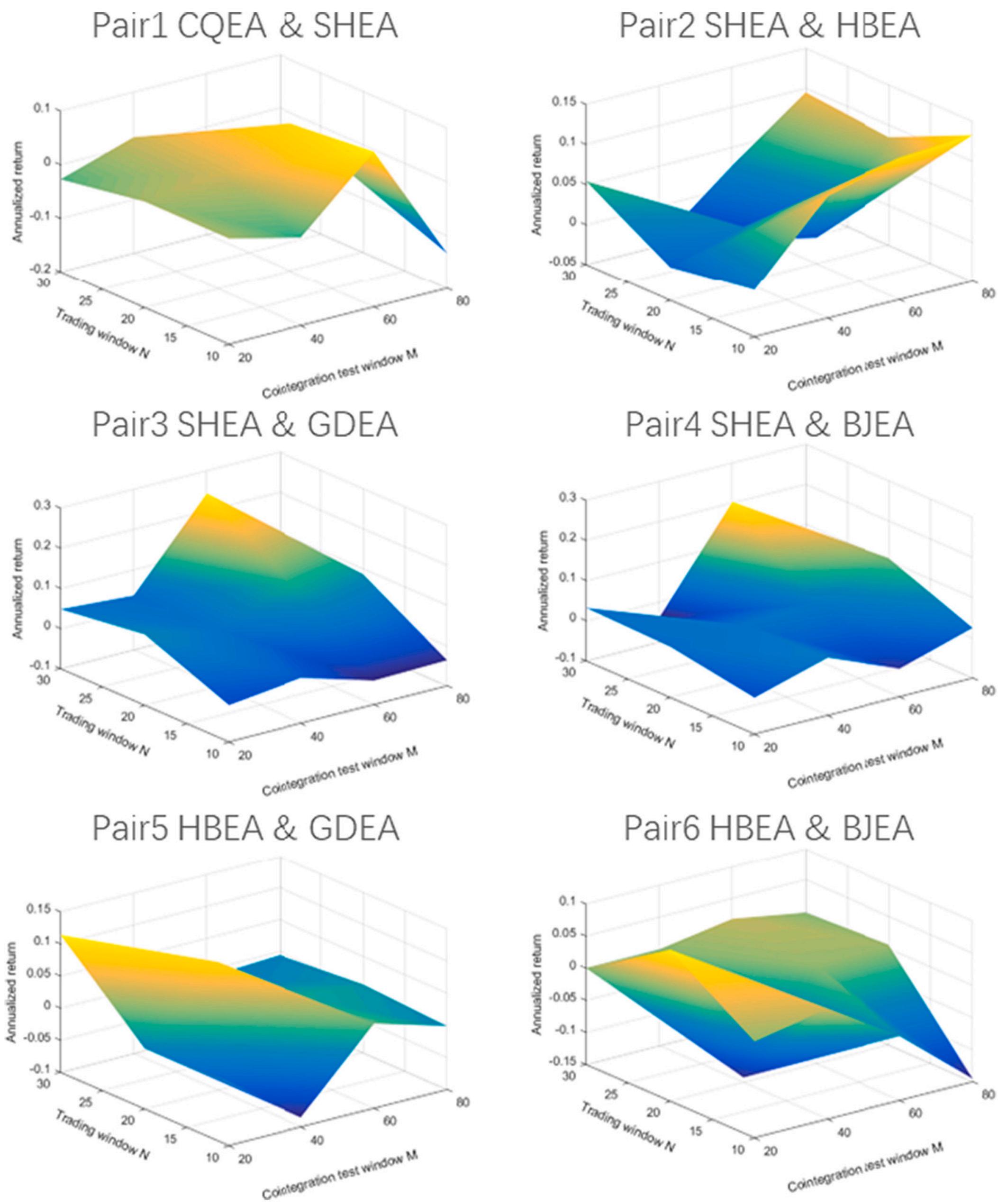

Fig. 10. The influence of the trading window and co-integration test window.

Data availability

The data that has been used is confidential.

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