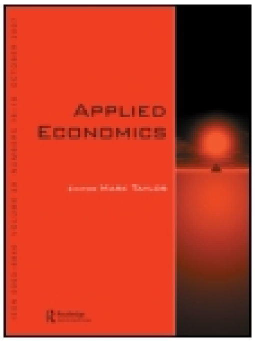

Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Pairs trading and selection methods: is cointegration superior?

Nicolas Huck & Komivi Afawubo

Applied Economics, 2015
Vol. 47, No. 6, 599–613, http://dx.doi.org/10.1080/00036846.2014.975417

Routledge
Taylor & Francis Group

Pairs trading and selection methods: is cointegration superior?

Nicolas Huck[a,*] and Komivi Afawubo[b,c]

[a]*ICN Business School – CEREFIGE, Nancy-Metz, France*
[b]*University of Lorraine – CEREFIGE, Nancy, France*
[c]*University of Franche-Comté, CRESE, Besançon, France*

Pairs trading is a popular dollar-neutral trading strategy. This article, using the components of the S&P 500 index, explores the performance of a pairs trading system based on various pairs selection methods. Whereas large empirical applications in the literature focus on the distance method, this article also deals with well-known statistical and econometric techniques such as stationarity and cointegration which make the trading system much more demanding from a computational point of view. Trades are initiated when stocks deviate from their equilibrium. Our results confirm, after controlling for risk and transaction costs, that the distance method generates insignificant excess returns. While a pairs selection following the stationarity criterion leads to a weak performance, this article reveals that cointegration provides a high, stable and robust return.

Keywords: pairs trading; trading rules; distance; cointegration; stationarity

JEL Classification: G11

I. Introduction

In its most common form, pairs trading involves forming a portfolio of two related stocks whose relative pricing departs from its 'equilibrium'. It is linked to cointegration (Bossaerts, 1988; Bossaerts and Green, 1989) and correlation in stock prices, mean reversion, overreaction (De Bondt and Thaler, 1985; Lo and Mackinlay, 1990), contrarian strategies (Jegadeesh and Titman, 1993) and also to the law of one price. Pairs trading is one way to select stocks and to build a long/short dollar-neutral portfolio. In reality, even such strategies require some outlay, if only to meet margin calls and brokerage fees.

By going long on the relatively undervalued stock and short on the relatively overvalued stock, a profit may be made by unwinding the position upon 'convergence' of the spread. The success of pairs trading, especially statistical arbitrages, depends heavily on the modelling and forecasting of the spread time series. The ability to anticipate the 'direction' of this spread is a key point. Whilst the strategy appears simple and has, in fact, been widely implemented by traders and hedge funds, owing to the proprietary nature of the area there has been a limited amount of published research until a recent burst of interest in the last few years. This includes several books on the subject (Vidyamurthy, 2004; Whistler, 2004;

*Corresponding author. E-mail: nicolas.huck@icn-groupe.fr

Ehrman, 2006). These strategies exhibit, at least according to the first studies including an application over several decades, positive and significant risk-adjusted returns which are not due exclusively to a short term reversion phenomenon. Pairs trading questions market efficiency.

The academic literature can be divided into three main categories according to the methodology considered to select and trade pairs:

- The minimum distance approach,
- Combined forecasts and Multi-Criteria Decision Methods (MCDM),
- The modelling of mean reversion (stationarity, cointegration, etc.)

The most popular reference in the first category is Gatev *et al.* (1999, 2006). It also includes Papadakis and Wisocky (2008) and Engelberg *et al.* (2009), Do and Faff (2010, 2012), Jacobs and Weber (2011), Mori and Ziobrowski (2011), Broussard and Vaihekoski (2012) and Huck (2013). These papers explore different dimensions and implications of pairs trading strategies: accounting information, news, liquidity, sensitivity, transaction costs, etc.

Gatev *et al.* (2006), like many traders, envision a simple algorithm for choosing pairs. The rule follows the general outline of first 'find stocks that move together' then 'take a long short position when they diverge' using a distance measure. They include a trading system and the management of a portfolio and consider a very large number of stocks using the Center for Research in Security Prices (CRSP) database (about 2300 securities). This paper shows that pairs trading after costs can be profitable. As a possible explanation, they indicate that pairs traders could be the disciplined investors taking advantage of the undisciplined over-reaction displayed by individual investors. This point is in line with Jegadeesh and Titman (1995). The first version has been known for about 10 years and Do and Faff (2010), replicating the Gatev *et al.* (2006) methodology with more recent data, report that the results of this strategy are declining.

Pairs trading requires the selection and the trading steps to be parameterized in some way. Gatev *et al.* (2006) use a simple SD strategy to select and trade stocks. With daily data, they form pairs over a 12-month period and trade them over the next 6 months. Among the candidates chosen during the first stage, if prices diverge by more than two SDs, a long/short position is open. As underlined by the authors, both the 12- and 6-month periods are chosen arbitrarily. The distance approach merely exploits the statistical relationship of a pair at a price level. As the approach is normative and economic free, it has the advantage of not being exposed to model mis-specification and mis-estimation. On the other hand, this strategy lacks forecasting ability: if a 'divergence' is observed, the assumption is that prices should converge in the future because of the law of one price. When equilibrium is reached or at the end of the 6-month trading period, the positions are closed out.

The second group of papers (Huck, 2009, 2010) combines neural networks for the purpose of forecasting and multi-criteria decision aids (Outranking methods, Electre III (Figueira *et al.*, 2005)) for the selection of pairs. This approach is rather different from the others because it is developed without reference to any equilibrium model. At the moment, it has not been built for large indexes. This pairs trading system will not be discussed in this work.

Several methodologies, coming from an econometric standpoint, have been used to model the expected mean reversion phenomenon:

- The cointegration concept (Engle and Granger, 1987; Johansen, 1988) can be an attempt to parameterize pairs trading. Generally speaking, the framework is as follows: first, choose two cointegrated stock price series, then open a long/short position when stocks deviate from their long-term equilibrium and finally, close the position after convergence or at the end of the trading period. Mathematical aspects of pairs trading and cointegration are discussed in Chiu and Wong (2011).
- Testing stationarity of the price ratio between the two stocks is also an alternative (Baronyan *et al.*, 2010).
- A stochastic approach is used by Elliott *et al.* (2005) and Do *et al.* (2006). In a continuous setting, the first of these articles models the difference between the two stock prices using a mean reverting Gaussian Markov chain model. The second studies the behaviour of the series at the return level.

Most of the time, this third group of works suffers from the financial and practical point of view, and from the fact that the real data application, if there is one, considers only a very limited number of stocks.

The articles based on a distance criterion or on combined forecasts and MCDM propose fairly developed trading systems and the management of a portfolio over a period of many years. On the other hand, these mathematical considerations can provide analytical results about the supposed speed of convergence of a given series, the first time passage or the optimal threshold for opening and closing positions.

The contribution of this article is empirical and is based on the S&P 500 index components. It aims at filling a lack of large and complete applications dealing with pairs trading performance and well-known econometric methods such as stationarity and cointegration. An article like Baronyan *et al.* (2010) performs a comparison between some methods using a small index: the Dow Jones Industrial Average (30 stocks). This leads to a piece of work which is quite demanding from a computational point of view compared to the distance method which is much faster.

The empirical results confirm the weak performance of the distance approach in the last years with US data. A pairs selection method based on the stationarity of the price ratio does not provide positive and significant returns after transaction costs. Cointegration generates very high and stable returns which are robust to transaction costs, risk factors and data-snooping.

The rest of this article is organized as follows. Section II reviews the different pairs selection approaches. The data and the design of the application are presented in Section III. Empirical results based on distance, stationarity and cointegration are provided in Section IV. They cover dimensions like transaction costs, sensitivity, stability, sector composition, risk exposure and data-snooping bias. Section V concludes the article.

II. Pairs Selection

This section discusses three selection methods that are suitable for pairs trading:

- the distance method,
- the stationarity of the price ratio and
- the cointegration between stock prices.

Exploring the full universe of pairs ($\frac{N^*(N-1)}{2} = 124750$ with S&P 500 index components, N being the number of stocks under consideration) may be highly time consuming. This is especially true using techniques like stationarity or cointegration. Following Papadakis and Wisocky (2008), in order to speed up computations, pairs selection is only performed using pairs that are likely to have high comovement. If the return of two stocks, between the beginning and the end of the selection/formation period, differs by more than 10%, the pair is automatically discarded from the whole process. About 80% of the pairs will be affected in the applications.

The minimum distance method

The distance method is now widely used in the academic literature since Gatev *et al.* (2006). Details can also be found in Do and Faff (2010) or in Engelberg *et al.* (2009). The framework can be divided into two stages (formation period and trading period).

Initially, for each pair, we define a measure of closeness. For each stock, we form pairs by finding the partner that minimizes the sum of squared differences (SSD) in the normalized daily prices (inclusive of dividends). Both prices are scaled to start at \$1. Among these pairs, for example, following Gatev *et al.* (2006), the top 20 pairs with the lowest SSD become candidates to be traded.

$$\mathrm{SSD}_{i,j} = \sum_{t=1}^{T} \left(P_t^i - P_t^j\right)^2 \tag{1}$$

with P_t^i and P_t^j the normalized prices for stock i and stock j on day t, and T the number of trading days in the formation period.

Prices are once again scaled to \$1 at the beginning of the trading period. Then, during the trading period, a long/short position (one dollar short in the higher priced stock and one dollar long in the lower priced stock) is initiated in a pair whenever its normalized price difference, or spread, diverges by more than a trigger, which is generally a multiple of the SD from the historical spread computed over the formation period. Positions are unwound after convergence or automatically at the end of the trading period. This two-step sequence (formation/trading) is, whatever the selection method, repeated every month. The formation period has a fixed length: one or two years for example in this article. The data of the formation period are mobile windows with a 21-day lag.

Stationarity and ADF test

In order to generate profits in a pair-trade, the price ratio between the two stocks needs to have a constant mean and a constant volatility over time. A deviation of the price ratio from this equilibrium state can thus be interpreted as a trading opportunity. In this article, the selection method is based on the unit root test developed by Dickey and Fuller (1979): this econometric method is simple and popular. Alternative tests to the Augmented Dickey–Fuller (ADF) approach include for example Kwiatkowski *et al.* (1992). The ADF test, without trend, for a unit root assesses the null hypothesis of a unit root using the model:

$$y_t = c + \phi y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + \varepsilon_t \qquad (2)$$

where Δ is the differencing operator, such that $\Delta y_t = y_t - y_{t-1}$. The number of lagged terms, p, is determined empirically (up to 10 lags) so that the mean zero error term ε_t in the tested equation is serially uncorrelated. The null hypothesis of a unit root is:

$$H_{\mathrm{o}} : \phi = 1 \qquad (3)$$

under the alternative hypothesis, $\phi < 1$. The existence of a unit root in the price ratio indicates pairs trading conditions are met. In the stationarity and cointegration (see below) based approaches, the tests of the selected pairs are always significant at a 1% rate (or less). After the selection of a pair, if the price ratio diverges, from its historical mean $\overline{y_t}$, by more than a predefined threshold, a long/short position is open. The opening threshold is based on the SD of the error term. Each month, the eligible pairs for the next 6 months are the pairs with the lowest ADF t-statistics.

Cointegration

The concept of cointegration has been used in the pairs trading context by Vidyamurthy (2004), Lin *et al.* (2006), Bogomolov (2010) and Galenko *et al.* (2012). It shares connection with the frequency of historical reversal in the price spread used in Do and Faff (2010) working with the distance criterion. This additional metric improves the performance of their pairs distance trading system.

Cointegration incorporates the idea of mean reversion between stock prices. If two stocks are cointegrated, it means they share a long-term equilibrium relationship. Pairs trading, whatever the selection method, will try to exploit deviations from an equilibrium asset-pricing framework with nonstationary common factors (Jagannathan and Viswanathan, 1988; Bossaerts and Green, 1989; Chen and Knez, 1995). The application of the cointegration concept to stock price analysis is that a system of nonstationary stock prices in level form can share common stochastic trends (Stock and Watson, 1988). As developed in Gatev *et al.* (2006), if the long and short components fluctuate with common nonstationary factors, then the prices of the component portfolios would be cointegrated and the pairs trading strategy would be expected to work.

The most familiar cointegration test has been developed by Engle and Granger (1987). This is a two-step approach. Consider $P_{1,t}$ and $P_{2,t}$ are the prices of stocks 1 and 2 at time t and are $I(1)$ processes (in order to avoid spurious regression). The first step requires the regression of $P_{1,t}$ against $P_{2,t}$

$$P_{1,t} - \beta P_{2,t} = \mu + \varepsilon_t \qquad (4)$$

where μ denotes an intercept. Potential cointegration between the two stocks is examined via the analysis of the order of integration of the residuals ε_t using Dickey and Fuller (1979) test. Stocks are cointegrated if the residuals of the regression are stationary.

Instead of using the Engle and Granger (1987) methodology, the Johansen (1988) approach is considered in this article. It takes the form of a likelihood ratio test and avoids the asymmetry problem in treating variables. This approach tests the hypothesis of r unrestricted cointegrating relationships in the unrestricted Vector Autoregressive (VAR) model. The null hypothesis of both the trace and maximum tests is that there is no cointegration and the alternative is that there is cointegration. The critical values may be found in Johansen (1996). As a preliminary step before the Johansen (1988) test, a likelihood ratio test (longer lags versus shorter lag lengths) is used to determine the optimal lag length (up to 10 lags): this is a common approach in specifying VAR models.

Cointegrated pairs with the highest trace statistics will be kept as eligible pairs for the trading step. During this last step, a deviation of the relation $P_{1,t} - \beta P_{2,t}$ from its historical mean, μ, will be interpreted as a trading opportunity.

III. Data and Design

This section presents in details the pairs trading systems based on the selection methods introduced in the previous section.

Basics

The data used in this application are the prices of the S&P 500 stocks[1] (inclusive of dividends). These stocks are among the most liquid in the world. As a consequence, transaction costs will be relatively low. In a pairs trading context, they will be estimated using Do and Faff (2012). A selection procedure starts every 21 trading days (about 1 month) and the trading/eligibility period of a pair lasts 126 trading days (about 6 months, 6×21 days). The length of the trading period is chosen so that the selection process is recent and round-trips have time to occur using a reasonable opening trigger. If the eligibility/trading period of each pair lasts for 6 months, the 'entire portfolio' is the sum of six overlapping 'sub-portfolios' staggered by 1 month. The trading results presented in the next section cover the period from August 2000 to September 2011 (134 months). In fact, computation/trading starts and ends 5 months before and after so that the results always refer to a period with a 'complete portfolio'.

If the selection of parameters like the length of the formation and trading periods or the opening and closing triggers is done in a coherent way according to the trading system, it remains an arbitrary choice. This study considers two different lengths for the formation period (1 year (252 trading days) or 2 years (504 trading days)) and 2 or 3 SDs for the opening trigger. Needless to say the greater the trigger, the lower the number of openings and trades during the trading period. If most authors like Gatev *et al.* (2006) consider the 2-SD rule, a more selective scheme is also examined. As a consequence, for each selection method (distance, stationarity, cointegration), four parameterizations will be performed.

Evaluating the stability of trading rules matters (Falbo and Pelizzari, 2011). As underlined in Huck (2013), the results of pairs trading are known to be highly sensitive to these key parameters. The aim of this article is of course not to find an 'optimal' parameterization of pairs trading strategies. The objective is to establish whether or not, from a quite general point of view, one of the three selection methods (distance, stationarity, cointegration) may be considered as generating a significant and positive excess return. Testing multiple strategies/trading rules on the same data set leads to the well-known problem of data-snooping. This issue will be controlled using Hansen (2005) test for Superior Predictive Ability.

Return computation, transaction costs and benchmarks

Since there are potentially several openings and closings during the 6-month eligibility period for a given pair, portfolio return computation is not a trivial issue. Following Gatev *et al.* (2006) and others, excess returns are computed in order to evaluate the performance of the strategies. Two measures of excess return have been proposed: the return on committed capital and the fully invested return. The flexibility of hedge funds' funding leads to choose the second one because it seems more realistic. Opening and closing could happen on the same day as the trigger is reached: a popular alternative is a 1-day delay. The way returns are computed in this article differs slightly from the rest of the literature:

- The excess return of the portfolio is first computed on a daily basis as the mean excess return among all pairs (equal weighted portfolio, at least ten) opened a given day in the entire portfolio (which could be considered as the sum of six portfolios that start 1 month apart). That way, the day-by-day composition of the portfolio is easily known (number of pairs, sectors).
- Diversification is a crucial matter in portfolio and risk management. Some selection methods and opening triggers (especially with 3 SD), from time to time, could lead the whole portfolio to be composed of less than 10 activated

[1] The sample really considers 500 stocks only at the end of the trading period due to initial public offerings/newcomers in the index: Google in 2004 for example.

pairs. In that case, the 'missing' positions will be filled by a long position in the market index. This switch from pairs trading positions to long exposure to the market occurs during a weak number of days as mentioned in Tables 3 and 4.

- The daily return (excluding transaction costs) of the portfolio at time t, $R_{Portfolio,t}$ is computed as:

$$R_{Portfolio,t} = \frac{\sum_{i=1}^{Pairs_t} R_{i,t}}{Pairs_t} \tag{5}$$

where $Pairs_t$ is the number of open pairs on day t and $R_{i,t}$ the return of the price ratio of the ith pair open on day t. If $Pairs_t < 10$, $R_{i,t} = X_t$, $\forall i \in [Pairs_t + 1; 10]$ where X_t is the excess return of the market on day t.

- The estimation of pairs trading transaction costs in this article is based on Do and Faff (2012). They consider these costs have three components: commissions, market impact (average one-way cost (commission + market impact) of 30 bps (10 + 20) in our sample) and short-selling constraints (constant loan fee of 1% per annum payable over the life of each trade). Using the average number of trades per 6-month trading period, monthly estimations of transaction costs can be computed[2] for each strategy. These quite conservative values are reported in Tables 3 and 4.

IV. Empirical Results

The pairs trading results/performances are examined through different dimensions/questions:

- Does pairs trading generate profits without transaction costs?
- Are pairs trading profits robust to transaction costs?
- Does one selection method dominates the others?
- Are all methods (stationarity, cointegration) as parameter sensitive as the distance method?
- Is pairs trading still profitable after accounting for traditional risk factors?
- Does pairs trading outperform the S&P 500 index/equity premium?
- Which conclusions can be drawn about the activity sectors dimension (in-sample/ formation, out-of-sample/ trading)?

Formation period and sector composition

Tables 1 and 2 focus on two different aspects of the pairs selection, of which there are 6 ways ((distance, stationarity, cointegration) × (1- or 2-year formation period)). Table 1 reports the percentage of identical eligible pairs between strategies. Whatever the combination, the proportion of pairs which are chosen the same month as eligible pairs by two different selection methods is weak. Proportions are always below 13% indicating strategies are clearly based on very different pools of eligible pairs. The highest percentages of common eligible pairs are obtained with:

- distance 1-year and distance 2-year,
- stationarity 2-year and cointegration 2-year.

Table 2 provides information about the sector composition, based on the GICS taxonomy, of eligible/

Table 1. Percentage of identical eligible pairs between strategies

		1 year			2 years	
		Distance	Stationarity	Cointegration	Cointegration	Stationarity
2 years	Distance	12.4	0.8	0.5	3.1	9.1
	Stationarity	1.8	1.9	0.6	12.8	
	Cointegration	0.6	1.0	0.9		
1 year	Cointegration	1.8	9.8			
	Stationarity	6.2				

[2] As an example, see Table 3, transaction costs for the 1-year formation period, distance method, 2 SDs are 0.38%. $0.38 \approx \frac{(0.30*4*2*1.5)+1}{12}$.

Table 2. Sector composition (%) of eligible pairs between strategies

			1 year			2 years		
S&P 500	GICS code		Distance	Stationarity	Cointegration	Distance	Stationarity	Cointegration
8.2	10	Energy	10.8	7.8	8.5	9.3	8.5	8.3
5.8	15	Materials	7.2	6.0	5.4	5.9	5.3	5.9
12.4	20	Industrials	11.8	12.5	12.7	11.8	12.6	13.0
16.4	25	Consumer discretionary	8.6	16.6	16.5	10.9	16.3	16.0
8.2	30	Consumer staples	17.2	8.7	8.6	20.5	9.4	9.4
10.2	35	Health care	10.5	11.7	10.4	9.3	12.3	11.4
16.2	40	Financials	18.7	15.9	15.9	17.6	15.5	15.7
14.0	45	Information technology	8.9	13.0	13.8	8.5	11.1	11.9
1.6	50	Telecommunication services	1.1	1.5	1.7	1.2	1.2	1.1
7.0	55	Utilities	5.2	6.4	6.5	5.1	7.9	7.3

candidate pairs and of the S&P 500 index. Pairs selection based on stationarity or cointegration leads to the same distribution as the index (eligible or traded pairs). This point has been evaluated via a χ^2 test in Tables 3 and 4. Differences are observed when comparing the pairs selection based on distance against the composition of the S&P 500 index. The three main points are an over-weighting of the Consumer Staples sector (GICS 30) and an under-weighting of the Consumer Discretionary (GICS 25) and Information Technology (GICS 45) sectors. This result is not surprising. The distance method, during the selection process, favours low volatile stocks. The sector distribution of traded pairs comes close to the repartition of the market index.

Pairs trading sometimes focus on pairs with stocks within the same sector. With the S&P 500 index, this proportion is about 11.5%. Whatever the selection method, for eligible or activated pairs, the proportion observed in our empirical results does not differ from the real proportion computed with the index.

Performance and portfolio composition

The main information provided in Tables 3 and 4 is as follows:

- Whatever the selection method, the opening trigger or the length of the formation period, the trading strategies, without transaction costs, have generated positive excess returns during the period we considered (August 2000 to September 2011).
- The significance of the individual monthly excess returns is tested using t-statistics based on Newey–West SEs with six lags and the consistent p-values of the bootstrap approach developed by Hansen (2005). On the one side, with t-statistics, 10 of 12 parameterizations have positive and significant excess returns at 5% level. The two failures occur with a 1-year formation period associated with distance or stationarity and a three SEs opening trigger. On the other side, the Hansen (2005) methodology reports all trading strategies have significant positive excess returns (ignoring transaction costs).
- As mentioned in Tables 3 and 4, the monthly estimations of transaction costs go from 0.19 bps for the strategy with the lowest average number of trades (2-year formation period, cointegration method, 3 SEs) to 0.38 bps (1-year formation period, distance method, 2 SEs). Including transaction costs, robust strategies at 5% level are the following:
  - Cointegration whatever the length of the formation period or the opening trigger. Returns are especially high with monthly excess returns, including transaction costs, greater than 1.38% (1.68–0.30) and going up to about 5% over a period of more than 10 years. These are clearly the main and

Table 3. Results: 1-year formation period

Method	Design of the strategy (1-year formation period)					
	Distance		Stationarity		Cointegration	
Opening trigger (nb of σ)	2	3	2	3	2	3
Excess returns (in \$, per 100\$, per month)						
Without transaction costs	0.33	0.27	0.48	0.36	2.08	5.86
σ	1.51	1.75	2.89	3.25	2.59	3.83
t-Statistics (Newey–West)	2.91	1.83	2.20	1.58	7.92	15.70
Consistent p-values (Hansen)	0.00	0.03	0.02	0.01	0.00	0.00
Trend (p-value)	−0.003 (0.44)	−0.002 (0.68)	0.003 (0.66)	−0.002 (0.79)	−0.012 (0.04)	−0.010 (0.25)
Median	0.28	0.23	0.44	0.68	2.03	5.49
Skewness	0.17	0.21	0.46	0.37	0.28	0.44
Kurtosis	4.80	4.29	6.16	6.91	4.55	3.42
Min	−4.54	−4.73	−8.79	−10.95	−6.49	−4.23
Max	6.25	6.60	12.67	14.51	11.19	17.82
Monthly returns > 0 (%)	61.19	59.70	58.21	58.96	80.60	97.01
Daily returns > 0 (%)	52.03	51.42	51.53	50.82	57.54	65.73
Sharpe Ratio	0.22	0.16	0.17	0.11	0.80	1.53
Monthly serial correlation	0.09	0.11	0.07	0.05	0.39	0.67
Monthly transaction costs (estimation)	0.38	0.28	0.40	0.30	0.33	0.20
Consistent p-values (Hansen) with T.C	1.00	0.47	0.31	0.26	0.00	0.00
Break/Stability (August 2000–September 2008 versus October 2008–September 2011)						
Mean (SD) August 2000 to September 2008	0.36 (1.5)	0.27 (1.7)	0.31 (2.9)	0.28 (3.3)	2.02 (2.6)	5.68 (3.8)
Mean (SD) October 2008 to September 2011	0.29 (1.6)	0.33 (1.8)	1.09 (2.7)	0.75 (3.0)	2.34 (2.5)	6.62 (3.8)
t-Test	0.22	−0.17	−1.38	−0.74	−0.60	−1.28
Chow test (F distribution)	0.61	1.17	3.00	1.72	8.52*	8.36*
*Significant at the 5% level						
Break date (Bai and Perron, 2003)					July 2008	July 2008
Trading statistics and portfolio composition (per pair, per 6-month period)						
Non traded pairs (%)	4.93	20.75	5.07	14.93	3.81	43.21
Non convergent pairs (%)	45.49	52.95	41.68	53.40	60.00	44.66
Single round trip pairs (%)	33.28	21.38	34.18	26.16	28.28	11.87
Multiple openings pairs (%)	16.31	4.93	19.07	5.52	7.91	0.26
Profitable trades (%)	62.59	58.31	61.90	57.45	66.82	76.00
Non Convergent profitable trades (%)	27.93	37.85	26.11	35.41	47.76	69.79
Number of openings (σ)	1.5 (0.9)	1.0 (0.7)	1.6 (1.0)	1.1 (0.7)	1.2 (0.6)	0.6 (0.5)
Average time open (%)	57.0	41.4	60.4	47.0	45.2	13.6
Average number of open pairs per day (σ)	70.5 (12.0)	50.9 (14.1)	77.9 (11.9)	58.0 (14.3)	55.3 (9.3)	17.2 (6.6)
Days with less than 10 actives pairs (%)	0.00	0.00	0.00	0.00	0.00	13.59
Days with less than 5 actives pairs (%)	0.00	0.00	0.00	0.00	0.00	1.03
Average time (days) of a convergent trade (σ)	28.3 (23.4)	33.5 (23.5)	29.0 (25.2)	36.0 (26.0)	34.5 (24.0)	35.5 (20.1)
σ of price ratio returns (formation period)	1.27	1.27	2.44	2.44	2.52	2.52
Correlation between returns (formation period, eligible pairs)	0.57	0.57	0.33	0.33	0.33	0.33

(*continued*)

Table 3. Continued

Method	Design of the strategy (1-year formation period)					
	Distance		Stationarity		Cointegration	
Opening trigger (nb of σ)	2	3	2	3	2	3
Sectors: concordance/contingency χ^2 test *p*-value						
S&P 500 versus candidate pairs	0.00	0.00	0.99	0.99	1.00	1.00
S&P 500 versus traded pairs	0.00	0.00	0.99	1.00	1.00	1.00
traded pairs versus candidate pairs	0.21	0.00	0.94	0.92	0.97	0.90
Factor model (*t*-stat)						
Intercept	0.31 (3.2)	0.25 (2.1)	0.60 (3.2)	0.49 (2.2)	2.19 (11.1)	6.17 (18.9)
Market	0.00 (−0.1)	0.02 (0.5)	0.09 (1.1)	0.11 (1.2)	0.02 (0.5)	−0.12 (−1.4)
SMB	0.07 (1.6)	0.04 (0.7)	−0.01 (−0.1)	0.00 (0.0)	−0.04 (−0.5)	−0.23 (−1.7)
HML	−0.02 (−0.4)	0.01 (0.2)	−0.18 (−2.1)	−0.20 (−2.0)	−0.21 (−2.3)	−0.41 (−2.9)
MOM	−0.12 (−5.1)	−0.15 (−5.9)	−0.24 (−5.7)	−0.26 (−5.3)	−0.21 (−5.9)	−0.30 (−5.6)
REV	0.12 (2.1)	0.17 (2.5)	0.20 (2.0)	0.23 (1.7)	0.33 (4.5)	0.46 (3.8)
r^2	0.32	0.36	0.39	0.38	0.34	0.26
Long and short positions						
Mean monthly excess returns: long (σ)	0.55 (3.56)	0.55 (3.68)	0.42 (5.53)	0.31 (5.64)	1.27 (5.42)	2.90 (5.30)
Mean monthly excess returns: short (σ)	0.23 (3.23)	0.28 (3.24)	−0.06 (4.51)	−0.05 (4.36)	−0.81 (4.66)	−2.96 (4.95)
Intercept (Factor model): long (*t*-stat)	0.44 (3.0)	0.44 (2.6)	0.40 (2.4)	0.37 (1.6)	1.18 (6.8)	2.96 (9.7)
Intercept (Factor model): short (*t*-stat)	0.14 (1.2)	0.20 (1.4)	−0.19 (−1.1)	−0.13 (−0.8)	−1.00 (−5.8)	−3.21 (−11.0)

most impressive empirical finding of this article. Even if the frameworks are very different, these results are in line with the positive contribution of the frequency of historical reversal in the price spread used to augment a distance approach in Do and Faff (2010). In some way, cointegration generalizes this metric.

– Strategies with a 2-year formation period and a high level for the opening trigger.
– The use of several parameterizations (12) leads to take into account a data-snooping bias. In order to provide a proper adjustment, the Hansen (2005) methodology is performed. With or without transaction costs, the main conclusions are highly robust indicating that at least one trading strategy (cointegration trading strategies in fact) is profitable.

- These results are in line with the empirical existing literature dealing with pairs trading and the distance method. The weak and declining performance (Gatev *et al.*, 2006; Do and Faff, 2010), in the recent years, of the most documented parameterization (1-year formation period with a 2 SD trigger) is confirmed in our study: including transaction costs, a small negative monthly excess return (−0.05 = 0.33 − 0.38) is observed. This article also shows that pairs trading returns are sensitive, whatever the selection technique, to key parameters like the length of the formation period or the opening trigger.
- Figure 1 compares the cumulative excess returns (including transaction costs) of the different strategies against the equity premium. The indexes based on pairs trading are smoother than the one referring to the equity premium. Cointegration performed well whatever the market conditions.
- The parameterization with the best monthly excess returns (Cointegration, 1-year formation period, 3 SEs) reports a 97% proportion of months (134) with positive excess returns (without transaction costs). If this number

Table 4. Results: 2-year formation period

Method	Design of the strategy (2-year formation period)					
	Distance		Stationarity		Cointegration	
Opening trigger (nb of σ)	2	3	2	3	2	3
Excess returns (in \$, per 100\$, per month)						
Without transaction costs	0.44	0.47	0.58	0.64	1.68	3.77
σ	2.00	2.54	2.59	3.21	2.59	4.09
t-Statistics (Newey–West)	3.18	3.00	2.54	3.37	7.29	10.22
Consistent p-values (Hansen)	0.00	0.00	0.00	0.01	0.00	0.00
Trend (p-value)	−0.002 (0.60)	0.001 (0.84)	−0.003 (0.60)	−0.002 (0.69)	−0.003 (0.65)	−0.005 (0.59)
Median	0.28	0.58	0.58	0.52	1.60	3.32
Skewness	−0.14	−0.65	0.42	0.62	0.31	0.74
Kurtosis	3.21	5.23	4.95	4.87	3.06	5.83
Min	−5.61	−10.37	−6.93	−7.78	−4.06	−8.88
Max	5.21	7.15	11.44	12.01	8.89	22.59
Monthly returns > 0 (%)	58.21	60.45	58.96	58.21	73.13	83.58
Daily returns > 0 (%)	51.46	51.17	51.89	51.14	56.19	59.00
Sharpe ratio	0.22	0.19	0.23	0.20	0.65	0.92
Monthly serial correlation	0.04	0.00	0.06	−0.02	0.29	0.41
Monthly transaction costs (estimation)	0.29	0.20	0.31	0.23	0.30	0.19
Consistent p-values (Hansen) with T.C	0.11	0.02	0.09	0.05	0.00	0.00
Break/Stability (August 2000–September 2008 versus October 2008–September 2011)						
Mean (SD) August 2000 to September 2008	0.46 (2.0)	0.41 (2.6)	0.48 (2.5)	0.50 (3.1)	1.61 (2.6)	3.55 (4.2)
Mean (SD) October 2008 to September 2011	0.46 (1.9)	0.77 (2.4)	0.98 (2.7)	1.20 (3.5)	1.97 (2.4)	4.66 (3.8)
t-Test	−0.01	−0.73	−0.98	−1.12	−0.72	−1.39
Chow test (F distribution)	0.30	0.39	2.79	2.91	3.17*	4.92*
*Significant at the 5% level						
Break date (Bai and Perron, 2003)						July 2008
Trading statistics and portfolio composition (per pair, per 6-month period)						
Non traded pairs (%)	19.03	45.86	13.43	34.89	12.09	47.16
Non convergent pairs (%)	50.60	41.64	51.42	49.40	56.53	43.21
Single round trip pairs (%)	24.25	10.82	27.54	13.62	25.97	9.14
Multiple openings pairs (%)	6.12	1.68	7.61	2.09	5.41	0.49
Profitable trades (%)	61.04	58.79	58.89	59.14	64.00	71.11
Non Convergent profitable trades (%)	38.40	45.78	35.17	46.00	45.94	64.89
Number of openings (σ)	1.0 (0.8)	0.6 (0.6)	1.1 (0.7)	0.7 (0.6)	1.1 (0.6)	0.5 (0.5)
Average time open (%)	42.0	24.9	49.9	32.9	43.2	15.6
Average number of open pairs per day (σ)	51.3 (14.3)	30.4 (14.0)	63.7 (14.3)	40.4 (15.9)	53.2 (12.4)	19.8 (9.6)

Days with less than 10 actives pairs (%)	0.00	2.63	0.00	0.00	0.00	18.79	
Days with less than 5 actives pairs (%)	0.00	0.00	0.00	0.00	0.00	2.56	
Average time (days) of a convergent trade (σ)	32.2 (25.1)	36.4 (24.5)	33.7 (25.6)	38.1 (25.7)	36.2 (24.9)	37.5 (19.8)	
σ of price ratio returns (formation period)	1.45	1.45	2.47	2.47	2.54	2.54	
Correlation between returns (formation period, eligible pairs)	0.54	0.54	0.33	0.33	0.34	0.34	
Sectors: concordance/contingency χ^2 test *p*-value							
S&P 500 versus candidate pairs	0.00	0	00	0.62	0.62	0.89	0.89
S&P 500 versus traded pairs	0.00	0	00	0.84	0.91	0.92	0.80
traded pairs versus candidate pairs	0.00	0	00	0.63	0.57	0.96	0.66
Factor model (*t*-stat)							
Intercept	0.48 (3.9)	0.53 (3.2)	0.67 (4.0)	0.75 (3.4)	1.84 (10.3)	4.08 (14.5)	
Market	−0.02 (−0.4)	0.02 (0.3)	0.06 (1.6)	0.00 (0.0)	0.02 (0.4)	−0.01 (−0.1)	
SMB	−0.04 (−0.3)	−0.01 (−0.1)	−0.06 (−0.5)	0.00 (0.0)	0.00 (0.0)	−0.14 (−1.2)	
HML	−0.06 (−0.9)	−0.08 (−1.0)	−0.08 (−1.3)	−0.16 (−2.0)	−0.33 (−2.9)	−0.48 (−2.7)	
MOM	−0.17 (−6.6)	−0.21 (−5.3)	−0.20 (−6.7)	−0.26 (−6.3)	−0.18 (−3.9)	−0.32 (−3.7)	
REV	0.18 (2.0)	0.20 (2.0)	0.16 (2.3)	0.21 (2.3)	0.27 (3.2)	0.53 (4.0)	
r^2	0.26	0.28	0.27	0.28	0.33	0.32	
Long and short positions							
Mean monthly excess returns: long (σ)	0.55 (4.10)	0.65 (4.39)	0.65 (5.65)	0.69 (5.93)	0.98 (5.32)	1.88 (5.22)	
Mean monthly excess returns: short (σ)	0.11 (3.63)	0.18 (3.68)	0.09 (4.80)	0.07 (5.07)	−0.70 (4.57)	−1.89 (4.47)	
Intercept (Factor model): long (*t*-stat)	0.40 (2.3)	0.54 (2.5)	0.56 (3.4)	0.63 (3.1)	0.92 (5.8)	1.91 (9.1)	
Intercept (Factor model): short (*t*-stat)	−0.07 (−0.4)	0.02 (0.1)	−0.10 (−0.6)	−0.12 (−0.6)	−0.92 (−6.3)	−2.16 (−10.9)	

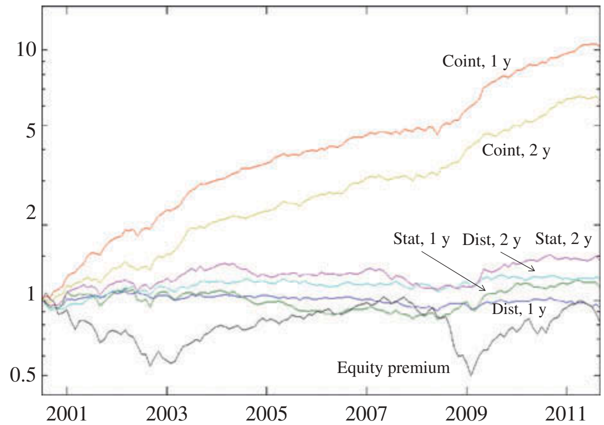

Fig. 1. Cumulative excess returns (log scale) including transaction costs pairs trading strategies with a 2-SD opening trigger versus equity premium

appears very high, it has to be compared to the 85% obtained by Gatev *et al.* (2006) with their top-20 strategy over a period of about 40 years (474 months).

The S&P 500 index is known in the literature to have been subject to excess comovement (Shiller, 1989; Vijh, 1994; Barberis *et al.*, 2005). This effect could question our results. Kasch and Sarkar (2014) improve the methodology dealing with the analysis of this empirical finding. The period they consider covers the one studied in this article. They show that the permanent changes in market value and return comovement, previously attributed to S&P 500 index additions, reflect well-established regularities in asset returns independent of index membership.

The proportion of profitable trades, a good directional forecasting ability, is a key point for the success of a trading strategy. Whatever the parameterization/method, as we could imagine with monthly positive excess returns, the proportions of profitable trades (at least 57%), ignoring transaction costs, are significantly greater than 50% which is a benchmark to consider with dollar-neutral position. For cointegration-based strategies, more than 64% of the trades are profitable. Using a classification slightly different from Do and Faff (2010), eligible pairs are split into four categories:

(1) Pairs that never trade throughout the trading period.
(2) Pairs that do open but never converge in time during the 6-month trading period. This part represents the behaviour of about 50% of activated pairs. All nonconvergent trades can be divided into two groups: winners and losers. This sub-split is very informative.
(3) Pairs that have one round-trip (profitable by definition) trade. The higher the opening trigger, the higher the ratio between the proportion of pairs that do open but never converge in time and the proportion of pairs that have one round-trip trade.
(4) Pairs that have multiple openings (at least 2), possibly a final nonconvergent trade. At most 19% of eligible pairs have two or more openings.

Even if all strategies have a proportion of profitable trades which is high, some have weak and insignificant excess returns. This point is explained by a large number of unprofitable trades when focusing on nonconvergent trades (rates of success can fall below 40%) and the absence of stop-loss: the possibility of trades leading to very important losses whereas profits are (more or less) limited[3] to the amplitude of the opening trigger. This confirms that a large part of pairs trading profits comes from the first days after trade initiation and that the introduction of a stop loss mechanism or a limitation of the open period of nonconvergent trades could be useful. Engelberg *et al.* (2009) indicate that the profitability of the distance-based strategy decreases exponentially over time. The most successful parameterizations (cointegration combined with a restrictive opening trigger, 3 SD) are the only cases where the proportion of profitable nonconvergent trades stays (well) above 50%: this approach reduces nonconvergent risk.

Some comparisons between the two most interesting selection methods, distance and cointegration, can be done:

- The cointegration approach chooses eligible pairs with a greater level of volatility of the price ratio (about 2.5 versus 1.3) and a weaker

[3] The part of the initial deviation greater than the opening threshold plus the part exceeding the crossing with the equilibrium after convergence.

correlation (about 0.33 versus 0.55) between the returns of the components.

- Normalizing opening triggers in percentage, the triggers are slightly lower for the distance method than for the cointegration approach. Even if cointegration strategies have very high excess returns, they still have convergence times greater than those of the distance method (about 30 days). These excess returns cannot be explained by the selection/choice of pairs which are likely to converge very quickly. The profits of cointegration approaches come much more from a good ability to forecast direction than from the detection of very short-term deviations.

As motivated by Gatev *et al.* (2006) and Engelberg *et al.* (2009), a Fama and French (1993) three-factor regression[4] augmented by two other factors is performed in order to analyse the risk exposure of pairs trading monthly returns. The two additional factors control for the empirical findings of Jegadeesh and Titman (1993), Jegadeesh (1990) and Lehmann (1990). The independent variables are standard factor returns:

- the market excess return ($R_m - R_f$) where R_f is the 30-day Treasury bill return,
- a size factor: the difference between small and big stocks (SMB),
- a value factor: the difference between value and growth stocks (HML),
- a momentum factor: the difference between portfolios of year-long winners minus year-long losers (MOM),
- a reversal factor: the difference between portfolios of last month losers minus last month winners (REV).

In line with the literature, our pairs trading excess returns are market neutral: the exposure to the market is insignificant. Furthermore, between the different strategies, the signs of this parameter vary. The exposures to momentum and reversals have the predicted signs and are statistically significant at 5% level in nearly all cases. Risk adjusted alpha are statistically significantly positive for all strategies excluding transaction costs. Including costs, alpha remains highly positive for cointegration-based strategies. The significance of these returns shows that the performance of pairs trading with cointegration, even after accounting for data-snooping bias, is robust to standard risk factors.

As a contrarian strategy, it is important to examine the returns of the long and short components of pairs: it provides a better understanding of the pairs trading profits. The monthly excess returns and the intercepts of the five-factor model are reported in Tables 3 and 4. Dealing with cointegration-based strategies, results indicate that the abnormal returns of the portfolio are equally driven by the long and short positions. This symmetry shows, in our sample, that the selection of pairs based on cointegration is a powerful tool to exploit mean reversion. Compared to Gatev *et al.* (2006), this is a major difference. They observe, in a distance framework during a period of about forty years ending in 2002, that more than two thirds of their abnormal returns come from the short part of the portfolio.

The period considered in this article involves 2008 financial crisis. Through different dimensions, the stability of the performances around this event is examined. Between August 2000 and September 2011, for 11 of the 12 parameterizations, the returns do not exhibit a significant trend at 5% level. The exception concerns one strategy dealing with cointegration (1-year formation period, 2 SDs opening trigger): a slight decline is observed. Splitting data around September and October 2008, the key observations are the following:

- Whatever the strategy, using a t-test, there is no significant difference in returns between pre- and post-crisis periods. A slight increase of the results can nevertheless be noticed for all cointegration-based strategies.
- A Chow (1960) test indicates, at 5% level, the presence of a structural break around this crisis for 3 of the 4 cointegration-based methods.[5] The linear regressions of the post-crisis data show an increase of the constants and significant negative trends. These structural breaks pointed out by the Chow test are in fact explained by the very high performance of the cointegration-based strategies during the 6-month period starting in October 2008.

[4] Data and details on construction of these factors series can be found from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5] The fourth one, 2-year formation period, 2 SD, is significant at 10% level.

- In the Chow test, the date of the break is an input. In order to be more general, the Bai and Perron (2003) test is also used. The breaks which have been detected by this approach at 5% level are reported in Tables 3 and 4. For each of the three strategies mentioned above, a single break in July 2008 is found. With a 3-month difference, this is in line with the Chow test and the hypothesis (October 2008) that has been made.

V. Concluding Remarks

This article extends the literature on pairs trading strategies in providing new empirical results for real-world applications. The contribution of this article lies on a rigorous evaluation of different methods to select and to trade pairs. While the most documented selection technique is based on a distance criteria, more advanced pairs selection techniques like stationarity and cointegration are considered here.

Our results confirm the weak excess returns observed in the recent publications for the minimum distance method. The trades initiated following the stationarity of the price ratio are not able to generate, after transaction costs, large and significant excess returns. The key empirical fact revealed by this study concerns cointegration. After controlling for risk factors, transaction costs and data-snooping biases, cointegration-based pairs trading exhibits high and robust positive alpha. During a period of more than 10 years, even the least profitable parameterization dealing with cointegration delivers excess returns greater than 1.38% per month. Returns can rise up to 5% per month. Cointegration reduces significantly nonconvergence risk.

Points to be explored on that topic stay numerous and include:

- A comparison with international stock indices in other developed countries (e.g. EuroStoxx 600, Nikkei 225), which are less documented than the US market, to see whether the results of this article hold.
- A deeper analysis of the sources of pairs trading profits especially with cointegration: Is the birth of the divergence informative? What is the impact of market overreaction?
- If pairs trading returns are not related to the equity premium, does the volatility/Vix index matter? Do and Faff (2010) regress pairs returns against market volatility over the same month but did not find any significant effect. A new direction could analyse the influence of conditioning openings to a certain level of volatility/Vix.

References

Bai, J. and Perron, P. (2003) Critical values for multiple structural change tests, *Econometrics Journal*, **6**, 72–8. doi:10.1111/1368-423X.00102

Barberis, N., Shleifer, A. and Wurgler, J. (2005) Comovement, *Journal of Financial Economics*, **75**, 283–317. doi:10.1016/j.jfineco.2004.04.003

Baronyan, S., Boduroglu, I. and Sener, E. (2010) Investigation of stochastic pairs trading strategies under different volatility regimes, *Manchester School*, **78**, 114–34.

Bogomolov, T. (2010) *Pairs Trading in the Land Down Under*, SSRN eLibrary. Available at http://dx.doi.org/10.2139/ssrn.1717295

Bossaerts, P. (1988) Common nonstationary components of asset prices, *Journal of Economic Dynamics & Control*, **12**, 347–64. doi:10.1016/0165-1889(88)90045-0

Bossaerts, P. and Green, R. (1989) A general equilibrium model of changing risk premia: theory and tests, *Review of Financial Studies*, **2**, 467–93.

Broussard, J. P. and Vaihekoski, M. (2012) Profitability of pairs trading strategy in an illiquid market with multiple share classes, *Journal of International Financial Markets, Institutions & Money*, **22**, 1188–201. doi:10.1016/j.intfin.2012.06.002

Chen, Z. and Knez, P. (1995) Measurement of market integration and arbitrage, *Review of Financial Studies*, **8**, 287–325. doi:10.1093/rfs/8.2.287

Chiu, M. C. and Wong, H. Y. (2011) Mean–variance portfolio selection of cointegrated assets, *Journal of Economic Dynamics and Control*, **35**, 1369–85. doi:10.1016/j.jedc.2011.04.003

Chow, G. C. (1960) Tests of equality between sets of coefficients in two linear regressions, *Econometrica*, **28**, 591–605. doi:10.2307/1910133

De Bondt, W. F. M. and Thaler, R. (1985) Does the stock market overreact?, *The Journal of Finance*, **40**, 793–805. doi:10.1111/j.1540-6261.1985.tb05004.x

Dickey, D. A. and Fuller, W. A. (1979) Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, **74**, 427–31.

Do, B. and Faff, R. (2010) Does simple pairs trading still work?, *Financial Analysts Journal*, **66**, 83–95. doi:10.2469/faj.v66.n4.1

Do, B. and Faff, R. (2012) Are pairs trading profits robust to trading costs?, *Journal of Financial Research*, **35**, 261–87. doi:10.1111/j.1475-6803.2012.01317.x

Do, B., Faff, R. and Hamza, K. (2006) *A New Approach to Modeling and Estimation for Pairs Trading*, Monash University, Caulfield.

Elliott, R. J., Van Der Hoek, J. and Malcolm, W. P. (2005) Pairs trading, *Quantitative Finance*, **5**, 271–76. doi:10.1080/14697680500149370

Engelberg, J., Gao, P. and Jagannathan, R. (2009) *An Anatomy of Pairs Trading: the Role of Idiosyncratic News, Common Information and Liquidity*, SSRN eLibrary.

Engle, R. F. and Granger, C. W. J. (1987) Co-integration and error correction: representation, estimation and testing, *Econometrica*, **55**, 251–76. doi:10.2307/1913236

Ehrman, D. (2006) *The Handbook of Pairs Trading: strategies Using Equities, Options and Futures*, John Wiley, Hoboken, NJ.

Falbo, P. and Pelizzari, C. (2011) Stable classes of technical trading rules, *Applied Economics*, **43**, 1769–85. doi:10.1080/09603100802676239

Fama, E. F. and French, K. R. (1993) Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics*, **33**, 3–56. doi:10.1016/0304-405X(93)90023-5

Figueira, J., Greco, S. and Ehrgott, M. (2005) *Multiple Criteria Decision Analysis: State of the Art Surveys*, Springer Science Business Media, New York.

Galenko, A., Popova, E. and Popova, I. (2012) Trading in the presence of cointegration, *Journal of Alternative Investments*, **15**, 85–97.

Gatev, E., Goetzmann, W. N. and Rouwenhorst, K. G. (1999) Pairs trading: performance of a relative-value arbitrage rule, NBER Working Paper 7032, National Bureau of Economic Research, Cambridge, MA.

Gatev, E., Goetzmann, W. N. and Rouwenhorst, K. G. (2006) Pairs trading: performance of a relative-value arbitrage rule, *Review of Financial Studies*, **19**, 797–827. doi:10.1093/rfs/hhj020

Hansen, P. R. (2005) A test for superior predictive ability, *Journal of Business and Economic Statistics*, **23**, 365–80. doi:10.1198/073500105000000063

Huck, N. (2009) Pairs selection and outranking: an application to the S&P 100 index, *European Journal of Operational Research*, **196**, 819–25. doi:10.1016/j.ejor.2008.03.025

Huck, N. (2010) Pairs trading and outranking: the multi-step-ahead forecasting case, *European Journal of Operational Research*, **207**, 1702–16. doi:10.1016/j.ejor.2010.06.043

Huck, N. (2013) The high sensitivity of pairs trading returns, *Applied Economics Letters*, **20**, 1301–4. doi:10.1080/13504851.2013.802121

Jacobs, H. and Weber, M. (2011) *Losing Sight of the Trees for the Forest? Pairs Trading and Attention Shifts*, SSRN eLibrary. Available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2023539 (accessed 3 November 2014).

Jagannathan, R. and Viswanathan, S. (1988) Linear factor pricing, term structure of interest rates and the small firm anomaly, Working Paper 57, Department of Finance, Northwestern University, Evanston, IL.

Jegadeesh, N. (1990) Evidence of predictable behavior of security returns, *The Journal of Finance*, **45**, 881–98. doi:10.1111/j.1540-6261.1990.tb05110.x

Jegadeesh, N. and Titman, S. (1993) Returns to buying winners and selling losers: implications for stock market efficiency, *The Journal of Finance*, **48**, 65–91. doi:10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, N. and Titman, S. (1995) Overreaction, delayed reaction, and contrarian profits, *Review of Financial Studies*, **8**, 973–93. doi:10.1093/rfs/8.4.973

Johansen, S. (1988) Statistical analysis of cointegration vectors, *Journal of Economic Dynamics & Control*, **12**, 231–54. doi:10.1016/0165-1889(88)90041-3

Johansen, S. (1996) *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press, Oxford.

Kasch, M. and Sarkar, A. (2014) *Is There an S&P 500 Index Effect*?, SSRN eLibrary. Available at http://dx.doi.org/10.2139/ssrn.2171235

Kwiatkowski, D., Phillips, P. C., Schmidt, P. *et al.* (1992) Testing the null hypothesis of stationarity against the alternative of a unit root, *Journal of Econometrics*, **54**, 159–78. doi:10.1016/0304-4076(92)90104-Y

Lehmann, B. N. (1990) Fads, martingales, and market efficiency, *The Quarterly Journal of Economics*, **105**, 1–28. doi:10.2307/2937816

Lin, Y.-X., Michael, M. and Chandra, G. (2006) Loss protection in pairs trading through minimum profit bounds: a cointegration approach, *Journal of Applied Mathematics and Decision Sciences*, **2006**, 1–14. doi:10.1155/JAMDS/2006/73803

Lo, A. W. and Mackinlay, A. C. (1990) When are contrarian profits due to stock market overreaction?, *Review of Financial Studies*, **3**, 175–205. doi:10.1093/rfs/3.2.175

Mori, M. and Ziobrowski, A. J. (2011) Performance of pairs trading strategy in the US REIT market, *Real Estate Economics*, **39**, 409–28. doi:10.1111/j.1540-6229.2010.00302.x

Papadakis, G. and Wisocky, P. (2008) Pairs trading and accounting information, Working Paper, MIT Sloan School of Management, Cambridge, MA.

Shiller, R. J. (1989) Comovements in stock prices and comovements in dividends, *The Journal of Finance*, **44**, 719–30. doi:10.1111/j.1540-6261.1989.tb04387.x

Stock, J. H. and Watson, M. W. (1988) Variable trends in economic time series, *Journal of Economic Perspectives*, **2**, 147–74. doi:10.1257/jep.2.3.147

Vidyamurthy, G. (2004) *Pairs Trading, Quantitative Methods and Analysis*, John Wiley, Hoboken, NJ.

Vijh, A. M. (1994) S&P 500 trading strategies and stock betas, *Review of Financial Studies*, **7**, 215–51. doi:10.1093/rfs/7.1.215

Whistler, M. (2004) *Trading Pairs – Capturing Profits and Hedging Risk with Statistical Arbitrage Strategies*, John Wiley, Hoboken, NJ.