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Long-run relations among equity indices under different market conditions: Implications on the implementation of statistical arbitrage strategies

Christos Alexakis *

Department of Economics, University of Piraeus, 80 Karaoli and Dimitriou str, 185 33 Piraeus, Greece

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A B S T R A C T

Compared with previous research, the present work extends existing literature by considering long-run relations among major international stock market indices, under different market conditions, and the implications of these relations on the implementation of statistical arbitrage strategies. The examined data contain two bust phases interrupted by a mild bullish period. Employing cointegration analysis, reported results initially indicate that changes in market performance affect the stability of long-run relations, therefore suggesting that arbitrageurs should perform rebalancing among the examined indices when a change in a market trend is evident. Furthermore, extreme market performance harms the mean-reverting properties of a potential long-run relation while moderate market performance points to cointegration between a pair of indices. However, the absence of a stationary spread does not suggest the potential of abnormal returns realization, in the short-run, through exploitation of deviations from its mean value. The applicability of our results may be of importance to market participants since the cointegration approach has recently received considerable attention by hedge funds adopting statistical arbitrage strategies.

1. Introduction and literature review

The present study examines long-run relations among stock market indices, under different market conditions, and the implications of these relations on the implementation of Statistical Arbitrage (SA)

* Tel.: +30 2104142300.
E-mail address: calexakis@tutors.eap.gr.

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strategies. There is considerable literature in financial economics concerning the validity of various forms of the Efficient Market Hypothesis (EMH), Cuthbertson (1996) provides a thorough review. EMH implies that in liquid markets, where asset prices will be the result of unconstrained demand and supply equilibria, the current price should accurately reflect all the information that is available to the players in the market. In other words, the price of an asset at time t is equal to the price of the asset at time $t-1$ plus a random term which reflects the impact of new unpredictable information. This is why the model that is most commonly assumed for stock price movement is a log-normal process; that is, the logarithm of the stock price is assumed to exhibit a random walk. However, because the random walk is a martingale, the mean value of the predicted increment is zero. Therefore, knowing the past history of a random walk is not much help in predicting forward-looking increments. The condition is very different for stationary processes. Armed with the knowledge that stationary processes are mean reverting, one can predict the increment to be greater than or equal to the difference between the current value and the mean. The prediction is guaranteed to hold true at some point in the future realizations of the time series.

Given that stock price predictability may lead to abnormal returns, testing mean reversion has been the objective of many researchers since 1960. While initial studies (Fama, 1965; Samuelson, 1965; Working, 1960) could not reject the random walk hypothesis, later findings are mixed. Some studies suggest stock prices are either mean reverting (Chaudhuri and Wu, 2004, 2003; Balvers et al., 2000; Grieb and Reyes, 1999; Urrutia, 1995; Fama and French, 1988; Lo and MacKinlay, 1988; Poterba and Summers, 1988) or random walk (unit root) processes (Narayan and Narayan, 2007; Narayan and Smyth, 2007, 2004; Kawakatsu and Morey, 1999; Zhu, 1998; Choudhry, 1997; Huber, 1997; Liu et al., 1997).

Since there is no consensus as to whether stock prices are mean reverting or unit root processes, assuming that the joint hypothesis of risk neutrality and market efficiency holds (and thus lack of stock price mean-reversion property), we cannot apply trading strategies that rely upon unconditional variance in order to realize excess returns. However, previous research suggests the existence of stationary linear relations among log data of either share prices or stock indices. Based on this result, prior literature suggests the construction of SA strategies exploiting the mean-reverting properties of linear relations among financial data (Jacobsen, 2008; Canjels et al., 2004; Hogan et al., 2004; Bondarenko, 2003; Laopodis and Sawhney, 2002; Tatom, 2002; Harasty and Roulet, 2000; Forbes et al., 1999; Wang and Yau, 1994).

Reviewing relevant literature, Gori (2009), Gatev et al. (2006) and Vidyamurthy (2004) mention that SA is attributed to Nunzio Tartaglia, a Wall Street quant who was at Morgan Stanley in the mid 1980s. Tartaglia's group of former academics employed statistical methods to develop trading programs, executable through automated trading systems, which replaced traders' intuition and skills with disciplined, consistent filter rules. SA techniques are widely used by hedge funds, Wall Street companies, and even sophisticated independent investors trying to profit from temporary deviations of equity prices from their fundamental value. In academic literature, SA is opposed to arbitrage (deterministic). In deterministic arbitrage a sure profit can be obtained from being long in some securities and short in others. In SA there is a statistical mispricing of one or more assets based on the expected value of these assets. In other words, SA conjectures statistical mispricings or price relationships that are true in expectation, in the long run, when repeating a trading strategy. One of the most popular trading strategies is Pairs Trading (PT). PT is a relatively simple technique: "Find two stocks whose prices have historically moved together, when the spread between the two widens, short the winner and buy the loser; if history repeats itself, prices will converge and the arbitrageur will profit" (Pole, 2007). PT is a trading strategy that aims to exploit temporal deviations from an equilibrium price relationship between two securities. This is given by a long position in one security and a short position in another security in such a way that the resulting portfolio is market neutral (which typically translates in having a beta equal to zero). This portfolio is often called a spread. According to Gori (2009), in the framework of spread modelling, among the more recent techniques we find that cointegration is probably the most popular approach in quantitative trading strategies adopted by hedge funds and a reasonable amount of literature has been published on it.

The main objective of this study is to examine cointegrating relations among equity indices with the implementation of SA strategies exploiting the mean-reversion property of the implied long-run relations. Bondarenko (2003) and Hogan et al. (2004) defined SA as an attempt to exploit the long-horizon trading opportunities revealed by cointegration relationships. Furthermore, according to Alexander and Dimitriu (2005), compared with other conventional methods, cointegration performs better as a way of applying SA strategies. Overall, cointegration methodology is a powerful tool for long-term investment analysis. A number of asset management firms now base allocations on cointegration analysis. In addition, when portfolios are constructed on the basis of returns analysis, frequent rebalancing will be necessary. However, as suggested by Alexander (2001), the power of cointegration analysis is that optimal portfolios may be constructed on the basis of common long-run trends among asset prices, and they will not require extensive rebalancing.

Compared with previous research, the present work aims to extend the existing literature by considering if changes in market performance alternate the mean-reverting properties of long-run relations among major international stock market indices and, as a result, affect implementation of SA strategies on the variables under consideration. The examined data contain two bust phases interrupted by a mild bullish period. Employing cointegration analysis, reported results initially indicate that changes in market performance affect stability of long-run relations, therefore suggesting that arbitrageurs should perform rebalancing among the examined indices when a change in a market trend is evident. Furthermore, extreme market performance harms the mean-reverting properties of a potential long-run relation while moderate market performance points to cointegration between a pair of indices. However, the absence of a stationary spread does not suggest the potential of abnormal returns realization, in the short-run, through exploitation of deviations from its mean value. Since the cointegration approach is widely used by hedge funds adopting SA or PT strategies, we believe our results are of significant importance, suggesting that when a change in market performance is evident then fund managers should keep in mind the necessity of rebalancing.

The remainder of this paper includes a description of the examined data, in Section 2, and research organization along with the employed methodology, in Section 3, followed by model specification and results on cointegration rank tests as well as tested hypotheses, in Section 4. Finally, Section 5 provides a summary and conclusions.

2. Data description

Data employed in this paper include weekly closing prices of stock market indices. In order to leave out any structural effects arising from the introduction of the Euro, we choose to examine an eight-year period: *2001:01:05-2008:12:26*. The examined indices are the US S&P 500, the UK FTSE 100, the German DAX and the Japanese Nikkei 225.

In order to examine cointegrating relations among the examined indices under different market conditions, we have split the sample into three sub-samples. Although structural change is obvious from visual inspection of data in Fig. 1, in order to further justify our choice to split the sample, we apply a breakpoint test, suggested by Chow (1960), on a linear regression of the relationship among log data of the examined variables.[1] According to the results of the Chow test, with a zero p-value, we reject the null of no breaks at the starting points of the second and the third sub-samples. In addition to the latter documentation of the three sub-samples, in order to reveal market performance, we define positive (negative) weekly index returns as Up (Down) market returns. Furthermore, following Fabozzi and Francis (1977), we redefine Up (Down) market returns as Substantially Up (Substantially Down) market returns when the weekly return of an index is larger (lower) than the sum (difference) between average market return and half of one standard deviation measured over the full sample.

Considering the market performance of the US S&P 500 index, in the first sub-sample there are 39 Up and 53 Down market returns while 66.04% of the Down returns are also Substantially Down market returns. In the second sub-sample there are 153 Up and 108 Down market returns while 47.06% of the Up returns are also Substantially Up market returns. In the third sub-sample there are 28 Up and 36 Down market returns while 72.22% of the Down returns are also Substantially Down market returns.

[1] Our choice to apply the Chow breakpoint test on a linear regression among log data of the examined indices is justified by the results of our analysis in Section III where, employing full-sample data, Eq. (7) describes an existing cointegrating relation among the examined variables.

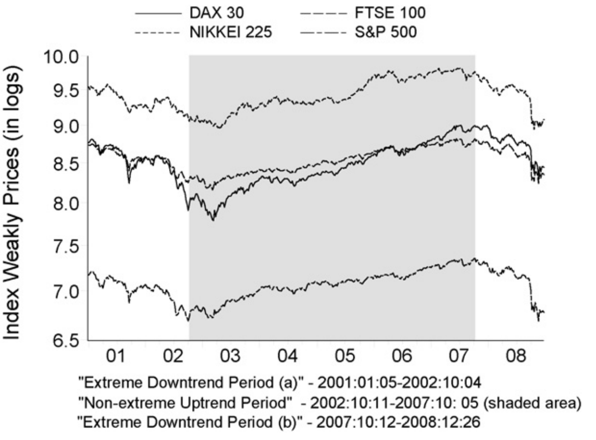

Fig. 1. Plots of data (weakly index prices) in logs.

Examining market performance of the British FTSE 100 index, in the first sub-sample there are 40 Up and 52 Down market returns while 59.62% of the Down returns are also Substantially Down market returns. In second sub-sample there are 151 Up and 110 Down market returns while 43.71% of the Up returns are also Substantially Up market returns. In the third sub-sample there are 26 Up and 38 Down market returns while 71.05% of the Down returns are also Substantially Down market returns.

Regarding market performance of the German DAX index, in the first sub-sample there are 40 Up and 52 Down market returns while 71.15% of the Down returns are also Substantially Down market returns. In second sub-sample there are 156 Up and 105 Down market returns while 46.15% of the Up returns are also Substantially Up market returns. In the third sub-sample there are 25 Up and 39 Down market returns while 58.97% of the Down returns are also Substantially Down market returns.

Finally, focusing on market performance of the Japanese Nikkei 225 index, in the first sub-sample there are 43 Up and 49 Down market returns while 75.51% of the Down returns are also Substantially Down market returns. In the second sub-sample there are 151 Up and 110 Down market returns while 52.32% of the Up returns are also Substantially Up market returns. In the third sub-sample there are 28 Up and 36 Down market returns while 72.22% of the Down returns are also Substantially Down market returns.

While there is no commonly agreed-upon definition for a “bear” market, broadly defined, a “bear” market represents a substantial decline of at least 20% in stock prices over a period of several months. This characteristic is met in the market performance of all examined indices in the first and third sub-samples. Furthermore, examining each stock market index, in the first and third sub-periods, we find that the number of Down returns characterized as Substantially Down returns is sufficiently higher than 50%. In this way we identify first and third sub-samples as “extreme downtrend period (a)” and “extreme downtrend period (b)” respectively.

According to market analysts, a “bull” market is a prolonged period in which share prices raise faster than their historical average. Considering individual market performance of each stock market index, in the second sub-period we find that the number of Up returns characterized as Substantially Up returns is 47.06% (S&P 500), 43.71%, (S&P 500), 46.15% (DAX 30), and 52.32% (Nikkei 225). That is, only for the DAX 30 the number of Up returns characterized as Substantially Up returns is slightly higher than 50%. In this way we identify the second sub-sample as a “Non-extreme uptrend period.”

Overall, the sample under consideration contains “extreme downtrend period (a)” followed by “non-extreme uptrend period” and “extreme downtrend period (b).” A “non-extreme uptrend period” is characterized as a period of moderate market performance and “extreme downtrend periods (a) and (b)” are thought to be periods of extreme market performance. The “extreme downtrend period (a)” falls within the sub-sample of *2001:01:05-2002:10:04* and the data include 92 observations. The “non-extreme uptrend period” falls within the sub-sample of *2002:10:11-2007:10:05* and the data comprise

261 observations. The "extreme downtrend period (b)" falls within the sub-sample of *2007:10:12-2008:12:26* and the data consist of 64 observations.

3. Methodology and research organization

The empirical section is comprised of three parts. First, employing full-sample data we investigate if there is a cointegrating relation among the examined indices. In the second part of our analysis, splitting the sample in three sub-periods, we examine if market performance affects the statistical evidence of possible cointegrating relations, indicated by the results of the first empirical part. Finally, as indicated by the results of the second part, in the third empirical part we shed more light on the second sub-sample, characterized as "non-extreme uptrend period," in order to reveal differences between cointegrating relations from full-sample and second sub-sample data.

We apply the Johansen (1988, 1996) and Johansen and Juselius (1990) methodology of the Cointegrated VAR Model. As noted by Gonzalo (1994) and Kremers et al. (1992), the Johansen and Juselius approach performs better, or at least as well as, the Dickey–Fuller cointegration test of Engle and Granger (1987). In addition, the selected procedure is invariant to different normalizations (Hamilton, 1994) and thus the test outcome does not depend on the chosen normalization. Our results were obtained using CATS in RATS version 2 (Dennis et al., 2005).

The error correction form of the examined unrestricted VAR model is described here:

$$\Delta x_t = \Pi x_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \,\Delta x_{t-i} + \phi D_t + \varepsilon_t, \quad \varepsilon_t \sim iid\, N_P(0, \Omega), \quad t = 1, \ldots, T \tag{1}$$

where:

$$x_t \text{ is a vector of four variables}: \quad [\, lge_t, \quad ljp_t, \quad luk_t, \quad lus_t \,] \sim I(1), \tag{2}$$

[2] and D_t is a vector of deterministic variables such as a constant term and intervention dummies.

The set of variables is defined by:

- lge_t: Germany, Frankfurt Stock Exchange, DAX, Price Index, (in logs).
- ljp_t: Japan, Tokyo Stock Exchange, NIKKEI 225, Price Index, (in logs).
- luk_t: United Kingdom, London Stock Exchange, FTSE 100, Price Index, (in logs).
- lus_t: United States, New York Stock Exchange, S&P 500, Price Index, (in logs).

We do not think it is appropriate to include a linear trend in our model since that would indicate stock market predictability, which is highly unlikely. In the main part of our analysis we choose to restrict the constant term to lie in the cointegrating space and, when proper, we include dummy variables as unrestricted to the cointegrating space.

Performing model specification, we choose the optimal number of lags using Schwarz, Hannan-Quinn and Akaike Information Criteria along with a Likelihood Ratio (LR) test. Following Juselius and MacDonald (2003), in order to secure valid statistical inference we need to control for the largest of observations by dummy variables or omit the most volatile periods from our sample. Since the volatile periods could potentially be highly revelatory we followed the Juselius and MacDonald approach. The dummy variables used in our models are permanent impulse dummies $Dyyyy.mm.dd_t$ (equal to one at *yyyy:mm:dd*, and equal to zero otherwise).

Performing cointegration tests, our main objective is to investigate if there is a long-run relation, with a non-zero intercept, among the examined stock market indices. Applying Johansen (1988, 1996) and Johansen and Juselius (1990) methodology of the cointegrated VAR model, we examine the existence of a long-run relation with a non-zero intercept based upon the estimated eigenvalues, $\hat{\lambda}_i$, and the trace test, τ_{p-r}.

[2] In the third empirical part, x_t vector, instead of four variables, may include combinations among three indices or between pairs of the examined indices.

Table 1
Trace test for cointegration rank.

R	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$
0	4	1	0.079	58.584[a]	53.945
1	3	2	0.037	24.244[b]	35.070
2	2	3	0.015	8.727[b]	20.164
3	1	4	0.006	2.439[b]	9.142

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

Furthermore, we perform hypotheses testing regarding multivariate stationarity, univariate normality, and variable exclusion. In the presence of $I(1)$ series, Johansen and Juselius (1990) developed a multivariate stationarity test which has become the standard tool for determining the order of integration of the series within a multivariate context. The multivariate stationarity test is a LR test distributed as chi-square with (p–r) degrees of freedom, [$\chi^2(3)_{95\%} = 7.815$]. Testing univariate normality, we apply the Doornik and Hansen (2008) test, distributed as $\chi^2(2)$, [$\chi^2(2)_{95\%} = 5.991$]. In order to test variable exclusion we apply a LR test distributed as chi-square with r degrees of freedom, [$\chi^2(1)_{95\%} = 3.841$].

Furthermore, in cases where existent cointegrating relations are detected, we test the null hypothesis of long-run weak exogeneity for each one of the examined indices. According to Juselius (2006), the hypothesis that a variable has influenced the long-run stochastic path of the other variables of the system, while at the same time has not been influenced by them, is called the hypothesis of "no levels feedback" or long-run weak exogeneity. Long-run weak exogeneity test is a LR test distributed as chi-square with r degrees of freedom.

Apart from this general organization of our research, in the first empirical part we perform estimates of the MA representation of our model. Using MA representation, we can express potential relations between the variables of the system as functions of the cumulated shocks. Hence, we can better understand our results from testing hypotheses of potential cointegrating relations.

Finally, we perform detailed long-run identification by testing the validity of over-identifying restrictions on the implied cointegrated vectors.

4. Model specification and results on cointegration rank and tested hypotheses

As mentioned, performing model specification, we choose the optimal number of lags using Schwarz, Hannan-Quinn and Akaike Information Criteria along with a LR test while, in order to secure valid statistical inference, we choose to control for the largest of observations with the use of dummy variables.

In the first part of our analysis, examining full-sample data, we have employed a model with two lags and twenty eight (28) dummy variables, described in Eq. (3).

$$\Delta x_t = \alpha(\beta', \rho') \begin{pmatrix} x_{t-1} \\ 1 \end{pmatrix} + \Gamma_1 \, \Delta x_{t-1} + \phi D_t + \varepsilon_t \tag{3}$$

Being sufficiently confident about the specification of our model, we shall try to determine the rank. Reported results, in Table 1, suggest rejection of the null hypothesis of $r = 0$ while a cointegration rank equal to one is accepted, with 95% significance. Overall, we have evidence that our system contains one cointegrating relation and, as a result, three common trends.

Considering results reported in Table 2, with rank = 1, we cannot accept the exclusion of any of the variables of the system. Overall, we have a system where the employed variables are non-stationary and significant, therefore they cannot be excluded. Univariate normality test outcomes suggest that residual properties are within acceptable levels. Furthermore, we accept the hypothesis of long-run weak exogeneity for luk_t and lus_t.

Table 2
Hypotheses testing with $r = 1$.

lge_t	ljp_t	luk_t	lus_t
28.268[c,a]	30.886[c,a]	28.263[c,a]	25.226[c,a]
4.282[d,b]	2.039[d,b]	2.758[d,b]	4.310[d,b]
13.543[e,a]	8.012[e,a]	9.400[e,a]	8.878[e,a]
12.244[f,a]	13.033[f,a]	2.993[f,b]	1.980[f,b]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.
[c] Multivariate Stationarity test is a LR test, distributed as $\chi^2(3)$.
[d] Doornik and Hansen (2008) univariate normality test, distributed as $\chi^2(2)$.
[e] Variable Exclusion is a LR test, distributed as $\chi^2(1)$.
[f] Long-run Weak Exogeneity test is a LR test, distributed as $\chi^2(1)$.

Up to this point we have considered the cointegrated VAR model (3) with rank = 1 imposed. The MA representation of (3) is given by:

$$x_t = C\sum_{i=1}^{t}\varepsilon_i + C^*(L)\varepsilon_t + \text{deterministic components} \tag{4}$$

where:

$$C = \beta_\perp(\alpha'_\perp \Gamma \beta_\perp)^{-1}\alpha'_\perp = \widetilde{\beta}_\perp \alpha'_\perp \tag{5}$$

is the long-run impact matrix and:

$$C^*(L) = \sum_{i=0}^{\infty} C_i^* L^i \tag{6}$$

is a convergent matrix polynomial in the lag operator L.

The outcomes of long-run weak exogeneity test provide us with a hint regarding the identification of luk_t and lus_t as two of the common stochastic trends of our system. However, given that $p = 4$ and $r = 1$, we must identify if the third common stochastic trend is due to lge_t or ljp_t.

Normalizing to the common stochastic trends (without imposing any other restrictions), the C matrix should demonstrate the long-run effect of the cumulated shocks (=common stochastic trends) on the variables of the system. Using MA representation, we can express potential relations between the variables of the system as functions of the cumulated shocks. In this way we can understand better our results from testing hypotheses of potential cointegrating relations. In the MA representation $a'_\perp$ determines the common stochastic trends and $\tilde{\beta}_\perp$ their loadings.

Regarding the dynamics of our system, we are able to draw useful results from the significant coefficients in $\tilde{\beta}_\perp$. Therefore, in Tables 3a–3d, we observe that luk_t, has a significant positive impact on lge_t, ljp_t, and itself. However, the positive impact of luk_t on lus_t is insignificant. Concerning lus_t, we observe that it has a significant positive impact on lge_t, ljp_t, and itself. However, the positive impact of lus_t on luk_t is insignificant. In Tables 3a and 3b, assuming that ljp_t is the third common stochastic

Table 3a
MA representation (with normalization to ljp_t, luk_t and lus_t).

	Coefficients of the common trend: $\hat{\alpha}_\perp$		
	Common trend 1	Common trend 2	Common trend 3
lge_t	−0.297[a]	−0.284[a]	−0.792[a]
ljp_t	0	0	1
luk_t	1	0	0
lus_t	0	1	0

[a]Rejection of the null with 95% significance.
[b]Acceptance of the null with 95% significance.

Table 3b
Decomposition of the trends (with normalization to ljp_t, luk_t and lus_t).

	Loadings to the common trend: $\hat{\hat{\beta}}_{\perp}$		
	Common trend 1	Common trend 2	Common trend 3
lge_t	1.910[a]	1.285[a]	−0.724[a]
ljp_t	1.686[a]	1.032[a]	0.292[b]
luk_t	1.451[a]	0.344[b]	−0.187[b]
lus_t	0.468[b]	1.212[a]	−0.222[b]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

Table 3c
MA representation (with normalization to lge_t, luk_t and lus_t).

	Coefficients of the common trend: $\hat{\alpha}_{\perp}$		
	Common trend 1	Common trend 2	Common trend 3
lge_t	0	1	0
ljp_t	−0.358[a]	−1.263[a]	−0.374[a]
luk_t	0	0	1
lus_t	1	0	0

[a]Rejection of the null with 95% significance.
[b]Acceptance of the null with 95% significance.

Table 3d
Decomposition of the trends (with normalization to lge_t, luk_t and lus_t).

	Loadings to the common trend: $\hat{\hat{\beta}}_{\perp}$		
	Common trend 1	Common trend 2	Common trend 3
lge_t	1.285[a]	−0.357[b]	1.910[a]
ljp_t	1.032[a]	−1.024[a]	1.686[a]
luk_t	0.344[b]	−0.379[b]	1.451[a]
lus_t	1.212[a]	−0.307[b]	0.468[b]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

trend of the system, we observe that it has a significant negative impact on lge_t. However, its impact on luk_t, lus_t and itself is insignificant. In addition, in Tables 3c and 3d, assuming that lge_t, luk_t and lus_t are the three common stochastic trends of the system, we observe that lge_t has a significant negative impact on ljp_t. However, its impact on luk_t, lus_t and itself is insignificant. Considering the outcomes of Tables 3a–3d, we suggest with confidence that there are two common stochastic trends due to luk_t and lus_t.

Our suggestions are verified by the estimates of the C matrix, which is invariant of the chosen normalization. That is, in Table 4 we observe that the column vectors corresponding to Germany and Japan are insignificant, while the UK and the USA have significant column vectors. However, taking

Table 4
Long-run impact matrix $\hat{C}$.

	$\sum \varepsilon_{ge}$	$\sum \varepsilon_{jp}$	$\sum \varepsilon_{uk}$	$\sum \varepsilon_{us}$
lge_t	−0.357[b]	−0.724[a]	1.910[a]	1.285[a]
ljp_t	−1.024[a]	0.292[b]	1.686[a]	1.032[a]
luk_t	−0.379[b]	−0.187[b]	1.451[a]	0.344[b]
lus_t	−0.307[b]	−0.222[b]	0.468[b]	1.212[a]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

Table 5
Long-run identification.

	$\mathcal{H}_1$		$\mathcal{H}_2$	
	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1$	$\hat{\beta}_1$
lge_t	−0.044[a]	1.693[a]	−0.033[a]	1.257[a]
ljp_t	−0.035[a]	1	−0.031[a]	1
luk_t	−0.013[a]	−2.794[a]	0	−2.319[a]
lus_t	−0.013[b]	−1.854[a]	0	−1.561[a]
Constant		13.166[a]		10.752[a]
LogLikelihood	6905.262		6903.759	
LR statistic			3.006	
p-Value			0.222	
$\chi^2(2)_{95\%}$			5.991	

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

into account that the impact of lge_t on ljp_t is bigger in magnitude than that of ljp_t on lge_t we choose to consider lge_t as the third common stochastic trend of the system.

Given the results of our prior analysis, regarding the identification of variables, we shall try to test hypotheses, considering the long-run identification of the examined system. In Table 5, we begin our analysis with the unrestricted model $\mathcal{H}_1$, normalizing the β vector to ljp_t. Although normalization on ljp_t, leads to an identified cointegrating relation, we choose to impose two over-identifying restrictions.

Given the importance of a zero error correction term for Δluk_t and Δlus_t we test the validity of model $\mathcal{H}_2$ where, as already indicated by the results in Table 2, we accept the joint hypothesis of long-run weak exogeneity for the UK and the USA. Estimated coefficients of the error correction terms represent the short-run speed of adjustment; their magnitude and significance are of great importance regarding the results of our study. If the coefficient of a term is zero, then the error correction does not come from that variable. Considering our analysis to this point, we argue that we have one cointegrating relation among the examined indices, where luk_t and lus_t are clearly the pushing forces, while lge_t and ljp_t are purely adjusting.

In summation, the long-run relation implied by model $\mathcal{H}_2$ is:

$$\beta_1 : \quad ljp_t = -10.752 - 1.257 \cdot lge_t + 2.319 \cdot luk_t + 1.561 \cdot lus_t + stat.error. \tag{7}$$

This cointegrating relation seems to be stable in the short-run as well, as we can infer from the negative sign and significance of the coefficients corresponding to Δlge_t and Δljp_t in α matrix. In other words, DAX and NIKKEI seem to adjust very well to the long-run relation. From the significance of the coefficients in matrix Π (Table 6) we observe that there are significant relations between short-run and long-run parameters. That is, we can infer that DAX and NIKKEI are significantly affected from the cointegrating relation.

In the second empirical part, splitting the examined sample into three sub-periods, we perform cointegration tests and hypotheses testing in each sub-sample. We have employed a model with two lags and one dummy variable in the first sub-period, a model with two lags and fifteen (15) dummy variables in the second sub-period and, finally, a model with two lags and nine dummy variables in the third sub-period. Equation three (3) describes the model employed in the three sub-periods.

Table 6
Estimates of the $\hat{\Pi}$ matrix (model: $\mathcal{H}_2$).

	lge_t	ljp_t	luk_t	lus_t	*Constant*
Δlge_t	−0.042[a]	−0.033[a]	0.077[a]	0.052[a]	−0.357[a]
Δljp_t	−0.040[a]	−0.031[a]	0.073[a]	0.049[a]	−0.339[a]
Δluk_t	0	0	0	0	0
Δlus_t	0	0	0	0	0

[a] Rejection of the null with 95% significance.

Table 7
Trace test for cointegration rank.

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$
"Extreme downtrend period (a)"					
0	4	1	0.261	45.842[b]	53.945
1	3	2	0.130	18.598[b]	35.070
2	2	3	0.038	6.063[b]	20.164
3	1	4	0.029	2.610[b]	9.142
"Non-extreme uptrend period"					
0	4	1	0.111	64.262[a]	53.945
1	3	2	0.073	33.835[b]	35.070
2	2	3	0.032	14.268[b]	20.164
3	1	4	0.022	5.866[b]	9.142
"Extreme downtrend period (b)"					
0	4	1	0.296	50.681[b]	53.945
1	3	2	0.215	28.887[b]	35.070
2	2	3	0.185	13.868[b]	20.164
3	1	4	0.019	1.172[b]	9.142

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

The results, in Table 7, suggest the acceptance of a cointegration rank equal to zero regarding both first and third sub-periods. Alternatively, considering the second sub-period, with 95% significance, the null hypothesis of $r=0$ is rejected while a cointegration rank equal to one is accepted. However, considering a "non-extreme uptrend period," results from hypotheses testing, in Table 8, suggest borderline acceptance of stationarity of the examined variables as well as acceptance of exclusion of lge_t, ljp_t and lus_t.

In the third part of our analysis, focusing on the second sub-period and taking into account the aforementioned outcomes from variable exclusion tests, we initially choose to perform tri-variate cointegration tests. That is, we examine three cases, testing if there is at least one cointegrating relation among a) lge_t, ljp_t and luk_t, b) lge_t, luk_t and lus_t and c) ljp_t, luk_t and lus_t. Results, in Table 9, suggest acceptance of $r=1$ in the first case while $r=2$ is suggested for the other two cases. However, considering results from hypothesis testing, in the first case we should accept exclusion of lge_t and ljp_t. In the second case, with $r=1$, we should accept exclusion of lus_t while, with $r=2$, we should accept stationarity of all

Table 8
Hypotheses testing with $r=1$.

lge_t	lip_t	luk_t	lus_t
"Extreme downtrend period (a)"			
22.426[c,a]	22.434[c,a]	19.817[c,a]	20.222[c,a]
2.340[d,b]	1.053[d,b]	4.080[d,b]	1.918[d,b]
0.114[e,b]	8.181[e,a]	14.597[e,a]	10.392[e,a]
"Non-extreme uptrend period"			
7.321[c,b]	7.516[c,b]	7.014[c,b]	7.224[c,b]
2.630[d,b]	0.066[d,b]	1.529[d,b]	3.044[d,b]
2.182[e,b]	1.917[e,b]	6.247[e,a]	1.025[e,b]
"Extreme downtrend period (b)"			
16.987[c,a]	15.870[c,a]	16.817[c,a]	16.310[c,a]
0.516[d,b]	0.564[d,b]	1.227[d,b]	0.495[d,b]
1.041[e,b]	6.084[e,a]	2.938[e,b]	6.185[e,a]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.
[c] Multivariate Stationarity test is a LR test, distributed as $\chi^2(3)$.
[d] Doornik and Hansen (2008) univariate normality test, distributed as $\chi^2(2)$.
[e] Variable Exclusion is a LR test, distributed as $\chi^2(1)$.

Table 9
Tri-variate trace tests for cointegration rank and hypotheses testing (non-extreme uptrend period).

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	lge_t	ljp_t	luk_t
0	3	1	0.103	42.622[a]	35.070	7.454[c,a]	7.557[c,a]	7.197[c,a]
1	2	2	0.033	14.420[b]	20.164	3.622[d,b]	0.855[d,b]	2.361[d,b]
2	1	3	0.022	5.852[b]	9.142	2.060[e,b]	3.569[e,b]	6.696[e,a]
r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	lge_t	luk_t	lus_t
0	3	1	0.107	52.467[a]	35.070	6.435[c,a]	6.136[c,a]	6.364[c,a]
1	2	2	0.068	23.213[a]	20.164	1.289[c,b(*)]	1.186[c,b(*)]	1.361[c,b(*)]
2	1	3	0.019	4.941[b]	9.142	2.788[d,b]	1.856[d,b]	2.927[d,b]
						5.715[e,a]	6.089[e,a]	2.984[e,b]
						16.951[e,a(**)]	8.150[e,a(**)]	12.556[e,a(**)]
r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	ljp_t	luk_t	lus_t
0	3	1	0.089	44.395[a]	35.070	7.201[c,a]	7.592[c,a]	7.207[c,a]
1	2	2	0.046	20.302[a]	20.164	2.862[c,b(*)]	2.770[c,b(*)]	2.377[c,b(*)]
2	1	3	0.031	8.135[b]	9.142	0.039[d,b]	1.005[d,b]	2.618[d,b]
						4.343[e,a]	7.197[e,a]	1.772[e,b]
						7.930[e,a(**)]	7.688[e,a(**)]	3.364[e,b(**)]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.
[c] Multivariate Stationarity test is a LR test, distributed as $\chi^2(2)$, [$^*\chi^2(1)$].
[d] Doornik and Hansen (2008) univariate normality test, distributed as $\chi^2(2)$.
[e] Variable Exclusion is a LR test, distributed as $\chi^2(1)$, [$^{**}\chi^2(2)$].

variables. In the third case, $r=1$ is borderline rejected while, with $r=2$, we should accept stationarity of all variables as well as exclusion of lus_t both with $r=1$ and $r=2$.

Given the results we have obtained, we chose to further investigate second sub-period performing bi-variate cointegrated tests in all possible pairs of the examined variables. That is, we examine six cases, testing if there is at least one cointegrating relation between a) lge_t and ljp_t, b) lge_t and luk_t, and c) lge_t and lus_t, d) ljp_t and luk_t, e) ljp_t and lus_t and f) luk_t and lus_t. Results, in Table 10, suggest acceptance of $r=1$ in cases (a), (b), (d) and (f) while, in cases (c) and (e) we reject $r=1$ and accept stationarity of the examined variables. In addition, performing hypotheses testing, in cases (a), (d) and (f) we accept stationarity and exclusion of the examined variables.

Given these results, we shall try to test hypotheses considering the identification of the long-run relation between lge_t and luk_t. In Table 11, we begin our analysis with the unrestricted model $\mathcal{H}_1^*$, normalizing the β vector to lge_t. Although normalizing on lge_t leads to an identified cointegrating relation, we choose to impose an over-identifying restriction. That is, as already indicated (in Table 10), testing the validity of model $\mathcal{H}_2^*$, we accept the hypothesis of long-run weak exogeneity for the UK.

However, as suggested by Mavrakis (2009), considering a bi-variate long-run relation, in order to recommend implementation of statistical arbitrage strategies, the implied cointegrating vector should be $(1, -1)$, implying stationarity of the spread between the examined variables. In other words, in order to suggest implementation of statistical arbitrage strategies, there should be a stationary spread between lge_t and luk_t. However, considering models $\mathcal{H}_3^*$ and $\mathcal{H}_4^*$, we reject long-run homogeneity hypothesis as well as joint long-run weak exogeneity and long-run homogeneity hypothesis. That is, there is no potential for abnormal return realization, in the short-run, through exploitation of spread deviations from its mean value. Results from Augmented Dickey–Fuller (Dickey and Fuller, 1981) unit root tests (Table 12) verify our evidence, indicating acceptance of the null hypothesis that the spread is $I(1)$.

Considering our analysis to this point, we argue that we have one cointegrating relation between the two examined indices where luk_t is the pushing force and lge_t is purely adjusting. In summation, in the second sub-period the long-run relation implied by model $\mathcal{H}_2^*$ is:

$$\beta_1^*: \quad lge_t = -5.940 + 1.691 \cdot luk_t + stat.error. \tag{8}$$

Table 10
Bivariate trace tests for cointegration rank and hypotheses testing (Non-extreme uptrend period).

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	lge_t	ljp_t
0	2	1	0.076	26.256[a]	20.164	1.012[b,c]	1.196[b,c]
1	1	2	0.022	5.683[b]	9.142	4.583[d,b]	0.878[d,b]
						1.196[e,b]	1.012[e,b]

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	lge_t	luk_t
0	2	1	0.074	25.003[a]	20.164	5.552[c,a]	5.917[c,a]
1	1	2	0.019	5.103[b]	9.142	1.984[d,b]	3.607[d,b]
						5.917[e,a]	5.552[e,a]
						12.640[f,a]	3.054[f,b]

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	lge_t	lus_t
0	2	1	0.084	38.527[a]	20.164	0.160[c,b]	0.111[b,c]
1	1	2	0.059	15.858[a]	9.142	4.031[d,b]	2.998[d,b]
						0.111[e,b]	0.160[e,b]

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	ljp_t	luk_t
0	2	1	0.061	24.180[a]	20.164	1.284[c,b]	1.234[c,b]
1	1	2	0.030	7.943[b]	9.142	0.827[d,b]	2.022[d,b]
						1.234[e,b]	1.284[e,b]

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	ljp_t	lus_t
0	2	1	0.063	26.676[a]	20.164	0.485[c,b]	0.537[c,b]
1	1	2	0.037	9.794[a]	9.142	0.035[d,b]	2.495[d,b]
						0.537[e,b]	0.485[e,b]

r	$p-r$	i	$\hat{\lambda}_i$	τ_{p-r}	$C_{95\%(p-r)}$	luk_t	lus_t
0	2	1	0.065	23.896[a]	20.164	0.800[c,b]	0.785[c,a]
1	1	2	0.025	6.444[b]	9.142	1.710[d,b]	2.591[d,b]
						0.785[e,a]	0.800[e,b]

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.
[c] Multivariate Stationarity test is a LR test, distributed as $\chi^2(1)$.
[d] Doornik and Hansen (2008) univariate normality test, distributed as $\chi^2(2)$.
[e] Variable Exclusion is a LR test, distributed as $\chi^2(1)$.
[f] Long-run Weak Exogeneity test is a LR test, distributed as $\chi^2(1)$.

Table 11
Long-run identification (non-extreme uptrend period).

	$\mathcal{H}_1^*$		$\mathcal{H}_2^*$		$\mathcal{H}_3^*$		$\mathcal{H}_4^*$	
	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1$	$\hat{\beta}_1$	$\hat{\alpha}_1$	$\hat{\beta}_1$
lge_t	−0.075[a]	1	−0.062[a]	1	−0.013[a]	1	−0.009[b]	1
luk_t	−0.025[a]	−1.670[a]	0	−1.691[a]	−0.006[a]	−1	0	−1
Constant		5.736[a]		5.940[a]		−0.328[a]		−0.158[b]
LogLikelihood	2209.961		2208.434		2207.568		2203.868	
LR statistic			3.054		4.788		12.187	
p-Value			0.081		0.029		0.002	
$\chi^2(1)_{95\%}$, [$^*\chi^2(2)_{95\%}$]			3.841		3.841		5.991[*]	

[a] Rejection of the null with 95% significance.
[b] Acceptance of the null with 95% significance.

Table 12
Augmented Dickey-Fuller unit root test on spread (=lge_t–luk_i).

Lags	Significance level			*T*-statistic
	99%	95%	90%	
0	−3.447	−2.868	−2.570	−1.329[a]

[a] Acceptance of the null with 95% significance.

Table 13
Estimates of the $\hat{\Pi}$ matrix (model: $\mathcal{H}_2^*$).

	lge_t	luk_t	*Constant*
Δlge_t	−0.062[a]	0.105[a]	−0.368[a]
Δluk_t	0	0	0

[a] Rejection of the null with 95% significance.

This cointegrating relation seems to be stable in the short-run as well, as we can infer from the negative sign and significance of the coefficient corresponding to Δlge_t in α matrix (Table 11). In other words, DAX seems to adjust very well to the long-run relation. From the significance of the coefficients in matrix Π (Table 13) we observe there is a significant relation between short-run and long-run parameters. That is, we can infer that DAX is significantly affected from the cointegrating relation.

5. Summary and conclusions

Compared with previous research, we extend existing literature by considering long-run relations among major international stock market indices, under different market conditions. Also, we investigate the implications of these relations on the implementation of SA strategies. Our empirical results may be valuable to market participants since the cointegration approach has recently received considerable attention from hedge funds adopting SA or PT strategies.

According to Alexander (2008), the prices (and log prices) of stock market indices are integrated, and integrated processes have infinite unconditional variance, thus there is little point in attempting to use past prices to forecast future prices in a univariate time series model. However, when two or more indices are cointegrated, there is a multivariate model revealing information about the long-run equilibrium in the system.

In investigating long-run relations among four major international stock market indices we have found one cointegrating relation. Considering the nature of this relation, one could give the interpretation of a portfolio of assets explaining an index identified as the adjusting variable. According to Alexander (2001), if the allocation in a portfolio is designed so that the portfolio explains that index, then the portfolio should be cointegrated with the index. That is, based on that finding one could set up a SA strategy in order to exploit the mean-reverting properties of the stationary linear relation between the examined indices.

Taking into account structural changes due to alternation in market performance, our results indicate that one should be cautious about applying such arbitrage strategies. That is, further investigating the long-run relation among the examined stock market indices, we have divided the sample into three sub-periods in order to re-examine the suggested linear relation under different market conditions. The examined sub-samples contain two bust phases interrupted by a mild bullish period.

Employing cointegration analysis, reported results initially indicate that changes in market performance affect the stability of long-run relations, suggesting that arbitrageurs should perform rebalancing among the examined indices when a change in market trend is evident. Furthermore, extreme market performance harms the mean-reverting properties of a potential long-run relation while moderate market performance points to cointegration between a pair of indices. However, the absence of a stationary spread does not suggest the potential of abnormal returns realization, in the short-run, through exploitation of deviations from its mean value.

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