Stock market cointegration in Europe

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Abstract

In this paper we try to uncover long-run dependency structures by testing for cointegration among six major European stock indices during the first eleven years and four months of the 21^{st} century. We find strong support for one cointegrating vector, indicating that the national stock markets follow the same long-run growth path, and that no market is likely to have substantially greater or worse relative performance over time. This can be attributed to the wide-spread economic and financial integration of the markets, e.g. through the EU or EMU. Further, the cointegration relationship means that traditional risk diversification techniques based on covariance lose their effectiveness in the long run. We find the that U.K. is weakly exogeneous and will be the first market to be hit by events that do not affect all countries simultaneously, but that later spread to the others. In addition, we investigate short-run causal relationships, to determine which markets have a significant short-term effect on the others, and determine how the effects of different events will spread in the region.

1 Introduction

The analysis of dependency structures between stock markets is of central importance in international finance research. Having a knowledge of this, might contribute to the understanding of stock price movements and the prediction of these. Statistical theory offers a number of econometric techniques to evaluate linkages between economic time series such as stock price indices. The most commonly used statistical measure of stock market dependence is *covariance*. It provides a measure of short-term, or even instantaneous, co-movements between random variables. A large portion of existing finance theory, such as the Capital Asset Pricing Model (CAPM), is based on covariance between asset returns. Covariance is, however, subject to several limitations when evaluating stock markets linkages.

Firstly, covariance is a time varying quantity, and, as such, it is of limited use when determining long-term dependency structures. It is a well known fact that covariances tend to increase in times of stock market distress, as stocks generally co-move to a larger extent in such times. Secondly, covariance only explains co-movements that are affected by systematic risk factors in the economy. Over time, the actual outcome of relative movements between economic time series might be completely different from what is implied by the covariance, due to idiosyncratic risk factors. Finally, covariance only enables evaluation of co-movements between two variables at a time. It does not provide a single, coherent measure of dependence between a larger set of time series.

In recent decades, *cointegration* has emerged as an alternative statistical method for evaluating dependencies between time series. A set of time series is said to be cointegrated if each series is integrated of order d, commonly denoted $I(d)$, where $d > 0$, but there exists a linear combination of the series which is integrated of order c, i.e. $I(c)$, where $c < d$. It is commonly acknowledged that stock prices tend to follow non-stationary $I(1)$ processes, whereas their relative returns tend to follow stationary $I(0)$ processes. Stationarity in this context refers to a time series that stochastically fluctuates around a constant mean with constant autocovariance function.[1] Such a series returns to its mean an infinite number of times as time goes to infinity, whereas a non-stationary time series, in contrast, will grow infinitely large as time goes to infinity. The existence of a cointegrating linear combination of stock prices, hence implies that this combination will stay bounded over time. [2]

[1]For a complete definition of stationarity we refer to Brockwell and Davis (1991)

[2]For a further intuitive and non-mathematical description of cointegration, we refer to Murray (1994)

In contrast to covariance, cointegration typically captures long-term relationships between stock prices, due to the stationarity of the linear combination. Since this will remain bounded over time, cointegrated stocks tend to stay together in the long run, implying that they share a common, possibly stochastic, trend. Any temporary deviation from this trend is expected to reverse in the long run, which is equivalent to cointegrated stocks exhibiting error-correcting mechanisms. These act to reduce deviations from the equilibrium cointegrating relationship, and ensure that the linear combination consistently returns to its mean. Given these long-run stationary properties, cointegration has particular appeal as a statistical tool for evaluating market dependencies. Furthermore, there are no limitations to the number of variables that can enter into a cointegrating relationship, suggesting a clear advantage over the covariance framework.

The purpose of this paper is to evaluate dependencies between six European stock markets in the first 11 years of the 21^{st} century in a cointegration framework. In addition to evaluating long-run dependencies implied by cointegration, we also investigate short-run causal relationships between the markets. Emprically, we use daily closing stock index values for the major exchanges in Sweden, the U.K., France, Spain, Austria and Netherlands. While a majority of earlier research focuses either on determining the number of cointegrating linear combinations (Kasa, 1992; Corhay et al., 1993), or investigate how globalization has affected market linkages (Blackman et al., 1994), we aim to extend the analysis by investigating both short-run and long run causal relationships between the six stock markets. This approach is similar to Masih and Masih (2002), which is the most recent study analyzing both cointegration dependencies and short run linkages between national indices. However, Masih and Masih (2002) focus on the effects of globalization on stock markets in four different contintents, whereas the purpose of our study is to analyze interdependencies within the European region in recent years and evaluate what conclusions can be drawn from the uncovered relationships.

It is well known that the economies in Europe have faced extensive economic integration over the past decades, as the flows of labor, goods and capital across national boundaries have increased dramatically. Indeed, this development has been further accelerated by the increasing number of member states of the European Union (EU) and the European

Monetary Union (EMU). As a consequence, stock markets across Europe have become increasingly interdependent. In contrast to earlier research, in which the impact of globalization on market dependencies is evaluated, this paper rather assumes that the European stock markets are closely linked, and aims to investigate causal relationships within the region. We believe that much can be learnt from investigating cointegration using recent data and evaluating the findings in light of recent events.

We find strong evidence of at least one cointegrating linear combination among these markets. This implies that the European stock markets are mutually interdependent in the long run and tend to move together, none deviating significantly from the rest. Among other things, this reduces the benefits of traditional methods of diversification based on covariance. In addition, the data suggests that the U.K. stock market is weakly exogenous among the six indices, implying that the U.K. is the first market to respond to exogeneous shocks, which later spread to the other markets. This could be explained by the U.K. being the Europe's leading financial centre, thus more easily adaptable to changing market conditions.

The paper is structured in the following manner. Section 2 provides a review of previous literature and research related to cointegration techniques and cointegration of stock markets. Thereafter, a thorough description of the data used in the study, along with summary statistics, is given in section 3. In section 4 we present the various econometric techniques used to analyze the data and to test for cointegration. Results from these tests, and our comments on these, are presented in section 5. Further interpretations and implications of our results are provided in section 6, whereas a summary of our conclusions is given in section 7.

2 Previous literature

Cointegration has been widely discussed throughout econometric and economic literature. The concept was first introduced by Granger (1981) and Granger and Weiss (1983) as a statistical property of long-term interdependent time series. Engle and Granger (1987) is, however, the generally cited work in research related to cointegration. In this paper, an extension of the framework was provided, as well as a two-step procedure for testing for cointegration between time series. In addition, critical values for these tests were determined, based on a Monte-Carlo simulation. Additional methods were introduced by Johansen (1988) and Johansen and Juselius (1990), enabling testing for cointegration in a vector autoregressive (VAR) framework, based on maximum-likelihood estimation.

Following this development, a wealth of papers examining cointegration of various economic variables have been produced. Kasa (1992) examined cointegration between stock markets in Japan, the U.S., the U.K., Germany and Canada during the years 1974 to 1990 and found a common stochastic trend driving these stock markets, by adopting the Johansen (1988) method. A similar, yet less significant, result for European equity indices over the period 1975-1991 was provided by Corhay et al. (1993), based on the Engle and Granger (1987) as well as the Johansen (1988) procedures. Moreover, Choudhry (1997) investigated long-run relationships between six Latin American indices and the U.S. stock market, and detected significant long term linkages based on data from 1989 through 1993, by using the Johansen (1988) framework. In addition, Blackman et al. (1994) implemented a combination of the Engle and Granger (1987) and Johansen (1988) approaches, and were able to present some evidence of long-term dependencies between 17 major stock exchanges across the world in the period after, but not before, the development of global financial markets. In contrast, Masih and Masih (2002) provided results supporting the hypothesis of interdependencies between six important world stock markets in the pre-globalization era as well as the post-globalization era, based on the Johansen (1988) method.

These findings are, however, not uncontradicted. Richards (1995) argued that previous results in favour of cointegration between equity indices are based on inaccurate statistical methods. In particular, the results presented by Kasa (1992) were questioned and further examined by Richards, who claimed that Kasa incorrectly failed to take the small number of degrees of freedom into account when determining critical values. By adjusting critical test statistics to allow for finite sample bias, Richards found that the hypothesis of no cointegration could no longer be rejected.

In the same paper, Richards further argues that cointegration between stock markets is unlikely to be observed, since this would enable significant predictability of stock returns, as any deviation from the cointegration relationship would be expected to reverse in the long run. This would imply a violation of the weak form of the efficient market hypothesis, which states that stock prices cannot be predicted by analyzing historical price data (Fama, 1970). Richards however points out that no conclusions regarding market efficiency can be drawn without considering risk-adjusted returns. This is also claimed by Masih and Masih (2002).

The idea that cointegration precludes efficient markets was first discussed by Granger (1986), who stated that "If x_t and y_t are a pair of prices from a jointly efficient, speculative market, they cannot be cointegrated." Similar comments have been provided by Baillie and Bollerslev (1989), Hakkio and Rush (1989), Booth and Mustafa (1991), and others.

A dissenting view was provided by Dwyer and Wallace (1992) who defined an efficient market as "...one in which there are no risk-free returns above opportunity cost available to agents given transaction costs and agents' information." Based on this definition, Dwyer and Wallace showed mathematically, from a time series point of view, that equal expected rates of returns of two assets (i.e. market efficiency) is not inconsistent with cointegration. A similar conclusion was provided by Lence and Falk (2005), who demonstrated that asset prices are determined by preferences and endowment processes, regardless of whether markets are efficient or not. Given this result, Lence and Falk argued that asset prices are cointegrated if, and only if, their endowment processes are cointegrated and preferences satisfy certain conditions. As a consequence, cointegration was concluded not to be at odds with market efficiency.

Yet another contribution to the debate was added by Davies (2005) who examined regime-switching cointegration relationships between stock indices in the U.S., the U.K., Japan, Germany, Switzerland, Australia and Canada, i.e. similar to the data analyzed by Kasa (1992) and Richards (1995). By introducing a two-regime Markov model of the long-run relationships, Davies provided significant evidence of cointegration, suggesting that cointegration relationships are subject to structural breaks. This would imply an explanation of the failure to detect cointegration by Richards (1995), who conformed to a single-regime treatment of data.

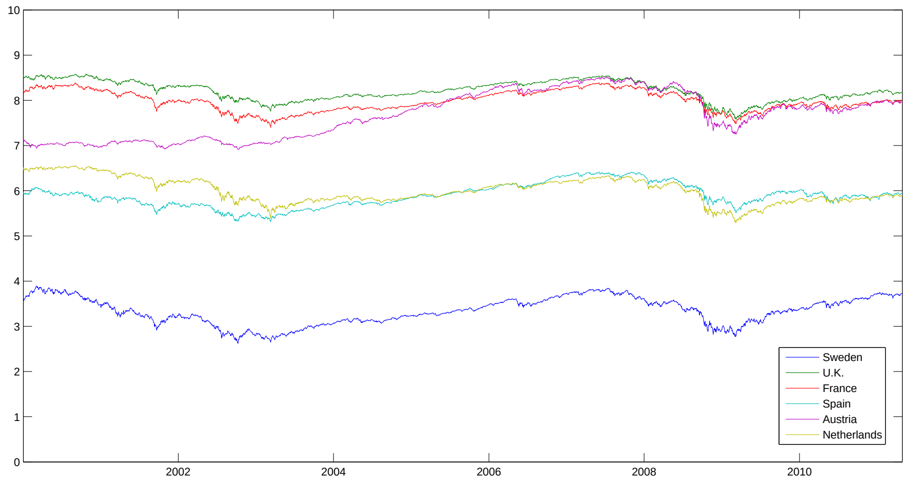
3 Data

We use daily closing stock price index data for equity markets in Sweden, the U.K, France, Austria, Netherlands and Spain in our study. This data set has particular appeal, given that all of the included countries are members of the European Union (EU), and hence can be expected to be highly economically and financially integrated. In addition, four of the indices – France, Spain, Austria and Netherlands – are members of the European Monetary Union (EMU), implying an even stronger degree of financial integration between these countries.

The index data are obtained from the Datastream database, and correspond to official stock exchange indices in each country, i.e. OMX (Sweden), FTSE (U.K.), CAC (France), IBEX (Spain), ATX (Austria) and AEX (Netherlands). Each index is equivalent to the weighted average price development of all publicly traded stocks in each market, however corrected for dilutions, splits and dividends. Thus, the data corresponds to actual value evolutions throughout the period examined. This is of particular importance, as cointegration between indices has limited economic significance if dividends are not accounted for. (See e.g. Richards (1995) for a further discussion of this) For the same reason, all index values are Euro adjusted, and thus reflect stock prices as perceived by an investor with a Euro-denominated portfolio.

The time period of the analysis extends from January, 2000, throughout April, 2011, which corresponds to 11 years and 4 months of data, or 2955 observations. During this time, at least two periods of substantial stock market distress can be observed – the burst of the IT bubble during the first years of the 2000's and the global financial crisis of 2007-2009, following the collapse of the U.S. housing market. In addition, the booming years in between these two crises are captured, enabling cointegration analysis on both types of market climates.

Figure 1: Plot of 6 log-transformed European stock exchange indices for the period 1/1/2000 - 29/4/2011.



In line with earlier studies, (e.g. Kasa 1992; Richards 1995; Davies 2005), all index values are log-transformed, enabling examination of relative changes in index values, as opposed to absolute changes. The log-transformed equity index values are plotted in Figure 1.

Although cointegration tests mainly concern log-prices (see section 4), it is nevertheless informative to get an idea of the characteristics of the log-returns associated with the data set. Summary statistics for log-returns are reported in table 1, which indicate that all six markets seem to display rather similar levels of return volatility. The average return throughout the period is close to zero for all markets. Moreover, it seems that none of the log-returns are normally distributed, as the kurtosis tests indicate fat tails, suggesting too many extreme daily returns for the data to demonstrate normality.

Nearly all six markets demonstrate the largest daily drops in the last months of 2008, i.e. coincident with the global financial crisis prevailing at the time. The Swedish stock market, however, demonstrates the largest daily drop in September 2001, but nevertheless show extreme negative returns in 2008 as well. The largest daily spikes occured in late 2008 and early 2009, in all six markets.

The similarity between stock market returns is further confirmed by their correlation coefficients, which are summarized in table 2 and demonstrate strictly positive co-movements

	Mean	Std. dev.	Max	Min	Kurtosis
France	-0.00008	0.014	0.10	-0.093	8.47
Spain	-0.00005	0.014	0.11	-0.089	8.60
Austria	0.0003	0.015	0.12	-0.10	11.9
U.K.	-0.0001	0.013	0.084	-0.080	7.85
Netherlands	-0.0002	0.016	0.10	-0.096	9.12
Sweden	0.00003	0.017	0.11	-0.085	6.39

Table 1: Summary statistics for daily stock index returns between January, 2000 and April, 2011.

between markets. Note, however, that Sweden, the U.K., France, Spain and Netherlands seem to be generally more correlated, whereas the Austrian market consistently demonstrates relatively low correlation with the other markets.

	France	Spain	Austria	U.K.	Netherlands	Sweden
France	1	-	-	-	-	-
Spain	0.89	1	-	-	-	-
Austria	0.65	0.64	1	-	-	-
U.K.	0.85	0.77	0.60	1	-	-
Netherlands	0.93	0.84	0.60	0.83	1	-
Sweden	0.83	0.77	0.61	0.75	0.79	1

Table 2: Contemporaneous correlations between log-returns of stock market indices.

Nothing is, however, said about the significance level for the statistics in table 1 and 2. They merely provide a rough indication of the characterisitics of the log-returns in each market.

4 Methodology

This section provides a review of the mathematical properties of cointegrated time series and the various estimators we use in our study. As noted in section 2, the two generally adopted procedures for testing for cointegration are those suggested by Engle and Granger

(1987) and Johansen (1988). The former is better suited for bivariate cointegration analysis, whereas the latter is the one generally used in studies involving multivariate analysis of time series. As our analysis involves more than two stock indices, we adopt the Johansen maximum likelihood framework, in line with a majority of earlier studies.

The Johansen procedure starts out from a p-dimensional VAR process $X_t = \left(X_t^{(1)}, ..., X_t^{(p)}\right)'$, with stationary Gaussian iid errors $\varepsilon_t = \left(\varepsilon_t^{(1)}, ..., \varepsilon_t^{(p)}\right)'$. Such a process can be expressed as

$$X_t = \mu + \Pi_1 X_{t-1} + \cdots + \Pi_k X_{t-k} + \varepsilon_t, \tag{1}$$

where μ is a $p \times 1$ vector of unrestricted intercepts and $\Pi_i,\ i = 1, \ldots, k$ denotes $p \times p$ matrices of coefficients. Eq. (1) can be rewritten on error-correction form as

$$\Delta X_t = \mu' + \Gamma_1 \Delta X_{t-1} + \cdots + \Gamma_{k-1} \Delta X_{t-k} + \Pi X_{t-k+1} + \varepsilon_t, \tag{2}$$

where $\Delta = 1 - L$, with L as the lag operator, $\Gamma_i = -\left(I - \Pi_1 - \cdots - \Pi_i\right),\ i = 1, \ldots, k-1$ and $\Pi = I - \Pi_1 - \cdots - \Pi_k$. Here, I denotes the identity matrix. It is assumed that X_t is $I(1)$, from which follows that ΔX_t is $I(0)$. When written in the form of Eq. (2), it is easily observed that the VAR process is governed by both short-run dynamics captured by the Γ_i matrices and a long-run component, governed by the Π matrix. The latter, commonly denoted the *impact matrix*, is central to the cointegration relationship. It is the rank of this matrix that determines the dimension of the cointegration space through the number of linearly independent cointegrating vectors in the system. In general, the rank r can take any value $0 \leq r \leq p$, depending on the characteristics of the matrix.

If $r = p$, the impact matrix is said to be of full rank, in which case the original X_t process can be shown to be stationary which precludes cointegration and violates our assumption of $X_t \sim I(1)$. Furthermore, if $r = 0$, Π is a null matrix, in which case Eq. (2) only contains short-run components, which, again, contradicts cointegration. If, however, $0 < r < p$, Π can be factored as

$$\Pi = \alpha\beta' \tag{3}$$

where α and β are two $p \times r$ matrices. Since both ΔX_t and ε_t are stationary, we can conclude that the term $\alpha\beta' X_t$ is also stationary. It can be shown that the space spanned by the column vectors of β correspond to the linear combinations of X_t that are stationary, commonly denoted cointegrating vectors. Moreover, the row vectors of α provide an indication of the relative weights of the cointegrating vectors on each stock index time series in X_t.

The key problem in the Johansen procedure is to determine the number of linearly independent cointegrating vectors, i.e. the rank of Π. This is done by maximum-likelihood estimation of the space spanned by β, which is the space spanned by the r canonical variates corresponding to the r largest squared canonical correlations between the residuals R_{0t} and R_{kt} from the regression of ΔX_t and X_{t-k} respectively on the lagged differences. According to Johansen (1988), the first r canonical variables can be calculated as the first r eigenvectors of $S_{k0}S_{00}^{-1}S_{0k}$ with respect to S_{kk}, where $S_{ij} = \frac{1}{T}\sum_{t=1}^{T} R_{it}R_{jt}', i, j = 0, k$ are the product moment matrices of the residual vectors R_{0t} and R_{kt}.

In order to find the eigenvectors, one must first determine the corresponding eigenvalues $\lambda_1, ..., \lambda_p$ (in decreasing order of magnitude), which is done by solving the equation $|\lambda S_{kk} - S_{k0}S_{00}^{-1}S_{0k}| = 0$. The eigenvectors are then found through the expression $S_{kk}ED = S_{k0}S_{00}^{-1}S_{0k}E$, where E is the matrix with the eigenvectors as columns, and D is the diagonal matrix with the eigenvalues as diagonal entries. In essence, λ_i $, i = 1, \ldots, p$, provides an indication of how well linear combinations of X_t given by the eigenvectors, correlate with the stationary part of the process. If the linear combination given by an eigenvector is non-stationary, this correlation is small, whereas it will be substantial whenever an eigenvector yields a cointegrating linear combination.

Testing for the presence of cointegration, is consistent with testing the null hypothesis that there are at most q cointegrating vectors, or equivalently

$$H_0 : r \leq q.$$

To evaluate this hypothesis, Johansen derives the maximized likelihood function

$$L_{max}^{-2/T} = |S_{00}| \prod_{i=1}^{r} \left(1 - \hat{\lambda}_i\right),$$

from which likelihood ratio tests for the value of r can be derived. Johansen suggests two such tests: the trace test and the maximum eigenvalue test, where we denote the test statistics by A_{trace} and A_{max} respectively. These are calculated as

$$A_{trace} = -T \sum_{i=q+1}^{p} \ln(1 - \hat{\lambda}_i),$$

$$A_{max} = -T \cdot \ln(1 - \hat{\lambda}_{q+1}).$$

Both tests evaluate the null hypothesis that $r \leq q$, $q < p$. Their alternative hypotheses, however, differ. The trace test has the alternative hypothesis that there exists at most p cointegrating vectors, whereas the maximum eigenvalue test has the alternative hypothesis that there exists $q + 1$ cointegrating vectors. The implication of this difference is that A_{trace} will tend to be a more efficient than A_{max} in cases when the eigenvalues are evenly distributed, since it considers all of the $n - q$ smallest eigenvalues. In contrast, A_{max} is more suitable when eigenvalues are relatively large or relatively small.

In practice, the testing procedure for both tests is rather a sequence of tests, where the null hypothesis that $r = 0$ is first tested, and if rejected, a second null hypothesis that $r \leq 1$ is tested, and so on, until the null hypothesis that $r \leq q^*$ cannot be rejected. Since this is implies that we can dismiss that $r \leq q^* - 1$, but not $r \leq q^*$, such a result suggests that there are q^* cointegrating vectors in the system.

In addition to determining the long-term characteristics implied by the impact matrix Π, we evaluate short run dynamics as suggested by the Γ_i matrices in Eq. (2). Whenever the coefficients in these matrices are significantly non-zero, there is evidence of short-run correlations between variables in ΔX_t and ΔX_{t-i} , $i = 1, ..., k$. This provides an indication of how well one time series is useful in forecasting another.

Prior to conducting cointegration analysis, we use two unit-root tests, in order to test for presence of unit roots in the data. Recall that the Johansen procedure requires the original time series X_t to be $I(1)$. This assumption is by no means guaranteed to hold, and hence, it must be validated before cointegration analysis is conducted.

The first unit-root test we adopt is the augmented version of the Dickey and Fuller (1979) test. This is based on an autoregressive model, and has the form of

$$\Delta x_t = \alpha + \beta t + \gamma x_{t-1} + \delta_1 \Delta x_{t-1} + \cdots + \delta_{n-1} \Delta x_{t-n+1} + \varepsilon_t, \tag{4}$$

where x_t represents an individual stock index time series, the intercept α represents a drift in x_t and β corresponds to a possible time trend in Δx_t. Furthermore, $\delta_i \Delta x_{t-i}$, $i = 1, \ldots, n-1$ corresponds to the additional contribution of the augmented model compared to the simple Dickey-Fuller test and allows capturing of possible serial correlation in Δx_t. The γ coefficient is, however, the parameter of central interest. It provides an indication of whether there is a unit root or not in the data. To evaluate this, the Augmented Dickey-Fuller procedure simply tests the hypothesis

$$H_0 : \gamma = 0$$

against the alternative that $\gamma < 0$. If $\gamma = 0$, x_t can be concluded to be non-stationary, as it needs to be differenced to become stationary. In contrast, if $\gamma < 0$, x_t is already stationary, and it does not require differencing in order to demonstrate stationarity.

In the second unit root test, we adopt the Philips and Perron (1988) procedure. This is based on a non-parametric test, and therefore enables a robustness check of the results obtained from the regression in Eq. (4). The Philips-Perron test is similar to the Augmented Dickey-Fuller test, but has the somewhat simpler form

$$x_t = \alpha' + \beta' t + \gamma' x_{t-1} + \varepsilon_t, \tag{5}$$

where the α' represents an intercept and β' a possible time trend in x_t. Again, γ' is the coefficient of central interest, as it determines whether x_t has a unit root or not. In contrast to the Dickey-Fuller test, the Philips-Perron procedure however assumes that the lagged level variable is endogenous, and therefore adopts test statistics that are robust to serial correlation in the error term. In essence, we test the null hypotheis

$$H_0 : \gamma' = 1,$$

against the alternative that $\gamma' < 1$. If H_0 is rejected, x_t can be concluded to be stationary. Consequently, failure to reject H_0 implies non-stationarity.

5 Results

In this section, we present the quantitative results obtained from unit root tests and the Johansen procedure, as well as tests of short-run dynamics, as outlined in section 4.

As noted, it is important to determine whether the original time series are non-stationary, as cointegration analysis only can be performed on data that is at least $I(1)$. Results from the Augmented Dickey-Fuller and Philips-Perron unit root tests for the levels index data for each stock market are reported in table 3. Note that each test is conducted on two different models – one in which fluctuations around a constant mean is considered, and the other with stationary fluctuations around a time trend, corresponding to the βt and $\beta' t$ terms in Eq. (4) and Eq. (5). Optimal lag-choice for the Augmened Dickey-Fuller test was determined by minimizing the Akaike Information Criterion (AIC).

	Augmented Dickey-Fuller		Philips-Perron	
	Constant	Constant and trend	Constant	Constant and trend
France	-0.869	-1.093	-5.570	-5.579
Spain	-1.280	-0.820	-3.940	-4.637
Austria	-0.249	0.575	-1.561	-1.102
U.K.	-0.977	-1.331	-5.013	-5.333
Netherlands	-1.083	-2.147	-4.678	-6.262
Sweden	-1.123	-0.942	-4.300	-4.925

Table 3: Test statistics for Augmented Dickey-Fuller and Philips-Perron unit-root test of national stock index data. 1%, 5% and 10% critical values for the Augmented Dickey-Fuller are -3.430, -2.860 and -2.570 respectively for the constant model, and -3.960, -3.410 and -3.120 for the trend model. Corresponding critical values for the Philips-Perron tests are -20.700, -14.100 and -11.300 for the constant model, and -29.500, -21.800 and -18.300 for the trend model.

Table 3 shows that none of the test statistics fall below the critical values, and hence the null hypothesis of unit roots is not rejected in any of the tests. Thus, we cannot preclude that the index series are non-stationary. This result is in line with previous studies, which typically show that stock prices follow $I(1)$ processes. However, in order to confirm the order of integration, we also conduct unit root tests on the differenced index series. The results are reported in table 4.

As can be seen, the null hypothesis of a unit root in the differenced data is rejected at the 1% level in all tests. We thereby conclude that the differenced stock index series is a stationary process. By definition, a time series is $I(1)$ if it is non-stationary and its corresponding differenced time series is stationary. Hence, we find that the level time series all follow $I(1)$ processes, allowing us to perform cointegration tests.

	Augmented Dickey-Fuller		Philips-Perron	
	Constant	Constant and trend	Constant	Constant and trend
France	-40.472***	-40.451***	-1744.273***	-1744.177***
Spain	-39.689***	-39.678***	-1703.987***	-1703.987***
Austria	-38.401***	38.401***	-1640.977***	-1640.496***
U.K.	-41.015***	-41.001***	-1773.379***	-1773.227***
Netherlands	-40.518***	-40.502***	-1767.298***	-1767.164***
Sweden	-42.171***	-42.177***	-1757.544***	-1757.496***

Table 4: Test statistics for Augmented Dickey-Fuller and Philips-Perron unit-root tests of differenced national stock index data. 1%, 5% and 10% critical values for the Augmented Dickey-Fuller are -3.430, -2.860 and -2.570 respectively for the constant model, and -3.960, -3.410 and -3.120 for the trend model. Corresponding critical values for the Philips-Perron tests are -20.700, -14.100 and -11.300 for the constant model, and -29.500, -21.800 and -18.300 for the trend model. 1 %, 5% and 10% significance levels are indicated by ***, ** and *.

In the next step of the analysis, we perform the Johansen procedure on the index levels data throughout the full time period, by evaluating both maximum eigenvalue statistics and trace statistics. Two different lag-lenghts are evaluated: $k = 11$ and $k = 1$. The former is determined by minimizing the Akaike Information Criterion (AIC), and the latter by minimizing the Schwartz Bayesian Information Criterion (SBIC). The results are reported in table 5.

In the case of $k = 11$, the trace test as well as the maximum eigenvalue test yield that the null hypothesis that $r = 0$ can be rejected at the 5% level, but not at the 1% level. The lowest rank at which failure to reject H_0 at a 5% level occurs is $r \leq 1$, suggesting rather strong evidence of one cointegrating vector in the $k = 11$ lag model. Even stronger significance is, however, provided by the $k = 1$ model, as this provides rejection of $r = 0$ already at the 1% level for both test statistics. The first failure to reject H_0 at the 1 % level occurs at $r \leq 1$, implying strong support of one cointegrating vector in the $k = 1$ case.

Following this result, we estimate the α and β coefficients of the impact matrix. The β

	Test statistics				Critical values			
	$k = 11$		$k = 1$		1%		5%	
H_0	Trace	Max.	Trace	Max.	Trace	Max.	Trace	Max.
$r = 0$	101.5290[1]	40.9136[1]	103.5051	46.7349	103.18	45.10	94.15	39.37
$r \leq 1$	60.6155[5]	23.6038[5]	56.7703[1,5]	27.8934[1,5]	76.07	38.77	68.52	33.46
$r \leq 2$	37.0117	16.7470	28.8768	12.3116	54.46	32.24	47.21	27.07
$r \leq 3$	20.2647	12.1105	16.5652	9.2156	35.65	25.52	29.68	20.97
$r \leq 4$	8.1542	4.8475	7.3496	5.1833	20.04	18.63	15.41	14.07
$r \leq 5$	3.3067	3.3067	2.1664	2.1664	6.65	6.65	3.76	3.76

Table 5: Johansen trace and maximum eigenvalue tests for the number of cointegrating vectors. H_0 is rejected when test statistics exceeds critical values. k refers to the number of lags, where $k = 11$ minimizes AIC and $k = 1$ minimizes SBIC. [1] and [5] indicates the lowest rank at which failure to reject H_0 occurs, when comparing with 1% and 5% critical values respectively, implying that the number of cointegrating vectors correspond to this rank.

coefficients correspond to the cointegrating linear combination normalized on the Swedish index, whereas the α coefficients provide an indication of how well each index responds to fluctuations in the common stochastic trend in the long run.

Results are summarized in table 6, and consistently demonstrate significant β coefficients for both lag lengths. Graphs of the mean-errors of the cointegrating linear combination of the indices implied by the estimated β coefficients in the $k = 1$ and $k = 11$ models are plotted in figure 2. Note that mere inspection supports that the series are stationary, as they do not show any evidence of exploding at any point. Instead, they repeatedly return to their means, as stationary series are expected to do.

As for the α coefficients, all countries demonstrate significance in the $k = 11$ case, implying that all markets respond after 11 days to deviations in the cointegration relationship. According to the sizes of the respective α coefficients, Sweden, Netherlands and France seem to be responding relatively forcefully to such deviations, whereas Spain, Austria and U.K. respond somewhat weaker.

Similar results are reported in the $k = 1$ case, with the exception of U.K, which fails to demonstrate a significantly non-zero α coefficient. This result suggests that, whenever

	Beta		Alpha	
	$k = 11$	$k = 1$	$k = 11$	$k = 1$
France	-12.61053***	-22.30528***	0.0020373***	0.0008382***
Spain	10.17726***	19.38743***	0.0012632***	0.000533**
Austria	-3.564853***	-7.253815***	0.0014524***	0.0006073***
U.K.	14.06196***	31.37779***	0.0010222**	0.0001942
Netherlands	-7.295103***	-17.38582***	0.0023424***	0.0009639***
Sweden	1.0000	1.0000	0.0024933***	0.0009921***

Table 6: Johansen estimated α and β coefficients of the impact matrix, defined as $\Pi = \alpha\beta'$. The β coefficients are normalized on the Swedish stock index series. k refers to the number of lags, where $k = 11$ minimizes AIC and $k = 1$ minimizies SBIC. 1%, 5% and 10% significance levels are indicated by ***, ** and * respectively.

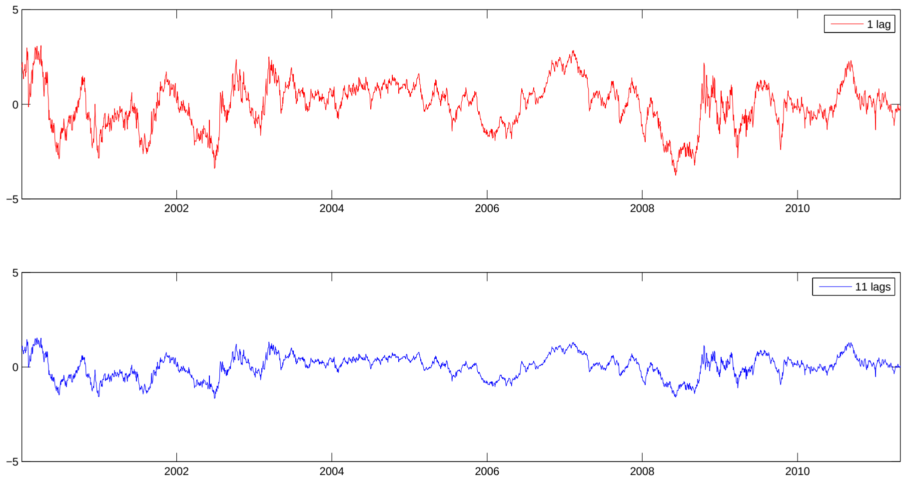
there is a deviation from the cointegration relationship, all markets other than the U.K. market will adjust in order to reduce the disequilibrium. One implication of this is that the U.K. stock market is likely to be the first to display any effect of an external economic shock among the six indices. The other stock markets will thereafter respond to this change in the long run, as indicated by the size of their respective α coefficients. The results in table 6 suggest that Sweden, Netherlands and France are the three most responsive indices, whereas Spain and Austria demonstrate a relatively weak reaction to fluctuations in the common trend.

The effect of the α coefficients can be understood by inspecting the error-correcting representation of the cointegrating relationship, which is an equivalent representation of the cointegrating relationship. Recall that Eq. (1) can be rewritten on error-correcting form as

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + \cdots - \beta\mu + \Gamma_k X_{t-k} + \varepsilon_t, \tag{6}$$

where $\Gamma_i = -I + \Pi_1 + \cdots + \Pi_i, \quad i = 1, ..., k$. Note that $\Gamma_k = \Pi = \alpha\beta'$. The error-correction equation is a VAR in differences, with one additional term made up of the level at k lags. Recall that β is the matrix of cointegrating vectors, however in our case the results show strong support for only one cointegrating vector. In the error-correction representation, the α vector is multiplied by the stationary linear combination obtained

Figure 2: Plot of the estimated cointegrating linear combination of stock indices.



from the cointegration relationship. Thus there is a direct relationship between the change in the ith series, $\Delta X_t^{(i)}$, and the level of the series obtained from the cointegrating vector, $\beta' X_t$, the strength of which is measured by the α coefficient for that series, $\alpha^{(i)}$. For several indices, the α coefficient measures the dependence on all cointegrating series, and the differences ΔX_t are dependent upon all of them in the error-correction representation.

The choice of the number of lags in the the VAR representation from which the cointegrating relationship is estimated affects the responsiveness of the constituent series to deviations of the cointegration linear combination. Inspecting the error-correction representation in Eq. (6), we can conclude that the smaller the lag, the sooner the indices start to correct the deviations of the cointegration series. For the estimated model with $k = 1$ lags, as indicated by the SBIC, already the next day following a deviation do the indices start to correct the deviation. In the $k = 11$ case, as indicated by the AIC, there is an 11-day lag until a correction begins. Thus we expect the linear combination of indices to adjust more rapidly in the former case, since in the latter case the model does not respond to any deviations that have taken place during the last 10 days. The level term in the error-correction representation continues to affect the change in all variables with non-zero α coefficients until the linear combination has returned to its mean.

In the concluding part of the analysis, we evaluate the directions of short-run dynamics in the $k = 1$ model, as this specification provides strongest evidence of one cointegrating vector, according to the results reported in table 5. Given that $k = 1$ and $r = 1$, Eq. (6) implies that the first difference in stock index i can be written as

$$\Delta X_t^{(i)} = -\beta^{(i)}\mu^{(i)} + \sum_{j=1}^{p} \gamma_j^{(i)} \Delta X_{t-1}^{(j)} + \alpha^{(i)} \sum_{j=1}^{p} \beta^{(j)} X_{t-1} + \varepsilon_t^{(i)},$$

where $\alpha^{(i)}$ and $\beta^{(j)}$ are the already estimated coefficients presented in table 6. The $\gamma_j^{(i)}$ coefficients indicate the short-run responses to changes in other market indices. Note that the first difference in X_t is equivalent to log-returns of the indices. If there is a significant non-zero relationship between the daily log-return of one market at time t and the daily log-return of another market at time $t-1$ (or the same market at time $t-1$), the $\gamma_j^{(i)}$ coefficients will capture this dependency. Results are reported in table 7.

	ΔFrance$_t$	ΔSpain$_t$	ΔAustria$_t$	ΔU.K.$_t$	ΔNetherl.$_t$	ΔSweden$_t$
ΔFrance$_{t-1}$	-0.15**	-0.20***	-0.18***	-0.064	-0.098	-0.036
ΔSpain$_{t-1}$	0.031	0.11***	0.07	-0.011	0.0044	0.036
ΔAustria$_{t-1}$	-0.069***	-0.044**	-0.023	-0.021	-0.041	-0.11***
ΔU.K.$_{t-1}$	0.018	0.0015	0.048	-0.045	0.032	0.11**
ΔNetherl.$_{t-1}$	0.056	0.061	0.10**	0.063	-0.00088	0.027
ΔSweden$_{t-1}$	0.073**	0.033	0.067**	0.037	0.063**	-0.020

Table 7: Short run responses between stock market log-returns. 1%, 5% and 10% significance levels are indicated by ***, ** and * respectively.

As shown, the only market that is not affected by any other market is the U.K., supporting the claim that U.K. is the first market to display the effects of an exogenous shock. This result suggests that the U.K. is weakly exogenous to the system. In turn, the U.K. affects the Swedish stock market, which thereafter impacts stock markets in France, Austria and Netherlands. By the same logic, the French market influences indices in Spain and Austria, and the Austrian market effects the French, Spanish and Swedish stock indices, whereas the Dutch market has significant effects on the Austrian market. Spain, in contrast, seems to be the only market that has no evident impact on other indices. An overview of these directions of causality are illustrated in figure 3. Note, that the data suggest that there are unidirectional as well as bidirectional relationships.

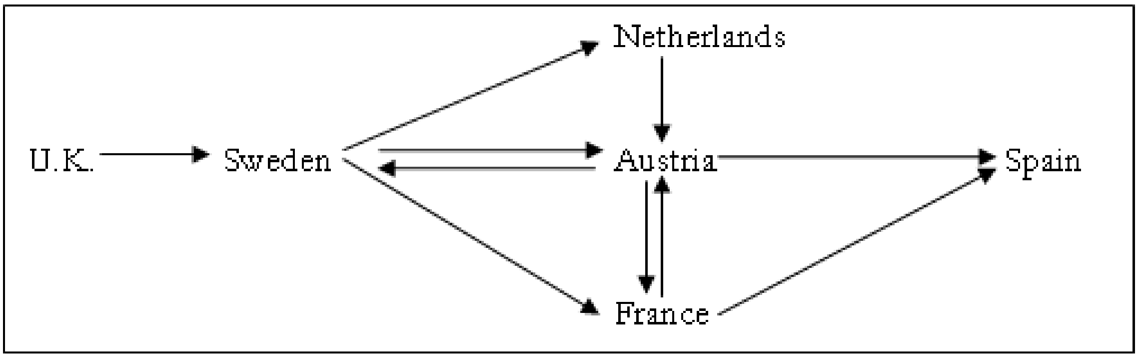


Figure 3: Short-run linkages between stock market log-returns.

6 Implications

Our tests indicate strong support for one cointegrating vector among the six equity indices, as described in the previous section. We will interpret the uncovered cointegration relationship and analyze its financial implications. In order to do so, it is important to have a thorough understanding of its characteristics as a statistical measure.

As mentioned, through specifying that the linear combinations of the cointegration space follow a stationary process, cointegration is a measure of long-term dependence. A stationary process has constant mean, and it will always retract back towards the mean if it has deviated from it. In fact, a stationary process will cross the mean an infinite amount of times as time tends to infinity – in other words there is zero probability that the series will diverge never to return to the mean. Additionally, the idiosyncratic noise in each index will not have any effect on the final outcome of the relative movements, since we know that the series will converge to the mean sooner or later. Thus, exogeneous, random effects that affect individual indices will abate over time. Indeed, for any stationary series $Z_t = \mu + \sum_{j=0}^{+\infty} \theta_j \varepsilon_{t-j}$ we must have $\sum_{j=0}^{+\infty} |\theta_j| < +\infty$, leading to the effects of individual perturbations ε_i becoming arbitrarily small over time. Although being somewhat counterintuitive, this is not a contradiction, but simply a statement of the cointegration – exogeneous shocks will affect individual contituent assets in the cointegration relationship, but since markets are integrated, these will die out over time or spread to the other markets, maintaining the long-run relationship between them. Furthermore, it would be fair to assume that there are dependencies that can not be spotted if only investigating time series pairwise, and as mentioned above cointegration can indeed be a joint property of several time series.

Be that as it may, there are a few problems with cointegration that must be kept in mind when interpreting our results from a point of view of their economic significance. One such thing is the fact that cointegration is unlikely to be observed among tradable assets in efficient markets. The stationarity of a linear combination of assets would imply that risk-free arbitrage strategies could be devised, as there is no uncertainty about that the portfolio of assets constructed from the cointegrating relationship will revert back to its mean once a deviation has taken place. The feasibility of arbitrage strategies is equivalently an effect of that the idiosyncratic risk factors of the constituent assets have no lasting impact on the final outcome of the relative movements.

With these properties of cointegration in mind, we analyze the economic significance of the results obtained from our statistical tests. Being a long-term, unchanging relationship, we used a long time period to estimate the cointegrating vector, as explained in the previous section. The essence of cointegration is that the relationship will hold over an extended period of time, or the time series could not be considered stationary, and the measure as such would be of little use. Furthermore, our study is to the best of our knowledge the most recent investigation of cointegration among equity indices, thus allowing us, for example, to analyze the behaviour of the cointegrating vector during and after the financial crisis.

Since we found significant cointegration among our data, this indicates that a linear combination of European stock indices can be described by a stationary time series representation. But what does this really mean? We already know that they are highly correlated and exhibit strong comovement, mostly due to the correlation. So what does cointegration bring to the table? The correlation between the indices tells us that if one index goes up, the others tend to do that as well on the same day. However, over time this might translate into very different outcomes for the index levels, so nothing can be said about these over any longer period of time. One could calculate the monthly correlation, or the yearly one, or whichever period one prefers, but the idiosyncratic components of the index returns will make the explanatory power of the correlation very blunt in the long run. Cointegration, rather than stipulating that assets will comove simultaneously, describes an inherent lag in the comovements. Inspecting the plot of the cointegrating linear combination in figure 2, it deviates quite substantially from its mean, but always falls back. Assume that the linear combination is at its equilibrium, and then some stock markets with predominantly positive weights in the linear combination have higher relative return than the rest. Then the series will deviate positively from the mean, as can be seen at multiple occasions in the plot. However, since the linear combination always comes back to the mean, a period will follow when the indices with predominantly negative weights have a higher relative return. Thus, over time, the indices tend to follow each other, although the comovements exhibit a lagging behaviour. Thus this dependency structure hypothesized by the cointegration measure, and as confirmed by our statistical tests, is really nothing more than a lead-lag structure in relative returns among the indices with negative and positive weights in the linear combination.

An economic interpretation of correlation among stock indices is straightforward - European stock markets exhibit simultaneous comovement because they are all affected by the same economic events, and they are all affected at the same time. Geographical proximity and a high degree of economic integration in various forms naturally increase the correlation. Cointegration makes a slightly different statement. Events that affect all indices in relation to their exposure to systematic risk factors leave the cointegration vector unaltered, or affects it only marginally. Cointegration is an expression of another type of economic integration of national markets – the cointegrating vector changes as a result of events that affect only one country, or certain countries disproportionately, effects that then abate as the national stock indices again approach each other. Alternatively, cointegration measures the effect of events that affect different countries at different points in time – they begin in one country and then spread to the others. The statistically significant cointegration among the European indices tells us that in addition to being affected simultaneously by many global events and that events in one market tend to have an effect on other markets in the region, as shown by the high correlation among the indices, the indices tend to follow each other in the long run. It is unlikely that one index will deviate from the rest for an extended period of time, i.e. that it has significantly lower or higher relative growth rate.

A number of factors could explain these dependencies between relative growth rates. If the deviation of some indices is caused by a favourable macroeconomic climate, these effects are likely to spread to other European economies, given the strong degree of economic integration and capital mobility. In such cases, other financial markets will tend to maintain the co-integrating relationship by following the initial deviating markets. In contrast, if the extreme performance in the deviating market is rather caused by inaccurate expectations, or irrational fad behaviour, this deviation will be likely to reverse, leading the deviating index to experience a period of lower relative growth.

Furthermore, the existence of cointegration in Europe has several other important implictions. Firstly, it implies that there are no real benefits from diversifying a portfolio among the six indices in the long run, since these stock markets will be likely to move together in this time frame. Hence, investors with long-run holding periods will face limited risk reduction possibilities through international diversification across these six markets. Investors failing to take cointegration into account, and basing their portfolio diversification solely on covariance, will find themselves exposed to much higher risk than expected. Traditional portfolio diversification techniques are based on minimizing the idiosyncratic risk factors – but the stationarity of the cointegrating relationship leads to that any idiosyncratic effects will die out over time, impliying limited gains from traditional diversification in the long run.

The strong evidence of co-integration in our results possibly suggest significant predictability of returns in the long run, as claimed by Richards (1995). This is due to the stationary characteristics of the cointegrating linear combination, which is expected to return to its equilibrium whenever there is a deviation from this state. However, no conclusions regarding whether this is a violation of the efficient market hypothesis can be drawn from our reults unless risk-adjusted returns are considered. Market effciency is only violated if co-integration enables risk-adjusted returns above the risk free rate. In addition, the convergence speeds of the linear combinations must be considered, in order to evaluate whether these are fast enough to generate risk-free returns. Furthermore, we have not adressed structural breaks in this paper, yet such phenomena are detected by e.g. Davies (2005). Structural breaks is a potential source of unpredictability, since they imply time varying co-integrating vectors. Unless these variations can be predicted, the possible prediction benefits implied by co-integration relationships might be lost.

From the results we can deduce what dependency structures are in place between the different countries. One important parameter in this analysis is the α values of the estimated cointegration relationship, which measures the degree of response exhibited by a series to deviations of the linear combination from its long-run mean. In other words, it is this parameter that drags the series back to equilibrium, through acting on the constituent indices. Obviously, the greater the magnitude of the α coefficients, the more rapid the adjustment to the mean. Furthermore, the sign of the α coefficients determine the direction of the change, depending on whether the cointegration linear combination is above or below its mean. Thus note that the change in any one variable given by the error-correction term can work either to bring series back towards the mean or further away from it. On average, though, the effect to bring the series back to the mean will be stronger than the opposite.

In the cointegration model with $k = 11$ lags, all indices had statistically significant alpha coefficient, implying that all indices are affected by the deviations. In the $k = 1$ case, the U.K. was the only country where the index did not have a statistically significant α coefficient, indicating that it does not respond to deviations of the cointegration linear combination. Thus, another important conclusion from our study is the exogenous properties of the U.K. market. Since the data does not support that any other market within the sample has temporal causal effects on the London exchange, we conclude that this index is to a large extent independent from the other five markets. Our results indicate that the other markets, more often than not, lag the London stock exchange by one or a few days, implying that the effects of an external shock is first displayed by the London exchange, and thereafter spread throughout the other five stock markets successively. Hence, it seems that new information is absorbed more effectively by the U.K. stock market, compared to the rest of the indices. This can be interpreted in light of the events of the recent financial crisis. The cointegration relationship would indicate that the U.K.

would respond first to certain events, which is also what could be seen during the crisis. It is a common fact that the financial crisis originated in the United States and then spread to Europe. In Europe, the U.K. was the first country where the financial crisis manifested itself, with decreased GDP growth and bankruptcies. The U.K. bank *Northern Rock* was the first bank in Europe to fail and be taken over by the government as the crisis hit, in the beginning of 2008.

One explanation of this phenomenon is uncovered by considering the relative market capitalizations of the six indices. The London stock exchange, is one of the largest stock exchanges in the world. By far, it exhibits the largest market capitalization in the European region. As of December 2010, the total market capitalization of the stocks traded on the London exchange amounted to approximately 3400 000 MUSD, whereas the French stock market, which is the second largest in Europe, demonstrated a corresponding value of 2800 000 MUSD. [3]

Masih and Masih (2002) discuss the implications of market capitalization to stock market independence, and refer to the differential information hypothesis. According to this theory, if the cost of information search is constant across different markets, regardless of market size, then a large market will have more incentives to search for mispricings, compared to a small market. As a consequence of this, at each point in time, the larger market will have access to more information than a small market. This suggests that the asset prices in the larger market will tend to reflect information to a larger extent than prices in a smaller market. Hence, the superior size of the U.K. stock market, compared to the other five indices, offers a possible explanation of its exogenous characteristics.

Another possible explanation of the exogeneous properties of the U.K. is the country's position as Europe's financial centre. Furthermore, our result is in line with Masih and Masih (2002), which show that the U.K. stock market has influential importance to stock indices across the world. Most studies mapping stock market linkages across the world, however, typically indentify the U.S. stock market as exongenous to other markets. This is not surprising, given the strong global economic influence of the U.S. economy. In addition, due to strong financial linkages between the U.S. and the U.K. economies, one

[3] Stock market capitalizations have been collected at World Federation of Exchanges (WFE)

can expect that the U.S. stock market has particularly strong impact on the London index. This is supported by the results provided by Masih and Masih (2002), and further suggests that performance in the U.S. stock market is a potential source of external shocks to the European indices, initially reflected by the U.K. index.

There are still many questions that are unanswered about cointegration as a measure of market dependencies. One open debate is whether cointegration violates the efficient market hypothesis, a contribution to which would be to investigate the risk-adjusted return of a cointegrating vector, which is an interesting idea for future research. The research about regime-switching models based on Markov chains could also be extended with more generous models. Instead of the cointegrating relationship switching between two fixed values, a model where cointegration switches between a state of being active and a state where no cointegration is present could be investigated. Cointegration remains a very relevant statistical measure and any research that would continue to clarify its implications for real-world economic events would be very welcome.

7 Conclusions

Our statistical tests showed that the six European equity indices treated in this study follow a cointegration relationship with one cointegrating vector, which indicates that the indices tend to move together in the long run. There is a lead-lag structure in the relative returns of the indices, and periods of positive or negative relative returns will be followed by reversals. Our findings imply that events that affect only one market at first, such as favourable macroeconomic conditions, will later spread to the other markets and effects of idiosyncratic events only present in one market will abate over time. This could be explained by the high level of economic and financial integration among the countries. The existence of long-run dependencies between relative performance further means that portfolio diversification techniques based on covariance will be less effective in the long run. We further investigated the effect on the indices of deviations of the cointegrating linear combination from its mean, and find that the U.K. is weakly exogeneous and thus will be the first market to respond to events that later spread to the other countries. This could be explained by the the U.K. being Europe's financial centre and the largest stock market in Europe, and by its close ties to the United States, the world's largest economy. Evidence of this relationship could be seen during the recent financial crisis, when the U.K. was the country to be hit first by the crisis, before any of the other countries noticed any effects.

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