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JOHANSEN COINTEGRATION ANALYSIS OF AMERICAN AND EUROPEAN STOCK MARKET INDICES:

An Empirical Study

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Title: Johansen Cointegration Analysis of American and European Stock Market Indices: An Empirical Study

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Purpose: The aim of this study is to investigate and conclude any such cointegration relationships between 4 specified European stock markets and the American stock market. Using data from the last 8 years, which includes the "Global Financial Crisis" commencing 2007, can help investors determine possible international diversification benefits over periods of time including times during extreme economic downturn.

Methodology: The Johansen's Cointegration Method to determine the existence of any cointegrating vectors between selected indices.

Empirical Foundation: 8-year (April 2001-April 2009) daily closing prices of the following indices have been used: S&P500, FTSE100, DAX30, CAC40, OMX30.

Conclusion: Cointegration analysis using the Johansen Method on 3 different sample periods (2-, 4-, and 8-year samples) concluded evidence of one cointegrating vector in the 2 and 8 year samples while the 4 year data gave mixed results suggesting the economic shock (Global Financial Crisis) of 2007 and on may have affected those results. Overall, we conclude little diversification benefits between the markets studied in the long-term, but see possible opportunities for excess returns in the short-term.

1. Introduction and Purpose

The objective of this study is to analyze the connections that exist amongst the United States and four major European stock markets. Specifically, we conduct a cointegration analysis of four European stock markets and the American stock market to test for the existence, and indeed extent of the co-movement that is evident over 2, 4 and 8 year time periods. Cointegration can be viewed as the statistical expression of the nature of equilibrium relationships, with cointegrated variables sharing common stochastic trends. The results of the study will aid us to gain insight into how international stock market cointegration contributes to portfolio diversification strategy, primarily in the context of the institutional investor.

The connection between stock markets is of vital importance to international equity investments, both in terms of managing risk and maximizing returns. Diversification strategy provides risk management and return maximization. By estimating the extent of connection between stock markets in different countries, we can assess the potential benefits available to investors through international diversification between the markets studied. As the level of international stock market cointegration increases, the benefit of diversification falls. Indeed, according to Narayan (2005) whether stock markets are cointegrated carries important implications for portfolio diversification.

Onay (2006) states that the international investor aims to minimize portfolio risk at a given level of expected return. Furthermore, modern portfolio theory proposes that risk is minimized when there is a low correlation between assets, where the portfolio return is measured by its mean, and risk by standard deviation. Accordingly, it is clear that there is potential for portfolio diversification in all cases where there is less than perfect positive correlation (Onay, 2006).

2. Motivation of the Research

Many studies such as Arshanapalli and Doukas (1993) have concentrated around a shock to the global equity market and the implications for various international stock markets. Arshanapalli and Doukas looked at the 1987 stock market crash: comparing co-movements prior to and following the shock and found that, in general, the relationship between markets increased after the shock. We reasoned that a study that measures the cointegration between stock markets incorporating tests on 2, 4 and 8, year sample periods could increase the knowledge base around the selected global markets, testing Arshanapalli and Doukas' findings by looking at the current economic crisis on hand over the past two years or so, also known as the 'Global Financial Crisis'. Do cointegration patterns change because of the crisis? What effects has the crisis had on market relationships? Are there any benefits from diversification in the long or short run? We hope to answer these questions and address any other findings we may come across during our study.

We feel that since 2001 the world economic situation has changed as a result of many factors, particularly in Europe. Ever-increasing membership numbers within the European Union, as well as the introduction of a common European currency have fundamentally changed economies within Europe and its surrounding neighbors. Stock markets are also becoming more globally diversified through acquisitions and mergers like the NYSE merger with Euronext in 2007 (NYSE Euronext Merger, 2007).

Another factor that may influence change among different global markets is the emergence of new products and financial practices, such as the increasing trend of trading Exchange-traded Funds (ETF). The use of ETFs provide a diversified equity investment opportunity; as ETFs trade like stocks, but can include a multitude of varied securities (Christy, 2006). ETFs provide a simple way for investors to enter markets that may have had certain barriers to entry in the past, creating an increase in capital mobility.

According to Fuhr (2001), ETFs allow an investor to increase or reduce their exposure to specific sectors, industries, styles, and specifically in our case, different countries. Fuhr's article suggested that from 2001, the use of ETFs would quadruple over the next five years. Validating this prediction, an article by Carly (2008) again draws attention to the increased prominence of ETFs in the investing world not only by institutional investors, but also by advisors and the average investor. Factors such as these have changed the investing landscape, and suggest that further investigation of cointegration with new data and new perspectives would be both useful and relevant.

We therefore see it necessary to conduct research into how the US stock market – still a global economic cornerstone – moves with its European counterparts and vice versa. Quantification of the degree to which the markets are connected would materially augment the establishment of beneficially-diversified stock market portfolios for all investors with interests within Europe and/or the United States.

3. Literature review

Since the influential work of Engle and Granger (1987), cointegration has emerged as a powerful technique for investigating common trends in multivariate time series, providing a sound methodology for modeling both long run and short run dynamics in a system. The interest in cointegration literature has increased significantly as a result of this work and has given rise to other important contributions to the subject.

Ghosh et al (1999) purports that financial theory hypothesizes that in the long run, certain pairs of financial time-series data are projected to move together. Ghosh et al also claim that short run deviations will be brought back to equilibrium due to investors' tastes and preferences, market forces and government regulations. However, it is the understanding of how these short-term movements are related to each other that will help to understand the economic relationships between the markets in our study more completely.

Lucas (1997) and Alexander (1999) demonstrate applications of cointegration analysis in their studies, in relation to trading strategies such as index tracking and arbitrage, as well as to portfolio asset allocation. Lucas and Alexander suggest index tracking and portfolio optimization based on cointegration rather than correlation alone may result in higher asset returns. Accordingly, if Lucas and Alexander's claim is valid, our study of cointegration between the US and European markets could be used to assist in addressing index tracking and portfolio optimization. Adding to the current literature in this area will provide for more proof, for or against the use of cointegration in this manner from an international diversification standpoint.

Maneschiold (2006) analyzed cointegration between Baltic stock markets and major international stock markets, including UK, France, Germany, US and Japan. The cointegration analysis indicated that German markets dominate the long-term relationship with Baltic stock markets. Furthermore, the overall results suggest that international investors can obtain a long term benefit from diversification due to the absence of cointegration of Baltic and international capital markets. This study concentrated more

on the emerging Baltic Markets and their movements compared to the major international markets using cointegration, whereas our study will focus on the US versus larger established European Markets, incorporating data over the past 8 years.

Kasibhatla et al (2006) study cointegration between major West European stock markets (CAC40, DAX30, FTSE100). Their findings supported the notion that there is cointegration between the markets, and identified the CAC40 as being weakly exogenous. There can be excess returns in the short term by diversifying internationally, however due to the long run cointegration, Kasibhatla et al claim that there is no benefit of long-term international portfolio diversification (between CAC40, DAX30, FTSE100). This study, to the best of our research and knowledge, is the closest to our own focus area – namely, studies that have been conducted with the major indices and their possible cointegration relationships. Kasibhatla et al employ the Johansen Cointegration Methodology mainly because they found it was the most common method used to study long-term cointegration relationships along with their references to support this claim.

Another study closely related to our paper is Yang et al's (2003) analysis of cointegration between US and international stock markets over a 32 year sample period – Yang et al's finding was that there was no long-run pattern of cointegration. They do see an increase of cointegration in the latter part of their sample period, but conclude that due to the weak cointegration overall, there are diversification benefits to US investors from splitting their equity portfolio between the countries studied. These results are based on analysis of the larger markets including Japan, United Kingdom, and Germany. They did however find an increasing integration between the US and many smaller markets. Their data consisted of time-series from 1970 to 2001. Our study is data from 2001 to 2009 and as mentioned before, during a time of changing capital markets, increased globalization, and a huge negative shock to the markets (the Global Financial Crisis turmoil).

Allen and MacDonald (1995) analyzed the benefits of international diversification to Australian investors, using monthly index data for 16 countries. Both the Engle-Granger (1987) and Johansen (1988) cointegration tests were used to measure these diversification

benefits. As was the case in other selected studies such as Taylor and Tonks (1989) and Allen and MacDonald (1995) found that different cointegration testing methods yielded different results in certain cases. Also, evidence of cointegration between the analyzed data subsets was found, indicating that there is little benefit to the investor by diversifying internationally. Taylor and Tonks (1989) studied the impact of abolition of U.K. exchange controls, and the effect of this on the integration of U.K. and overseas stock markets. They concluded that there appears to be no long-run gain from diversification owing to the apparent increase in the degree to which markets move together.

Fadhlaoui et al (2008) analyzed the short and long-run relationships between seven developed equity markets (US, Canada, UK, France, Germany, Italy and Japan) with Czech-Republic, Hungary and Poland to evaluate evidence of cointegration. As with our study, this was done to identify potential international diversification benefits. In the short-term, it was found that there was a lower level of cointegration between the aforementioned developed equity markets, and those of Central Europe. This short-term analysis was performed using the correlation matrix, whereas the latter long-term analysis employed the use of the Johansen cointegration test. The Johansen test revealed no evidence of a long-term relationship (cointegration) between the two groups of markets. It can therefore be said that the increased financial integration between equity markets internationally has not detracted from the potential diversification benefits available to investors in this particular market.

Bessler and Yang (2003) conducted a study into the dynamic structure of nine major stock markets (Australia, Japan, Hong Kong, UK, Germany, France, Switzerland, USA and Canada) using Johansen's maximum-likelihood model, and found only one cointegrating vector. They infer that the US market is the only stock market that has a long-term contribution to the price levels in other markets.

Onay (2007) suggests that there are long-term diversification opportunities in Bulgaria and Romania due to the lack of cointegration with the European Union. This study is

concentrated around the accession negotiations with the EU, and demonstrates the fact that diversification benefits are negatively related to the underlying level of cointegration between markets. Onay highlights the possible benefits of investing in those countries that are new entrants or prospective entrants to the EU, due to their lack of cointegration with developed markets, supporting possible effects of the European Union on cointegration.

There is significant academic literature that examines linkages and long-term co-movements between international stock markets via the use of cointegration analysis techniques. The existence of such linkages between international stock markets suggests diversification benefits are not significant (Kasa, 1992). Although Kasa may have a point, we feel that this claim fails to consider the dynamic nature of economies, as well as new industries, newly developed stock markets, the current financial crisis, etc. Accordingly, our study will add to the existing literature on cointegration with new insight and updated data.

To the best of our knowledge, a study looking at the cointegration on the US and a handful of the major European markets in recent years has not been conducted in the manner we have described, namely by analyzing the recent economic downturn in the past 2 years, along with looking at a 4 and 8 year timeframe with a view to examining diversification benefits from different perspectives in the current April-May 2009 economic environment. Our study will analyze the European stock markets in a similar fashion to Maneschiold (2006), Yang et al (2003) and Kasibhatla et al (2006) in order to determine the level of cointegration and subsequent potential diversification benefits on offer. However, we will employ a shorter time horizon, referring to our three sample periods, and therefore establish diversification benefits that would be of greater relevance to institutional investors who trade on various markets simultaneously.

As mentioned, many of the studies relating to the cointegration of emerging markets to the larger established markets have found possible diversification benefits while other studies have found a high degree of cointegration, indicating that long-term

diversification is not likely to be beneficial. All of the studies we have examined do agree that cointegration is a good parameter to determine possible co-movements between equity markets, with the most popular process undoubtedly being Johansen's methods.

4. Data

While our research is similar to that of Kasibhatla et al, we differ in that we look at cointegration in terms of a larger number of markets. That is, as well as including the FTSE 100 (London), CAC 40 (Paris) and DAX 30 (Frankfurt) in our study, we also include the OMX 30 (Stockholm) and the S&P 500 (New York). From the results, the extent of the linkages amongst European markets and between European markets and the S&P500 will be evident, and therefore provide guidance to investors regarding how to manage portfolio diversification.

The sample data is retrieved from Datastream and consists of daily closing prices from the following three time periods for each of the indices mentioned above:

- **2 year sample period:** April 2007 – April 2009
- **4 year sample period:** April 2005 – April 2009
- **8 year sample period:** April 2001 – April 2009

The following sections describe the components of each index.

S&P500: The S&P500 index (Standard and Poor's) is the most common equity benchmark referred to when looking at the US stock market. This diverse index represents over 70% of the total US market capitalization. It is comprised of leading companies from over 100 unique sectors of the US economy, rather than simply the largest 500 US listed securities. Due to the diversified sector coverage, most analysts chose to use the S&P as their preferred US benchmark index. The fact that the S&P 500 is diversified across different sectors differentiates it from most European indices that are comprised of firms on a purely market capitalization basis. Due to the market capitalization weighting system used in the S&P 500, the larger firms (in market capitalization terms) have a greater influence on the index value (Bloomberg.com, 2009).

FTSE100: FTSE 100 (Financial Times Share Exchange) is the major index of the London Stock Exchange. It is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange. It represents about 80% of the value of all issues traded. It is similar to the S&P500 in that it is weighted by market capitalization, however is unique in that it re-weights each of its components everyday to better represent the actual market state. The index was developed on January 3, 1984 with a base level of 1000 (Bloomberg.com, 2009).

CAC40: The CAC 40 Index (Compagnie des Agents de Change) is the most commonly used benchmark tracking index for the Paris Bourse. It was started in 1987 at an initial value of 1000. The index is comprised of the 40 largest and most liquid stocks trading on the exchange. The weightings of the index are determined by the value of the outstanding shares to the public, otherwise known as a float-weighted index. A slight difference of index methodology, however is the most commonly used index representing the Paris Bourse (Euronext.com, 2009).

DAX30: The DAX 30 (Deutscher Aktien Index) is used to calculate the performance of the 30 largest stocks on the Frankfurt Exchange in terms of order book volume and market capitalization. The DAX is largely made up of diversified industrials, specialty chemical, automotive and multi-utility stocks. It is the most commonly used benchmark representing the Frankfurt Stock Exchange (Bloomberg.com, 2009).

OMX30: The OMX 30 Stockholm index is a capitalization-weighted index of the top 30 stocks based on the largest volume of the trading on the Stockholm Stock Exchange. The equities use free float shares in the index calculation. The OMX 30 is made up of firms from various industries, with the heaviest contributors to the index being from the telecommunication and apparel/footwear sectors. Again, the OMX30 is the most widely recognized and most commonly used index representing the Stockholm Stock Exchange and was started in 1986 at a base level of 125 (Bloomberg.com, 2009).

The five indices mentioned above for our study are all the most commonly used for the market they represent. For the entire 8 year daily data sample timeframe, there are a total of 2072 observations. The 4 year data sample consists of 1036 observations and the 2 year data sample of 518 observations. Due to different non-trading days in each of the countries, the entire sample data is vigorously examined to ensure consistent data between the 5 indices. If an index is missing a trading day, we insert a data point consistent with the previous day's closing price, to ensure all dates match and also to represent zero transactions completed on that particular day. The five indices are used as a barometer for each of the markets and each are re-adjusted on a consistent basis to ensure proper weighting; therefore capturing what each is setup to accomplish, to represent their respective markets.

Indices will not be converted to a common currency. We use the logs of the daily closing prices of the indices in their local currency to better capture the co-movements in the different markets. Alexander (2001) strongly advocates cointegration analysis between markets should be completed in each indices local currency for this reason. Not converting to a common currency will eliminate any possible exchange rate volatility.

5. Methodology

The economic literature surrounding the co-movements of stock markets agrees on neither the existence nor the extent of linkages between international stock markets. This can be attributable to different choices of markets, sample periods, frequency of observations and different methodologies. Furthermore, the literature surrounding cointegration analysis does not include a study on the markets we are testing. However, reviews of past studies provide us with insight, guidance and reasoning as to what cointegration methods should be used in our study.

5.1 Introduction of Cointegration

Cointegration analysis can be used to evaluate the co-movement of a long-term asset price within an equilibrium model. Firstly, cointegration analysis establishes a long term relationship by calculating long-run equilibrium asset prices. Next, correlations within an error correction model are estimated. Therefore, stochastic trends common to the respective time series are found prior to the cointegration analysis.

If the cointegration analysis indicates that there is a cointegrating vector, we infer that the tested series will not drift apart in the long-term, and will revert to equilibrium levels following any short-term drift that may take place. In the context of this study, the presence of a cointegrating vector means that diversification benefits available to investors are reduced. In contrast, if no cointegrating vector is found, we infer that diversifying a stock portfolio amongst the markets in question does provide benefit.

Our cointegration analysis will include five stock market indices: four within Europe, with the USA being the fifth market. The study concentrates on 2-year, 4-year and 8-year time frames in order to identify how cointegration patterns of the selected markets may have changed in the recent past, and indeed if these trends can be expected to continue. The reason we look at three different time periods is so that we can analyze short and long-term trends in respect to the current financial recession. The 2-year time frame will concentrate on data that represents the actual current recession, with the 4-year time

frame bringing in data representing the time immediately prior to the recession. The 8-year period will give us a better holistic view of the long-term integration of markets. Information from our study could benefit investors in assisting with possible short- and long-term diversification techniques and guidance.

Cointegration analysis was introduced by Engle and Granger in the early 1980s, with improvements and additions made in subsequent years. Cointegration is a modeling process that incorporates non-stationarity with both long-term relationships and short-term dynamics. To examine time series in financial data using cointegration, the time series in its level form should be non-stationary and integrated of order 1, written as I(1). Integrated of order 1 means the series becomes stationary after differentiating it once. Variables are said to be cointegrated if they are I(1) and have a linear combination which is stationary without the need to differentiate the data.

Cointegration is the underlying methodology we use to analyze the relationships between the US and specified European markets to determine possible international diversification benefits. It allows us to identify co-movements between markets where if cointegration exists, diversification benefits are adversely affected and vice versa. As per our literature review, cointegration is recognized as an acceptable method in analyzing co-movements.

There are two main cointegration methods that have consistently been used throughout past studies which are: 1) Engle-Grangers Two Step Estimation Method; and 2) Johansen's Maximum Likelihood Method using either the Trace Statistic and/or the Maximum Eigenvalue Statistic.

Our study uses the Johansen's Method due to reasons mainly relating to the shortfalls of Engle-Grangers Two Step Estimation Method. The Two Step Estimation Method is very easy to run, however it needs a larger sample size to avoid possible estimation errors and can only be run on a maximum of two variables (Brooks 2008). It also doesn't allow for hypothesis testing on the cointegrating relationships themselves, unlike Johansen's method (Brooks 2008). Since we are also examining a total of 5 markets, we want the

ability to examine them in a multivariate framework, allowing for the possible discovery of more than one cointegrating vector, which the Engle-Granger Method cannot accomplish. In this situation, Johansen's Method better suits the data, due the fact that it can examine more than two test variables, and can treat all test variables as endogenous.

5.2 Unit Root Testing

Implementing the Johansen's Cointegration method involves some initial testing of the time series to ensure I(1), in other words testing for unit roots. In order to validate this characteristic in our time series data, we utilize two different unit root tests, the Augmented Dickey-Fuller Test (ADF) and the Phillip-Perron Test (PP). In general, the ADF and PP tests are consistent with each other; however we include both as to ensure accuracy regarding the unit root conclusion. Our study will test each time series individually to ensure non-stationarity at the levels of the data, and also run the unit root tests on the first differences to ensure I(1). The equation for the ADF is given below:

$$\Delta y_t = a_0 + a_1 y_{t-1} + \sum_{i=1}^{p} a_i \Delta y_{t-i} + \varepsilon_t \qquad \textbf{(1)}$$

It must be noted that in order to select each model's optimal lag length we maximize the log-likelihood function of the corresponding model. That is done by selecting the model with the lowest SBIC (Schwartz Bayesian Information Criterion). Cross-checking of the results using the AIC (Akaike Information Criterion) ensures accuracy.

The PP test is very similar to the ADF test. The main reason we also conduct a PP test is because the ADF test loses power for sufficiently large values of p, the number of lags (Ghosh et al, 1999). It includes an automatic correction to the Dickey-Fuller process for auto-correlated residuals (Brooks 2008). The PP test is a more comprehensive theory of unit root non-stationarity. The regression is as follows where u_t is serially correlated:

$$y_t = b_0 + b_1 y_{t-1} + u_t \qquad \textbf{(2)}$$

5.3 Johansen's Cointegration Method

After completion of unit root testing on our time series, assuming all our time series are integrated of the same order, we conduct a bivariate Johansen test between each of our 5 indices within our 3 sample periods, which result in 10 different market relationships for each sample that can provide additional insight in specific international diversification strategy. The main analysis we conduct is a multivariate Johansen test on all 5 of the indices so that we can investigate cointegration involving all variables instead of analysis only at the bivariate level.

The Johansen process is a maximum likelihood method that determines the number of cointegrating vectors in a non-stationary time series Vector Autoregression (VAR) with restrictions imposed, known as a vector error correction model (VEC). Johansen's estimation model is as follows:

$$\Delta X_t = \mu + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \alpha\beta' X_{t-i} + \varepsilon_t \qquad \textbf{(3)}$$

X_t = (n x 1) vector of all the non-stationary indices in our study

Γ_i = (n x n) matrix of coefficients

α = (n x r) matrix of error correction coefficients where *r* is the number of cointegrating relationships in the variables, so that $0 < r < n$. This measures the speed at which the variables adjust to their equilibrium. (Also known as the adjustment parameter)

β = (n x r) matrix of *r* cointegrating vectors, so that $0 < r < n$. This is what represents the long-run cointegrating relationship between the variables.

In determining lag lengths for the Johansen's procedure, we chose between using Akaike's (AIC) and the Schwarz's Bayesian (SBIC) information criterion processes. The SBIC is usually more consistent but inefficient, while AIC is not as consistent but is usually more efficient (Brooks, 2008). In our study, we select a population of 8 year daily data and are taking 3 different samples within this data (8 year, 4 year, and 2 year). As per Brooks (2008), SBIC will usually give a larger average variation in

selected model orders between these three different sample periods within the same population and AIC is known to avoid this situation, therefore our study prefers to use AIC over SBIC in determining lag lengths. Literature surrounding cointegration analysis have used both AIC and SBIC with neither alternative firmly agreed upon between studies.

Johansen (1991) defines two different test statistics for cointegration under his method: the Trace Test and the Maximum Eigenvalue Test. The Trace test is a joint test that tests the null hypothesis of no cointegration (H_0: r = 0) against the alternative hypothesis of cointegration (H_1: r $\geq$ 0). The Maximum Eigenvalue test conducts tests on each eigenvalue separately. It tests the null hypothesis that the number of cointegrating vectors is equal to *r* against the alternative of *r+1* cointegrating vectors. (Brooks, 2008)

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{g} \ln(1-\hat{\lambda}_i) \quad \textbf{(4)}$$

$$\lambda_{max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1}) \quad \textbf{(5)}$$

$\mathbf{r}$ = number of cointegrating vectors under the null

$\hat{\lambda}_i$ = estimated *i*th ordered eigenvalue from the $\alpha\beta'$ matrices

A significantly non-zero eigenvalue indicates a significant cointegrating vector.

As part of our methodology, we normalize the resulting cointegrating relationship on the log of the FTSE100 index so that the coefficient on this variable is equal to 1. The majority of past studies use the largest stock market index (in terms of market capitalization) for normalization (Kasibhatla et al, 2006), however we chose to use the FTSE100, as it gave more interpretable results than those given when data was normalized on the S&P500. Further support for the choice of the FTSE100 in the normalization procedure comes from Juselius (2006), who purports that in cointegrating relationships, the ratios between coefficients are the same, regardless of the which variable is used to normalize the data.

We conduct further tests by imposing restrictions on each of the variables so that we can isolate whether or not a particular variable has a significant impact to the cointegrating equation. These tests will indicate whether only a subset of the variables in X_t from equation **(3)** is actually required to obtain a stationary linear combination (Brooks, 2008). In other words, conducting restriction tests on the Vector Error Correction Model (VECM) allow us to identify which of the indices are required to create a cointegrating relationship. Thus, the relative importance of each index can be evaluated in terms of its cointegration properties. The test is accomplished by imposing the restriction that a variable's beta is equal to 0, hence the null hypothesis is B=0. If the null hypothesis is rejected, the coefficient is significant and must be included in the cointegrating equation. By imposing restrictions, we can isolate whether or not a particular variable has a significant impact on the cointegrating equation.

For clarity, we list the individual steps in our methodology for our cointegration analysis of the 5 indices. All tests are carried out separately on 2 year, 4 year, and 8 year data. Please note all tests were conducted in using EViews 6.0 statistical software.

1. Unit Root Tests (ADF and PP)
2. Johansen's cointegration testing (Bivariate and Multivariate)
3. Trace test
4. Max Eigenvalue test
5. Normalization against FTSE100
6. Imposition of restrictions on the VECM for each variable

6. Results

This section details all results from the testing we conducted. Results are presented in order of the three sample periods in our study. Since all tests are done on each of the sample periods, this section is broken down by sample period (2-, 4-, and 8-year), with exception to the Unit Root Test results presented in the first sections. All testing was conducted using EViews 6.0 statistical software.

6.1 Unit Root Testing

The Augmented Dickey-Fuller (ADF) test shows for all 5 indices that the level data was non-stationary; however stationarity was reached after the first difference. As discussed in the Methodology section, this means all of our data is integrated of order one, I (1), a requirement for Johansen's cointegration analysis. Our test results are significant at the 1% significance level for the 2-, 4- and 8-year sample periods, under all model specification options. These test results were very straight forward, therefore we felt it unnecessary to display in the body of this study.

The Phillip-Perron (PP) test is also conducted in order to confirm the test results of the ADF and ensure non-stationarity of the indices. The PP test, like the ADF test, indicates significance for all sample periods, rejecting the null hypothesis of stationarity at the 1% level. ***Please note full results for the ADF and PP tests are displayed in the appendix.***

6.2 Bivariate Cointegration Testing

Bivariate cointegration testing is conducted using EViews as a precursor to multivariate cointegration testing. Johansen's testing procedure is employed, as described previously in the methodology section. The results for 2, 4 and 8 year time periods are displayed below in table 1. Bivariate cointegration test results provide additional insight, and are used in conjunction with the multivariate Johansen calculations.

Table 1 – Bivariate Johansen's Cointegration Test Results (2-, 4-, and 8-year)

Null Hypothesis (Ho): Series are not cointegrated. Implication of null hypothesis rejection is that there is an underlying relationship between the variables selected.

	2 Year Data		4 Year Data		8 Year Data	
Series Tested	**P-Value**	**Null Hypothesis**	**P-Value**	**Null Hypothesis**	**P-Value**	**Null Hypothesis**
S&P500/FTSE100	0.0149	Rejected**	0.0056	Rejected**	0	Rejected**
S&P500/CAC40	0.2523	Fail to reject	0	Rejected**	0.0259	Rejected**
S&P500/DAX30	0.0213	Rejected**	0.3687	Fail to reject	0.0201	Rejected**
S&P500/OMX30	0.289	Fail to reject	0.3649	Fail to reject	0.1401	Fail to reject
FTSE100/CAC40	0.1267	Fail to reject	0.0225	Rejected**	0.0011	Rejected**
FSTE100/DAX30	0.0193	Rejected**	0.0026	Rejected**	0.0410	Rejected**
FTSE100/OMX30	0.3775	Fail to reject	0.3979	Fail to reject	0.1279	Fail to reject
CAC40/DAX30	0.128	Fail to reject	0.5156	Fail to reject	0.5475	Fail to reject
CAC40/OMX30	0.4441	Fail to reject	0.6089	Fail to reject	0.2316	Fail to reject
DAX30/OMX30	0.3017	Fail to reject	0.0218	Rejected**	0.0010	Rejected**

*****Rejected at the 5% significance level***

S&P500/FTSE100

The results indicate a solid cointegrating relationship between the S&P500 and FTSE100 over each of the sample periods. Such a relationship was expected, and we infer there are no inherent benefits brought on by diversification between these two markets over any of the time periods tested in the long-term.

S&P500/CAC40

Whilst cointegration was observed between the S&P500 and the CAC40 over the 4 and 8 year sample periods, this relationship was not evident in the last 2 years. This suggests the departure from equilibrium levels of the CAC40 and the S&P500 differed in the last 2 years from its 4 and 8 year levels. This situation also applies to the relationship between the FTSE100 and the CAC40.

S&P500/DAX30

There was no cointegration evident over the 4 year sample period between the S&P500 and DAX30, however results suggest cointegration for the 2 and 8 year periods. The presence of cointegration in 2 and 8 year sample periods suggest to the authors that diversification benefits available to investors between these markets are unclear, despite the lack of cointegration in the 4 year sample period.

FTSE100/DAX30

Like the S&P500 and FTSE100 results, the DAX30 and FTSE100 also display evidence of cointegration over each of the sample periods.

DAX30/CAC40

The DAX30 and the CAC40 show no evidence of cointegration over any of the 3 sample periods, implying potential benefits from diversification.

OMX30/S&P500; OMX30/FTSE100; OMX30/CAC40

There is no observable cointegration between the OMX30 and any of the following three indices: S&P500; FTSE100; and CAC40, in any of the 3 sample periods. Investors may therefore derive benefits from splitting equity investments between the OMX30 and any of the three aforementioned markets.

OMX30/DAX30

Although cointegration was observed between the DAX30 and the OMX30 over the 4 and 8 year sample periods, this trend was not continued in the most recent sample period. This change reflects, like the CAC40 and the S&P500 example, the drift away from equilibrium levels of either or both the DAX30 and/or the OMX30 in the last 2 years from its 4 and 8 year levels.

Comparisons of analysis across time series data

The last 2 years of index data show a decrease in bivariate cointegration relationships with only 3 out of the 10 possible cointegration relationships evident. This compares to 6

cointegration relations in the 8 year sample period and 5 in the 4 year sample period. Movements of indices from their equilibrium levels in the 2 year sample period suggest that individual stock markets react differently to macroeconomic shocks in the short-term 2 year sample period, referring to the economic crisis. This implies that the resilience of a cointegrating relationship must be considered by investors wishing to benefit from international stock market diversification. That is, it appears that some cointegrating relationships remain valid over all sample periods while others can deviate in the short-term.

6.3 Johansen Cointegration Testing (Multivariate)

Following the bivariate testing, multivariate Johansen testing is carried out, as per the process outlined in the methodology section. Results for the 2-, 4-, and 8- year sample periods are presented in the following three subsections.

6.3.1 Johansen Test Results: 2-Year Sample Data

Table 2 – 2-Year Johansen Cointegration Results – Trace Test

Sample (April 30 2007-April 30 2009)

Included Observations = 515 after adjustments

Trend Assumption = Intercept (no trend) in CE and Test VAR

Series Included = Ln_SP500, Ln_FTSE100, Ln_DAX30, Ln_CAC40, Ln_OMX30

Rank (0,0) - (Determined by AIC)

Hypothesized Number of Cointegrating Equations	Trace Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	119.4955	69.81889	0.0000	Yes
At Most 1	41.97466	47.85613	0.1594	-
At Most 2	21.62305	29.79707	0.3199	-
At Most 3	9.440676	15.49471	0.3262	-
At Most 4	3.405619	3.841466	0.0650	-

The Trace Test in Table 2 indicates the existence of 1 cointegrating equation at the 5% significance level. This cointegrating equation means that one linear combination exists between the variables that force these indices to have a relationship over the entire 2 year time period, despite potential deviation from equilibrium levels in the short-term.

In order to confirm the results of the Johansen's Trace test, we also display the results of the Maximum Eigenvalue Test in table 3 below.

Table 3 – 2-Year Johansen Cointegration Results – Max-Eigenvalue Test

Hypothesized Number of Cointegrating Equations	Max-Eigenvalue Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	77.52080	33.87687	0.0000	Yes
At Most 1	20.35161	27.58434	0.3173	-
At Most 2	12.18237	21.13162	0.5297	-
At Most 3	6.035057	14.26460	0.6087	-
At Most 4	3.405619	3.841466	0.0650	-

The Maximum Eigenvalue Test also shows 1 cointegrating equations at the 5% level confirming the Trace Test. Therefore these two tests confirm a cointegrating relationship over the 2 year sample period.

Analyzing the normalized cointegrating coefficient in the VECM allows us to understand how the indices adjust in the 2 year time period. The results are displayed in table 4.

Table 4 – 2-Year Normalized Cointegrating Coefficients

(Standard errors in parentheses) [t statistics in brackets] Log likelihood 7976.30

Ln_FTSE100	Ln_SP500	Ln_DAX30	Ln_CAC40	Ln_OMX30
1.000000	-1.343696	0.576766	0.201765	-0.213074
	(0.14311)	(0.19586)	(0.17779)	(0.08013)
	[-9.38922]	[2.94485]	[1.13487]	[-2.65905]

Since we have identified the existence of one cointegrating equation, we can say that a stable equilibrium relationship is present. The results are normalized on the FTSE100. Due to the normalization process, the signs are reversed to enable proper interpretation.

The S&P500 and OMX30 have the expected signs and are statistically significant according to the *t* values shown. We interpret the coefficients as follows:

- A 1% increase in the S&P500 leads to a 1.34% increase in the FTSE100 in the long run
- A 1% increase in the OMX30 leads to a 0.21% increase in the FTSE100 in the long run

The DAX30 and CAC40 have negative relationships with the FTSE100, although only the DAX30's *t* value indicates significance at the 5% level in the cointegrating equation.

The 2-year cointegrating coefficient results above are in accordance with the 2 year chi-squared restriction test conducted showing which variables are significant to the cointegrating equation. (See table 5 below)

Table 5 – 2 Year Chi-Squared Test (Test of coefficient significance)

Null Hypothesis: B=0. If rejected, coefficient is significant to the cointegrating equation.

Index	Chi-Squared Test Statistic	Probability	Significance at 5% level
S&P500; B(1,1)	54.69815	0.0000	Yes (null Rejected)
FTSE100; B(1,2)	17.62159	0.000027	Yes (null Rejected)
DAX30; B(1,3)	5.873867	0.015367	Yes (null Rejected)
CAC40; B(1,4)	1.002563	0.316691	No (null fail to reject)
OMX30; B(1,5)	6.172583	0.012975	Yes (null Rejected)

From table 6 below, the speed of adjustment back to equilibrium is represented by the error correction term, also known as the adjustment factor (alpha). It is of note that the S&P500 has a slower speed of adjustment than the FTSE100, DAX30, CAC40 and OMX30, all of which demonstrate similar adjustment speeds. This implies that in the

short run, all European index variables are somewhat equally responsive to their last period's equilibrium error.

Examining the t-statistics on the variables in the Error Correction results in Table 6, also indicates the S&P500 is weakly exogenous to the system because the error correction term is not significantly different from zero. This indicates that the S&P500 is the first market to display any effects from a shock, and will then disseminate this shock to other markets in the system.

Table 6 – 2 Year Sample Error Correction (Speed of Adjustment)

((-1) = Differenced once) (Standard errors in parentheses) [t statistics in brackets]

Error Correction:	**LN_FTSE100 (-1)**	**LN_S_P500(-1)**	**LN_DAX30(-1)**	**LN_CAC40(-1)**	**LN_OMX30(-1)**
Cointegrating Equation	-0.146928	0.006316	-0.126950	-0.152421	-0.115323
	(0.02092)	(0.02401)	(0.02151)	(0.02241)	(0.02225)
	[-7.02206]	[0.26311]	[-5.90178]	[-6.80186]	[-5.18205]

The fact that the European adjustment speeds are similar is very important to consider, especially in an era where day trading is on the increase. Investors can capitalize on the speed at which information is integrated in to the various European stock markets, however due to their similar adjustment speeds, there is little to no advantage available regarding the choice of one European market over another in the short-term.

6.3.2 Johansen Test Results: 4-Year Sample Data

Table 7– 4-Year Johansen Cointegration Results – Trace Test

Sample (April 30 2005-April 30 2009)

Included Observations = 1033 after adjustments

Trend Assumption = Intercept (no trend) in CE and Test VAR

Series Included = Ln_SP500, Ln_FTSE100, Ln_DAX30, Ln_CAC40, Ln_OMX30

Rank (1,1) – determined by AIC

Hypothesized Number of Cointegrating Equations	Trace Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	71.87812	69.81889	0.0339	Yes
At Most 1	43.66727	47.85613	0.1171	-
At Most 2	17.43114	29.79707	0.6081	-
At Most 3	6.975403	15.49471	0.5805	-
At Most 4	0.255465	3.841466	0.6133	-

The trace test indicates the existence of 1 cointegrating equation at the 5% level. Hence there is one linear combination that exists between the variables, driving a relationship over the total 4 year period of the sample. The indices can vary from their equilibrium levels in the short-term.

The max-eigenvalue test displayed below in Table 8 indicates no cointegration at the 5% significance level, in contrast to the trace test shown in table 5. Therefore, the results derived from the trace test may be difficult to interpret. For this reason, we will use alternative measures to evaluate the extent of cointegration or otherwise that exists in the 4 year time period.

Table 8 – 4-Year Johansen Cointegration Results – Max-Eigenvalue Test

Hypothesized Number of Cointegrating Equations	Max-Eigenvalue Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	28.21085	33.87687	0.2039	No
At Most 1	26.23612	27.58434	0.0736	-
At Most 2	10.45574	21.13162	0.7011	-
At Most 3	6.719938	14.26460	0.5228	-
At Most 4	0.255465	3.841466	0.6133	-

Table 9 – 4-Year Normalized Cointegrating Coefficients

(Standard errors in parentheses) [t statistics in brackets] Log likelihood 17462.00

Ln_FTSE100	Ln_SP500	Ln_DAX30	Ln_CAC40	Ln_OMX30
1.000000	-0.173658	-0.139545	-0.563026	0.113041
	(0.10636)	(0.04285)	(0.12929)	(0.07914)
	[-1.63276]	[-3.25645]	[-4.35485]	[1.42839]

Based on the Johansen cointegration test, it is unclear whether or not the 4 year sample has a cointegrating vector, due to contrasting results from the trace test and maximum-eigenvalue tests that were conducted. The trace test indicted one cointegrating vector, whilst the max-eigenvalue test showed no cointegrating vector.

As in the 2 year data, results are normalized on the FTSE100. Assuming the trace test is correct, we conducted further tests on the identified cointegrating equation. The *t* test results from Table 9 above indicate that the DAX30 and CAC40 indicate significance, but the S&P500 and OMX30 do not. The OMX30 also has a negative relationship with the FTSE100, in contrast to the positive relationship shown by the other coefficients.

Further evidence that there is no cointegrating equation arises on analysis of the results from the Chi-squared restriction test. The restriction tests in table 13 indicate that none of

the tested indices are statistically significant to the cointegrating equation. Also, the fact that only one in 5 of the adjustment coefficients are statistically significant further supports the suggestion of no cointegrating vector (See table 14 for results Error Correction). These results further support the maximum eigenvalue test that indicated a lack of a cointegrating vector for the 4 year time period.

Table 13 – 4 Year Chi-Squared Test (Test of coefficient significance)

Null Hypothesis: B=0. If rejected, coefficient is significant to the cointegrating equation.

Index	Chi-Squared Test Statistic	Probability	Significance at 5% level
S&P500; B(1,1)	0.203167	0.652176	No(null fail to reject)
FTSE100; B(1,2)	1.875148	0.170887	No(null fail to reject)
DAX30; B(1,3)	0.782481	0.376384	No(null fail to reject)
CAC40; B(1,4)	1.252541	0.263068	No(null fail to reject)
OMX30; B(1,5)	0.254801	0.613715	No(null fail to reject)

Table 14 – 4-Year Sample Error Correction (Speed of Adjustment)

((-1) = Differenced once) (Standard errors in parentheses) [t statistics in brackets]

Error Correction:	LN_FTSE_100(-1)	LN_S_P500(-1)	LN_DAX30(-1)	LN_CAC40(-1)	LN_OMX30(-1)
Cointegrating Equation	-0.046401	0.010063	0.001494	-0.005305	-0.003191
	(0.02180)	(0.02566)	(0.02383)	(0.02358)	(0.02469)
	[-2.12868]	[0.39214]	[0.06267]	[-0.22495]	[-0.12925]

The conclusion that no cointegrating vector exists for the 4 year sample period suggests that over the period April 2005-April 2009, there is no equilibrium to which the variables have a tendency to return to in the long run.

Cointegration characteristics of the data may have been adversely affected over the past 4 years, due to the financial crisis that arose 2 years into the sample period, which brought with it erratic and volatile movements in global stock markets.

Yavas (2006) purports that international market co-movement increases following unexpected exogenous shocks. This implies diversification benefits are reduced after such events. Yavas' analysis is based on the behavior of the U.S., German and Japanese markets before and after the September 11, 2001 terrorist events in the United States. The lack of cointegration over the 4 year sample means that in this period, there was potential for diversification benefits. The fact that cointegration is evident in the 2-year but not the 4-year sample suggests that the five indices studied became more closely related in the period following the economic shock brought on by the onset of the global financial crisis. This is also in line with Arshanapalli and Doukas' (1993) study around the 1987 market crash.

6.3.3 Johansen Test Results: 8-Year Sample Data

Table 15 – 8-Year Johansen Cointegration Results – Trace Test

Sample (April 30 2001-April 30 2009)

Included Observations = 2068 after adjustments

Trend Assumption = Intercept (no trend) in CE and Test VAR

Series Included = Ln_SP500, Ln_FTSE100, Ln_DAX30, Ln_CAC40, Ln_OMX30

Rank (1,1) – determined by AIC

Hypothesized Number of Cointegrating Equations	Trace Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	83.74752	69.81889	0.0026	Yes
At Most 1	39.70868	47.85613	0.2331	-
At Most 2	20.78167	29.79707	0.3714	-
At Most 3	6.800119	15.49471	0.6010	-
At Most 4	0.001399	3.841466	0.9688	-

Johansen's Trace test indicates 1 cointegrating equation at the 5% level for the 8-year sample data in Table 15 above. The Max Eigenvalue test also indicates 1 cointegrating equation at the 5% level, confirming the trace test in Table 15. This means that according

to the Johansen procedure, there is one linear combination that exists between the variables over the 8 year time period.

Table 16 - 8-Year Johansen Cointegration Results – Max-Eigenvalue Test

Hypothesized Number of Cointegrating Equations	Max-Eigenvalue Statistic	0.05 Critical Value	Probability	Significance at 5% level
None	44.03884	33.87687	0.0022	Yes
At Most 1	18.92701	27.58434	0.4202	-
At Most 2	13.98155	21.13162	0.3665	-
At Most 3	6.798720	14.26460	0.5132	-
At Most 4	0.001399	3.841466	0.9688	-

Table 17 – 8-Year Normalized Cointegrating Coefficients

(Standard errors in parentheses) [t statistics in brackets] Log likelihood 34182.85

Ln_FTSE100	Ln_SP500	Ln_DAX30	Ln_CAC40	Ln_OMX30
1.000000	-0.077641	-0.158893	-0.506759	0.002093
	(0.06106)	(0.03687)	(0.05422)	(0.03959)
	[-1.27163]	[-4.30906]	[-9.34589]	[0.05286]

Since we have identified the existence of one cointegrating equation, we can say that a stable equilibrium relationship is present. As per the 2 and 4 year examples, the 8 year sample results are normalized on the FTSE100.

In the 8 year timeframe, the DAX30 and CAC40 display statistical significance at the 5% level, and exhibit the expected positive relationship with the FTSE100.

We interpret the coefficients as follows:

- A 1% increase in the DAX30 leads to a 0.16% increase in the FTSE100 in the long run
- A 1% increase in the CAC40 leads to a 0.51% increase in the FTSE100 in the long run

In contrast to the 2 year sample results, the S&P500 and OMX30 are not statistically significant according to the *t* values shown.

The 8-year cointegrating coefficient results above are in accordance with the 8-year Chi-squared restriction tests conducted. Table 18 shows the FTSE100, DAX30 and CAC40 as being significant at the 5% level on imposition of zero value restrictions as per tables 11 and 13. Here, the entire 8 year period is tested, and shows that over the period, the S&P500 and OMX30 are not are significant contributor to the cointegrating vector that exists in relation to these variables.

The speed of adjustment is shown by the error correction terms in Table 19. The DAX30 and OMX30 both indicate statistical significance, and over the 8 year sample period, are faster to adjust than the other tested indices, all of which are statistically insignificant. Put another way, the burden of adjustment back to equilibrium in the system rests on the DAX30 and OMX30, with the other variables displaying weak exogeniety.

Table 18 – 8-Year Chi-Squared Test (Test of coefficient significance)

Null Hypothesis: B=0. If rejected, coefficient is significant to the cointegrating equation.

Index	Chi-Squared Test Statistic	Probability	Significance at 5% level
S&P500; B(1,1)	1.077688	0.299215	No(null fail to reject)
FTSE100; B(1,2)	21.62292	0.000003	Yes(null rejected)
DAX30; B(1,3)	10.70062	0.001071	Yes(null rejected)
CAC40; B(1,4)	19.52159	0.000010	Yes(null rejected)
OMX30; B(1,5)	0.001669	0.967413	No(null fail to reject)

Table 19 – 8-Year Sample Error Correction (Speed of Adjustment)

((-1) = Differenced once) (Standard errors in parentheses) [t statistics in brackets]

Error Correction:	**LN_FTSE100(-1)**	**LN_S_P500(-1)**	**LN_DAX30(-1)**	**LN_CAC40(-1)**	**LN_OMX30(-1)**
Cointegrating Equation	-0.013702	0.023638	0.044229	0.025932	0.028701
	(0.01297)	(0.01427)	(0.01698)	(0.01535)	(0.01445)
	[-1.05618]	[1.65648]	[2.60535]	[1.68971]	[1.98595]

7. Results Discussion

In this section, we will discuss four key ideas: listed (a) – (d):

(a) The results from bivariate and multivariate tests provided somewhat contrasting results. The bivariate tests showed a decrease in the number of cointegrated relationships between each of the sample periods. In the 8 year sample, 6 cointegrated relationships were evident, with 5 cointegrated relationships apparent in the 4 year sample, and 3 in the 2 year sample. As a general comment, we could say that at the bivariate level, the amount of cointegration seems to decrease with the sample size. However, these results should not be considered without the information gained from conducted multivariate testing. Despite the fact that the bivariate tests indicate 5 cointegrated relationships, the multivariate Johansen procedure suggested evidence of no cointegrated vectors over the 4 year sample, thus making the 4 year bivariate results somewhat meaningless.

(b) Bivariate cointegration results showed the S&P500/FTSE100 as being strongly cointegrated across all 3 sample periods. This relationship is the only one to remain stable over all samples. The only cointegrating relationships found for the CAC40 were with the S&P500 and FTSE100 over the 4 and 8 year samples. It is apparent that cointegration involving the CAC40 is non-existent in the 2 year sample, suggesting that market turmoil over the past 2 years was integrated into the French stock market differently to the other studied markets.

Within Europe, the FTSE100/DAX30 relationship displayed the highest degree of cointegration of the Euro zone indices, closely followed by FTSE100/CAC40. Interestingly, the OMX30 was the least cointegrated index across all time periods; however a cointegrating relationship between the OMX30 and DAX30 was evident over the 4 and 8 year samples.

(c) Through analysis of the multivariate tests, more in-depth information was found regarding the relationships between the different indices. The results obtained indicate a

cointegrating vector in the 2 and 8 year sample periods, with no evidence of cointegration over the 4 year time frame.

The implications derived from the *2-year* multivariate test are that the S&P500 is the leading cause of disequilibrium in the system, thereby feeling the effects of an economic shock before the other indices. Following the integration of the shock into the S&P500, the disturbance is filtered through to the remaining indices in the system, all of which are statistically significant. In short periods of time, however, there are possibilities to diversify between the markets and create excess returns through trading.

In the long-term, adjustments are made to the system which indicates there is a relationship over the entire 2-year sample period, indicating a lack of diversification benefits available to investors in the system.

The fact that cointegration is evident in the 2 year sample but not the 4 year is supported by Yavas (2006), who claims that after an exogenous shock, cointegration is expected to increase. Yavas draws on evidence from the behavior of the US, German and Japanese markets immediately following the market downturn brought upon by the terrorist event in the US on September 11, 2001. Despite this notion not being tested specifically on the markets tested in our study, it does appear that this phenomenon also holds true in the case of our study.

As discussed in the section 6 – Results (above), the *4-year* data sample suggests no cointegration. However, this result was somewhat inconclusive due to inconsistencies between the Trace and Max-Eigenvalue tests; therefore there is a *possibility* that excess returns can be achieved through diversification in the 4-year timeframe. Based on the results of the 2 and 8 year sample periods both showing evidence of cointegration, the nature of the inconclusive results in the 4-year data implies that the global economic crisis may have affected these findings.

The *8-year* data results give a holistic view of the system relationships in a longer-term perspective. Although the 4-year sample proved inconclusive in terms of the existence of cointegration, the 8-year sample strongly indicates a presence of co-movement in the system. The short-term results given by the VECM in the 8 year sample show that the DAX30 and OMX30 adjust significantly in order to return to equilibrium levels, meaning the S&P500, FTSE100 and CAC40 are shown to be weakly exogenous. Due to the existence of cointegration over the 8-year sample, there is little to no long-run portfolio benefit from diversifying between the studied markets.

(d) Equity market co-movements, according to Gilmore and McManus (2006), can arise from international trade, increase in capital mobility, relaxation of controls on international capital movements, as well as the creation of economic unions. One can therefore infer from Gilmore and McManus (2006) that the level of cointegration between stock market indices is largely based on the prevailing regulatory and political environment. The convergence of financial regulations and political policy within Europe could thus contribute to an increase in observable Euro zone stock market cointegration.

8. Limitations – Reliability and Validity

Following the study, a number of factors emerge that must be considered when making conclusions from the results that were reached. Subsequent research undertaken in the area of cointegration should take into account the limitations found in this study.

As always, there are limitations in terms of the reliability and validity of the results. We can separate these limitations into two distinct groups: data limitations and model limitations.

Data limitations of the study come in the form of frequency, sample period and number of markets tested. To allow a more complete picture of the cointegration patterns that exist within Europe and the USA, it could be advantageous to include higher frequency data – perhaps hourly data, rather than the daily data used in this study. The 8-year sample period we selected covered approximately one business cycle, however if long-term cointegration patterns were to be analyzed, a longer time period would be needed to ensure validity of the results. Also, a larger selection of markets could be tested to gain a more holistic view as to the cointegration patterns of European and American economies.

Another data limitation arising from the study is the fact that the indices we selected are not formed in an identical manner (please note they are still the best representations of their respective markets). Future studies may want to formulate consistent indices to ensure no information is lost owing to irregular index construction.

It must be acknowledged that the period of September 2007-April 2009 is seen as an abnormally large market correction, and is not representative of an average downturn expected at the conclusion of a business cycle. Thus, cointegrating relationships that were found in the study may not be indicative of long-term relationships one could expect to see in the future, however our study was designed to examine the cointegration properties around such an abnormal market.

Limitations of the model are mainly related to the use of the Johansen procedure of cointegration analysis. The Johansen method has a high probability of generating outliers, as well as high variance. It is also very sensitive to the lag length selected for the Vector Error Correction Model (Brooks, 2008).

An additional limitation of this study is the fact that the cointegration testing conducted is static, and therefore not accurate in terms of predicting cointegrating relationships in the future. As discussed in the literature review, studies of cointegration within European stock markets have yielded varying conclusions. However, many of these studies, according to Gilmore and McManus (2006), have assumed stability in the long-run relationships. This assumption is not necessarily warranted, as "linkages may be time-varying and episodic". One proposal to account for the potential time-variance in cointegration studies has been suggested by Gregory and Hanson (1996), whose method detects structural breaks in the data, revealing support of long-run relationships not captured by static tests.

According to Maddala and Kim (1998), Johansen's procedure is also very sensitive to the assumption that errors are independent and normally distributed. If indeed errors are not normally distributed, it has been found that it is more likely that the null hypothesis of no cointegration is rejected, despite there being a possibility of no cointegrating relations (Huang and Yang, 1996). Another criticism of the Johansen procedure is the difficulty associated with interpreting results. That is, other types of cointegration tests allow for greater clarity when comparing results across studies.

9. Concluding Remarks

The conclusions drawn from our research and testing are four-fold:

(a) From our study, we conclude that due to strong evidence of cointegration, there is a very limited benefit available to investors from portfolio diversification between the S&P500, FTSE100, DAX30, CAC40 and OMX30 over the long run. This is supported by the findings showing a cointegrating vector in the 2 and 8 year sample periods. The 4 year sample proved inconclusive.

(b) The findings also show that cointegration can be affected by an economic shock such as the present global financial crisis. Continual short-term testing of the cointegrating relationship between these studied indices may uncover possibilities to make excess returns in the period of recovery.

(c) In the short-run, according to adjustment coefficients, there are possibilities of excess returns based on the different speeds of adjustment prevailing in each market. Investors can therefore gain excess returns by actively managing their portfolio with consideration of these adjustment speeds. Further analysis of these short-term relationships could be undertaken in order to formulate a trading strategy between the indices studied.

(d) Long-term cointegration of the studied markets implies that diversification is not necessarily beneficial.

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11. Appendix

Appendix A – Full Results of Unit Root Testing

Augmented Dickey-Fuller (ADF) Test Results						
8 Year Data		**Adj. T-stat**	**Prob**	**1%**	**5%**	**10%**
Ln_S&P500	Intercept	-1.122885	0.708800	-3.433315	-2.862736	-2.567453
	Trend & int.	-0.961955	0.947200	-3.962487	-3.411983	-3.127897
	None	-0.746106	0.393400	-2.566081	-1.940977	-1.616596
Ln_S&P500 (-1)	Intercept	-36.995420	0.000000	-3.433315	-2.862736	-2.567453
Ln_FTSE100	Intercept	-1.455531	0.556200	-3.433320	-2.862738	-2.567454
	Trend & int.	-1.541330	0.815200	-3.962494	-3.411986	-3.127898
	None	-0.681457	0.422000	-2.566083	-1.940977	-1.616596
Ln_FTSE100(-1)	Intercept	-22.100890	0.000000	-3.433320	-2.862738	-2.567454
Ln_DAX30	Intercept	-1.487341	0.540100	-3.433312	-2.862735	-2.567452
	Trend & int.	-2.133717	0.526000	-3.962483	-3.411981	-3.127895
	None	-0.402983	0.538700	-2.566080	-1.940977	-1.616596
Ln_DAX30(-1)	Intercept	-47.386680	0.000100	-3.433314	-2.862736	-2.567453
Ln_OMX30	Intercept	-1.163310	0.692300	-3.433312	-2.862735	-2.567452
	Trend & int.	-1.525181	0.821000	-3.962483	-3.411981	-3.127895
	None	-0.195523	0.615900	-2.566080	-1.940977	-1.616596
Ln_OMX30(-1)	intercept	-44.826540	0.000100	-3.433314	-2.862736	-2.567453
Ln_CAC40	intercept	-1.342553	0.611600	-3.433320	-2.862738	-2.567454
	Trend & int.	-1.395658	0.862300	-3.962494	-3.411986	-3.127898
	none	-0.970456	0.297100	-2.566083	-1.940977	-1.616596
Ln_CAC40(-1)	intercept	-22.545730	0.000000	-3.433314	-2.862736	-2.567453
4 Year Data		Adj. T-stat	Prob	1%	5%	10%
Ln_S&P500	intercept	-0.328111	0.918200	-3.436456	-2.864124	-2.568198
	Trend & int.	-1.062373	0.933300	-3.966948	-3.414165	-3.129190
	none	-0.707364	0.410400	-2.567200	-1.941130	-1.616493
Ln_S&P500 (-1)	intercept	-37.471250	0.000000	-3.436462	-2.864127	-2.568199

Ln_FTSE100	intercept	-0.917676	0.782900	-3.436456	-2.864124	-2.568198
	Trend & int.	-1.632199	0.779800	-3.966948	-3.414165	-3.129190
	none	-0.337093	0.563800	-2.567200	-1.941130	-1.616493
Ln_FTSE100(-1)	intercept	-35.408640	0.000000	-3.436462	-2.864127	-2.568199
Ln_DAX30	intercept	-1.587388	0.488700	-3.436456	-2.864124	-2.568198
	Trend & int.	-1.319474	0.882400	-3.966948	-3.414165	-3.129190
	none	0.223848	0.751100	-2.567200	-1.941130	-1.616493
Ln_DAX30(-1)	intercept	-33.363850	0.000000	-3.436462	-2.864127	-2.568199
Ln_OMX30	intercept	-1.160938	0.693000	-3.436456	-2.864124	-2.568198
	Trend & int.	-1.694458	0.753300	-3.966948	-3.414165	-3.129190
	none	-0.017967	0.676600	-2.567200	-1.941130	-1.616493
Ln_OMX30(-1)	intercept	-32.586620	0.000000	-3.436462	-2.864127	-2.568199
Ln_CAC40	intercept	-0.365482	0.912400	-3.436456	-2.864124	-2.568198
	Trend & int.	-1.268632	0.894600	-3.966948	-3.414165	-3.129190
	none	-0.556963	0.475900	-2.567200	-1.941130	-1.616493
Ln_CAC40(-1)	intercept	-16.005840	0.000000	-3.436462	-2.864127	-2.568199
2 Year Data		Adj. T-stat	Prob	1%	5%	10%
Ln_S&P500	intercept	-0.431920	0.900900	-3.442795	-2.866922	-2.569697
	Trend & int.	-2.276928	0.445300	-3.975941	-3.418553	-3.131788
	none	-1.404752	0.149100	-2.569451	-1.941438	-1.616287
Ln_S&P500 (-1)	intercept	-27.026450	0.000000	-3.442820	-2.866933	-2.569703
Ln_FTSE100	intercept	-0.761324	0.828500	-3.442795	-2.866922	-2.569697
	Trend & int.	-2.874553	0.171700	-3.975941	-3.418553	-3.131788
	none	-1.148968	0.228600	-2.569451	-1.941438	-1.616287
Ln_FTSE100(-1)	intercept	-24.977530	0.000000	-3.442820	-2.866933	-2.569703
Ln_DAX30	intercept	-0.689069	0.847000	-3.442795	-2.866922	-2.569697
	Trend & int.	-2.703450	0.235600	-3.975941	-3.418553	-3.131788
	none	-1.067335	0.258500	-2.569451	-1.941438	-1.616287
Ln_DAX30(-1)	intercept	-23.617640	0.000000	-3.442820	-2.866933	-2.569703
Ln_OMX30	intercept	-1.144551	0.699400	-3.442795	-2.866922	-2.569697

	Trend & int.	-2.194862	0.490900	-3.975941	-3.418553	-3.131788
	none	-1.361975	0.160800	-2.569451	-1.941438	-1.616287
Ln_OMX30(-1)	intercept	-22.864580	0.000000	-3.442820	-2.866933	-2.569703
Ln_CAC40	intercept	-0.793074	0.819800	-3.442795	-2.866922	-2.569697
	Trend & int.	-3.074881	0.113500	-3.975941	-3.418553	-3.131788
	none	-1.352927	0.163400	-2.569451	-1.941438	-1.616287
Ln_CAC40(-1)	intercept	-11.371630	0.000000	-3.442820	-2.866933	-2.569703

Phillip Perron Test Results						
8 Year Data		Adj. T-stat	Prob	1%	5%	10%
Ln_S&P500	**Intercept**	-1.202492	0.6756	-3.43331	-2.86274	-2.56745
	Trend & int.	-1.04411	0.9362	-3.96248	-3.41198	-3.1279
	None	-0.70482	0.4116	-2.56608	-1.94098	-1.6166
Ln_S&P500 (-1)	**Intercept**	-50.83025	0.0001	-3.43331	-2.86274	-2.56745
Ln_FTSE100	**Intercept**	-1.563885	0.501	-3.43331	-2.86274	-2.56745
	Trend & int.	-1.691558	0.755	-3.96248	-3.41198	-3.1279
	None	-0.693629	0.4166	-2.56608	-1.94098	-1.6166
Ln_FTSE100(-1)	**Intercept**	-49.56438	0.0001	-3.43331	-2.86274	-2.56745
Ln_DAX30	**Intercept**	-1.425678	0.5711	-3.43331	-2.86274	-2.56745
	Trend & int.	-2.079089	0.5566	-3.96248	-3.41198	-3.1279
	None	-0.422141	0.5312	-2.56608	-1.94098	-1.6166
Ln_DAX30(-1)	**Intercept**	-47.43574	0.0001	-3.43331	-2.86274	-2.56745
Ln_OMX30	**Intercept**	-1.133771	0.7044	-3.43331	-2.86274	-2.56745
	Trend & int.	-1.493209	0.832	-3.96248	-3.41198	-3.1279
	None	-0.197721	0.6151	-2.56608	-1.94098	-1.6166
Ln_OMX30(-1)	**Intercept**	-44.84384	0.0001	-3.43331	-2.86274	-2.56745
Ln_CAC40	**Intercept**	-1.465765	0.551	-3.43331	-2.86274	-2.56745
	Trend & int.	-1.547731	0.8129	-3.96248	-3.41198	-3.1279
	None	-0.983405	0.2918	-2.56608	-1.94098	-1.6166
Ln_CAC40(-1)	**Intercept**	-48.50076	0.0001	-3.43331	-2.86274	-2.56745

4 Year Data		Adj. T-stat	Prob	1%	5%	10%
Ln_S&P500	**Intercept**	-0.328111	0.9182	-3.43646	-2.86412	-2.5682
	Trend & int.	-1.062373	0.9333	-3.96695	-3.41417	-3.12919
	None	-0.707364	0.4104	-2.5672	-1.94113	-1.61649
Ln_S&P500 (-1)	**Intercept**	-37.47125	0	-3.43646	-2.86413	-2.5682
Ln_FTSE100	**Intercept**	-0.917676	0.7829	-3.43646	-2.86412	-2.5682
	Trend & int.	-1.632199	0.7798	-3.96695	-3.41417	-3.12919
	None	-0.337093	0.5638	-2.5672	-1.94113	-1.61649
Ln_FTSE100(-1)	**Intercept**	-35.40864	0	-3.43646	-2.86413	-2.5682
Ln_DAX30	Intercept	-1.587388	0.4887	-3.43646	-2.86412	-2.5682
	Trend & int.	-1.319474	0.8824	-3.96695	-3.41417	-3.12919
	None	0.223848	0.7511	-2.5672	-1.94113	-1.61649
Ln_DAX30(-1)	Intercept	-33.36385	0	-3.43646	-2.86413	-2.5682
Ln_OMX30	Intercept	-1.160938	0.693	-3.43646	-2.86412	-2.5682
	Trend & int.	-1.694458	0.7533	-3.96695	-3.41417	-3.12919
	None	-0.017967	0.6766	-2.5672	-1.94113	-1.61649
Ln_OMX30(-1)	Intercept	-32.58662	0	-3.43646	-2.86413	-2.5682
Ln_CAC40	Intercept	-0.354502	0.9141	-3.43646	-2.86412	-2.5682
	Trend & int.	-1.372064	0.8686	-3.96695	-3.41417	-3.12919
	None	-0.525766	0.489	-2.5672	-1.94113	-1.61649
Ln_CAC40(-1)	Intercept	-35.53998	0	-3.43646	-2.86413	-2.5682
2 Year Data		Adj. T-stat	Prob	1%	5%	10%
Ln_S&P500	Intercept	-0.43192	0.9009	-3.4428	-2.86692	-2.5697
	Trend & int.	-2.276928	0.4453	-3.97594	-3.41855	-3.13179
	None	-1.404752	0.1491	-2.56945	-1.94144	-1.61629
Ln_S&P500 (-1)	Intercept	-27.02645	0	-3.44282	-2.86693	-2.5697
Ln_FTSE100	Intercept	-0.761324	0.8285	-3.4428	-2.86692	-2.5697
	Trend & int.	-2.874553	0.1717	-3.97594	-3.41855	-3.13179
	None	-1.148968	0.2286	-2.56945	-1.94144	-1.61629
Ln_FTSE100(-1)	Intercept	-24.97753	0	-3.44282	-2.86693	-2.5697

Ln_DAX30	Intercept	-0.689069	0.847	-3.4428	-2.86692	-2.5697
	Trend & int.	-2.70345	0.2356	-3.97594	-3.41855	-3.13179
	None	-1.067335	0.2585	-2.56945	-1.94144	-1.61629
Ln_DAX30(-1)	Intercept	-23.61764	0	-3.44282	-2.86693	-2.5697
Ln_OMX30	Intercept	-1.144551	0.6994	-3.4428	-2.86692	-2.5697
	Trend & int.	-2.194862	0.4909	-3.97594	-3.41855	-3.13179
	None	-1.361975	0.1608	-2.56945	-1.94144	-1.61629
Ln_OMX30(-1)	Intercept	-22.86458	0	-3.44282	-2.86693	-2.5697
Ln_CAC40	Intercept	-0.589368	0.87	-3.4428	-2.86692	-2.5697
	Trend & int.	-2.755506	0.2148	-3.97594	-3.41855	-3.13179
	None	-1.681993	0.0876	-2.56945	-1.94144	-1.61629
Ln_CAC40(-1)	Intercept	-25.40551	0	-3.44282	-2.86693	-2.5697