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International interdependence and dynamic linkages between developed stock markets

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Abstract

This study investigates interdependence and dynamic linkages using daily values of seven indices from five European countries (UK, Germany, France, Italy, Spain), United States of America and Japan. We find that the U.S. market is the leading stock market in the world and the UK stock market is the leading one in Europe. An interesting point is that the German stock market seems not to have a strong effect on the other markets, with its influences embedded in FTSE's 100 influences.

JEL Classification: G10; G15

Keywords: International financial markets, International Interdependence, Dynamic Linkages, Cointegration Analysis, Impulse Response Function

1. Introduction

The interdependence between stock markets has been an issue of increasing interest over the last two decades. The large amount of research from 1970 until now has concluded that international influences are increasing in time. Studies with data from '60s and '70s found little or no co-variation among national stock markets (Granger and Morgenstern, 1970, Grubel and Fadner, 1971, and many others). Explanations for these findings are the barriers to international capital flows and exchange controls, the lack of free trade, the dissimilar government policies, the discriminate taxation on international capital investment, lack of information on foreign securities and investor bias against foreign securities. The conclusion of these studies is that stock markets across borders are segmented, and risk reduction through international portfolio diversification is possible.

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From 1980 until now, the international stock markets have been influenced more and more by globalization. Many researchers in a lot of studies claim that equity markets are associated with long and short run relationships. Most of them argue that the United States (U.S.) stock market has a major impact on the other markets and a leading character (Eun and Shim (1989), Fischer and Palasvirta (1990), Hamao, Masulis and Ng (1990), and many others). The October 1987 crash and the behavior of the international stock markets has been examined by a lot of researchers. Malliaris and Urrutia (1992) examined causal relationships among six stock markets and they conducted unidirectional and bi-directional causality tests by the means of Granger methodology. They found no lead-lag relationships for the pre and post October crash period. However, they detected important feedback relationships and unidirectional causality during the month of the crash. Arshanapali and Doukas (1993) claimed that the degree of international co – movements in stock price indices has changed significantly since the crash, with UK, German and French stock markets related with the U.S. market only after the crisis. Previous studies before the crisis (Jaffe and Westerfield, 1985, Schollhammer and Sand, 1987), have reported substantial interdependence among these markets.

There are a number of different factors that have contributed to the increasing interdependence between the international stock markets since 1980. Initially, the institutional and technological changes that occurred in the early 1980s led to a closer relationship. International barriers and differences prevented capital mobility before 1980, barriers and differences like the withholding tax on interest payments, transaction costs (the commission charges for overseas securities tend to be above average levels), low volume of transactions in a lot of markets (so greater price volatility) and finally the difficulties with the supply of information (different accounting systems between the international economies). Since 1980 a lot of barriers have been removed because of institutional changes like the deregulation of the capital markets, the abolition of the withholding tax on interest payments (especially by the United States of America). Additionally, technological changes have caused development in communications and trading systems. Nowadays there are many overseas securities listed in various stock exchanges while investors have immediately information from every stock market in the world and are able to conduct transactions everywhere and from everywhere on the planet.

In this paper, we study the linkages among seven stock markets (the US market, five European markets and the Japanese) by using their basic indices. First, we examine if there are long run relationships in the period under scrunity (cointegration analysis). From the results of the cointegration analysis we have evidence about the indices that are very important for international stock market influences. Then, we examine the causal effects between the value changes of the indices to see if the U.S. market is the most important stock market in the world and the leading one. We test the behavior of the five European stock markets in order to extract conclusions on the transmission of information in the European Union and which stock market is the one that leads the others. Finally, we test how rapidly the movements in one market are transmitted to the other stock markets with the impulse response functions.

The organization of the paper is as follows. Section II reviews the methodology used in the paper. Section III presents the data, the descriptive statistics and the results of the econometric method. Finally, in section IV the conclusions are presented.

2. Methodological issues

2.1 Stationarity

A y series is said to be stationary if the mean and autocovariances of the series do not depend on time. The canonical example of a nonstationary series is a random walk:

$$y_t = y_{t-1} + \varepsilon_t \tag{1}$$

where ε is a stationary random disturbance term. The random walk is a differenced stationary series since the first difference of y is stationary ($y_t - y_{t-1} = \varepsilon_t$). A difference stationary series is said to be integrated and denoted as I(d). The order of integration d is the number of unit roots contained in the series, the number of differencing operations it takes to make the series stationary.

To test for the presence of stochastic non stationarity in our data we investigate the integration order using the Augmented Dickey – Fuller test (ADF test, 1979). The ADF test provides the appropriate test statistics to determine whether the series contain a unit root with a constant plus a time trend, a unit root with a constant not a time trend or a unit root without constant and time trend. The more general ADF test is based on the following regression model:

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

with p the number of lags selected to ensure that the residuals are white noise, c the constant term, t the time trend and Δ denotes differencing.

We used the τ and Φ statistics in order to examine if there is a stochastic trend in the series. There is a stochastic trend in the series if coefficients β, δ are equal to zero. A stochastic trend is one that cannot be forecast because the residual's variance is time dependent.

The critical values used in this study are the MacKinnon critical values for unit root tests.

2.2 Cointegration

The investigation of the existence of interdependence between stock markets can be based on the cointegration theory (Granger and Weiss, 1983, and Engle and Granger, 1987). Two series are said to be cointegrated of order d, b, denoted as CI(d,b), if they are both integrated of order d and there is a linear combination of them which is I(d-b) where b > 0. In general terms, two variables are said to be cointegrated when a linear combination of the two is stationary, even though each variable is non - stationary. The stationary linear combination is called cointegrating equation.

The main idea behind cointegration is a specification of models that include beliefs about the long run, bivariate or multivariate, relationships between different stock market indices. Cointegration between indices implies that these indices are linked in the long run even though they are not stationary - something that contradicts the cross border market efficiency hypothesis. If prices are cointegrated, this implies market inefficiency since one price can be used to forecast the other value.

The method used for the cointegration test is the Johansen method (1988). The Johansen method applies the maximum likelihood procedure to determine the presence of cointegrating vectors in non - stationary time series and detects the number of cointegrating vectors. Johansen adopts a framework that is based on the assumption that introducing sufficient lags will allow for a well-behaved disturbance term. The Johansen procedure analyses bivariate and multivariate cointegration, directly investigating cointegration in the VAR (Vector Autoregression) model.

Denote the VAR model of order p:

$$y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + \varepsilon_t \tag{3}$$

Where y_t is a k – vector of non – stationary I(1) variables, c the constant term, A_i are matrices of coefficients to be estimated and ε_t is a vector of innovations. The VAR can be rewritten as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t \tag{4}$$

$$\text{where } \Pi = \sum_{i=1}^{p} A_i - I \quad \text{and} \quad \Gamma_i = -\sum_{j=i+1}^{p} A_j$$

The information on the coefficient matrix Π is decomposed as $\Pi = \alpha\beta'$ where the elements of α matrix are the adjustment parameters and the β matrix contains the cointegrating vectors with each column to be a cointegrating vector. Γ_i are the interim multipliers. If the coefficient matrix Π has reduced rank $r < k$, then there exists $k * r$ matrices α and β each with rank r such that Π is stationary. Johansen's method is to estimate the Π matrix in an unrestricted form and then to test whether we can reject the restrictions implied by the reduced rank of Π.

The null hypothesis in the Johansen's cointegration test is that there are at most r cointegrating vectors. Two possible test statistics can be used for the hypothesis of the existence of r cointegrating vectors. The first one is the Likelihood Ratio (LR) test statistic, which is also called trace test and is given by:

$$Q_r = -T \sum_{i=r+1}^{k} \log (1-\lambda_i), \tag{5}$$

where λ_i are the k – r smaller squared canonical correlations and T is the number of observations.

The second one is the maximum Eigenvalue test which compares the hypothesis of r cointegrating vectors against that of r – 1 cointegrating vectors. The maximum Eigenvalue test statistic is given by:

$$Q_{max} = - T \log (1- \lambda_{r+1}) = Q_r - Q_{r+1} \tag{6}$$

The critical values used in this study have been tabulated by Osterwald - Lenum (1992). If the LR is bigger than the critical value, then we conclude that the indices do have a long run relationship.

Following Johansen's procedure, we first examine the cointegration relationships in bivariate models. The results from the bivariate models show us the indices that have the most long run relationships. We use the information from the bivariate models and we examine the issue of cointegration in multivariate models in order to test when the relationships become stronger and when weaker. We use multivariate models with 3, 4, 5, 6 and 7 indices and we test which groups have a long run relationship, which groups don't have and which indices have the biggest effect on these relationships.

2.3 Short Run Dynamic Models

In order to examine the causal effects between the value changes of the indices, we explore the short run dynamics by performing bivariate and multivariate Granger causality tests for cointegrating systems.

The method used is performed directly on the least square estimators of the coefficients of the VAR process specified in the returns of the data series. The VAR model will be performed in the first differences so that the indices will be integrated of order one. The model that has been used is:

$$\Delta y_t = \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + u_t \tag{7}$$

where Δ denotes first differences of the indices data series, y_{t-i} is the vector of the optimal lagged values on the first differences of all the indices and u_t being the white noise error term. The optimal own lag for the models have been chosen according to the Akaike Information Criterion (Akaike, 1973).

A Granger's causality test is a linear precedence test. The idea of causality has to do with predictability. In our study, there is causality if the index X causes the index Y, with respect to the given information set that includes X and Y, and if present Y can be better forecasted by using past values of X than by not doing so. If there is causality, the past history of an index can help to predict the value movements of the other indices, something that obviously implies market inefficiency.

Following the above method we test for Granger causality in bivariate models in order to examine which indices are the most influential among all the examined indices. Then we run trivariate models, which are based on the most influential indices. We use this kind of models in order to see which indices can create the appropriate model which explains the stock exchange movements as we try to find the multivariate causality relationships. The criterion we use in order to accept or drop an index data series is the Final Prediction Error criterion (FPE, Hsiao, 1981). The FPE criterion is defined as:

$$FPE\ (n*, k) = \frac{T+n*+k+1}{T-n* - k-1} \quad \frac{RSS}{T} \qquad (8)$$

where n* is the optimal lag n of stock returns that minimizes FPE(n)[1], k is the lag length on the additional independent variable and RSS is the sum of squared residuals. If the model with the extra index gives FPE bigger than the FPE without it, then this index is dropped from the model. If the model with the extra index gives FPE lower than the FPE without it, then this index is included in the model. The number of the lag term of this index in the model is the one that gives the minimum FPE.

This step is applied to all the indices one at a time. The same procedure is used for models with more indices until all remaining indices are either included in or discarded from the model. The purpose of this method is to create a specified model for the examined indices.

2.4 Impulse Response Functions

An impulse response function measures the time profile of the effect of a shock on the behavior of the data series. With the impulse response analysis we can examine how rapidly the movements in one market are transmitted to the other stock markets.

1. FPE(n) is formula (8) with n* = n but without k.

Consider a simple bivariate VAR(p):

$$\Delta y = a_1 \Delta y_{t-1} + b_1 \Delta x_{t-1} + \varepsilon_1$$
$$\Delta x = a_2 \Delta y_{t-1} + b_2 \Delta x_{t-1} + \varepsilon_2 \quad (9)$$

A shock to the y index affects the y index and is also to all the endogenous variables through the dynamic structure of the VAR. A shock to the y index is a change in innovation ε_1. A change in ε_1 will immediately change the values of y but also all the future values of y and x since lagged values of the two indices appear in both equations. The impulse response function measures the effect of a one standard deviation shock on y index, on current and future movements on both the two indices.

The bivariate VAR(1) can be transformed to a vector moving average representation:

$$\Delta y = \varphi_1 \varepsilon_1$$
$$\Delta x = \varphi_2 \varepsilon_2 \quad (10)$$

The coefficients φ can be used to generate the effects of the shocks. The accumulated effects of the impulses can be obtained by the appropriate summation of the coefficients of the impulse response function.

If the innovations ε_1 and ε_2 are uncorrelated, then the impulse response function is straightforward. However, the innovations are usually correlated, so that they have a common component, which cannot be associated with a specific variable[2]. This common factor is being attributed to the variable that comes first in the VAR model. So it is very important which variable will be first in the system because the results are not invariant to the ordering of the variables in the VAR. In this study the first variable is the returns data series of the stock market that has the stronger long run and short run relationships.

The reason we use the impulse response function in systems with two variables is to see how many days it takes for the impulse responses to decay following a shock. If the impulse responses converge to zero after one day (the system is stationary), then we have a very high degree of market integration. Generally, the greater the speed of adjustment the greater the capital market integration.

3. Empirical Results

3.1 Data

The data set used in this study consists of seven Indices values. In particular, five out

2. For econometric reasons, the errors are orthogonolized by Cholesky Decomposition so that the covariance matrix of the resulting innovations is diagonal.

of seven indices that are used are European. The European indices are FTSE 100, DAX 30, CAC 40, Madrid General, MibTel and come from the United Kingdom, Germany, France, Spain and Italy respectively. The other two indices are the Dow Jones Industrial (DJI) from the New York Stock Exchange (U.S. market) and the Nikkei index from the Stock Exchange of Tokyo (Japan).

The data used in this study concern the period Tuesday 2nd January of 1995 to Friday 31st August of 2001 and are obtained directly from their stock exchanges. We stopped the data series in 31/8/2001 because the events of 11th of September 2001 in the United States had a major impact in the running of the tests.

The created data series from the examined period consists of 1684 daily observations. For econometric reasons, in the working days that a stock market did not open but the other stock markets were active the value that has been used is that of the previous day.

The returns used in each of the time series are computed as follows:

$$r_t = log \frac{P_t}{P_{pt}}$$

r_t : the day return
P_t : the value of the index
P_{pt} : the value of the index the previous working day

3.2 Descriptive Statistics

Table 1 provides summary statistics for the return series of the seven indices. The Madrid general has the biggest mean return (0.062%) and DAX 30 the biggest standard deviation (1.397%). The Nikkei has the lowest return (-0.036%) and FTSE 100 the lowest standard deviation (1.040%). The kurtosis measures indicate that the return series are leptokurtic compared to the normal distribution. The Jarque – Bera (1987) for joint normal kurtosis and skewness rejects the normality hypothesis.

Table 2 presents the correlation coefficients between stock market returns. The coefficients are positive and generally different from zero in all cases. The DJI has the biggest correlation coefficients with the indices from the biggest European markets, the UK's and Germany's. The correlation between the European markets is very high, a result that shows the degree of integration between these markets. Interesting points in this Table are the high coefficients between the central stock markets of Europe (UK, Germany and France) and the high correlation between the Spanish stock market and the contiguous markets of France and Italy.

Table 3 reports the Augmented Dickey - Fuller statistics for both the logarithm of

Table 1

	DJI	FTSE 100	DAX 30	CAC 40	MIBTEL	MADRID GEN.	NIKKEI
Mean	0.057%	0.033%	0.054%	0.054%	0.052%	0.062%	-0.036%
Median	0.057%	0.012%	0.058%	0.000%	0.004%	0.052%	0.000%
Maximum	7.088%	4.345%	6.106%	6.097%	7.881%	5.726%	7.823%
Minimum	-7.305%	-4.418%	-12.715%	-7.192%	-8.735%	-8.954%	-8.303%
Std. Dev.	1.112%	1.040%	1.397%	1.336%	1.378%	1.256%	1.507%
Skewness	-0.275	-0.201	-0.671	-0.165	-0.024	-0.586	0.035
Kurtosis	7.185	4.486	8.849	5.051	6.765	7.442	6.584
Jarque - Bera	1249.20	166.12	2525.72	302.71	994.04	1479.94	900.86

Autocorrelations	DJI	FTSE 100	DAX 30	CAC 40	MIBTEL	MADRID GEN.	NIKKEI
1	-0.054	0.041	-0.022	0.001	-0.008	0.033	-0.061
2	-0.048	-0.086	-0.020	-0.018	0.005	-0.019	-0.027
3	-0.020	-0.081	-0.015	-0.051	0.011	-0.027	-0.038
4	-0.001	-0.008	0.002	-0.022	0.062	-0.008	-0.009
5	0.017	0.010	0.020	-0.012	-0.028	0.005	0.001

Table 2

Correlation Matrix						
	FTSE 100	DAX 30	CAC 40	MIBTEL	MADRID GENERAL	NIKKEI
DJI	0.426	0.422	0.409	0.346	0.398	0.124
FTSE 100		0.640	0.685	0.584	0.623	0.242
DAX 30			0.689	0.580	0.663	0.241
CAC 40				0.653	0.718	0.217
MIBTEL					0.646	0.194
MADRID GENERAL						0.194

the stock price and the logarithmic first difference (returns). The hypothesis of a single unit root in the logarithm of the stock price is accepted but strongly rejected in the logarithmic first differences. Thus, like most financial time series, all the data series are integrated of order one, I(1).

The models used for the ADF statistics are all without constant and time trend except for the case of DJI, which has constant term. The τ and φ statistics that are not

Table 3

INDEX	LEVELS	returns
DJI	-2.348	-25.576**
FTSE 100	1.426	-26.554**
DAX 30	1.657	-24.421**
CAC 40	1.697	-25.050**
MIBTEL	1.407	-23.288**
MADRID GEN.	1.896	-13.988**
NIKKEI	-1.126	-25.579**

*** denotes significance at the 1% level of significance.*

reported here but are available by the authors, showed that there is stochastic trend in the data series.

3.3 Cointegration

The null hypothesis of no cointegration between the examined index values against at least one cointegrating vector is tested with the Johansen's (1988) method of maximum likelihood estimation of bivariate and multivariate models. We assume that there is no deterministic trend in data and we use models with an intercept (no trend) in the cointegrating equation but not in the Vector Autoregression (VAR) part. The lag length is chosen by applying the Akaike Information Criterion on the unrestricted undifferenced VAR model. The number of the lag lengths is the minimum, which ensures that the residuals in each equation of the models are uncorrelated. The Akaike Information Criterion (AIC) is computed as $AIC = -2l/T + 2k/T$ where l is the maximized log likelihood and k is the number of regressors.

Table 5 presents the bivariate cointegration results between the examined stock indices. We use the Johansen trace statistic (LR) to accept or reject the null hypothesis of zero cointegrating vectors or at most one. The critical values to accept the null hypothesis that there is no cointegrating vector are 19.96 and 24.60 at the 5% and 1% level of significance respectively. The hypothesis of at most one cointegrating relation is rejected if the trace statistic is bigger than the critical values (9.24 and 12.97 for the 5% and 1% level of significance respectively).

Table 4a reports the summary of the bivariate cointegration results. According to the Johansen method, DJI and FTSE 100 have the most long run relationships between the examined indices. The only case where the DJI and FTSE 100 are not

Table 4a

TESTS FOR COINTEGRATION – SUMMARY BIVARIATE MODELS							
	DJI	**DAX 30**	**CAC 40**	**FTSE 100**	**MADRID GEN.**	**MIBTEL**	**NIKKEI**
DJI	-	**YES**	**YES**	**YES**	**YES**	**YES**	NO
DAX 30	**YES**	-	NO	**YES**	**YES**	NO	NO
CAC 40	**YES**	NO	-	**YES**	NO	NO	NO
FTSE 100	**YES**	**YES**	**YES**	-	**YES**	**YES**	NO
MADRID GEN.	**YES**	**YES**	NO	**YES**	-	**YES**	NO
MIBTEL	**YES**	NO	NO	**YES**	**YES**	-	NO
NIKKEI	NO	NO	NO	NO	NO	NO	NO

Table 4b

TESTS FOR COINTEGRATION MULTIVARIATE MODELS (ALL THE INDICES)				
Indices	**Eigenvalue**	**Likelihood ratio**	**Hypothesis**	**Lags in VAR**
ALL THE INDICES	0.029	148.804*	H_0: r = 0	4
	0.020	99.908	H_0: r ≤ 1	
	0.012	66.237	H_0: r ≤ 2	
	0.010	45.427	H_0: r ≤ 3	
	0.008	27.989	H_0: r ≤ 4	
	0.005	14.058	H_0: r ≤ 5	
	0.003	5.359	H_0: r ≤ 6	

** denotes significance at the 5 % level of significance.*

cointegrated is that of the Nikkei. The Nikkei is the only index that has no long run relationship across all indices. This is normal because the Nikkei does not follow the movements of the other indices. From the European indices, FTSE 100 has five out of six cointegrating relationships, Madrid General four out of six, DAX 30 and MibTel three out of six long run relationships and CAC 40 has two.

From these results we have evidence that DJI and FTSE 100 are the most powerful indices since these two are the indices that have the most long run relationships.

Table 5

TESTS FOR COINTEGRATION

BIVARIATE MODELS

Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
DJI – DAX 30	0.007	20.431*	H_0: r = 0	4	DAX 30 – CAC 40	0.004	12.138	H_0: r = 0	4
	0.005	8.737	H_0: r ≤1			0.003	5.305	H_0: r ≤1	
DJI – CAC 40	0.007	22.912*	H_0: r = 0	4	DAX 30 - MIBTEL	0.005	14.731	H_0: r = 0	4
	0.006	10.721*	H_0: r ≤1			0.003	5.476	H_0: r ≤1	
DJI – FTSE 100	0.010	21.499*	H_0: r = 0	4	DAX 30 – MAD. G.	0.010	21.943*	H_0: r = 0	4
	0.003	5.115	H_0: r ≤1			0.003	4.481	H_0: r ≤1	
DJI – MIBTEL	0.007	20.646*	H_0: r = 0	6	DAX 30 – NIKKEI	0.007	14.162	H_0: r = 0	2
	0.005	9.238	H_0: r ≤1			0.002	2.564	H_0: r ≤1	
DJI – MAD G.	0.008	21.652*	H_0: r = 0	4	CAC 40 – MIBTEL	0.004	11.239	H_0: r = 0	4
	0.005	8.667	H_0: r ≤1			0.003	4.411	H_0: r ≤1	
DJI - NIKKEI	0.008	16.131	H_0: r = 0	2	CAC 40 – MAD. G.	0.008	18.031	H_0: r = 0	4
	0.002	2.625	H_0: r ≤1			0.003	5.290	H_0: r ≤1	
FTSE 100 – DAX 30	0.008	20.104*	H_0: r = 0	6	CAC 40 – NIKKEI	0.006	11.537	H_0: r = 0	2
	0.004	6.568	H_0: r ≤1			0.001	2.087	H_0: r ≤1	
FTSE 100 – CAC 40	0.007	20.096*	H_0: r = 0	4	MAD. G. - MIBTEL	0.010	24.345*	H_0: r = 0	4
	0.004	7.512	H_0: r ≤1			0.004	7.003	H_0: r ≤1	
FTSE 100 – MIBTEL	0.008	21.242*	H_0: r = 0	8	NIKKEI - MAD. G.	0.006	12.061	H_0: r = 0	2
	0.005	8.003	H_0: r ≤1			0.001	2.265	H_0: r ≤1	
FTSE 100 – MAD. G.	0.009	22.627*	H_0: r = 0	4	NIKKEI - MIBTEL	0.005	10.001	H_0: r = 0	2
	0.005	7.772	H_0: r ≤1			0.001	1.853	H_0: r ≤1	
FTSE 100 - NIKKEI	0.004	9.646	H_0: r = 0	2					
	0.001	2.255	H_0: r ≤1						

** and ** denotes significance at the 5 % and 1% level of significance respectively.*

From the cointegration analysis we can examine if the series are linked in the long run but not which series causes the other one. In our case, because of the seven indices that we use, we can test, by using multivariate models, which index is the one that is linked in the long run most of the time and we can conclude which indices are necessary in the cointegrating relationships through the examined groups.

We created groups of three indices in order to see which index there is in most of the cointegrating groups. The first groups we tested were those that had both the DJI and the FTSE 100. We made this choice because DJI and FTSE 100 had the most long run relationships in the bivariate models. Table 6, panel A (p. 26) presents these results from the Johansen method. As we can see, the only groups that do not have cointegration are those with MibTel and Nikkei.

The next step was to test three – variate models with DJI but without FTSE 100 (Table 6, panel B). The long run relationships are three out of ten and in every case the General Madrid is present. As we test three – variate models with the FTSE 100 but without the DJI (Table 6, panel C), we conclude that there is cointegration in five out of ten groups with the FTSE 100, Madrid General and the third index to give long run relationship in all the cases. Until now we deduce that the FTSE 100 and DJI do give the most cointegrating relationships with the Madrid General to play a special role in the long run relationships. Finally, as we test the models without the DJI and FTSE 100, but with the Madrid General (Table 6, panel D, p.26), we conclude that there is no long run relationship, result that indicates that the Madrid General has a special relationship with the stock markets of the United States and the UK.

After this evidence, we checked the long run relationships in multivariate models with four variables and the DJI, FTSE 100 and Madrid General as the base of each group. The results in Table 7 indicate that there are long run relationships in all the groups. As we test for cointegration in models with four indices but none of them the DJI, FTSE 100 or Madrid General, we conclude the acceptance of the null hypothesis of no cointegration. The last two results boost the evidence for the significance of these three indices.

In order to make this result more robust, we use models with five indices and with the DJI, FTSE 100 and Madrid General again as the base of each group. From the results of these tests (Table 8) we confirm the significance of the three indices and moreover, as can be seen in the Table, multivariate models without two of the three indices do not give cointegrating relationships.

The Johansen method, for cointegration in all indices, results in a long run relationship. The results of the method are reported in Table 4b.

In order to find out if there is an index that has a bigger effect on the above cointegrating effect, we checked for long run relationships in multivariate models with

Table 6 (Panels A & D)

TESTS FOR COINTEGRATION – MULTIVARIATE MODELS									
PANEL A: GROUPS WITH DJI AND FTSE 100					PANEL D: GROUPS WITH MADRID GENERAL BUT WITHOUT DJI AND FTSE 100				
Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
DJI – FTSE 100 – MAD. G.	0.012	41.544**	$H_0: r = 0$	4	MAD. G. – MIBTEL – CAC 40	0.010	31.302	$H_0: r = 0$	6
	0.008	20.905*	$H_0: r \leq 1$			0.005	14.212	$H_0: r \leq 1$	
	0.004	6.918	$H_0: r \leq 2$			0.004	6.268	$H_0: r \leq 2$	
DJI – FTSE 100 – CAC 40	0.010	36.150*	$H_0: r = 0$	4	MAD.G – MIBTEL – DAX 30	0.012	34.839	$H_0: r = 0$	6
	0.008	19.185	$H_0: r \leq 1$			0.005	14.763	$H_0: r \leq 1$	
	0.004	6.141	$H_0: r \leq 2$			0.004	6.901	$H_0: r \leq 2$	
DJI – FTSE 100 - DAX 30	0.011	34.915*	$H_0: r = 0$	6	MAD. G. – MIBTEL - NIKKEI	0.011	31.458	$H_0: r = 0$	4
	0.006	15.790	$H_0: r \leq 1$			0.004	13.204	$H_0: r \leq 1$	
	0.003	5.300	$H_0: r \leq 2$			0.003	5.716	$H_0: r \leq 2$	
DJI – FTSE 100 – MIBTEL	0.010	33.806	$H_0: r = 0$	8	MAD. G. – DAX 30 – CAC 40	0.012	33.972	$H_0: r = 0$	6
	0.007	16.981	$H_0: r \leq 1$			0.005	14.132	$H_0: r \leq 1$	
	0.003	4.466	$H_0: r \leq 2$			0.003	5.564	$H_0: r \leq 2$	
DJI – FTSE 100 - NIKKEI	0.009	25.220	$H_0: r = 0$	8	MAD. G. – DAX 30 – NIKKEI	0.013	34.163	$H_0: r = 0$	4
	0.004	9.579	$H_0: r \leq 1$			0.005	12.881	$H_0: r \leq 1$	
	0.001	2.091	$H_0: r \leq 2$			0.003	4.567	$H_0: r \leq 2$	
					MAD.G. – CAC 40 - NIKKEI	0.010	27.090	$H_0: r = 0$	4
						0.004	11.024	$H_0: r \leq 1$	
						0.003	4.578	$H_0: r \leq 2$	

*The critical values in the three - variate models for r = 0 are 34.91 and 41.07 at the 5% and 1% level of significance, for r ≤ 1 are 19.96 and 24.60 at the 5% and 1% level of significance and for r ≤ 2 the critical values are 9.24 and 12.97 at the 5% and 1% level of significance respectively. * and ** denotes significance at the 5 % and 1% level of significance respectively*

Table 6 (Panel B)

TESTS FOR COINTEGRATION

MULTIVARIATE MODELS

PANEL B: GROUPS WITH DJI BUT WITHOUT FTSE 100

Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
DJI – DAX 30 – CAC 40	0.007	28.280	$H_0: r = 0$	6	DJI – MAD. G. – NIKKEI	0.010	29.306	$H_0: r = 0$	4
	0.007	15.935	$H_0: r \leq 1$			0.006	12.156	$H_0: r \leq 1$	
	0.003	4.597	$H_0: r \leq 2$			0.002	2.759	$H_0: r \leq 2$	
DJI - DAX 30 – MAD. G.	0.013	39.501*	$H_0: r = 0$	6	DJI – MAD. G. – MIBTEL	0.011	39.507*	$H_0: r = 0$	8
	0.006	17.336	$H_0: r \leq 1$			0.007	21.443*	$H_0: r \leq 1$	
	0.004	7.148	$H_0: r \leq 2$			0.006	9.867*	$H_0: r \leq 2$	
DJI – DAX 30 – MIBTEL	0.009	30.798	$H_0: r = 0$	4	DJI - CAC 40 – NIKKEI	0.009	33.015	$H_0: r = 0$	4
	0.006	16.225	$H_0: r \leq 1$			0.008	18.323	$H_0: r \leq 1$	
	0.004	6.318	$H_0: r \leq 2$			0.003	5.267	$H_0: r \leq 2$	
DJI - DAX 30 - NIKKEI	0.009	33.097	$H_0: r = 0$	4	DJI - CAC 40 – MIBTEL	0.007	29.437	$H_0: r = 0$	6
	0.007	18.602	$H_0: r \leq 1$			0.007	17.115	$H_0: r \leq 1$	
	0.004	6.290	$H_0: r \leq 2$			0.003	5.445	$H_0: r \leq 2$	
DJI – MAD. G. – CAC 40	0.010	36.568*	$H_0: r = 0$	6	DJI – NIKKEI – MIBTEL	0.009	29.409	$H_0: r = 0$	4
	0.007	19.948	$H_0: r \leq 1$			0.005	14.340	$H_0: r \leq 1$	
	0.004	7.451	$H_0: r \leq 2$			0.003	5.091	$H_0: r \leq 2$	

*The critical values in the three - variate models for $r = 0$ are 34.91 and 41.07 at the 5% and 1% level of significance, for $r \leq 1$ are 19.96 and 24.60 at the 5% and 1% level of significance and for $r \leq 2$ the critical values are 9.24 and 12.97 at the 5% and 1% level of significance respectively. * and ** denotes significance at the 5 % and 1% level of significance respectively*

Table 6 (Panel C)

TESTS FOR COINTEGRATION									
MULTIVARIATE MODELS									
PANEL C: GROUPS WITH FTSE 100 BUT WITHOUT DJI									
Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
FTSE 100 - DAX 30 – CAC 40	0.009	30.209	$H_0: r = 0$	6	FTSE 100 – MAD. G. – NIKKEI	0.014	37.362*	$H_0: r = 0$	6
	0.005	14.499	$H_0: r \le 1$			0.006	13.374	$H_0: r \le 1$	
	0.003	5.504	$H_0: r \le 2$			0.002	3.053	$H_0: r \le 2$	
FTSE 100 - DAX 30 – MAD. G.	0.014	42.897**	$H_0: r = 0$	6	FTSE 100 – MAD. G. – MIBTEL	0.010	40.246*	$H_0: r = 0$	6
	0.009	19.580	$H_0: r \le 1$			0.008	23.032*	$H_0: r \le 1$	
	0.003	5.256	$H_0: r \le 2$			0.006	9.321*	$H_0: r \le 2$	
FTSE 100 – DAX 30 – MIBTEL	0.009	30.184	$H_0: r = 0$	6	FTSE 100 - CAC 40 - NIKKEI	0.010	32.697	$H_0: r = 0$	4
	0.007	15.401	$H_0: r \le 1$			0.005	16.395	$H_0: r \le 1$	
	0.003	4.387	$H_0: r \le 2$			0.005	7.855	$H_0: r \le 2$	
FTSE 100 – DAX 30 – NIKKEI	0.010	36.651*	$H_0: r = 0$	4	FTSE 100 - CAC 40 – MIBTEL	0.010	30.600	$H_0: r = 0$	6
	0.007	19.259	$H_0: r \le 1$			0.006	14.217	$H_0: r \le 1$	
	0.005	7.588	$H_0: r \le 2$			0.003	4.493	$H_0: r \le 2$	
FTSE 100 – MAD. G. – CAC 40	0.011	39.448*	$H_0: r = 0$	6	FTSE 100 - NIKKEI - MIBTEL	0.009	30.285	$H_0: r = 0$	4
	0.008	21.067*	$H_0: r \le 1$			0.005	14.951	$H_0: r \le 1$	
	0.004	7.181	$H_0: r \le 2$			0.004	6.941	$H_0: r \le 2$	

*The critical values in the three - variate models for r = 0 are 34.91 and 41.07 at the 5% and 1% level of significance, for r ≤ 1 are 19.96 and 24.60 at the 5% and 1% level of significance and for r ≤ 2 the critical values are 9.24 and 12.97 at the 5% and 1% level of significance respectively. * and ** denotes significance at the 5 % and 1% level of significance respectively*

Table 7

TESTS FOR COINTEGRATION				
MULTIVARIATE MODELS (FOUR INDICES)				
Indices	**Eigenvalue**	**Likelihood ratio**	**Hypothesis**	**Lags in VAR**
DJI - FTSE 100 - MAD. G. - MIBTEL	0.012	58.781*	H_0: r = 0	6
	0.011	39.272*	H_0: r ≤ 1	
	0.007	20.754*	H_0: r ≤ 2	
	0.005	8.299	H_0: r ≤ 3	
DJI - FTSE 100 - MAD. G. - DAX 30	0.014	56.388*	H_0: r = 0	8
	0.011	32.104	H_0: r ≤ 1	
	0.005	13.723	H_0: r ≤ 2	
	0.003	4.676	H_0: r ≤ 3	
DJI - FTSE 100 - MAD. G. - CAC 40	0.012	53.480*	H_0: r = 0	8
	0.009	33.966	H_0: r ≤ 1	
	0.007	18.138	H_0: r ≤ 2	
	0.004	6.981	H_0: r ≤ 3	
DJI - FTSE 100 - MAD. G. - NIKKEI	0.016	58.054*	H_0: r = 0	4
	0.010	31.602	H_0: r ≤ 1	
	0.007	14.624	H_0: r ≤ 2	
	0.001	2.297	H_0: r ≤ 3	
DAX 30 - CAC 40 - MIBTEL - NIKKEI	0.009	36.287	H_0: r = 0	4
	0.007	20.880	H_0: r ≤ 1	
	0.004	9.312	H_0: r ≤ 2	
	0.001	2.435	H_0: r ≤ 3	

*The critical values, in these models, for r = 0, are 53.12 and 60.16 at the 5% and 1% level of significance, for r ≤ 1 they are 34.91 and 41.07 at the 5% and 1% level of significance and for r ≤ 2 the critical values are 19.96 and 24.60 at the 5% and 1% level of significance respectively and finally for r ≤ 3, the critical values are 9.24 and 12.97. * and ** denotes significance at the 5 % and 1% level of significance respectively.*

six indices and one index to be excluded each time. Table 9 presents the results from these models and we conclude that the only group that does not contain cointegration is the one in which the DJI is absent.

This is a very interesting result because if we connect it with the results from the models with three and four indices, we conclude that the long run relationships are a result of the DJI conditions with the other stock markets and especially with London. The FTSE 100 is much more integrated with the other European stock markets than

Table 8

TESTS FOR COINTEGRATION									
MULTIVARIATE MODELS (FIVE INDICES)									
Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
FTSE 100 – DJI – MAD. G. – MIBTEL - DAX 30	0.018	82.469*	$H_0: r = 0$	4	FTSE 100 – DJI – MAD. G. - CAC 40 NIKKEI	0.017	79.847*	$H_0: r = 0$	4
	0.011	51.435	$H_0: r \leq 1$			0.011	51.593	$H_0: r \leq 1$	
	0.009	33.283	$H_0: r \leq 2$			0.010	32.788	$H_0: r \leq 2$	
	0.007	18.898	$H_0: r \leq 3$			0.006	15.084	$H_0: r \leq 3$	
	0.005	7.899	$H_0: r \leq 4$			0.003	5.744	$H_0: r \leq 4$	
FTSE 100 – DJI – MAD. G. – MIBTEL - CAC 40	0.018	90.561**	$H_0: r = 0$	2	INDICES WITHOUT DJI AND FTSE 100	0.016	67.852	$H_0: r = 0$	4
	0.015	60.123	$H_0: r \leq 1$			0.010	40.514	$H_0: r \leq 1$	
	0.010	34.871	$H_0: r \leq 2$			0.007	23.386	$H_0: r \leq 2$	
	0.007	18.557	$H_0: r \leq 3$			0.005	12.333	$H_0: r \leq 3$	
	0.004	6.099	$H_0: r \leq 4$			0.003	4.680	$H_0: r \leq 4$	
FTSE 100 – DJI – MAD. G. – MIBTEL - NIKKEI	0.017	80.073*	$H_0: r = 0$	4	INDICES WITHOUT DJI AND MAD. G.	0.014	65.708	$H_0: r = 0$	4
	0.012	51.999	$H_0: r \leq 1$			0.010	42.880	$H_0: r \leq 1$	
	0.008	32.048	$H_0: r \leq 2$			0.007	26.337	$H_0: r \leq 2$	
	0.007	18.187	$H_0: r \leq 3$			0.005	14.144	$H_0: r \leq 3$	
	0.004	5.965	$H_0: r \leq 4$			0.003	5.771	$H_0: r \leq 4$	
FTSE 100 – DJI – MAD. G. - DAX 30 – CAC 40	0.016	79.053*	$H_0: r = 0$	2	INDICES WITHOUT FTSE 100 AND MAD. G.	0.011	57.617	$H_0: r = 0$	4
	0.014	51.970	$H_0: r \leq 1$			0.009	38.672	$H_0: r \leq 1$	
	0.009	27.856	$H_0: r \leq 2$			0.007	24.063	$H_0: r \leq 2$	
	0.005	13.065	$H_0: r \leq 3$			0.004	12.492	$H_0: r \leq 3$	
	0.003	4.471	$H_0: r \leq 4$			0.003	5.536	$H_0: r \leq 4$	
FTSE 100 – DJI – MAD. G. - DAX 30 – NIKKEI	0.020	88.479**	$H_0: r = 0$	2					
	0.012	55.048*	$H_0: r \leq 1$						
	0.010	34.199	$H_0: r \leq 2$						
	0.006	17.696	$H_0: r \leq 3$						
	0.005	7.877	$H_0: r \leq 4$						

*The critical values, in these models, for $r = 0$, are 76.07 and 84.45 at the 5% and 1% level of significance, for $r \leq 1$ they are 53.12 and 60.16 at the 5% and 1% level of significance and for $r \leq 2$ the critical values are 34.91 and 41.07 at the 5% and 1% level of significance respectively. The critical values for $r \leq 3$ are 19.96 and 24.60 and finally for $r \leq 4$, the critical values are 9.24 and 12.97. * and ** denotes significance at the 5 % and 1% level of significance respectively.*

Table 9

TESTS FOR COINTEGRATION									
MULTIVARIATE MODELS (SIX INDICES)									
Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR	Indices	Eigenvalue	Likelihood ratio	Hypothesis	Lags in VAR
ALL THE INDICES WITHOUT NIKKEI	0.026	110.750*	$H_0: r = 0$	4	ALL THE INDICES WITHOUT FTSE 100	0.024	102.921*	$H_0: r = 0$	6
	0.013	67.108	$H_0: r \leq 1$			0.011	61.892	$H_0: r \leq 1$	
	0.010	44.626	$H_0: r \leq 2$			0.010	43.107	$H_0: r \leq 2$	
	0.009	27.845	$H_0: r \leq 3$			0.007	26.412	$H_0: r \leq 3$	
	0.004	13.215	$H_0: r \leq 4$			0.006	14.539	$H_0: r \leq 4$	
	0.003	5.755	$H_0: r \leq 5$			0.003	4.981	$H_0: r \leq 5$	
ALL THE INDICES WITHOUT CAC 40	0.020	105.103*	$H_0: r = 0$	4	ALL THE INDICES WITHOUT MAD. G.	0.026	104.357*	$H_0: r = 0$	4
	0.012	71.884	$H_0: r \leq 1$			0.012	60.539	$H_0: r \leq 1$	
	0.010	51.158	$H_0: r \leq 2$			0.010	39.501	$H_0: r \leq 2$	
	0.009	34.844	$H_0: r \leq 3$			0.007	22.561	$H_0: r \leq 3$	
	0.007	20.491*	$H_0: r \leq 4$			0.004	10.966	$H_0: r \leq 4$	
	0.005	8.232	$H_0: r \leq 5$			0.003	4.393	$H_0: r \leq 5$	
ALL THE INDICES WITHOUT DAX 30	0.022	112.732*	$H_0: r = 0$	6	ALL THE INDICES WITHOUT MIBTEL	0.020	104.311*	$H_0: r = 0$	6
	0.015	75.178	$H_0: r \leq 1$			0.013	70.585	$H_0: r \leq 1$	
	0.011	49.530	$H_0: r \leq 2$			0.011	49.118	$H_0: r \leq 2$	
	0.009	31.081	$H_0: r \leq 3$			0.010	30.279	$H_0: r \leq 3$	
	0.006	16.392	$H_0: r \leq 4$			0.006	13.873	$H_0: r \leq 4$	
	0.003	5.575	$H_0: r \leq 5$			0.003	4.324	$H_0: r \leq 5$	
					ALL THE INDICES WITHOUT DJI	0.020	101.914	$H_0: r = 0$	6
						0.013	68.076	$H_0: r \leq 1$	
						0.010	46.527	$H_0: r \leq 2$	
						0.008	29.149	$H_0: r \leq 3$	
						0.006	16.241	$H_0: r \leq 4$	
						0.003	5.730	$H_0: r \leq 5$	

*The critical values, in these models, for $r \leq 0$, they are 102.14 and 111.01 at the 5% and 1% level of significance respectively, for $r \leq 1$, they are 76.07 and 84.45 at the 5% and 1% level of significance, for $r \leq 2$ they are 53.12 and 60.16 at the 5% and 1% level of significance and for $r \leq 3$ the critical values are 34.91 and 41.07 at the 5% and 1% level of significance respectively. The critical values for $r \leq 4$ are 19.96 and 24.60 and finally for $r \leq 5$, the critical values are 9.24 and 12.97. * and ** denotes significance at the 5 % and 1% level of significance respectively.*

the DJI, as is only logical. About the role of the Spanish stock market in the cointegrating relationships, we must be very careful because the significance of the index in the multivariate models could happen because of the existence of the indices of DJI and FTSE 100, something that is enforced by the non-cointegrating relationships when these two indices are absent.

Someone might expect that because of the size of the German economy in the E.U., the DAX 30 would have an important role in the relationships, but the DAX 30 index does not give cointegration in most of the cases. A possible explanation could be that, although the UK and the German stock markets are the biggest in the E.U., FTSE 100 is the index that boosts the European markets in a long run relationship and that because of its relationship with the U.S. market. Finally, we can conclude that DJI is the most important for the long run relationships among the indices with FTSE 100's movements being too important for the markets in the European Union and Nikkei not to give cointegrating relationships.

3.4 Short Run Dynamics

We perform bivariate and multivariate Granger causality models to look at the short run dynamics of the indices. Our data series are integrated of order one, so variables are transformed to stationary by first differencing.

We tested the causalities between the indices in bivariate and multivariate models. The bivariate models answer the question how influential is each index towards the other indices. If an index causes the other one, then we have evidence of market inefficiency. Generally, if the lagged values can help us to predict the index's movements, then someone could develop a profitable trading rule, a rule that can be a proof for the market efficiency hypothesis rejection.

The results from the bivariate models are presented in Table 10. The optimal lag length has been chosen using the Akaike information criterion.

From the results in Table 10 we conclude that the United States stock market has a strong effect on all other markets. This reflects the dominant position of the U.S. economy in the world. On the other hand, the DAX 30, Madrid General, MibTel and Nikkei Granger cause two indices. A noticeable point is that the only European index that the DAX 30 causes is the CAC 40 and not the FTSE 100. On the contrary, the FTSE 100 causes the DAX 30.

From our results until now (cointegration and bivariate Granger causality tests), we deduce that the DJI and FTSE 100 are the most influential indices among those examined. Moreover, there are long run and short run relationships between the other markets. The question arises if, for example, the relationship between the Madrid General and DAX 30 simply reflects the reactions of these two markets to the DJI's

Table 10

GRANGER CAUSALITY TESTS BIVARIATE MODELS					
DJI	Granger causes	DAX 30	DAX 30	Granger causes	CAC 40
		CAC 40			Nikkei
		FTSE 100			
		Madrid General	CAC 40	Granger causes	DJI
		MibTel			DAX 30
		Nikkei			FTSE 100
					MibTel
FTSE 100	Granger causes	DJI			Nikkei
		DAX 30			
		CAC 40	Madrid General	Granger causes	DAX 30
		Nikkei			Nikkei
Nikkei	Granger causes	DJI	MibTel	Granger causes	DAX 30
		Madrid General			Nikkei

and FTSE's movements. One way to ascertain this indirect influence is to create a model, which will be based on the DJI and FTSE 100 and each time to add to this model the index that really has a major influence on the stock exchange relationships until no indices are useful in the model.

Using Hsiao's Final Prediction Error (FPE) procedure, we start from the bivariate model of the DJI and FTSE 100 with 3 lagged values from each index (results from the Granger causality bivariate models) and each time we include variables in the short run dynamic model. Table 11 presents the multivariate causality results with the variables of the model being the DJI (3 lags), FTSE 100 (3 lags), Nikkei (1 lag) and CAC 40 (2 lags). The method used for the estimations was the maximum likelihood and the GARCH models in order to correct the time series from heteroscedasticity.

It can be noticed from the Table, the DJI's previous two movements, drive the other stock markets (except the Nikkei which is caused with one lag). The FTSE 100 also affects the other indices as well as the CAC 40.

The indices that are not included in the models are the DAX 30, MibTel and Madrid General, a result that confirms that a) the FTSE 100 is the most important index in Europe with its movements leading the movements of the DAX 30 and the other European indices and b) the stronger economies and markets are the ones that exert influential significance.

Table 11

SHORT RUN DYNAMICS MULTIVARIATE MODELS				
	DJI	FTSE 100	NIKKEI	CAC 40
DJI (-1)	-0.050	0.169**	0.221**	0.186**
	-1.789	7.161	7.786	5.661
DJI (-2)	-0.003	0.051*	0.027	0.085**
	-0.114	2.058	0.726	2.619
DJI (-3)	-0.056	0.023	0.031	0.021
	-1.795	0.907	0.994	0.650
FTSE 100 (-1)	0.062	-0.055	0.116*	-0.015
	1.837	-1.671	2.573	-0.369
FTSE 100 (-2)	-0.086*	-0.107**	-0.043	-0.085*
	-2.534	-3.307	-0.922	-2.033
FTSE 100 (-3)	0.055*	-0.066*	-0.054	-0.085*
	2.018	-2.414	-1.538	-2.429
NIKKEI (-1)	-0.011	-0.046**	-0.108**	-0.038
	-0.557	-3.029	-3.936	-1.809
CAC 40 (-1)	0.030	0.003	0.128**	-0.063*
	1.185	0.149	3.724	-2.005
CAC 40 (-2)	0.068**	0.048*	0.017	0.024
	2.810	2.113	0.493	0.789
R^2	0.007	0.060	0.082	0.031
FPE	0.000124	0.000103	0.000211	0.000175

* *denotes significance at the 5% level of significance.*
** *denotes significance at the 1% level of significance.*

3.5 Impulse Response Function

In order to measure the time profile of the effect of a typical shock (i.e. positive residuals of one standard deviation) on the behavior of the series, we examine the pattern of dynamic responses of each of the indices to innovations in a particular market.

As we stated earlier, it is very important which variable will be first in the system because the results are not invariant to the ordering of the variables in the VAR. From the methods used until now, we have concluded that the conditions in the United States economy have a strong influence on the rest of the stock markets being examined. This is the reason why we concentrate our analysis on the responses of each of the markets to a shock in the United States market.

Table 12 presents the normalized impulse responses of the examined markets to a unit shock in the United States market. As can been seen from Table 12, innovations in the stock market of the United States are rapidly transmitted to all other markets. All the markets, except the Nikkei, have a strong response to the U.S. shock on day 1, a response that declines on day 2 and is eliminated on day 3.

Table 12

IMPULSE RESPONSE FUNCTION							
IMPULSE RESPONSE OF A MARKET TO THE UNIT SHOCK IN THE U.S. MARKET							
Period	**FTSE 100**	**DAX 30**	**CAC 40**	**MAD. G.**	**MIBTEL**	**NIKKEI**	**DJI**
1	-19.84	-19.74	-18.27	-17.71	-15.36	-5.62	-58.47
2	-8.15	-7.90	-5.94	-4.92	-4.51	-9.17	2.20
3	1.00	-0.55	0.66	0.43	0.57	0.21	1.84
4	3.95	3.21	1.80	1.69	0.91	2.28	-1.44
5	-0.55	-0.21	-1.21	-0.55	-0.78	0.69	-0.87

These normalized impulse responses are the estimates of moving average coefficients of the VAR model divided by their standard errors.

This strong response of the markets to the unit shock in the U.S. market is logical since the U.S. market is the last one that opens with the other ones to be closed or about to close. So the European stock markets and the Japanese are expected to react to the U.S. shock with a one-day lag. The U.S. market is so influential that the typical shock is not eliminated on day 1 but still exists on day 2 in a weaker condition. After these two days, the impulse response is close to zero with the transmission of the United States market being completed.

Finally, an interesting point from Table 12 is the almost identical way that the FTSE 100 and DAX 30 respond to U.S. shocks with the FTSE 100 reacting marginally stronger, a result that is logical because of the special relationship between the U.S. and the UK economy (as has been shown before).

4. Conclusions

In this study we examined the interdependence structure of seven major national stock markets for the period Tuesday 2nd January of 1995 to Friday 31st August of 2001. Our first concern was to see if there are linkages among the stock markets by using cointegration analysis. After watching for long-run relationships, we examined the causal effects between the value changes of the indices in order to see if the U.S. market is the most important stock market in the world and the leading one. At last, we checked the mechanism by which innovations in one stock market are transmitted to other markets over time.

From the bivariate cointegration analysis we conclude that the DJI and FTSE 100 have the most long run relationship. In order to test if there are indices that play a special role in the cointegrating relationships, we used multivariate models with groups of 3, 4, 5, 6 and 7 indices. From the results we conclude that without the DJI index there is no long run relationship, and, considering that there is cointegration among the indices, this result reinforces the argument that the U.S. market is the most important stock market in the world. From the European indices we conclude that there is evidence that the FTSE 100 is the index with the stronger linkage with the other European indices. The DAX 30 and CAC 40 seem to have weak long run relationships with the other indices. For the period examined, the Nikkei did not have the same value trend as the other indices, something that is obvious from the bivariate models (no long-run relationship for the Nikkei).

In order to examine how influential each index is towards the other indices, we used bivariate Granger causality models and we conclude that the U.S. causes all the other markets. The most influential index in the European Union is the FTSE 100, which causes the four biggest examined markets (U.S., German, French and Japanese market). The problem in the bivariate Granger causality analysis is that the causalities may happen because of the indirect influence between the indices. In order to avoid this problem, we created a multivariate short run dynamic model with the indices that do not have direct influence on the relationships between the indices to be excluded from the model. According to the methodology we used, the DJI, FTSE 100, Nikkei and CAC 40 are the indices that constitute the model, with the DJI as the leading index and the FTSE 100 driving the other European markets because of the U.S. influence. A very interesting point in the short run dynamic model is the absence of the DAX 30. Although the German and the UK stock markets are the biggest and most important in the European Union, the DAX 30, unlike the FTSE 100, seems not to have a strong effect on the other markets. A possible explanation for this finding is the special relationship between the two markets. In particular, the German and the UK stock markets do have a high degree of integration. However, these two indices do not have the same degree of integration with the U.S. economy. The UK and the U.S. economy do have a closer relationship. Because of the leading character of the DJI and its significant relationship with the FTSE 100, the FTSE 100 is the index that sets the tone of movements in the European Union with the DAX's influences being embedded in the FTSE 100's influences. An additional explanation might be that the German stock market has developed significantly since the mid 90's, although it has not yet reached the market capitalization and the transactions magnitude of the London Stock Exchange.

Finally, as we measure the time profile of the effect of a typical shock in the U.S. market, we find that the shock is strong enough to need two days to be eliminated. This finding is logical since the U.S. market is the last one that opens with the other ones being closed or about to close.

In this study, we have established that there still exists interdependence among the stock markets with the U.S. market as the most influential one and the UK stock market as the leading market in the European Union in the period under scrutiny.

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