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# The Long Term Dynamics of the European Stock Exchanges: «Leaders and Followers»

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**Abstract**

*The purpose of this article is to investigate the possibility of a long term predictive relationship among the major European stock markets, contrary to the prediction of the Efficient Market Hypothesis. Analytically, we examined the possibility of predictive relationships between the stock markets of Amsterdam, Athens, Brussels, Frankfurt, London, Madrid, Milan, Paris and Zurich for the 1992-1996 period.*

*The theory of cointegration and Error Correction Models (ECM), provide a method of testing the extent of possible links among the European equity markets. The statistical results indicated that the stock exchange of London «leads» and the Athens Stock Exchange «follows» some of the other European markets.*

**JEL Classification:** G14

## 1. The European Stock Market Links.

It is argued that the European markets have become integrated in the recent years and consequently are affected by the same factors and should react, at least to a certain extend, to the same news. For instance, news about the economic policy of Europe should affect all European stock markets, leading to a degree of positive correlation in their stock prices.

The integration process started with the relaxation of controls on capital movements and followed by the relaxation of exchange controls. Nevertheless, some forces make expected returns in different European markets positively related even if there are no financial transactions. For instance, if the demand increases in a European country, say A, which increases the expected earnings and dividends of domestic companies, it can also increase the expected earnings of a company, say X, which has its headquarters in another European country and sell its products in country A. Additionally, local recession in country A, which should affect its stock market, it is likely to decrease the demand for X's products and

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lower X's earnings, dividends and stock price in its national market. Consequently, changes in stock prices in country A and country B can be positively correlated to some degree even if no foreigner can buy stock in either country. This example, while trivial in some respects, points out that inter-European trade creates a link between at least some stocks in different national markets in Europe.

In addition to the above arguments, the last decade substantial improvements have been made in communication technology that have lowered the cost of international information flows and cross-border financial transaction costs. Today, transaction costs are relatively unimportant in buying and selling large blocks of stocks around the world. With improvements in communications and the ability to order trades over phone lines, the explicit cost of buying stocks in country B to someone in country A, is little more than the cost to someone in country B.

Finally, the globalization of financial activities has led to the argument that the behavior of stock prices is influenced by international psychological factors to a greater extent than before. For instance, it is widely believed that investors make comparisons of valuations in different countries, often using higher valuations in some countries as justification for investing in lower valued markets since it is believed that a process of «catching up» among stock markets is at work.

The empirical studies of the above arguments give contradictive results. Taylor and Tonks (1989) report a long run statistical relationship between the U.K. and other international stock markets. On the contrary Byers and Peel (1993), find little evidence of such relationship between U.S., U.K., Germany, Japan and Netherlands for the period 1979-1989. Blackman et al (1994) also report that there is no evidence of long run relationship between European stock markets for the period 1984-1989. In another study, Arshanapali and Doukas (1993), using daily data for the period 1987-1988 found evidence that the correlation between the major European stock markets has increased after the 1987 crash. Finally, Siriopoulos (1996), found evidence of interdependence between the small European markets after the 1987 crash and in another study reports a significant common trend between the small European markets and the U.S. and Japanese markets, (1997).

## 2. Stock Market Efficiency and «causality»

A market is efficient if prices rationally, fully and instantaneously reflect all relevant available information and no profit opportunities are left unexploited, Fama (1976). In an efficient market past information is of no use in predicting future prices and the market should react only to new information (news). Since news is unpredictable by definition, price changes or returns in an efficient market, cannot be predicted. Under the *Efficient Market Hypothesis* it is true that:

$$P_t = P^*_t/I_{t-1} + u_t \text{ or } E(u_t) = 0 \tag{2.1}$$

where $I_{t-1}$ is the information set available at time t-1, $P_t$ is the actual price at time t, $P^*_t$ is the expected price which is based on the information set $I_{t-1}$, so $P^*_t$ is uncorrelated with $u_t$, and additionally the forecast error $P_t-P^*_t$ is uncorrelated with variables in the information set $I_{t-1}$. Empirical tests for market efficiency

usually examine whether price changes or stock returns are uncorrelated with variables in the information set $I_{t-1}$[1].
A very popular way to test the existence of any temporal statistical relationship with predictive value between two time series, and consequently a test for market efficiency, is the Granger «causality» test.
Granger's definition for «causality» is in terms of predictability: A variable X causes another variable Y, with respect to a given information set that includes X and Y, if present Y can be better forecasted by using past values of X than by not doing so.
The presence of «causality» obviously implies market inefficiency: As pointed out earlier for a stock index, say j, under the *Efficient Market Hypothesis* (E.M.H.), it is true that:

$$E(\Delta P_{jt}/I_{t-1}) = 0 \tag{2.2}$$

where $I_{t-1}=[P_{j,t-1}, P_{j,t-2}, P_{j,t-3},\ldots\ldots\ldots P_{j,t-n}]$ and $P_{jt-1},\ldots\ldots P_{jt-n}$ the price history of the stock index j.

If it is also true that:

$$E(\Delta P_{jt}/H_{t-1}) = 0 \tag{2.3}$$

where $H_{t-1}=[P_{j,t-1}, P_{j,t-2}, P_{j,t-3},\ldots\ldots\ldots P_{j,t-n}, P_{k,t-1}, P_{k,t-2}, P_{k,t-3},\ldots\ldots\ldots P_{k,t-n}]$ and $P_{k,t-1},\ldots\ldots P_{k,t-n}$ the price history of a variable k different than j, then no «Granger causality» exists and the market is still efficient with respect to the information set $H_{t-1}$. The opposite case implies that the price history of stock index k can help to predict the price change of stock index j (variable k «Granger cause» variable j), and the market is inefficient with respect to the information set $H_{t-1}$.

## 3. The methodology used.

In Granger's methodology, when we test for «causality» we in fact test for precedence and for linear precedence, in particular. Thus, if we consider two time series as $Y_t$ and $X_t$, the series $X_t$ fails to Granger cause $Y_t$, if in a regression of $Y_t$ on lagged Y's and lagged X's the coefficients of the latter are zero.

That is, consider equations 3.1 and 3.2:

$$Y_t = \alpha + \sum_{i=1}^{n}\beta_i\, Y_{t-1} + \sum_{j=1}^{n}\gamma_i\, X_{t-1} + \varepsilon_t \tag{3.1}$$

$$X_t = \alpha + \sum_{i=1}^{n}\delta_i\, X_{t-1} + \sum_{j=1}^{n}\zeta_i\, Y_{t-1} + \nu_t \tag{3.2}$$

If in the above equations, $\gamma_i=0$ for i=1,2,....n in equation (3.1) we can conclude that $X_t$ fails to Granger cause $Y_t$. If also $\zeta_i=0$ for i=1,2,3.....n in equation (3.2) then $Y_t$ fails to «Granger cause» $X_t$. Then we can conclude that the two series are temporally uncorrelated.

If $\gamma_i\neq0$ for i=1,2,3...n in (3.1) and $\zeta_i=0$ for i=1,2,3....n in (3.2) then $X_t$ «Granger cause» $Y_t$. Also if $\gamma_i=0$ i=1,2,3....n in (3.1) and $\zeta_i\neq0$ i=1,2,3.....n in (3.2) then $Y_t$ «Granger cause» $X_t$.

[1] See, for instance, Cootner (1962), Fama (1965), Gowland and Baker (1970), Cutler, Poterba and Summers (1989), MacDonald and Taylor (1988, 1989, 1993), Spiro (1990), Frennberg and Hansson (1993), Jung and Boyd (1996), Al-Loughani and Chappel (1997).

Finally, if $\gamma_i$ and $\zeta_i$ are different from zero in equations (3.1) and (3.2) then we conclude that between $X_t$ and $Y_t$ there is a bi-directional «causality». Note that in all the above regressions $\varepsilon_t$ and $v_t$ should be white noise and uncorrelated at any lag other than t.

The «Granger causality» tests apart from the fact that they have been characterized as «*soft econometrics*», Rowley and Jain (1986), are usually performed on stationary data. Nevertheless, first difference transformation which is used to obtain stationarity, filters out low frequency (long run) information. Cointegration and error correction models reintroduce, in a statistically acceptable way, the low frequency information. The basic idea of cointegration is that two or more series move closely together in the long run, even though the series themselves are trended, the difference between them is constant. We may regard the cointegrating series as defining a long run equilibrium relationship and the difference between them to be stationary. The term equilibrium in this case suggests a relationship which on average has been maintained by a set of variables for a long period, Hall and Hendry (1988).

Following Engle and Granger (1987), cointegration can be defined as follows:

Consider two series $X_t$ and $Y_t$, which are both I΄(1) processes. If there exists a linear combination of X and Y say

$$z_t = X_t - \alpha Y_t \tag{3}$$

which is I~(0), we say that X and Y are cointegrated, where $\alpha$ is the cointegrating parameter.

Hence if $X_t$, $Y_t$ are both integrated of order one and cointegrated then the equilibrium error term $z_t$ will be integrated of order zero , and $z_t$ will rarely drift far from zero, if it has a zero mean, and will often cross the zero line. In other words equilibrium will occasionally occur, at least to close approximation.

If Xt and Yt are not cointegrated, the equilibrium error can wander widely and zero crossings would be very rare, suggesting that under such circumstances the concept of equilibrium has no practical implications, Engle and Granger (1987).

If two variables are cointegrated then according to the Granger Representation Theorem, Engle and Granger (1987), there must exist an Error Correction Representation of the following form:

$$Y_t = -\varrho_1 \hat{z}_{t-1} + \alpha + \sum_{i=1}^{n} \beta_i + \sum_{j=1}^{n} \gamma_i X_{t-1} + \varepsilon_t \tag{3.4}$$

$$X_t = -\varrho_2 \hat{z}_{t-1} + \alpha + \sum_{i=1}^{n} \delta_i X_{t-1} + \sum_{j=1}^{n} \zeta_i Y_{t-1} + \nu_t \tag{3.5}$$

where $z_{t-1}$ is implicitly defined in (3.3) and $\varrho_1+\varrho_2\neq 0$ and $\varepsilon_{1t}$ and $\varepsilon_{2t}$ are finite moving averages. Thus, changes in the variables $X_t$ and $Y_t$ are partly driven by the previous value of $z_t$.

An Error Correction model that incorporates errors from a cointegrating regression has some interesting temporal «causality» interpretations, (Granger, 1988). Cointegrated variables in the bivariate case must possess temporal «causality» in the Granger sense in at least one direction. For a pair of series to have an attainable equilibrium, there must be some causation between them to provide the necessary dynamics. It follows from this that since the Error Correction Term, $z_{t-1}$, must occur in at least one of the Error Correction Equations, it must improve the forecasting ability of at least on one of $X_t$ or $Y_t$. Thus, one important implication to emerge from the cointegration literature (Engle and Granger 1987), is that prices in an efficient speculative market cannot be cointegrated.

Apart from the cointegration analysis, suggested by Engle and Granger (1987), a cointegration technique derived by Johansen (1988, 1991) and Johansen and Juselius (1990), is alternatively proposed. This Maximum Likelihood approach (M.L.), in comparison to the Granger - Engle OLS approach provides consistent ML estimates of the whole cointegrating matrix, and produces a maximum likelihood-ratio statistic for the maximum number of distinct equilibrium vectors in the matrix. Additionally, test statistics for cointegration in the Granger-Engle (G.E.) approach, like the Augmented Dikey - Fuller test on the residuals of the cointegrating regression, cannot be compared with critical values from known distributions, as the distribution is a function of the whole data generation process (which is of course unknown). The above advantage make Johansen's approach preferable than the two step Granger Engle approach.

## 4. The Data Used

In our analysis we used daily closing prices, adjusted for dividends, stock splits and reverse stock splits, for the stock markets of Amsterdam, Brussels, Frankfurt, London, Madrid, Milan, Paris and Zurich for the time period from May 4, 1992 to June 5, 1998 with a total of 1590 observations for every series under investigation. In all cases we used the logarithmic transformation of the closing prices.

## 5. Results and Conclusions

The order of integration of a series (that is the number of times it must be differenced before attaining stationarity) may be ascertained by the application of a set of tests, commonly known as test for unit roots. A number of tests are available for testing whether a series is stationary. We performed the Augmented Dickey-Fuller (ADF) regression in order to ensure white noise residuals in the Dickey-Fuller regressions and the results are presented in Table I. It is clear from this table that the null hypothesis that any of the price series have unit roots cannot be rejected. This is confirmed by the ADF statistics which test for unit roots in the first differenced series. In each case the null hypothesis is easily rejected. Together with the results in the level series, it strongly implies that each of the stock price series are integrated of order one I~(1).

In Table 2 we present the L.M statistics for autocorrelation and ARCH effects for every series under investigation after transforming the series in order to obtain stationarity[1]. The statistical evidence indicates that all series exhibit significant ARCH effects except the Milan stock price index. In addition there is

[1] In that case we used the difference of the logarithmic transformation. The above transformation approximates the percentage price change and assuming that dividend is zero the above transformation equals to the stock return.

strong statistical evidence that some series exhibit serial correlation, i.e. Athens, Brussels, Frankfurt and Zurich. This is an evidence of violation of the Efficient Market Hypothesis since the autocorrelation pattern indicates that past price changes can help to predict future price changes.

In Table 3 we present the cointegration results with the Johansen methodology. The results indicate that the null hypothesis of no cointegration is violated in a number of cases, providing more evidence against the Efficient Market Hypothesis since the price movements of a stock index, can be forecasted by the price movements of another stock index. We must note here that since we use in our analysis nine variables we examined the possibility for cointegration in 36 pairs of variables. Thus, someone could expect that some of the cointegration statistics to be statistically significant due to chance.

In Table 4 we present the results of the Error Correction Models, which we formed in the case of the variables for which we have evidence for cointegration. For the choice of the lag length used in the error correction model, we used the Hendry's general to specific modeling strategy, eliminating lags with insignificant parameter estimates and taking into account model selection criteria like the Akaike criterion. From Table 4, according to the Error Correction Term estimates and their statistical significance, we can conclude that the London Stock Exchange plays a «leading» role since it precedes a significant number of other European Stock Exchanges. Analytically, the results indicate that London precedes the Stock Exchanges of Amsterdam, Athens, Brussels, Frankfurt, Madrid and Zurich.

On the other hand, the Athens Stock Exchanges plays a «follower» role since it is preceded by a number of other European Stock Exchanges, i.e. Frankfurt, London, Milan and Paris.

According to our results, there is evidence that there are stock price links among the European Stock Exchanges. The European national markets are expected to react, more or less, to some common factor affecting the European economy, but the faster or slower reaction of some of these national markets creates a «leader» and «follower» effect. In an effort to explain the results, the follower behaviour of Athens can be explained as a «trading hours effect» since Athens' closing time is before that of the other European Stock markets. Thus the closing prices in the European markets at some time, say t, may influence the closing price of Athens the next time period..

On the other hand, the leader behaviour of London could be explained as a «size effect». Since London is by far the larger stock Exchange in Europe we may expect London market to be much more reactive that the other markets due to the intense competition among market participants. Thus, news witch are quickly reflected on stock prices in London are reflected with some delay on the prices of the other European markets.

Finally, we think that it would be interesting to examine the leading lagging relationships of the European stock exchanges with the help of additional variables like the volume of trading or volatility measures and on the basis of ultra high frequency data. This will be done in a future research.

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**Table 1:** *A.D.F. test of the series*

| Variable | A.D.F. statistic Levels | A.D.F. statistic First Difference |
|---|---|---|
| **Amsterdam** | 1.99 | -19.39** |
| **Athens** | 1.17 | -17.55** |
| **Brussels** | 2.57 | -17.75** |
| **Frankfurt** | 1.84 | -18.72** |
| **London** | 0.59 | -18.83** |
| **Madrid** | 1.93 | -18.08** |
| **Milan** | 0.40 | -17.06** |
| **Paris** | 1.53 | -18.86** |
| **Zurich** | 1.68 | -20.67** |

*Double star(**) indicates significance at 99 % confidence interval.*

**Table 2:** *Autocorrelation and ARCH - L.M. test*

| Variable | Autocorrelation L.M. test | ARCH L.M. test |
|---|---|---|
| **Amsterdam** | 2.81 | 29.80** |
| **Athens** | 13.49** | 54.92** |
| **Brussels** | 6.00** | 13.73** |
| **Frankfurt** | 4.40* | 15.90** |
| **London** | 0.99 | 9.35* |
| **Madrid** | 0.47 | 13.08** |
| **Milan** | 1.78 | 0.21 |
| **Paris** | 0.85 | 10.36** |
| **Zurich** | 16.36** | 156.13** |

*Single star (*) indicates significance at 95 % confidence interval*
*Double star (**) indicates significance at 99 % confidence interval.*

**Table 3:** *Johansen cointegration test*

| Pair of Variables | Eigenvalue | Likelihood ratio | Cointegrating vectors |
|---|---|---|---|
| **Amsterdam – Athens** | 0.008 | 14.21 | 0 |
| **Amsterdam – Brussels** | 0.007 | 17.53 | 0 |
| **Amsterdam – Frankfurt** | 0.008 | 15.49 | 1 |
| **Amsterdam – London** | 0.013 | 22.13 | 1 |
| **Amsterdam – Madrid** | 0.003 | 9.90 | 0 |
| **Amsterdam – Milan** | 0.003 | 6.88 | 0 |
| **Amsterdam – Paris** | 0.003 | 6.76 | 0 |
| **Amsterdam – Zurich** | 0.004 | 9.50 | 0 |
| **Brussels – Athens** | 0.011 | 20.37 | 1 |
| **Athens – Frankfurt** | 0.009 | 17.84 | 1 |
| **Athens – London** | 0.009 | 15.76 | 1 |
| **Athens – Madrid** | 0.016 | 27.64 | 1 |
| **Athens – Milan** | 0.010 | 18.53 | 1 |
| **Athens – Paris** | 0.012 | 23.94 | 1 |
| **Athens – Zurich** | 0.006 | 12.34 | 0 |
| **Brussels – Frankfurt** | 0.017 | 32.65 | 1 |
| **Brussels – London** | 0.013 | 23.32 | 1 |
| **Brussels – Madrid** | 0.008 | 20.85 | 0 |
| **Brussels – Milan** | 0.004 | 11.41 | 0 |
| **Brussels – Paris** | 0.005 | 11.97 | 0 |
| **Brussels – Zurich** | 0.009 | 19.00 | 0 |
| **Frankfurt – London** | 0.009 | 12.62 | 1 |
| **Frankfurt – Madrid** | 0.013 | 24.55 | 1 |
| **Frankfurt – Milan** | 0.003 | 8.80 | 0 |
| **Frankfurt - Paris** | 0.003 | 8.32 | 0 |
| **Frankfurt - Zurich** | 0.006 | 15.32 | 0 |
| **London - Madrid** | 0.010 | 16.40 | 1 |
| **London - Milan** | 0.003 | 5.78 | 0 |
| **London - Paris** | 0.005 | 9.55 | 0 |
| **London - Zurich** | 0.012 | 20.07 | 1 |
| **Madrid - Milan** | 0.003 | 9.30 | 0 |
| **Madrid – Paris** | 0.005 | 10.60 | 0 |
| **Madrid - Zurich** | 0.009 | 19.87 | 1 |
| **Milan - Paris** | 0.006 | 12.62 | 0 |
| **Milan - Zurich** | 0.003 | 9.26 | 0 |
| **Paris - Zurich** | 0.003 | 8.31 | 0 |

**Table 4:** *Error correction results*

| Pair of Variables | ECT estimate and t statistic | «Causality» direction |
|---|---|---|
| **Amsterdam – Frankfurt** | -0.022 (6.64)** | Frankfurt «causes» Amsterdam |
| **Frankfurt – Amsterdam** | -0.008 (1.75) | |
| **Amsterdam – London** | -0.008 (2.87)** | London «causes» Amsterdam |
| **London – Amsterdam** | 0.001 (0.73) | |
| **Brussels – Athens** | -0.002 (2.21)** | Bi-directional «causality» |
| **Athens – Brussels** | -0.009 (3.86)** | |
| **Athens – Frankfurt** | -0.010 (3.96)** | Frankfurt «causes» Athens |
| **Frankfurt – Athens** | -0.001 (0.72) | |
| **Athens – London** | -0.008 (3.91)** | London «causes» Athens |
| **London – Athens** | -0.001 (0.88) | |
| **Athens – Madrid** | -0.010 (5.04)** | Bi-directional «causality» |
| **Madrid - Athens** | -0.005 (2.38)** | |
| **Athens – Milan** | -0.006 (3.87)** | Milan «causes» Athens |
| **Milan – Athens** | 0.0007 (0.42) | |
| **Athens – Paris** | -0.010 (4.60)** | Paris «causes» Athens |
| **Paris –Athens** | 0.001 (0.40) | |
| **Brussels – Frankfurt** | -0.008 (1.98)* | Bi-directional «causality» |
| **Frankfurt – Brussels** | -0.036 (5.02)** | |
| **Brussels – London** | -0.008 (3.75)** | London «causes» Brussels |
| **London – Brussels** | 0.001 (0.55) | |
| **Frankfurt – London** | -0.010 (3.50)** | London «causes» Frankfurt |
| **London – Frankfurt** | -0.0007 (0.35) | |
| **Frankfurt – Madrid** | -0.020 (4.24)** | Madrid «causes» Frankfurt |
| **Madrid – Frankfurt** | -0.005 (0.98) | |
| **London – Madrid** | -0.0003 (0.20) | London «causes» Madrid |
| **Madrid – London** | -0.007 (3.45)** | |
| **London – Zurich** | 0.02 (1.12) | London «causes» Zurich |
| **Zurich – London** | -0.012 (3.85)** | |
| **Madrid – Zurich** | 0.0004 (0.07) | Madrid «causes» Zurich |
| **Zurich - Madrid** | -0.030 (4.94)** | |