THE INFLUENCE OF FOREIGN MARKETS ON THE ATHENS STOCK EXCHANGE

By

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Abstract

This paper examines the influence of Standard and Poor 500 (SP-500) and Financial Times 100 (FT-100) stock price indices on the General Index (GEN) of the Athens Stock Exchange (ASE), which belongs to the European Emerging Markets. The methodological approach is based mainly on multivariate Box-Jenkins modelling. The results indicate that there is statistically significant causal effect of small magnitude from SP-500 on GEN and a weak but also statistically significant correlation between FT-100 and GEN. The explanatory power of both the causal effect and the correlation on GEN is smaller as compared with that of its own past history. The existence of substantial within — series correlation in GEN, but primarily its particular pattern, entails the rejection of the hypothesis, of weak-form market efficiency for ASE. However, ASE is informationally efficient in terms of the time required for the assimilation of new information from foreign markets. (JEL: G14, G15, C22, C32).

1. Introduction

Co-movement in stock prices in different countries is of interest for several reasons. Primarily it is of interest to investors who wish to obtain the maximum possible rate of return on their investment for a given risk, by properly allocating their investment portfolios. It is also of interest to the economic forecasters and policy makers as the covariation of stock prices: (a) can be considered as an alternative measure of financial integration, the latter being customarily assessed in terms of dispersion of interest rates between markets; (b) indirectly affect consumption and investment expenditures.

Since the establishment of the theoretical framework of modern financial theory (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) there have been numerous studies which have examined the covariation in the stock indices of most of the mature financial market world-wide and its importance in mean-variance portfolio analysis (e.g. Crubel, 1968; Solnik, 1974; Eun and Shim, 1989; Jeon and Furstenberg, 1990). A plethora of methodologies have been used for this purpose, including techniques of multivariate statistical analysis (e.g. principal component analysis (Feeney and Herst, 1967), factor analysis (Ripley, 1973), and cluster analysis (Panton et al., 1976), spectral methods (Granger and Morgenstern, 1970; Hilliard, 1979), OLS regression models (Eun and Resnick, 1984), multivariate time series methods (Dwyer and Hafer, 1988) and vector autoregressive models (Eun and Shim, 1989; Jeon and Furstenberg, 1990). In terms of time intervals daily data (Jeon and Furstenberg, 1990; Eun and Shim 1989), weekly data (Granger and Morgenstern, 1970) as well as monthly data (Agnon, 1974; Ripley, 1973) have been used.

Although there are some controversies as regards the conclusions of these studies (see Jeon and Furstenberg, 1990 for a review on this mater) there is a general agreement on several points, the most important of which are summarized below: (i) co-movement in share prices within a single Financial Market are clearly more pronounced than between different Markets; (ii) geographical proximity, as well as cultural ties (e.g. partnership in the British Commonwealth) increase the co-movement between the Markets; (iii) co-movement has been increased over the last years as a result of certain financial regulations (e.g. the financial services act of 1986 for the London Stock Exchange), political decisions (e.g. the 1987 accord for international co-operation in macroeconomic policymaking by the leaders of the Group of Seven in Louvre, France), and significant events of global importance (e.g. the stock market crash of October 1987 and the Gulf War in 1991); (iv) any lead - lag relationships are such that the resulting dynamic responses are consistent with the notion of informationally efficient financial markets.

From the methodological standpoint, testing the hypothesis of the so-called weak form efficiency (i.e. that share prices move independently of previous movements, and thus there are no patterns enabling the prediction of future price movements from studying charts of past prices), is the first, step to be followed is such studies. This is necessary because any effect of past prices on future prices of the same market should be taken into account before the co-movement of this market with other markets is considered. For the Mature Financial Market it has been well established that the hypothesis of weak form efficiency is not rejected (e.g. Brealy and Mayers, 1988).

In spite of the great number of studies which deal with Mature Financial Markets in regard to co-movement among markets, such studies for the socalled Emerging Financial Markets are relatively scanty (e.g. Lessard, 1973). Theodossiou et al. (1993) test for dependencies in the first and second moments of the joint distributions of the Greek and US stock returns in a GARCH framework using weekly data. They find that stock market returns in Greece are related to past US returns, but volatility in the two markets is not linked.

Studies of efficiency for the ASE as well as other emerging markets gave controversial results. Among the empirical studies examining efficiency in the Athens Stock Exchange (ASE) Niarchos and Georgakopoulos (1986) examined the effect of annual corporate profit reports on the share prices of ASE, and found a slow and gradual adjustment of stock returns to new information, which entails the rejection of efficiency. Stengos and Panas (1992) conclude that the Efficient Market Hypothesis (EMH) cannot be rejected in its weak and semistrong form for the banking sector of the ASE, while Niarchos and Alexakis (1997) examined the returns between common and preferred stocks and concluded that the EMH is rejected. As far as other emerging markets are concerned, Antoniou et al. (1997) tested the EMH in its weak form for the Istanbul Stock Exchange, and found that the hypothesis is rejected for many stocks. Urrutia (1995) reached to the same conclusion for the Latin American Markets. However, Cooper (1983), and Dockery and Vergari (1997) found that the hypothesis cannot be rejected for the Corean and the Budapest Stock Exchange respectively.

The purpose of this study is to examine the effect of Mature Financial Markets on the Athens Stock Exchange (ASE). To this end, the hypothesis of weak-form efficiency for ASE will first be tested. The methodology to be used is Box-Jenkins transfer function modelling. The proposed methodology has the comparative advantage over the methods usually employed for similar studies that, in addition to any lead-lag relationships, it also allows for contemporane-ous co-movements to be examined. The hypothesis of informational efficiency (in terms of the transmission and assimilation of information from other markets) for the ASE will also be examined and for this purpose it is necessary to use daily data rather than data of lower frequency.

ASE belongs to be European Emerging Markets together with the Lisbon, Istanbul and recently the stock exchanges of some of the East European excommunist countries. The capitalization of the Athens equity market as at the end of March, 1994 was 3.5 trillion drachmas (i.e. \$14.3 billion, approximately). In order to examine the effect of the Mature Markets on ASE, we selected New York, which in terms of capitalization value is the largest market in the world (in the late 80's and until 1990 the Tokyo market had taken the lead), and the London market which is the largest market of the European continent and the third largest worldwide after New York and Tokyo.

The rest of this paper is organised as follows: in section 2 we describe the available data and establish the methodological approach. Results and the associated comments are presented in section. 3. The concluding remarks are stated in section 4.

2. Data and Methodology

Daily values of the Standard and Poor-500 index and the FT-100 index are used for the New York and London markets respectively. For the ASE the General Index (GEN) will be used. This index comprises about a third of the companies listed in the ASE (53 of the 164 listed companies in 1992). It is important to use daily data as lower frequency data may obscure any lag relationships and informational efficiency will not be able to be tested. The period that the data cover is from January 8, 1990 until October 19, 1992. In the cases when one market was closed, the corresponding index has been given the value of the previous day. Totally there are 715 daily values. It should be mentioned that the three markets do not operate concurrently. ASE opens at 9.00 UTC, and closes at 11.00 UTC; The London International Stock Exchange (ISE) from 9.00 UTC to 17.00 UTC; The New York Stock Exchange (NYSE) from 14.30 UTC to 22.00 UTC. Hence, there is no overlap between ASE and NYSE but there is a two and a half hours overlap between ISE and NYSE and an overlap between ASE and ISE for the whole period that ASE is open.

Figure 1 represents the variations of GEN, SP-500 and FT-100 against time. The series have been adjusted so that all series start with the value 100. The actual values of GEN are shown in Figure 2. Some events with strong potential influence on share prices are spotted in the same Figure. As indicated by Figure 2 share prices rose sharply in ASE before July 1990. This remarkable rise coincided with the formation of a stable government after the parliamentary elections, the election of K. Karamanlis in the Presidency of the Republic, and the expectations that the city of Athens would undertake to host the 1996 Olympic Games. On the other hand the sharp decline in share prices that followed, may partly be attributed to the crisis in the Greek - FYROM relations, the invasion of Iraq into Kuwait and the assignment of the 1996 Olympic Games to Atlanta, USA.

Another point which should be mentioned as far as GEN is concerned is the imposition of limits outside of which changes in the daily share prices are not allowed to occur. On August the 18th 1982 a computerised tranding system started to operate in the ASE. At this date a limit of $\pm 10\%$ on the daily price changes was first applied for five shares of the banking saector. This limit was gradually extended and by December 24, 1992 it had been applied to all the shares. The numerical value of the limit was finally set to $\pm 8\%$ for shares with relatively higher volume of daily transactions and to $\pm 4\%$ for those with lower volume of daily transactions. Inevitably these limits have restricted the variability of GEN.

A stationary time series may usefully be described by its first and second moments (mean and variance) and either its autocorrelation functions, or its spectral density function. Because the autocorrelation function and the spectrum are transforms of each other, the two ways are equivalent. In finance, although there are analyses in the frequency domain (e.g. Granger and Morgenstern, 1970; Hilliard, 1979) it is much more usual to work in the time domain. The techniques to be used in this study are from the time domain. More specifically, Box-Jenkins univariate ARIMA modelling will be used to examine the dependence of the three indices from their own past. The analysis will also employ multivariate (transfer function) ARIMA modelling, to examine the effect of FT-100 and SP-500 on GEN.

The general form of a univariate ARIMA (p, d. q) model describing the current value Y_{t} of a stochastic time series by its own past is:

$$\Delta^{d} Y_{t} = \mu + \varphi_{1} \Delta^{dy}_{t-1} + \dots + \varphi_{p} \Delta^{dy_{t-p}} + \Theta_{1} \alpha_{t-1} + \Theta_{q} \alpha_{t-q} + \alpha_{t}$$

where Δ is the difference operation, d is the order of differencing (d = 0 if Y_t is stationary), μ is the mean of the series if the series is stationary, or just a reference point if it is non-stationary; $\phi_1, ..., \phi_{\rho}$, and $\Theta_1, ..., \Theta_q$ are the autoregressive and moving average coefficients; and a_t a random shock. By introducing the backward shift operator $B^k Y_t = Y_{t-k}$, equation (1) may be written as

$$\varphi(\mathbf{B}) (1 - \mathbf{B})^{o} \mathbf{Y}_{t} = \mu + \theta (\mathbf{B}) \alpha_{t}$$

where $\varphi(B) = 1 - \varphi_1 - \dots - \varphi_p B^p$, is the autoregressive polynomial; $\Theta(B) = 1 - \Theta_1 B - \dots - \Theta_q B^q$, is the moving average polyminial, and (1-B) is equivalent to the difference operator Δ . If seasonal components of seasonality s, or seasonal differencing, are included in the model in a multiplicative way, the model is denoted as ARIMA (p, d, q) (P, D, Q)_s.

It must be emphasised that Box-Jenkins models are empirical models, created from the data and it is important that the iterative model building process proposed by Box and Jenkins is followed (Box and Jenkins, 1976; McCleary and Hay, 1980). This process consists of (i) the identification, where the patterns of autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to identify a tentative model; (ii) the estimation, where the coefficients of the model are estimated, and their statistical significance is tested; (iii) the diagnosis, where the whiteness of the residuals is examined by ensuring that there are no significant correlations at low lags and that the value of the Ljung-Box statistic (LBQ) (Ljung and Box, 1978) is not statistically significant; and (iv) the metadiagnosis, where the model is compared with other rival models and the selection criteria are the parsimony and the residual mean square value of a model¹. While non — stationarity in levels is explicitly taken into account by ARIMA models, stationarity in the second moment, a condition which is necessary for an ARIMA model, is not and will be examined before the identification stage. In addition the augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979) will be used as an auxiliary method to test for non — stationarity in levels².

Once the univariate model for Y_t is constructed the dynamic effect of another series X_t may be examined by letting

$$Y_t = u_0 X_t + u_1 X_{t-1} + ... = u(B) X_t + N_t$$

where u(B) is known as the transfer function, u_0 , u_1 , ... as the impulse response weights and N_t a model for the noise component. Information about the character of the transfer function can be obtain from the pattern of the cross correlation function (CCF) between Y_t and X_t . It can be proved that under certain conditions the magnitude of the cross correlations at various lags of the CCF is directly proportional to the umpulse response weights (Box and Jenkins, 1970). It must be emphasised that only when both series are appropriately transformed is the CCF meaningful. Otherwise the magnitude of the cross - correlations is "contaminated" by the within — series correlation. The steps to be followed before the CCF is estimated are briefly described in Appendix 1.

Once the CCF of a particular case is estimated, the bivariate model can be estimated in the following way:

a) From the character of the estimated CCF we tentatively identify a transfer function ignoring the residuals of the model (noise component) at this stage. As the character of the CCF may imply more than one forms for the transfer function, the model is built, in general, on an iterative trial and error way similar to that for the univariate model discussed earlier.

b) The residuals are modelled by fitting and ARIMA model, which, is not necessarily the same with the original univariate ARIMA model for the dependent variable.

c) Having estimated separately the models for the transfer function and the noise, these are combined to assess the adequacy of the model as a whole.

As far as the assessment of the performance of a model is concerned, the coefficient of determination R^2 is not used in time series models as the possible existence of trends and/or constant terms³ leads to always very high values of R^2 . In all cases that R^2 is used as a measure of the performance of a model in this paper, trends and constants do not exist, so that only MA and/or AR terms, as well as the transfer function, are taken into account.

3. Results and discussion

Figures 3 and 4 show respectively, the plots of ACF and PACF for GEN. Both, the very slow decay for the ACF and the strong correlation with a magnitude close to 1.00 at lag 1 for the PACF suggest that GEN is non-stationary. The ACF and PACF (not shown) for SP-500 and FT-100 have similar patterns. Confirmation of non — stationarity is provided by the values of the ADF test which are presented in Table 1. The plots of the first differences of GEN, FT-100 and SP-500 against time (not shown here) reveal that the variability for GEN is not constant and variance non — stationarity seems to be present in these cases. For FT-100 and SP-500 there is no indication of variance nonstationarity. To examine the possibility that relatively lower variability is associated with relatively lower local mean levels, GEN was divided into segments of equal length and the local standard deviations (SDs) as well as the local variances were regressed against the local mean levels. The regressions of local SDs for GEN gave statistically significant slope coefficients as well as higher values of R than the regressions of local variances against local mean levels. These results suggest that the logarithmic transformation can render variance stationary series (Box and Jenkins, 1976). Henceforth the logarithms of GEN (LOGGEN) will be used.

Figures 5 and 6 show the plots of ACF and PACF for the first differences of LOGGEN. The 95% confidence interval in these plots is noted with the dashed lines on both sides of the vertical axis. It is apparent that there are several lags with significant as well as marginally significant correlations in all plots. The most pronounced autocorrelation is at lag 1 with magnitude 0.189 and 0.183 for

both the ACF and PACF. The character of the ACF and PACF suggest that this correlation could better be modelled by an MA component, but the general pattern of the ACF and PACF is such that no specific model is immediately distinguishable. Following the iterative process described previously, several tentative models were tested and some were found to be adequate. Metadiagno¬ sis showed that the best model for the LOGGEN series is an ARIMA (0, 1, 1) (0, 0, 1)₄ (0, 0, 1)₁₀ i.e. a multiplicative IMA model with MA components of 1st, 4th and 10th order. The values of the MA components of the model are shown in Table 2. The computer programme which was used for the estimation is the BMDP module 2T Liu 1988)⁴.

Figures 7 and 8 show the plots of the ACF and PACF for the residuals of the univariate model for the series of LOGGEN. There seem to be no significant correlations in these plots and the value of the LBQ statistic is 29 at lag 34. The critical LBQ value for 30 degrees of freedom (degrees of freedom = number of lags - number of parameters estimated) is 43.8 confirming that the hypothesis that the residuals are white noise cannot be rejected. The MA components at lags 4 and 10 may be associated with the existence of weekly and biweekly cycles in the share prices. In passing, it is also noted that in all the examined cases models with MA components gave lower RMS values than models with AR components. The same is true for multiplicative models as compared with additive models.

Caution is needed on how these results are interpreted from the point of view of financial theory. The existence of autocorrelation contradicts the hypothesis of week-form efficiency in the ASE, within the framework of constant expected returns. However, it is reminded that the GEN series was found to be variance non-stationary, hence, the hypothesis of constant expected returns in not valid in this case (because risk averse investors will require higher returns when variability increases). Without the assumption of constant expected returns the existence of autocorrelation in the returns time series does not necessarily contradict the hypothesis of week-form efficiency (Elton and Gruber, 1995). In the present case it is not the existence of autocorrelation itself, but its particular pattern (multiplicative seasonality) that makes us reject the hypothesis of weak form efficiency.

As far as the differenced SP-500 and GT-100 series are concerned, the plots of the ACF are shown in Figures 9 and 10 respectively. At no lag a correlation appears to be significant in either of the two Figures. The values of the LBQ statistic at lag 30 for the first differences of SP-500 and FR-100 are 33 and 32 respectively. The critical LBQ value at the 95% confidence level is 43.8, imply-

ing that both these series can be considered as white noise. Hence, the SP-500 and FT-100 series are random walks⁵, a result that is consistent with the hypothesis of weak form efficiency in these markets.

Given that both the first differences of FR-100 and SP-500 series are white noise it is easy to estimate the CCFs between each of these series and the GEN series by simply cross-correlating the residuals of the univariate models for LOGGEN and successively the first differences of SP-500 and FT-500 (as there is no within — series correlation in the first differences of the SP-500 and FT-100 series steps, 2, 3 and 4 of appendix 1 are not necessary). As LOGGEN is in logarithms, the SP-500 and FT-100 are also log-transformed and quoted as LOGSP and LOGFT, respectively, hereafter.

Figures 11 and 12 show the plots of the CCF between LOGGEN and LOGSP, and LOGGEN and LOFGT respectively. In Figure 11 there are significant correlations at lags -4, 1 and 3 and 10. The ones at lags -4 and 10 have no interpretation as far as financial theory is concerned. It should be mentioned at this point that as the 95% confidence level is used, it is expected that there will be one significant correlation in every 20 lags simply as a result of type I error. The correlation at lag 1 represents the effect of NYSE on the ASE because as metni[¬] oned previously there is no overlap in the working hours of these two markets, therefore, the effect of NYSE can only be realized in the ASE on the next day. It is difficult to decide whether the significant correlation at lag 3 can be attributed to the effect of the New York market or to randomness. It will be initially included in the transfer function model and its significance will be tested together with the correlation at lag 1.

The CCF between LOGGEN and LOGFT (Figure 12) has one significant correlation of magnitude 0.155 at lag 0 followed by a marginally significant correlation of magnitude 0.072 at lag 1. As there is a complete overlap between ASE and ISE during the working hours of ASE, this pattern of CCE is reasonable. The tentative transfer function model for this case includes two terms for the predictor variable corresponding to lags 0 and 1.

For the estimation of these two models the steps (a) to (c) were followed for each one. The results are shown in Table 3⁶. Results of the ARIMA models for the residuals are not quoted, because it was found that the models for the residuals in both cases have the same components with the corresponding original univariate models and the impulse response weights are statistically significant, as suggested by the patterns of the CCFs, confirming that there is an effect of both the NYSE and ISE on the ASE. It is also apparent that with the exception of the significant correlation at lag 3 in the CCFs of LOGGEN with LOGSP which is of uncertain origin the character of the effect of both markets on the ASE indicates that the hypothesis of informational efficiency is valid for the ASE.

It is interesting to examine whether or not the effect from ISE is direct or it represents an indirect effect from NYSE transmitted through ISE. To do so at first it is necessary to find the transfer function between FT-100 and SP-500. The residuals from this model will represent that part of the variation in FT-100 that is not related with SP-500 and, therefore, will be, by construction, orthogonal to SP-500. Those residuals together with SP-500 can be used as predictors in the transfer function. The CCF between the first differences of LOGSP and LOGFT is shown in Figure 13. There are two significant correlations at lags 0 and 1. The transfer function model, not quoted, confirms that the corresponding coefficients are statistically significant. The results on the transfer function model having as dependent variables LOGGEN and as independent variables the residuals of LOFGT (called LOGFTSP) and LOGSP are shown in Tables 4. Again results for the models for the residuals are not quoted, as these models are the same with the original univariate ones. In both cases there are significant impulse response weights at lag 0 for LOGFTSP and lags 1 and 3 for LOGSP. Hence, in addition to the effect from NYSE on ASE, there is a separate correlation (synchronous co-movement) between ISE and ASE. This is an interesting result as it provides further evidence that the ASE participates in the so-called global integration of the financial markets. At this point it should be noted that Theodossiou et al. (1993) found no interaction between the Greek and the German stock markets. However, they used weekly instead of daily data.

It is also interesting to assess the relative importance of the various "factors" on ASE. This can be done by examining the explanatory power of the univariate as well as the multivariate models with dependent variable LOGGEN. The factors to be examined are the within — series correlation, i.e. the series own past, NYSE, ISE, and the combined effect of NYSE and ISE. Table 5 shows the values of R for all the models created so far. The values in parentheses show the change in the value of R after the inclusion of a transfer function. The term over-modelling refers to a univariate model in which MA and /or AR components have been included, in addition to those required to render white noise residuals (if there exist any such components which are statistically significant). The purpose of doing this is to examine the possible improvement in the value of R caused by over-modelling as compared with the value of the same statistic accounted for by the factors mentioned previously.

From the figures of Table 5 it is evident that the series own past has a more important effect on LOGGEN than LOGET or LOGSP. The effects from LOGSP and LOGFT are equal in size and is small in magnitude. However, as already analysed, part of the LOGFT effect is attributed to the indirect transmission of the LOGSP effect on LOGGEN through LOGFT. On the other hand overmodelling improves only by about one point the explanatory power of the model. The inclusion of both the effect from NYSE and the correlation with ISE improves the R^2 value by about four points, but it still remains of lesser importance than the effect of the series own past.

Although a statistically significant effect from LOGSP on LOGGEN was found, its small magnitude implies that ASE is suitable for international portfolio diversification. It should also be noted that the causal effect of LOGSP to LOGGEN does not necessarily imply a trading rule for investors, at it refers to closing prices for both markets. To conclude, whether or not, a trading rule exists it is also necessary to examine the effect of the New York Market on the next day's opening value of GEN. If the GEN value at opening is not influenced by the closing SP-500 value of the previous day (i.e. the information from the New York Market has not been incorporated in GEN yet), then our results suggest a trading rule. However, opening prices for ASE were not available.

4. Summary and Conclusions

This paper has examined the effect of the New York and London Stock exchanges on the Athens stock exchange. The main conclusions are the following:

i) There is a statistically significant causal effect, small in magnitude, from SP-500 on GEN, and a contemporaneous co-movement between FT-100 and GEN. The causal effect of FT-100 on GEN is attributed to the indirect causal effect from SP-550 to GEN through FT-100.

ii) Any external effect is smaller compared with the effect of the past history of GEN.

iii) The pattern of the within — series correlation in GEN is counter evidence for the existence of weak form efficiency in ASE.

iv) In terms of the time required for the transmission and assimilation of new information from NYSE and ISE to ASE the market seems to be efficient

although some further investigation (e.g. use of data of different time period in order to explain the statistically significant coefficient at lag 3 in the transfer function model with SP-500, and availability of opening prices for ASE) is required.

Although this work examined the co-movement of ASE with mature financial markets, the study of the possible co-movement of ASE with other Emerging Markets is not of lesser importance, and it is worth-pursuing in a future work. If international fund managers revise their investment strategies for an emerging market not separately, but in conjunction with other emerging markets, then a significant co-movement among the emerging markets (or sets of emerging markets) is expected. As a considerable part of the total capitalization value of ASE is hold by foreign investors, the possible existence and extend of such a co-movement may, amongst others, reveal the role that ASE plays in international portfolios.

Appendix 1

Steps to be followed before the estimation of the CCF.

1. If the series Y_t and X_t are not stationary they must be differenced until stationarity is obtained. This is because, it is the non — stationarity inherent in many time series that accounts for most of the spurious relationships observed in time series analysis. By differencing, two new time series, W_t ant Z_t , are produced, according to the expressions:

$$W_t = (1 - B)^d X_t$$

 $Z_t = (1 - B)^k Y_t$

2. Find the ARIMA model for W_t:

$$\mathbf{W}_t = \boldsymbol{\varphi}^{-1}(\mathbf{B}) \; \boldsymbol{\theta}(\mathbf{B}) \boldsymbol{\alpha}_t$$

3. Use the inverse model to filter W_t:

$$\alpha_t = \varphi(\mathbf{B}) \, \Theta^{-1} \, (\mathbf{B}) \, \mathbf{W}_t$$

4. Use the same filter as in step (3) to "prewhiten" Z_t:

 $b_t = \varphi(B) \theta^{-1}(B) Z_t$

The purpose of following steps (3) and (4) is to remove from the dependent variable Z_t that pattern of autocorrelation that is also common to the independent series W_t .

5. Estimate the cross correlation function between a_t and b_t . The CCF, unlike the ACF, is asymmetric; that is CCF(-K) Φ CCF(K). Therefore, the character of the CCF gives information not only about the strength of a relationship, but also about the direction of the relationship, i.e. it indicates the causality. As a matter of fact one of the advantages of this methodology is that it is perfectly compatible with the notion of Granger causality (Granger, 1969). Theoretically-expected CCFs for bivariate relationships can be estimated (Box and Jenkins, 1970).

TABLE 1

Augmented Dickey - Fuller tests

VARIABLE	WITHOUT TRND	WITH TREND
GEN	-1.738 (-2.866)	-2.480 (-3.418)
SP-500	-1.161 (-2.866)	-2.527 (-3.418)
FT-100	-1.500 (-2.866)	-2.637 (-3.418)

Note: The number o lags is 5. Figures in brackets denote critical values at 95% level.

TABLE 2

The univariate multiplicative model for LOGGEN

Coefficient		Estimate	t - ratio
Туре	Order		
MA	. 1	-0.20	-5.32
MA	4	-0.10	-2.69
MA	10	-0.10	-2.49

Note: The series has been differenced once in levels.

TABLE	3
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Input Variable		LAG		
	0	1	2	3
LOGSP	·	0.23 (2.66)		0.28 (3.31)
LOGFT	0.34 (4.09)	0.19 (2.29		

Values of impulse response weights ui**

** Bivariate transfer function models for LOGGEN of the form:

 $LOGGEN = u_o X_t + u_1 X_{t-1} + u_2 X_{t-2} + u_3 X_{t-3} + N_t$

where X is either LOGSP or LOGFT, and N_t is noise t — ratio in parentheses.

TABLE 4

Transfer function model for LOGGEN with multiple inputs

Input Variable		Coefficient	
	Lag	Estimate	t-ratio
LOGFTSP	0	0.28	3.41
LOGSP	1	0.25	2.87
LOGSP	3	0.29	3.43

 $\begin{array}{c} \text{TABLE 5} \\ \text{R}^2 \text{ values for the various models} \end{array}$

R ² values	Change in R ² values	Factor
5.82	27) 19	Univariate model
8.48	(2.66)	FT-100
8.48	(2.66)	SP-500
9.94	(4.12)	FT-100 + SP-500
6.94	(1.12)	Overmodelling

Footnotes

1. A number of alternative model selection criteria have also been proposed (see Shibata, 1985 for a review). These are based on the selection of the model that minimizes the value of a parameter which is a function of the error variance and the number of the estimated parameters. This is done automatically by a computer programme, so that the researcher has little or no control on the identification of a model. Since it is often the case that this methodology leads to overmodel¬ ling (i.e. order(s) of AR and/or MA polymonial(s) higher than necessary) and/or luck of meaning for some of the components of the selected model, the traditional Box-Jenkins model building strategy was preferred in this study.

2. McCleary and Hay (1980) suggest that the plots of the ACF and PACF at the identification stage, as well as for the residuals of a model together with a detailed description of the model building process should always be quoted in order to make it possible to the reader to assess the validity and appropriateness of the model. This is rarely met in published works on time series. The iterative model building process is described with details for some cases in this study, however, it was not possible to do so in every case due to the large number of models examined.

3. In none of the models in this paper a constant term is included as in all cases constant terms were statistically insignificant.

4. To improve accuracy in the estimation of the coefficients of the model two estimating methods were used. First, the conditional least squares method which gives some first estimates of the coefficients. Subsequently these estimates are used as initial values for the so calles backscating method (see Liu (1988) for further details).

5. Although the term "random walk" is usually used in the literature for such cases, the mathematical definition of a random walk is more strict. The same comment applies also to the term "white noise". See further comments in Fama (1970).

6. Transfer function models of the form LOGGEN = $(\omega_1 X) / (1 - S_1 B) + N_t$ where Y is X is LOGSP or LOGFT were also considered. In all cases the coefficient S_1 was statistically insignificant.

References

- Agmon T. (1974), "The relations among Equity Markets in the United States, United Kingdom, Germany and Japan". Journal of Finance, 27, 839-855.
- Antoniou A., Ergul N., Holmes P., and Priestley R. (1997) "Technical Analysis, Trading Volume and Market Efficiency: Evidence from an Emerging Market", Applied Financial Economics, 7, 361-365.
- Box G. P. and Jenkins G. M. (1976), 'Time Series analysis: Forecasting and Control", Holden Day, San Francisco.
- Brealey A. R. and Myers S. C. (1988), Principles of Corporate Finance, McGraw Hill Co. Singapore.

- *Cooper J. C.* (1983), 'The Korean Stock Exchange: A qualitative and quantitative assessment", The Investment Analyst, 70, 5-12.
- Crubell H. (1968), "Internationally Diversified Portfolios: Welfare Gains and Capital Flows", American Economic Review, 58, 1299-1314.
- Dickey D. A., and Fuller W. A. (1979), "Distribution of the Estimates for Autoregressive Time Series with a Unit Root", Journal of the American Statistical Association, 74, 427-431.
- Dockery E., and Vergari F. (1997): 'Testing the Random Walk Hypothesis: Evidence for the Budapest Stock Exchange", Applied Economic Letters, 4, 627-629.
- Dwyer G. P. and Hafer R. W. (1988), "Are National Stock Markets Linked?", Federal Reserve Bank of St. Louis, Review, Vol. 39, 3-14.
- Elton J. E., and Griber M. J. (1995): "Modern Portfolio Theory and Investment Analysis", 5th Edition, Wiley, New York.
- *Eun C. S. and Resnick B. G.* (1984), "Estimating the Correlation of International Share Prices" Journal of Finance, 39, 1311-1324.
- *Eun C. S. and Shim S.* (1989), "International Transmission of Stock Market Movements", Journal of Financial and Quantitative Analysis, 24, 241-256.
- *Fama E.* (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work", Journal of Finance, 25, 383-416.
- *Feeney G. J. and Herst D.D.* (1967), "Stock Market Indices: A Principal Component Analysis", in Risk Aversion and Portfolio Choice, Herst D. D. and Tobin G. (eds), John Wiley and Sons, New York.
- *Granger C.* (1969), "Investigating causal relations by econometric models and cross-spectral methods", Econometrica, 37, 424-438.
- Granger C, and Morgenstern (1970), "Predictability of Stock Market Prices", MA: Lexington.
- *Hilliard J.* (1979), "The Relationship between Equity Indices and World Exchanges", Journal of Finance, 34, 103-114.
- Jeon B. N. and Von Furstenberg G. M. (1990), "Growing International Co-movement in Stock Price Indexes. Quarterly Review of Economics and Business, 30, 15-30.
- Lessard D. (1973), "International Portfolio Diversification: A Multivariate Analysis for a group of Latin American Countries", Journal of Finance, 28, 619-633.
- *Lintner J.* (1965), "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", Review of Economics and Statistics, 47, 13-37.
- Liu L. M. (1988), "Box-Jenkins Time Series Analysis" in BMDP Statistical Software manual, Vol. I, University of California Press.
- Ljung G. M. and Box G. E. P. (1978), "On a measure of lack of fit in time series models", Biometrica, 65, 297-309.
- Markowitz H. M. (1952), "Portfolio Selection", Journal of Finance, 7, 77-91.

- *McCleary R. and Hay R. A.* (1980), "Applied Time Series Analysis for the Social Sciences", Sage publications, Beverly Hills.
- Niarchos N. A. and Georgakopoulos M. C. m1986), "The Effect of Annual Corporate Profit Reports on the Athens Stock Exchange: an Empirical Investigation", Management International Review, 1986, 26, 64_72.
- Niarchos N. A. and Alexakis C. A (1997), "Stock Market Prices, Causality and Efficiency: Evidence from the Athens Stock Exchange", Applied Financial Economics, under publication.
- Panton D. Lesseg V., and Jou O. (1976), "Comovements of International Equity Markets: A Taxonomic Approach", Journal of Financial and Quantitative Analysis, 11, 415-432.
- Ripley D. (1973), "Systematic Linkage of National Stock Market Indices", Review of Economics and Statistics, 55, 356-361.
- *Sharpe W. F.* (1964), "Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk", Journal of Finances, 19, 425-442.
- Shibata R. (1985), "Various Model Selection Techniques in Time Series Analysis", in Handbook of Statistics, (eds Hannan E. J., Rishnaiah P. R., and Rao M. M.), 5, 179-187. North Holland, Amsterdam.
- Solkin B. (1997), "Why Not Diversify Internationally?", Financial Analyst Journal, 30, 48-54.
- *Theodosiou P., Koutmos G., and Negakis C.* (1993), "The Intertemporal Relation Between the U.S. and Greek Stock Markets: A Conditional Variance Tale Analysis", The International Journal of Finance, 5 (2) 492-504.
- Urrutia J. L. (1995), "Tests for Random Walk and Market Efficiency for Latin American Emerging Equity Markets", Journal of Financial Research, 18, 299-309.