Mean and variance causality between the Cyprus Stock Exchange and major equities markets

by

Eleni Constantinou[1*], Robert Georgiades[1], Avo Kazandjian[2]
and Georgios P. Kouretas[3**]

January 2005

Abstract

This paper examines the issue of mean and variance causality across four equities markets using daily data for the period 1996-2002. We apply the testing procedure developed by Cheung and Ng (1996) in order to test for mean and variance spillovers. The main findings are: (i) In contrast to the findings of previous studies, EGARCH-M processes characterize each stock returns series in all markets; (ii) There is substantial evidence of causality in both mean and variance with the causality in mean largely being driven by the causality in variance; and (iii) The results indicate the stock markets of Athens, London and New York are the major exporters of causality and the stock market of Cyprus is an importer of causality.

Key words: Causality, cross-correlation function, EGARCH-M, equity market, volatility spillovers

JEL Classification: C22, C52, G12

[1] Department of Accounting and Finance, The Philips College, 4-6 Lamias Street, CY-2100, Nicosia, Cyprus.
[2] Department of Business Studies, The Philips College, 4-6 Lamias Street, CY-2100, Nicosia, Cyprus.
[3] Department of Economics, University of Crete, University Campus, GR-74100, Rethymno, Greece.

*****This paper is part of the research project, *Cyprus Stock Exchange: Evaluation, performance and prospects of an emerging capital market*, financed by the Cyprus Research Promotion Foundation under research grant Π25/2002. We would like to thank the Cyprus Research Promotion Foundation for its generous financial support and the Cyprus Stock Exchange for proving us with its database. We would also like to thank Angelos Kanas for many helpful comments and discussions and for providing us with the GAUSS and OX codes for the estimation of the MS and ANN models. The usual disclaimer applies.

******Corresponding author: Fax 00302831077406, email: kouretas@econ.soc.uoc.gr .

1. Introduction

Emphasis on volatility grew out of the need to obtain reliable inputs in the pricing of financial products, such as options and futures, in developing optimal hedging techniques and all sorts of risk exposure from transactions with foreign economies. Early research on the stochastic behavior of price changes (returns) of financial assets is based on the assumptions of normality and constant variance (homoskedasticity). The seminal works of Mandelbrot (1963) and Fama (1965) found that the empirical distribution of price changes of financial assets is leptokurtic when compared to the normal distribution, thus rejecting the assumption of normality. Furthermore, Mandelbrot (1967) and Fielitz (1971) provide evidence rejecting the assumptions of homoskedasticity and independence over time.

In order to account for these 'anomalies', Engle (1982) developed the autoregressive conditional heteroskedastic (ARCH) methodology, which allows for the modeling of the time-varying volatility of the returns of financial assets. Bollerslev (1986) generalized this methodology, proposing the generalized autoregressive conditional heteroscedasticity (GARCH) methodology. Several variations of these models have appeared along with numerous empirical applications in the financial markets in the last decade [see Bollerslev et al. (1992) and Bera and Higgins (1993) for an extensive literature review].

Stock price changes (returns) movements are characterized by time-varying volatility which means that stock returns tend not to be independent but to exhibit "volatility clustering". This is the case where periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes. Numerous studies have extensively investigated the pattern of volatility of all major stock markets by applying Engle's (1982) ARCH model and Bollerslev's (1986) GARCH model. Studies like those of Bollerslev (1987) and Akgiray (1989) have shown that these models fit well to daily and weekly data for all major stock price indices. Moreover, Baillie and Bollerslev (1991), Barclay, Litzenberger (1990), Cheung and Ng (1990), Engle, Ito and Lin (1990), Hamao, Masulis and Ng (1990) and King and Wadhwani (1990) are studies that investigate the causation in conditional variance across financial asset returns. Finally, Baillie and Bollerslev (1989) have shown that ARCH effects tend to weaken as the frequency of the sampled data decreases, while Drost and Nijman (1993) have shown that ARCH processes converge to normality under temporal aggregation.

This paper examines the issue of volatility transmission between four equities markets. Specifically, we consider the Cyprus Stock Exchange (CSE) a relatively new emerging market, the Athens Stock Exchange (ASE) a small capital market that has gained the markets' attention in the late 1990s for its high returns at that time and which has been recently upgraded from an emerging capital market to a mature market. We also include in our analysis two of the most important capital markets those of London (LSE) and New York (NYSE).

The Cyprus Stock Exchange is the primary stock market in Cyprus. It is considered to be a small emerging capital market with a very short history since it was established in April 1993 when the inaugural Stock Exchange Law passed through the Cypriot House of Representatives. In July 1995 the Cypriot House of Representatives passed the laws for the stock exchange function and supervision, while additional laws led to the establishment of the Central Securities Depository. On 29 March 1996 the first day of transactions took place. The Cyprus Stock Exchange S.A. is supervised by the Ministry of Finance and the Minister of Finance is responsible for choosing the seven member executive committee that runs CSE. Furthermore, the

Securities and Exchange Committee is mostly responsible for the well functioning of the capital market of Cyprus. Trading takes place electronically through the Automated Trade System. The main index is the CSE General Price Index that reflects, approximately, 93% of the trading activity and 96% of the overall capitalization. In November 2000 the FTSE/CySE 20 was constructed with the cooperation of CSE, the Financial Times and the London Stock Exchange in order to monitor closer the market. To highlight the increasing need for regional capital market integration the FTSE Med 100 was created in June 2003 with the cooperation of CSE, ASE and the Tel-Aviv Stock Exchange.

Figure 1 shows the evolution of the CSE general price index. We can distinguish three main periods of the operation of CSE so far. The first period (29/03/96-30/06/96) is characterized by the low interest of mainly domestic investors, small trading volumes and low volatility and persistence of the general price index around its initial level of 100 units. The second period (01/07/99-31/10/00) is characterized by the presence of a rational bubble. The rational bubble is a phenomenon expected in emerging capital markets more frequently that in mature markets and it was due to the sudden overwhelming interest of domestic (many of them with limited knowledge of the operations of a capital market) and foreign investors for holding stocks of Cypriot companies in their portfolios. The bubble lasted one and a half years and left most of investors in frustration since they lost most of their initial invested capital. We can partially attributed this bubble to the bubble that emerged in the ASE which took place a year before. ASE is in many respects the market that influences the CSE and a close look in Figures 1 and 2 (the evolution of the ASE general price index) reveals the similarities in the pattern of the bubble. As a result of the burst of the rational bubble the last period (01/11/00-19/04/02) shows that the general index of CSE has eventually returned to it is initial level while currently is below the 100 units, (this pattern remains the same until today). Figures 3 and 4 show the evolution of the general price index of the LSE and NYSE respectively.

To examine for causality in both the variance and the mean between these four equities markets, this paper utilizes the two-stage Cross-Correlation Function (CCF) testing procedure developed by Cheung and Ng (1996). This testing procedure has certain advantages over alternative testing procedures based on multivariate GARCH modeling. Specifically, the CCF approach does not involve the simultaneous modeling of intra- and inter-series dynamics and thus, it is easier to implement than the multivariate GARCH based tests. Furthermore, in the multivariate GARCH modeling approach, there is uncertainty surrounding both the first- and second-moment dynamics, the potential interdependence between the series under examination, as well as the asymptotic distribution of the maximum likelihood estimator (Engle and Kroner, 1993). Consequently, there are several difficulties in correctly specifying an adequate multivariate GARCH model. The CCF testing procedure does not require modeling of the dynamics of the interaction of the series involved and thus is especially useful when the number of series under investigation is large, as is our case with four general price indices. Importantly, the CCF test has a well defined asymptotic distribution and is asymptotically robust to distributional assumptions. Finally, Cheung and Ng (1996) have shown, using Monte Carlo simulations, that the CCF test has 'considerable' power against the appropriate causality-in-variance alternative and is robust to nonsymmetric and leptokurtic errors. The implementation of the CCF testing procedure involves two steps. In the first, GARCH or Exponential GARCH (EGARCH), or EGARCH-in-Mean (EGARCH-M) models are fitted in each series. The choice between GARCH, EGARCH, and EGARCH-M is based on the criterion of which model better describes the distributional properties of each series. In the second, the cross correlation function is examined with reference to the standardized residuals from the GARCH modeling.[1] Cheung and Ng (1996) have implemented this approach to study the causal relationships between the NIKKEI 225 and the S&P 500 stock price indices, while Kanas and Kouretas (2002) studied the variance causality and spillovers among four Latin American official and parallel markets for foreign currency.

The main findings of the paper are summarized as follows. First, it is shown that an EGARCH(1,1)-M model with Generalized Error Distributions describe quite well the distributional properties of stock returns in the equities markets of Cyprus, Greece, the UK and the US. Second, there is substantial evidence of causality in both mean and variance with the causality in mean largely driven by the causality in variance, which implies that there are significant volatility spillovers effects from one market to another. Finally, the results indicate that the NYSE, the LSE and the ASE are exporters of causality to changes in the general index of the stock market of Cyprus which is shown to be an importer of causality. In addition, Cyprus Stock Exchange has no volatility effect on the three other international equities markets and this result is in line with the fact that the volume of transactions in the Cypriot stock market is substantially smaller compared to each of these markets. These results provide useful information to domestic and foreign investors in the capital market of Cyprus.

The organization of the paper is as follows. Section 2 discusses the cross-correlation function testing methodology. Section 3 describes the data and presents

[1] This two-stage method extends the procedures developed in Haugh (1976) and McLeod and Li (1983).

some preliminary results. Section 4 presents the EGARCH-M model. Section 5 reports and discusses the estimations of the model and the evidence of mean and variance causality for the CSE/ASE, the CSE/LSE and the CSE/NYSE stock market returns. Section 6 provides our conclusions.

2. The Cross-Correlation Function testing procedure

Consider two stationary and ergodic time series X_t and Y_t, and two information sets defined by $I_t = \{X_{t-j}, j \geq 0\}$ and $J_t = \{X_{t-j}, Y_{t-j}, j \geq 0)$. Then, Y_t is said to cause X_{t+1} in variance if[2]

$$E\{(X_{t+1} - \mu_{x,t+1})^2 / I_t\} \neq E\{(X_{t-1} - \mu_{x,t+1})^2 / J_t\} \tag{1}$$

where $\mu_{x,t+1}$ is the mean of X_{t+1} conditioned on I_t. Feedback (instantaneous causality) in variance occurs if X causes Y and Y causes X, namely if

$$E\{(X_{t+1} - \mu_{x,t+1})^2 / I_t\} \neq E\{(X_{t+1} - \mu_{x,t+1})^2 / J_t + Y_{t+1}\} \tag{2}$$

Similarly, Y_t is said to cause X_{t+1} in mean if

$$E\{(X_{t+1} / I_t\} \neq E\{(X_{t+1} / J_t\} \tag{3}$$

[2] The concept of causation in the second moment can be viewed as a natural extension of the Wiener-Granger causality in mean (Granger, Robins and Engle, 1986).

To empirically test for causality in mean and variance, we need to impose an additional structure in relations (1), (2) and (3). Suppose that mean equations for X_t and Y_t can be written as

$$X_t = \mu_{x,t} + \sqrt{h_{x,t}\varepsilon_t} \text{ and } Y_t = \mu_{Y,t} + \sqrt{h_{Y,t}\zeta_t}$$

where ε_t and ζ_t are two independent white noise processes with zero mean and unit variance. The conditional mean and variances are given by

$$\mu_{z,t} = \sum_{i=0}^{\infty} \varphi_{z,i}(\theta_{z,h}) Z_{t-i} \tag{4}$$

$$h_{z,t} = \varphi_{z,0} + \sum_{i=0}^{\infty} \varphi_{z,i}(\theta_{z,h})\{Z_{t-i} - \mu_{z,t-1})^2 - \varphi_{z,0}\} \tag{5}$$

where $\theta_{z,w}$ is a $p_{z,w}x1$ parameter vector; $W = \mu, h$; $\varphi_{z,i}(\theta_{z,\mu})$ and $\varphi_{z,i}(\theta_{z,h})$ are uniquely defined functions of $\theta_{z,\mu}$ and $\theta_{z,h}$; and $Z = X, Y$. Equations (4) and (5) reflect time series models such as the autoregressive moving average (ARMA) models for the mean and the GARCH models for the variance.

Consider next the squared standardized residuals for series X_t and Y_t, namely

$$U_t = ((X_t - \mu_{x,t})^2 / h_{x,t}) = \varepsilon_t^2 \tag{6}$$

$$V_t = ((Y_t - \mu_{Y,t})^2 / h_{Y,t}) = \zeta_t^2 \tag{7}$$

and the standardized residuals, ε_t and ζ_t. Let $r_{UV}(k)$ be the sample cross-correlation of the squared standardized residual series, and $r_{\varepsilon\zeta}(k)$ be the sample cross-correlation of the standardized residual series at lag k.

The CCF testing procedure is based on the $r_{UV}(k)$ and $r_{\varepsilon\zeta}(k)$ to test for causality in variance and causality in mean respectively. Specifically, to test the null hypothesis of noncausality in variance against the alternative hypothesis of causality at lag k, the CCF-statistic is given by

$$\text{CCF-statistic} = \sqrt{T} * \ r_{UV}(k) \tag{8}$$

Similarly, to test the null hypothesis of noncausality in mean against the alternative hypothesis of causality at lag k, the CCF-statistic is given by

$$\text{CCF-statistic} = \sqrt{T} * \ r_{\varepsilon\zeta}(k) \tag{9}$$

Cheung and Ng (1996) have shown that the CCF-statistics given in equations (8) and (9) have an asymptotic standard normal distribution. Using Monte Carlo simulations, these authors have also shown that this test '…has the ability to identify causality and reveal useful information on the causality pattern'. (Cheung and Ng, 1996, p. 40). Furthermore, it is robust to nonsymmetric and leptokurtic errors and asymptotically robust to distributional assumptions.

The empirical implementation of the CCF procedure is done in two stages. The first stage involves the estimation of univariate time-series models that allows for time variation in both conditional means and conditional variances. We employ an EGARCH-M model to model the time-varying variance for each series on the basis of several diagnostic tests. In the second stage, we construct the resulting series of squared residuals standardized by conditional variances. The CCF of these squared-standardized residuals is then used to test the null hypothesis of no causality in variance. In addition we examine the effect of causality in mean, if any, on tests for causality in variance and the interaction between the tests for causality in mean and variance. Depending on model specifications, causation in mean can exist with or without the presence of causality in variance and vice versa. This observation provides a motivation for our study to investigate the test performance when causation exists in both the mean and variance.

3. Data and preliminary results

The data consists of daily observations of the stock prices for the Cyprus Stock Exchange, the Athens Stock Exchange, the London Stock Exchange and the New York Stock Exchange. The sample covers the period 29 March 1996 (First day of transactions at CSE) to 19 April 2002. For the analysis we use the following indices to measure the behaviour of these four equities market. The general index of CSE, the general index of ASE, the Financial Times index, FTSE100 for LSE and the Dow Jones Industrial Average (DJIA) for NYSE. The data has been collected from CSE database and DATASTREAM. All series are taken in natural logarithms.

In order to avoid the problem of non-stationarity, which is a well known feature of stock price series, it is necessary to make use of first- (or higher) order differentiated data. To examine, whether the series under consideration are stationary, we apply the Elliot *et al*. (1996) GLS augmented Dickey-Fuller test (DF-GLS_u) and Ng and Perron (2001) GLS versions of the modified Phillips-Perron (1988) tests (MZ_a^{GLS} and MZ_t^{GLS}). The null hypothesis is that of a unit root against the alternative that the initial observation is drawn from its unconditional distribution and uses GLS-detrending as proposed by Elliott *et al*. (1996) and extended by Elliott (1999), to maximize power, and a modified selection criterion to select the lag truncation parameter in order to minimize size distortion. In the GLS procedure of Elliot *et al*. (1996), the standard unit root tests (without trend) are applied after the series are first detrended under the local alternative $\rho = 1 + \alpha / T$. This was found to provide substantial power gains for the DF-GLS$_u$ test resulting to power functions that lie just under the asymptotic power envelope. Ng and Perron (2001) find similar gains for the MZ_a^{GLS} and MZ_t^{GLS} tests. They also found that a modification of the AIC criterion (MIC), give rise to substantial size improvements over alternative selection rules such as BIC. For robustness, we then apply the Kwiatkowski *et al*. (1992) KPSS test for the null hypothesis of level or trend stationarity against the alternative of non-stationarity. The results of the unit root and stationarity tests are presented in Table 1. The results show that we are unable to reject the null hypothesis of non-stationarity with the DF-GLS$_u$ and MZ_a^{GLS} and MZ_t^{GLS} tests and we reject the null hypothesis of stationarity with the KPSS test for the levels of all four series. The results are reversed when we take the first difference of each stock price series which leads us to the conclusion that all variables are realizations of $I(1)$ processes.

Given these preliminary results we consider the first differences for the stock price in each market as:

$$\Delta p_t = 100 * (p_t - p_{t-1}) \tag{10}$$

which corresponds to the approximate percentage nominal change on each price obtained from time t to t-1.

We also calculate several descriptive statistics for monthly percentage changes in the stock prices. These descriptive statistics are reported in Table 2. The skewness and kurtosis measures indicate that all series are positively skewed and highly leptokurtic relative to the normal distribution. This result is further reinforced from the Jacque-Bera statistic which implies that we reject the null hypothesis of normality. These results are in line with the well established evidence of all previous econometric studies in the literature for the stock markets (mature and emerging), i.e.

that the distribution of daily stock returns is not the normal one. Rejection of normality can be partially attributed to intertemporal dependencies in the moments of the series. We also calculate the Ljung-Box (1978) portmanteau test statistics Q and Q^2 (for the squared data) to test for first- and second-moment dependencies in the distribution of the stock price changes. The Q statistic indicates that percentage monthly changes of each rates are serial correlated. This outcome can be interpreted as evidence against the market efficiency hypothesis for the CSE, which was expected given that this market is an emerging one. Furthermore, this outcome also helps us to justify the use of linear filters such as the autoregressive (AR) or the autoregressive vectors (VAR). The Q^2 statistics for all returns series are statistically significant, providing evidence of strong second-moment dependencies (conditional heteroskedasticity) in the distribution of the stock price changes. This finding implies that there is strong evidence for the presence of non-linear dependence between the stock indices. It is also evident that the size of the statistics improves as we move from an emerging market (CSE) towards the mature markets (LSE and NYSE).

4. The EGARCH-M model

This paper employs the EGARCH-in-Mean model developed by Koutmos and Theodossiou (1994) to study the time-series behaviour of the stock prices and returns of the capital markets of Cyprus, Greece, UK and US.

Specifically, we model official and black market exchange changes as follows:

$$R_t = a_0 + \sum_{i=1}^{r} a_i R_{t-i} + \phi\sigma^2 + \varepsilon_t \,, \qquad \varepsilon_t / \Omega_{t-1} \tag{11}$$

$$\log(\sigma_t^2) = \exp\{\alpha_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{i=1}^{p} b_i \log(\sigma_{t-i}^2)\} \tag{12}$$

$$g(z_t) = \theta z_t + [|z_t| - E|z_t|] \qquad (13)$$

where R_t are returns, ε_t is the stochastic error, Ω_{t-1} is the information set at time *t-1*, σ_t^2 is the conditional (time varying) variance, and z_t is the standardized residuals $(\varepsilon_t / \sigma_t)$. Conditional on Ω_{t-1}, ε_t is assumed to follow the Generalized Error Distribution (G.E.D.).

We specify equation (11) (conditional mean equation) as an autoregressive process of order $r[AR(r)]$. To find the appropriate lag length r for each return series, we consider the Akaike Information Criterion (AIC) for each series.

Equation (12) (conditional variance equation) reflects the EGARCH(p,q)-M representation of the variance of ε_t. According to the EGARCH-M representation, the variance is conditional on its own past values as well as on past values of a function of z_t, the standardized residuals $(\varepsilon_t / \sigma_t)$. The persistence of volatility implied by equation (12) is measured by $\sum_{i=1}^{p} b_i$ (Engle and Bollerslev, 1986). The unconditional variance is finite if $\sum_{i=1}^{p} b_i < 1$. In equation (13), the second term captures the ARCH effect, an effect similar to the idea behind the GARCH specification. A negative and statistically significant θ indicates that a leverage effect exists. We determine lag truncation lengths, p and q, using Likelihood Ratio (LR) tests of alternative specifications. On the basis of these tests, we found that an EGARCH-M (1,1) is chosen for all four markets.

Given a sample of T observations and the generalized error distribution for the exchange rate changes, we can write the log likelihood function for the EGARCH-M as

$$L(\Theta) = T\{\log(D/\lambda) - (1 + D^{-1})\log 2 - \log[\Gamma(1/D)]\} - (1/2)\sum_{t=1}^{T} |(\varepsilon_t)/(\lambda\sqrt{\sigma_t^2}|^D$$
$$- (1/2)\sum_{t=1}^{T} \log(\sigma_t^2) \quad (14)$$

where Θ is the parameter vector $(a_0, a_1, \phi, \alpha_0, \alpha_1, b_1, D, \theta)$ to be estimated.[3] We use the BFGS algorithm to maximize $L(\Theta)$.

Recently, there has been increasing interest in the causation in conditional variance across various financial asset price movements. The study of causality in variance is of interest because of its economic and statistical significance. First, changes in variance are said to reflect the arrival of information and the extent to which the market evaluates and assimilates new information. For example, Ross (1989) shows that in a no-arbitrage economy the variance of price changes is directly related to the rate of information flow to the market. Engle, Ito, and Lin (1990), however, attribute movements in variance to the time required by market participants to process new information or for policy coordination. Thus, the relation between information flow and volatility provides an interesting perspective from which to interpret the causation in variance between a pair of economic time series. Second, the causation pattern in variance provides insight concerning the characteristics and dynamics of financial asset prices.

5. Empirical results

Table 3 presents the estimates for the univariate EGARCH(1,1)-M model for stock price series for CSE, ASE, LSE and NYSE. All parameters are statistically

[3] $\Gamma(.)$ is the gamma function, λ is the constant given by $\lambda = \{\frac{2^{(-2/D)}\Gamma(1/D)}{\Gamma(3/D)}\}$. D is the scale parameter of the G.E.D. If $D = 2$ then G.E.D. becomes the standard normal distribution.

significantly greater than zero according to the *t*-statistics for all cases. The strength of significance for all price series is an indication of the appropriateness of the EGARCH-M model for the stock price data. Table 3 also reports the skewness and kurtosis of the standardized residuals. In all cases we see a fall in the degree of leptokurtosis compared to the one reported in Table 2 for all the stock price series. Thus, we can argue that the EGARCH-M model fully captures all linear and nonlinear dependencies in the changes of the stock prices for each market. However, the skewness and kurtosis coefficients indicate that standardized residuals for all stock prices exhibit strong deviations from normality. This justifies the use of the G.E.D. Finally, Table 3 shows that the degree of volatility persistence (measured by b_1) is less than unity in most cases and statistically significant. These results indicate that the fitted models are second-order stationary and that at least the second moment exists (Bollerslev, 1986). Furthermore, given that the values of these coefficients are between 0.95 and 0.99, there is evidence that the persistence in shocks to volatility is relatively large and that the response function of volatility of shocks decays at a relatively slow rate. The scale parameter of the G.E.D. are statistically different from two, justifying the use of the G.E.D. instead of the normal distribution. Finally, the estimated parameter θ is negative but not statistically significant implying no evidence of leverage effect.

We now turn to the application of the CCF test in order to investigate the causal relations between the stock returns of the four markets. Tables 4 and 5 report the calculated CCF-test statistic for ten leads (+1, +2, +3,….,+10) and ten lags (-1, -2, -3,….,-10). These tables also report the Ljung Box Q-statistics for various lag structures, namely (-2, +2), (-4, +4), (-6, +6), (-8, +8) and (-10, +10) (Gujarati, 1995). These diagnostics test the joint null hypothesis that all the cross-correlation statistics for the respective lag structures are simultaneously equal to zero against the alternative that at least one is statistically significant. We can summarize the overall statistical evidence that emerges from Tables 4 and 5 as follows. First, the CCF-test statistics over the period –10, -9,….,+9, +10 follow behavior which is in line with that of the CCF-test statistics reported in Cheung and Ng (1996). Second, the calculated Ljung-Box Q-statistics are in line with the results regarding the statistical significance of the CCF-test statistics for specific lags. Thus, the direction of the relationship can be traced by the sign of the CCF-test statistic. Given the above statistical analysis we move on to the economic interpretation of our estimations.

Table 4 reports the results for causality in mean across the four equities markets. As shown in this table, there is evidence of feedback (causality at lag 0) between Athens and Cyprus. There is also evidence of causality from Athens to Cyprus (at lags 1,2 and 3), from London to Cyprus (at lags 1,2 and 4) and from New York to Cyprus (at lags 1,2 and 5). Table 5 reports the results for causality in variance across the four equities markets. Causality in variance exists from ASE to CSE (at lags 0, 1 and 2), from LSE to CSE (at lags 1 and 2) and from NYSE to CSE (at lags 1 and 2). It is clear therefore that the general index of CSE receives volatility from all the other three international stock markets, i.e. the ASE, the LSE and the NYSE. It is significant to note that the causality in variance from ASE to CSE is statistically significant on the same day as well as with one and two days lags an outcome which is consistent with the fact that the Cypriot capital market is highly influenced from movements in the general index of the Greek capital market. Furthermore, the volatility spillover from the LSE and the NYSE is statistically significant with one day lag. This lagged influence is possibly due to the lack of synchronization in the trading between the capital market of Cyprus and those of London and New York.

Finally, from Table 5 we observe that the changes in the general index of CSE have no volatility influence on any of the other international financial markets.

Comparison of tables 4 and 5 indicates that the pattern of mean-causality is very similar to that of variance-causality. Thus, there is both mean-causality and variance-causality from Athens to Cyprus at lag 0, from Athens to Cyprus at lags 1and 2, from London to Cyprus at lags 1 and 2 and from New York to Cyprus at lags 1 and 5. This common pattern in the mean-causality and in the variance-causality leads us to address the issue of whether the identified mean-causality is due to the variance-causality. To explore this, we re-estimate the model given in equations (11) to (13) for the official markets without the variance term in the conditional mean equation, i.e. we estimate EGARCH instead of EGARCH-M models. The simple EGARCH, as opposed to the EGARCH-M, has the feature of not including the influence of the variance in the mean equation. We then apply the CCF testing procedure to the standardized and squared standardized residuals from the simple EGARCH models. The results indicate that the mean causality pattern is much different from the one found under the EGARCH-M models.[4] Specifically, the only evidence of mean causality is from Athens to Cyprus (at lags 0 and 1), while all the other evidence of mean causality has now disappeared. This leads us to the conclusion that the mean-causality is largely due to variance-causality.

Summarizing our results, we argue that the equities markets of Athens, London and New York are the major exporters of while the stock market of Cyprus is the sole importer of volatility.

6. Conclusions

[4] The results of these tests are not reported here to save space but are available upon request.

This paper examines the issue of mean and variance causality as well as of volatility spillovers among the stock markets of Cyprus, Greece, UK and the US using daily data during the period from 29 March 1996 to 19 April 2002. The empirical evidence presented in this paper indicates that time series of daily returns of these markets exhibit significant second moment dependence. There are several important findings which stem from our work. First, EGARCH-in-Mean processes satisfactorily characterize the daily stock returns of the equities markets of Cyprus, Athens, London and New York. Second, with the application of the CCF test developed by Cheung and Ng (1996), we test the hypothesis that causality-in-variance and causality-in-mean exist among the returns of these four stock markets. Furthermore, it is also shown that the stock markets of Athens, London and New York are the major exporters of volatility to that of Cyprus, while movements in the CSE general price index have no impact on the returns of the ASE, LSE and NYSE. Finally, from the overall results, we can conclude that, in all cases causality-in-mean is also associated with causality-in-variance. To explore whether the causality-in-mean is driven by the causality-in-variance, we re-estimate the EGARCH models excluding the variance terms in the mean equations. The results indicate that the causality–in-mean, which is present using the EGARCH-M models, disappears in most cases. This finding implies that the identified causality-in-mean is largely driven by causality in variance.

Overall, these results provide useful insights regarding the interdependencies of the stock markets of Cyprus, Greece, UK and the US markets. These results are useful for domestic and foreign portfolio managers that are considering in their portfolios equities from emerging markets such that of Cyprus.

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Table 1. Unit root and stationarity tests

Market	Variable			Statistic			
		t_μ	t_τ	MZ_a^{GLS}	MZ_t^{GLS}	η_μ	η_τ
CSE	p	-1.99 [3]	-2.32 [3]	-2.44 [5]	-1.25 [5]	1.355*	0.456*
	Δp	-11.44* [3]	-12.11* [3]	-29.86* [6]	-3.44* [5]	0.098	0.037
ASE	p	-1.22 [2]	-1.56 [3]	-2.57 [4]	-0.99 [3]	1.578*	0.908*
	Δp	-13.02* [3]	-13.57* [3]	-33.02* [4]	-11.23* [4]	0.122	0.077
LSE	p	-0.63 [4]	-2.55 [4]	-1.11 [6]	-1.55 [4]	2.199*	0.776*
	Δp	-14.22* [4]	-9.66* [4]	-18.22* [5]	-15.66* [5]	0.254	0.056
NYSE	p	-1.02 [4]	-2.33 [4]	-2.028 [6]	-1.09 [6]	1.992*	0.882*
	Δp	-11.22* [4]	-12.88* [4]	-30.011 [6]	-8.34* [6]	0.101	0.089

Notes: p and Δp are the prices and returns, respectively.

- The DF-GLS_u is due to Elliot et al. (1996) and Elliott (1999) is a test with an unconditional alternative hypothesis. The standard Dickey-Fuller tests are detrended (with constant or constant and trend). The critical values for the DF-GLS_u test at the 5% significance level are:-2.73 (with constant, t_μ) and -3.17 (with constant and trend, t_τ), respectively (Elliott,1999).
- MZ_a and MZ_t are the Ng and Perron (2001) GLS versions of the Phillips-Perron tests. The critical values at 5% significance level are: -8.10 and -1.98 (with constant), respectively (Ng and Perron, 2001, Table 1).
- η_μ and η_τ are the KPSS test statistics for level and trend stationarity respectively (Kwiatkowski *et al*. 1992). For the computation of theses statistics a Newey and West (1994) robust kernel estimate of the "long-run" variance is used. The kernel estimator is constructed using a quadratic spectral kernel with VAR(l) pre-whitening and automatic data-dependent bandwidth selection [see, Newey and West, 1994 for details]. The 5% critical values for level and trend stationarity are 0461 and 0.148 respectively, and they are taken from Sephton (1995, Table 2).

Numbers in brackets denotes the lag structure to ensure absence of serial correlation.
(*) indicates significance at the 95% confidence level.

Table 2. Descriptive Statistics – Daily Data

	CSE		ASE		LSE		NYSE	
	p_t	Δp_t	p_t	Δp_t	p_t	Δp_t	p_t	Δp_t
Mean	4.97	0.003	7.80	0.05	8.60	0.23	9.1	0.4
Standard Deviation	0.69	0.10	0.54	0.02	0.20	0.01	0.22	0.01
m_3	1.05*	7.60*	-0.31*	-0.10	-0.76*	-0.14*	-0.84*	-0.52*
m_4	0.20	354.1*	-0.90*	2.52*	-0.55*	0.95*	-0.44*	4.0*
JB	284.5*	7.9x 10^6	76.5*	400.9*	164.8*	62.2*	195.0*	1069.8*
$Q(24)$	1560.7	2570.1*	182.1*	145.5*	192.9*	100.0*	199.1*	141.0*
$Q^2(24)$	1670.7*	1990.0*	243.1*	187.1*	199.1*	143.9*	122.0*	191.1*

Notes: The average return is expressed in terms of $x10^3$; m_3 and m_4 are the coefficients of skewness and kurtosis of the standardized residuals respectively; JB is the statistic for the null of normality; $Q(24)$ and $Q^2(24)$ are the Ljung-Box test statistics for up to 24th-order serial correlation in the Δp_t and Δp_t^2 series, respectively. (*) denotes statistical significance at the 5 percent critical level.

Table 3. Maximum-likelihood estimates of EGARCH(1,1)-M model

Coefficient	CSE	ASE	LSE	NYSE
a_0	0.01 (0.53)	0.01 (1.30)	0.01 (0.91)	0.01 (1.20)
a_1	0.30 * (8.45)	0.42 * (8.10)	0.30 * (5.21)	0.35 * (7.00)
a_2	0.07 (1.30)	0.05 (0.60)	0.08 (1.06)	0.05 (0.99)
a_3	0.06 (1.49)	0.12 * (2.45)	0.04 (1.61)	0.06 (0.90)
ϕ	0.54 (1.54)	0.03 (0.12)	-0.01 (-0.003)	-0.01 (-0.02)
α_0	-0.36* (-2.90)	-0.36 * (-2.22)	-0.47 * (-2.30)	-0.21 * (-2.12)
α_1	0.31* (4.64)	0.21* (4.16)	0.22* (4.00)	0.19* (4.61)
b_1	0.99* (55.89)	0.97 * (41.50)	0.95* (30.90)	0.98* (40.12)
θ	-0.11 (-1.52)	-0.05 (-0.51)	-0.13 (-1.21)	-0.15 (-1.30)
LogLikelihood	1000.0	1001.1	997.1	990.0
D	0.336* (16.72)	0.422* (13.22)	0.752* (13.66)	0.687* (15.56)
m_3	0.25	-0.10	-0.13	-0.35
m_4	4.11	4.32	4.30	4.41
$Q(24)$	10.78	7.91	13.12	9.39
$Q^2(24)$	8.99	2.21	12.91	8.81

Notes: $\Delta p_t = 100[\log p_t - \log p_{t-1}]$; For all cases the mean equation is an AR(1); D is the scale parameter for the G.E.D., m_3 and m_4 are the coefficients of skewness and kurtosis of the standardized residuals respectively; $Q(24)$ and $Q^2(24)$ are the Lung-Box statistics of 24th order of the standardized residuals and squared standardized residuals, respectively. (*) indicates statistical significance at the 0.05 level. Numbers in parenthesis are *t*-statistics.

Table 4. Causality in Mean

Lag	CSE-ASE	CSE-LSE	CSE-NYSE
-10	-0.41	0.17	0.33
-9	-0.62	1.12	1.63
-8	0.11	0.62	-0.41
-7	-0.23	-0.36	-0.61
-6	-0.02	-1.61	-0.97
-5	-0.19	-0.21	-0.00
-4	-0.27	0.30	-0.42
-3	-0.16	0.02	-0.11
-2	-0.28	-0.26	0.36
-1	-0.49	0.19	-0.96
0	10.61*	-0.32	0.47
+1	9.91*	8.26*	7.11*
+2	6.38*	7.19*	4.72*
+3	5.22*	1.19	2.12
+4	1.16	4.77*	0.42
+5	-0.31	-0.92	4.62*
+6	0.02	-0.17	-0.39
+7	0.41	-0.01	0.91
+8	1.22	-0.39	-0.17
+9	0.63	-0.21	0.16
+10	-0.19	0.45	0.00
		Diagnostics	
Q (-2 to +2)	44.21* [0.00]	55.23* [0.00]	49.12* [0.00]
Q (-4 to +4)	25.66* [0.04]	44.13* [0.00]	33.55* [0.00]
Q (-6 to +6)	33.22* [0.00]	31.13* [0.00]	41.33* [0.00]
Q (-8 to +8)	33.16* [0.00]	37.01* [0.00]	31.22* [0.00]
Q(-10 to+10)	29.12* [0.00]	40.12* [0.00]	28.19* [0.00]

Notes:
1. This table reports the CCF-test statistics at the corresponding number of lags.
Positive lags (i.e. +1, +2, …, +10) are leads, and refer to causality tests from the second market to the first market. Negative lags (-1, -2, …, -10) refer to causality tests from the first market to the second market.
2. The CCF-test statistic follows the standard normal distribution.
3. The reported diagnostics are the Ljung-Box Q-statistics for various lag structures. The null hypothesis is that the cross correlation statistic is zero against the alternative that at least one is statistically different from zero.
4. The numbers is squared brackets below the Q-statistics are marginal levels of significance.
5. (*) indicates statistical significance at the 0.05 level.

Table 5. Causality in Variance

Lag	CSE-ASE	CSE-LSE	CSE-NYSE
-10	-0.36	0.22	0.39
-9	-0.38	0.26	-0.05
-8	-0.20	-0.13	0.48
-7	-0.08	-0.13	1.31
-6	0.28	0.31	0.15
-5	-0.00	-0.11	0.19
-4	-0.26	0.18	-0.21
-3	-0.30	0.09	-0.07
-2	-0.27	-0.03	0.18
-1	-0.44	0.14	1.02
0	6.23*	-0.03	0.16
+1	7.12*	9.31*	4.16*
+2	5.45*	6.68*	8.31*
+3	0.63	1.32	0.12
+4	-0.38	-0.22	-0.41
+5	-0.19	-0.02	-0.28
+6	-0.12	-0.20	0.81
+7	-0.43	-0.48	0.91
+8	-0.16	-0.32	-0.36
+9	-0.06	-0.33	-0.00
+10	-0.49	-0.37	-0.03
		Diagnostics	
Q (-2 to +2)	63.53* [0.00]	83.19* [0.00]	65.12* [0.00]
Q (-4 to +4)	67.41* [0.00]	81.21* [0.00]	70.19* [0.00]
Q (-6 to +6)	72.36* [0.00]	76.28* [0.00]	71.16* [0.00]
Q (-8 to +8)	61.19* [0.00]	71.01* [0.00]	84.26* [0.00]
Q(-10 to+10)	62.23* [0.00]	65.24* [0.00]	87.19* [0.00]

Notes:
1. This table reports the CCF-test statistics at the corresponding number of lags.
Positive lags (i.e. +1, +2, …, +10) are leads, and refer to causality tests from the second market to the first market. Negative lags (-1, -2, …, -10) refer to causality tests from the first market to the second market.
2. The CCF-test statistic follows the standard normal distribution.
3. The reported diagnostics are the Ljung-Box Q-statistics for various lag structures. The null hypothesis is that the cross correlation statistic is zero against the alternative that at least one is statistically different from zero.
4. The numbers is squared brackets below the Q-statistics are marginal levels of significance.
5. ** indicates statistical significance at the 0.05 level.

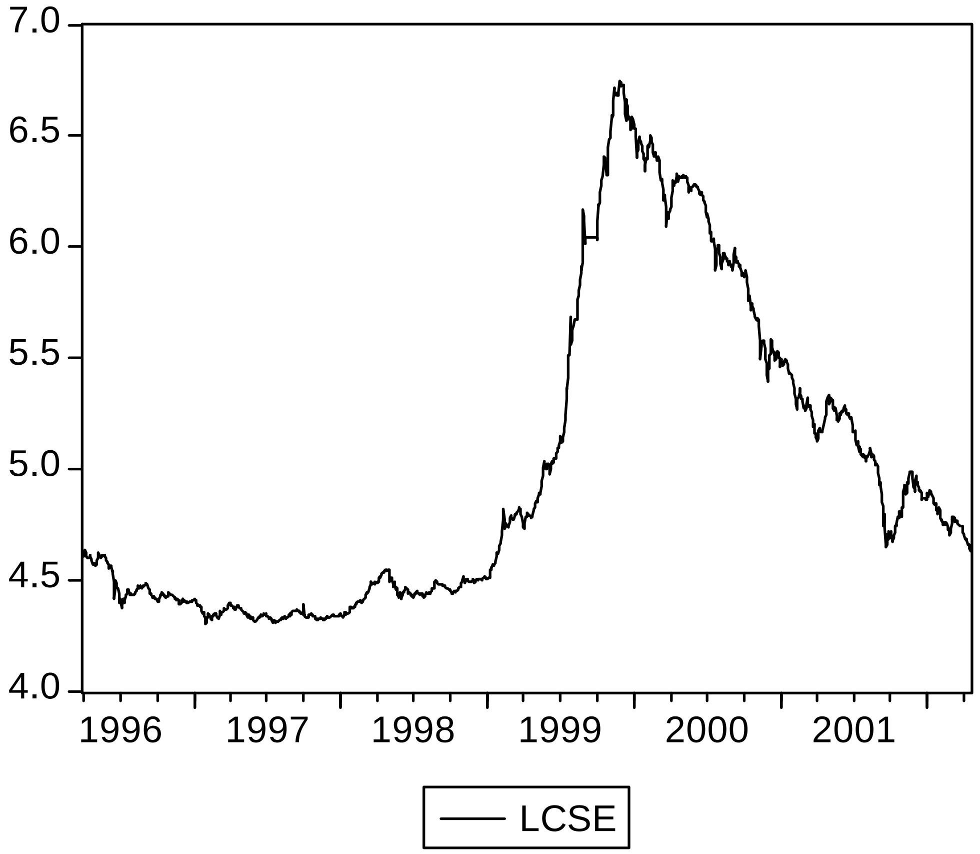

Figure 1. Evolution of the CSE general price index

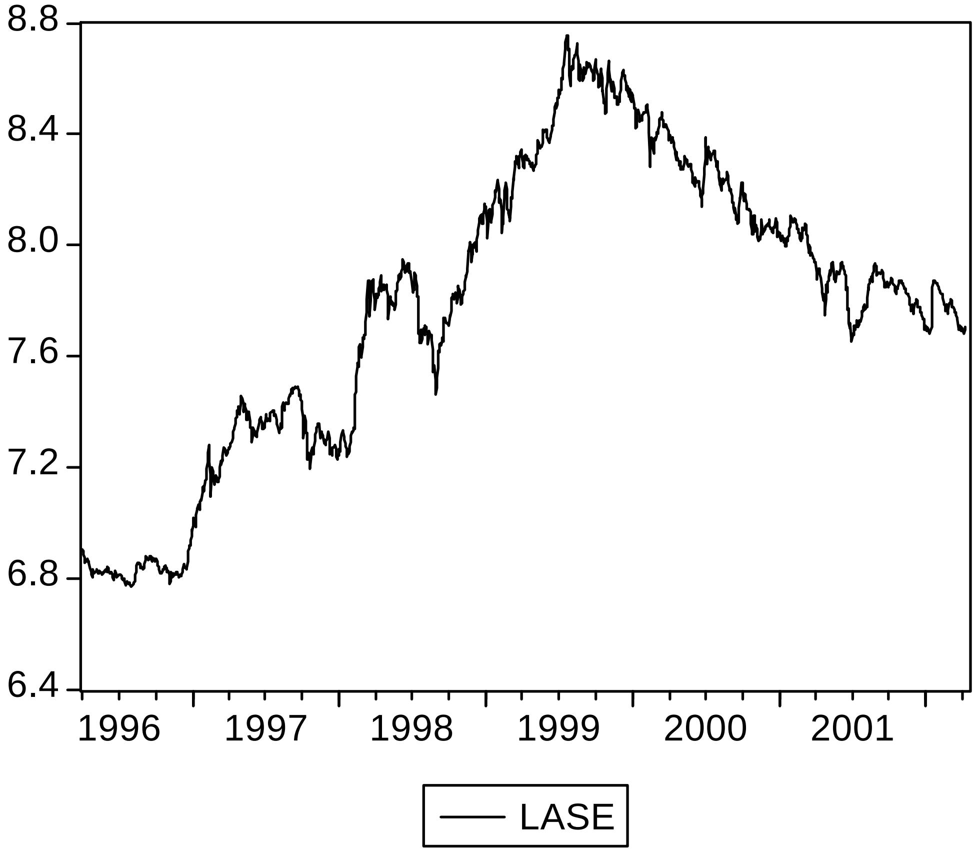

Figure 2. Evolution of the ASE general price index

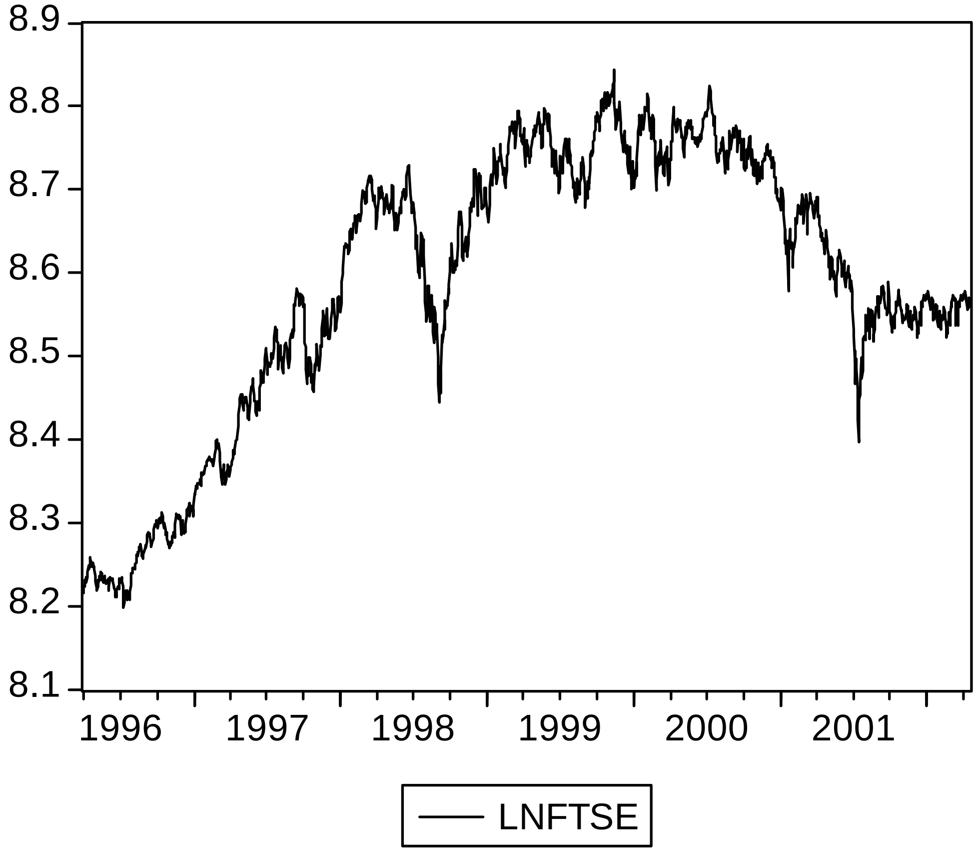

Figure 3. Evolution of the LSE FTSE100 price index

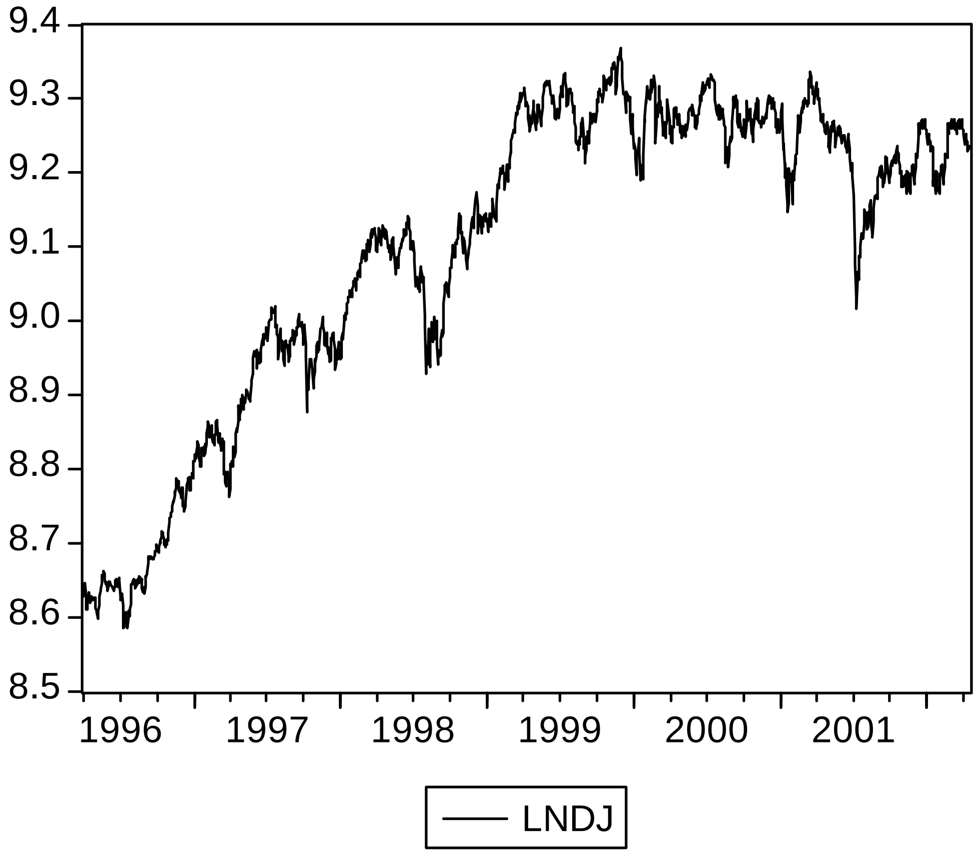

Figure 4. Evolution of the DJIA price index