Mean and Variance Causality Between the Cyprus Stock Exchange and Major Equity Markets[1]

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Abstract

In this paper we provide evidence of mean and variance causality across four equity markets. Specifically, we test for mean and variance spillovers among the stock markets of Cyprus, Athens, London and New York. For this purpose we apply the bivariate causality test developed by Cheung and Ng (1996) for daily data that covers the period of March 29, 1996 to April 19, 2002. Our study reveals several findings. First, we provide evidence that each stock returns series can be adequately modelled by EGARCH-M processes. Second, we report evidence in favour of causality in both mean and variance between the Cyprus capital market and the respective markets of Greece, UK and USA. Furthermore, we show that the causality in mean is driven by the causality in variance to a great extent. Finally, our results lead to the conclusion that the stock market of Cyprus is an importer of causality whereas the stock markets of Athens, London and New York are the major exporters of causality.

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

JEL Classification: C22, C52, G12.

1. Introduction

During the last fifteen years there has been a growing interest among portfolio managers for the emerging capital markets as they provide opportunities for higher asset returns compared to those of the developed markets. This was caused by the substantial increase of capital flows from the mature markets to the emerging markets of the South East Asia and the economies of transition of Central and Eastern European countries. The purpose was to invest in portfolios consisting to a great extent with securities from these new financial markets. Indeed, the study by Singh and Weisse (1998) reports that, during the period of 1989-1995 the inflow of funds in emerging markets amounted to 107.6 billion US dollars as opposed to a mere 15.1 billion US dollars in the previous period, 1983-1988. However, in the aftermath of the financial crisis in Southeast Asia, Latin America and Russia in 1997-1998 we have experienced a substantial increase in financial uncertainty as a result of the increased volatility that stock returns of the mature markets but mainly of those of the emerging markets exhibited.

Furthermore, during the same period we have experienced the negative contagion effects of the bankruptcy of several financial institutions such as the BCCI and Barrings international banks that has further led to the increased price volatility and financial uncertainty. Such financial uncertainty has increased the likelihood of financial institutions to suffer substantial losses as a result of their exposure to unpredictable market changes. Thus, these events have made portfolio managers and institutional investors to become more cautious in their investment decisions while

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[1] 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. The views expressed in this paper do not necessarily reflect those of either CRPF or CSE. An earlier version of this paper was presented at the 4th International Conference of the EEFS, Coibra, 19-22 May 2005, the 9th International Conference on Macroeconomic Analysis and International Finance, University of Crete, 26-28 May 2005, and the 37th Money, Macro and Finance Study Group Annual Conference, University of Crete, 1-3 September 2005 and thanks are due to conference participants for many helpful comments and discussions. We would also like to thank Angelos Kanas for many helpful comments and discussions and for computational assistance with the GAUSS code for the CCF test. The usual disclaimer applies.

it has also led for the increased need for a more careful study of price volatility in stock markets. Indeed, recently we observe an intensive research from academics, financial institutions and regulators of the banking and financial sectors to better understanding the operation of capital markets and to develop sophisticated models to understand and model these markets in a more coherent way. Modelling the stock returns volatility is of great importance especially in the case that the stock market has undergone different structural changes. Furthermore, it is important to study and model the price volatility of financial assets because we want to have reliable inputs in order to price alternative financial products (for example options and futures). Furthermore, modelling volatility is important for the innovation of optimal hedging techniques with respect to the risk exposure from transactions with foreign economies.

It becomes obvious therefore, that since the late 1980s there has been a growing interest in the study of causality in conditional variance across alternative financial asset price changes since such causation have far reaching economic and statistical implications. There are two main reasons calling for a thorough analysis of causation in conditional variance. The first reason is related to the role of news on changing causality pattern. Changes in variance are taken to reflect the arrival of new information and the extent to which the market evaluates and assimilates new information. Following this framework of analysis, Ross (1989) argues that in the case of a no-arbitrage economy the variance of price changes is directly linked to the rate that new information flows to the market. By contrast, Engle *et al*. (1990) argue that movements in variance reflect the time needed by market participants to process new information or it is the result in shifts in policy coordination among certain group of countries. Second, we can utilize the causation pattern in variance to study in depth the characteristics and dynamics of financial asset prices.

The seminal works of Mandelbrot (1963, 1967), Fama (1965) and Fielitz (1971) as well as subsequent work in the statistical properties of financial returns have led to the emergence of several stylized facts with respect to the characteristics of financial data. These characteristics can be summarized as follows: First, financial returns are leptokurtic and therefore we should not model their empirical distribution based on the assumption of normality. Second, that the variance of the errors does not follow the assumptions of homoskedasticity and independence over time. Third, that stock returns are negatively skewed and finally that they exhibit volatility clustering, which means that the squared returns have significant autocorrelation. This last stylized fact means that there are periods of large absolute changes tend to cluster together followed by periods of relatively small absolute changes.

Engle (1982), was the first study, to allow for the time-varying volatility of the returns of financial assets leading to the emergence of the autoregressive conditional heteroskedastic (ARCH) methodology. Bollerslev (1986) generalized this methodology, proposing the generalized autoregressive conditional heteroscedasticity (GARCH) methodology. During the last quarter of a century a number of variants of these models have been proposed while a voluminous literature of empirical applications has been emerged (see Bollerslev *et al*. (1992); Bera and Higgins (1993); Bollerslev *et al*. (1994) and Engle (2002) for an extensive literature review)[1].

This paper examines the issue of volatility transmission between four equity 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

[1] Bollerslev (1987) and Akgiray (1989) show that this class of models describe accurately daily and weekly data for all major stock price indices. Baillie and Bollerslev (1991), Barclay *et al*. (1990), Cheung and Ng (1990), Engle *et al*. (1990), Hamao *et al*. (1990) and King and Wadhwani (1990) provide evidence of causation in conditional variance across the returns of financial assets. Moreover, Baillie and Bollerslev (1989) show that ARCH effects tend to weaken as we move from high to low frequency data whereas Drost and Nijman (1993) have shown that ARCH processes converge to normality as we move from high to low frequency data.

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(a) 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 attribute the presence of 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(a) and 2(a) (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 its initial level while currently is below the 100 units, (this pattern remains the same until today). Figures 3(a) and 4(a) show the evolution of the general price index of the LSE and NYSE respectively. Finally, Figures 1(b) – 4(b) show the portfolio returns in the respective market[1].

To examine for causality in both the variance and the mean between these four equity markets, the present paper adopts the two-stage Cross-Correlation Function (CCF) testing methodology developed by Cheung and Ng (1996). The empirical analysis of causality in the mean and the variance is mainly based on estimating alternative multivariate GARCH modelling. However, the proposed CCF methodology has certain advantages over the ARCH/GARCH class of models in this context which provide the motivation for this study. We can summarize these advantages as follows. First, the application of the CCF is straightforward since does not require the simultaneous modeling of intra- and inter-series dynamics as the multivariate GARCH based tests. Second, Engle and Kroener (1993) have shown that the multivariate GARCH modelling methodology is subject to uncertainty for both the first- and second-moment dynamics, the potential interdependence between the series under examination and finally the asymptotic distribution of the maximum likelihood estimator. Third, as a consequence the specification of a multivariate GARCH model that adequately describes the data is a difficult task. Fourth, the CCF procedure is particularly useful in cases with a large number of time series, given that we are not required to specify the intra- and inter-series dynamics. Finally, Cheung and Ng (1996) have shown that the CCF test statistics have a well defined asymptotic distribution and they are asymptotically robust to distributional assumptions. Moreover, with the application of Monte Carlo simulations, they show that the CCF test has better power properties against the appropriate causality-in-variance alternative and is robust to nonsymmetric and leptokurtic errors. An additional motivation for the present study is that with this testing approach we can also test for the interaction between the tests for causality in mean and variance. Alternative model specifications can call for the existence for causation in mean independently of the existence of causality in variance or dependent on causality in variance

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[1] Constantinou *et al*. (2006) provide a comprehensive study for the characteristics of the Cyprus Stock Exchange.

as well as the opposite causal direction. Therefore, we are interested in examining the performance of the CCF test statistics when causation is present in both the mean and the variance.

We obtained several interesting results from our analysis. First, we have model the distributional properties of stock returns of the four equity markets by fitting an EGARCH(1,1)-M model with Generalized Error Distributions. Second, we observe that there is strong evidence for the existence of causality in both mean and variance with the causality in mean mainly driven by the causality in variance. This finding leads to the conclusion that there are substantial volatility spillovers effects from one market to another. Finally, the results indicate that the ASE, the LSE and the NYSE are exporters of causality to price changes in the stock market of Cyprus which is therefore considered to be an importer of causality. In addition, price movements in the Cyprus Stock Exchange do not create any volatility effect on each of the three other international equity markets. This result can be explained on the grounds 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 rest of the paper is structured as follows. In section 2 we present the cross-correlation function test. Section 3 describes the data and presents the results from unit root tests. In section 4 we provide a description of the EGARCH-M specification. Section 5 reports and discusses the estimated equations and the evidence of mean and variance causality between the four equity markets with our summary and concluding remarks given in section 6.

2. The Cross-Correlation Function

Following Cheung and Ng (1996) let us consider two stationary and ergodic time series X_t and Y_t as well as 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[1]

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

In equation (1) $\mu_{x,t+1}$ is defined as the mean of X_{t+1} conditional on the information set I_t. For feedback (contemporaneous causality) in variance to occur we require to occur if X causes Y and Y causes X, that is only if

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

By the same token, we define causality in mean running from Y_t to X_{t+1} if

$$E\{(X_{t+1} / I_t\} \neq E\{(X_{t+1} / J_t\}. \quad (3)$$

In order to test for causality in mean and variance for any two returns of financial assets, we impose an additional structure in equations (1) to (3). Let us assume that the mean equations for series X_t and Y_t can be written with following mathematical formulation:

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

ε_t and ζ_t are taken to represent two independent white noise processes with zero mean and unit variance. Moreover, the conditional mean and variances are written as:

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

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

[1] Causation in the second moment can be viewed as an extension of the Wiener-Granger causality in mean (Granger, Robins and Engle, 1986).

where $\theta_{z,w}$ is a parameter vector of dimensions $p_{z,w}$x1; Furthermore, we define $W = \mu, h$; $\varphi_{z,i}(\theta_{z,\mu})$ and $\varphi_{z,i}(\theta_{z,h})$ as unique functions of $\theta_{z,\mu}$ and $\theta_{z,h}$; and $Z = X, Y$. Equations (4) and (5) underline model specifications of time series including the autoregressive moving average (ARMA) models for the mean and the GARCH models for the variance.

The next stage of this causality methodology is to define the squared standardized residuals for series X_t and Y_t. These are given as:

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

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

with ε_t and ζ_t being the standardized residuals. Additionally, we define $r_{UV}(k)$ as the sample cross-correlation of the squared standardized residual series and $r_{\varepsilon\zeta}(k)$ as the sample cross-correlation of the standardized residual series at time lag k.

The quantities $r_{UV}(k)$ and $r_{\varepsilon\zeta}(k)$ are used to test for causality in variance and causality in mean respectively within the framework offered by the CCF testing methodology. We are able to test two independent hypotheses.

First, we can test the null hypothesis of noncausality in variance against the alternative hypothesis of causality at time lag k[1]. To this end the appropriate CCF-statistic is given by

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

Second, we can test the null hypothesis of noncausality in mean against the alternative hypothesis of causality at time lag k, the CCF-statistic is given by

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

The CCF procedure is applied in two steps[2]. First, we estimate models of the ARCH/GARCH family that allows for time variation in both conditional means and conditional variances for each univariate series. In our case we consider an EGARCH-M specification to model the time-varying variance for each stock returns based on several diagnostic tests typically employed in the literature. Second, we obtain the squared residuals of each estimated model and we then construct the series of squared residuals standardized by conditional variances. As we have already explained we use the cross correlation function of these squared-standardized residuals to test the null hypothesis of no causality in variance and/ or the null hypothesis of causality in mean. Such procedure will help us to identify whether any interaction between the tests for causality in mean and variance exists.

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. Recently, Panopoulou (2005) have applied this testing approach in order to study causality patterns between leading indicators for European economies before and after the introduction of Euro.

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 of 29 March 1996 (First day of transactions at CSE) to 19 April 2002.

[1]Cheung and Ng (1996) have shown that the CCF-statistics given in equations (8) and (9) have an asymptotic standard normal distribution. Furthermore, with the conduct of Monte Carlo experiments they show that this methodology is robust to nonsymmetric and leptokurtic errors and asymptotically robust to distributional assumptions.

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

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.

We begin our analysis by examining the stochastic properties of the time series. A well known feature of stock price series is that they are level and/or trend non-stationary and we are therefore required 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.

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	-0.60 [4]	-0.34 [4]	-0.14 [1]	-0.15 [1]	2.251*	0.619*
	Δp	-16.75* [3]	-16.63* [3]	-424.52* [3]	-14.56* [3]	0.221	0.136
ASE	p	-0.15 [1]	-0.56 [1]	-0.74 [4]	-0.65 [4]	2.883*	1.061*
	Δp	-31.93* [0]	-32.49* [0]	-753.13* [0]	-19.40* [0]	0.172	0.117
LSE	p	-0.19 [2]	-0.85 [2]	-0.20 [2]	-0.19 [2]	2.584*	1.121*
	Δp	-5.85* [11]	-7.19* [11]	-23.37* [11]	-3.39* [11]	0.306	0.036
NYSE	p	0.28 [0]	-1.33 [0]	0.26 [0]	0.28 [2]	3.771*	1.054*
	Δp	-3.96* [11]	-28.92* [11]	-14.93* [11]	-2.70* [11]	0.160	0.024

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).

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

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*.

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.

Coupled with the unit root tests we also calculate typically used 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. We can attribute to some extent the rejection of the normality assumption to the presence of intertemporal dependencies in the moments of the series. The calculated Ljung-Box (1978) portmanteau test statistics Q and Q^2 (for the squared data) which test for first- and second-moment dependencies in the distribution of the stock price changes are also reported. The Q statistic provides evidence that the percentage monthly changes of each price index are autocorrelated. 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). Furthermore, the Q^2 statistics for all returns series are statistically significant, implying the existence of strong second-moment dependencies (conditional heteroskedasticity) in the distribution of the stock price changes. This outcome 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

The first stage of this two step CCF testing procedure involves the estimation of an EGARCH-in-Mean model due to Koutmos and Theodossiou (1994). This is required in order to study the distributional properties of the stock prices and returns of the capital markets of Cyprus, Greece, the UK and the US,

We model stock returns as follows:

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

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

$$g(z_t) = \theta z_t + [|z_t| - E|z_t|], \tag{13}$$

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.).

Equation (11) (which is the conditional mean equation) is specified as an autoregressive process of order $r[AR(r)]$. To find the appropriate lag length r for each return series, we use the Akaike Information Criterion (AIC) to each stock returns series.

Equation (12) (which is the conditional variance equation) represents the EGARCH(p,q)-M specification of the variance of ε_t. According to this specification, we model the variance to be conditional on its own past values as well as on past values of a function of the standardized residuals z_t. As Engle and Bollerslev (1986) show the quantity $\sum_{i=1}^{p} b_i$ measures the persistence of volatility implied by equation (12). Furthermore, as for all the ARCH/GARCH class of models, we assume that the unconditional variance is finite if $\sum_{i=1}^{p} b_i < 1$, while the second term in equation (13) captures the ARCH effect. Finally, the coefficient θ measures the existence of a leverage effect which exists if we obtain a negative and statistically significant estimate of it.

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

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

where Θ is the parameter vector $(a_0, a_1, \phi, \alpha_0, \alpha_1, b_1, D, \theta)$ to be estimated[1]. The maximization $L(\Theta)$ is obtained with the use of the BFGS algorithm.

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[2]. The overall results indicate that all parameters are statistically significant and in addition we consider this significance which holds for all stock returns as a measure of good fit of the EGARCH-M model to the distributional properties of the returns. We also report the skewness and kurtosis statistics of the standardized residuals which further reinforce our observation that th chosen model is the appropriate one since it is clear that a fall in the degree of leptokurtosis compared to the one offered by the univariate descriptive diagnostics in Table 2 is well documented.

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

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[1] $\Gamma(.)$ 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.

[2] 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.

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. Figures in parenthesis are t-statistics.

Therefore, the overall results lead us to the conclusion that the EGARCH-M model accurately captures all linear and nonlinear dependencies in the changes of the stock prices for each market. However, based on the evidence provided by the skewness and kurtosis coefficients we model the empirical distribution of the standardized residuals with the G.E.D distribution since all stock returns show significant departures from normality. In fact the scale parameter of the G.E.D. is found to be statistically different from two, justifying the use of the G.E.D. instead of the normal distribution.

Table 3 also reports the estimates of the coefficient b_1 which measures the degree of volatility persistence. We observe that in most cases its value is less than unity (ranging from 0.95 to 0.99) and significant at standard levels of significance. These estimates lead to the conclusion 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. Finally, the estimates of the parameter θ take negative values but they are not statistically significant and therefore no evidence of leverage effect is evident.

Tables 4 and 5 report the calculated CCF-test statistic for ten leads (+1, +2, +3,….,+10) and ten lags (-1, -2, -3,….,-10) in order to investigate the causal relations between the stock returns of the four markets in a bivariate setting. We also report the calculated Ljung Box Q-statistics for various lag structures, namely (-2, +2), (-4, +4), (-6, +6), (-8, +8) and (-10, +10) as they are explained by 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. Several important findings stem from our estimates. First, we observe that the CCF-test statistics over the period –10, -9,….,+9, +10 follow a pattern that is not different from the one suggested in Cheung and Ng (1996). Second, the calculated Ljung-Box Q-statistics are in accordance with the results that we drew to analyze the statistical significance of the CCF-test statistics for certain lags and therefore, we can trace the direction of causation in the specific relationship with the utilization of the sign of the CCF-test statistic.

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

Table 4 (continuous)

Lag	CSE-ASE	CSE-LSE	CSE-NYSE
+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*	55.23*	49.12*
Q (-4 to +4)	25.66*	44.13*	33.55*
Q (-6 to +6)	33.22*	31.13*	41.33*
Q (-8 to +8)	33.16*	37.01*	31.22*
Q(-10 to+10)	29.12*	40.12*	28.19*

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 figures in 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

Table 5 (continuous)

		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 figures in brackets below the Q-statistics are marginal levels of significance.
5. ** indicates statistical significance at the 0.05 level.

We now move to the discussion of our results and the significance for economic policy purposes. 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 equity 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 capital market of Cyprus 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 capital markets.

Comparison of Tables 4 and 5 reveals an almost identical pattern of mean-causality and of variance-causality. Thus, we observe that 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. Given this common pattern in the mean-causality and in the variance-causality we next move to examine whether the identified causality-in mean is in fact explained by the causality-in variance. To this end, we re-estimate the model given in equations (11) to (13) for the stock returns without the variance term in the conditional mean equation. Thus, instead of estimating an EGARCH-M model we consider the estimation of an EGARCH model which does not include the influence of the variance in the mean equation. We once again calculate the standardized and squared residuals and we repeat the CCF testing procedure. The results show that the mean causality pattern differs substantially from the one resulted from the estimation of the EGARCH-M models[1]. Specifically, the only statistical significant evidence of mean causality is from Athens to Cyprus (at lags 0 and 1), while no other mean causality is evident. This finding implies that the mean-causality is mostly due to variance-causality.

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

6. Summary and Concluding Remarks

In this paper we analyse whether mean and variance causality as well as volatility spill-overs exist among the stock markets of Cyprus, Greece, the UK and the US using daily data during the period from 29 March 1996 to 19 April 2002. Preliminary analysis on these daily observations reveals that portfolio returns reflect second moment dependence which is statistically significant. The main findings of the present analysis are: First, the distributional properties of the daily stock returns of the equity markets of Cyprus, Athens, London and New York are well described by an EGARCH-in-Mean process. Second, the hypothesis that causality-in-variance and/or causality-in-mean is present among the returns of these four stock markets was tested with the application of the CCF bivariate test due to Cheung and Ng (1996). Third, our analysis has further revealed that the stock markets of Athens, London and New York appear to be the major exporters of volatility to the Cyprus stock market, while movements in the CSE general price index have no impact on the returns of the ASE, LSE and NYSE. Finally, it is shown that in all cases causality-in-mean is also associated with causality-in-variance.

These results are useful for domestic and foreign portfolio managers that are considering in their portfolios equity from emerging markets such that of Cyprus since they offer interesting insights regarding the interdependencies of the stock markets of Cyprus, Greece, the UK and the US markets.

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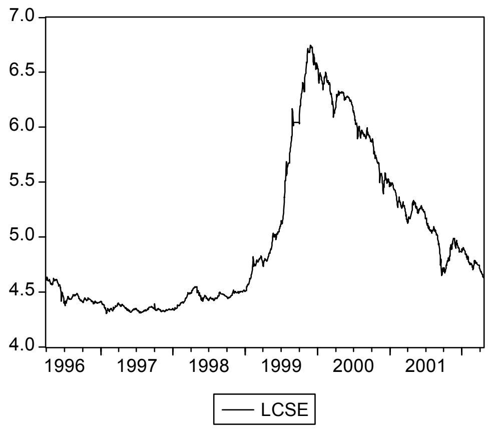

Fig. 1(a). Evolution of the CSE general price index

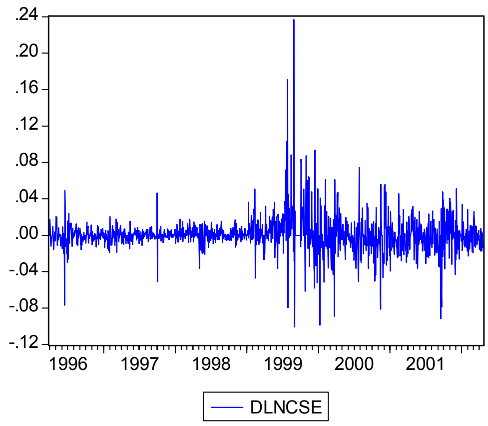

Fig. 1(b). The CSE general price index returns

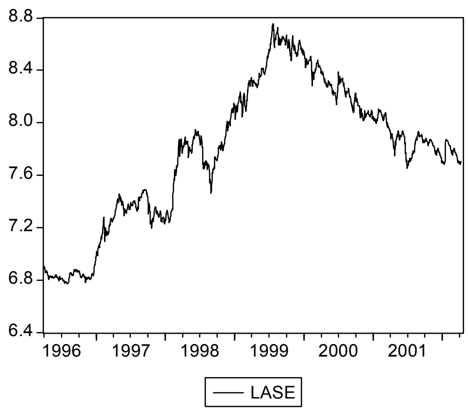

Fig. 2(a). Evolution of the ASE general price index

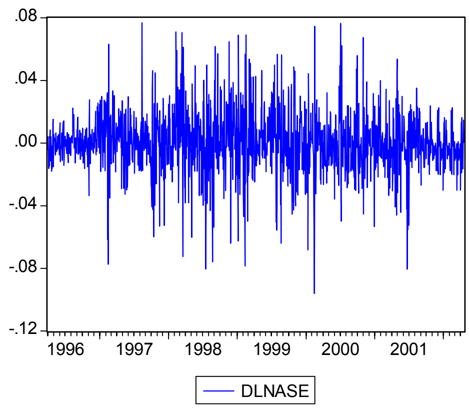

Fig. 2(b). The ASE general price index returns

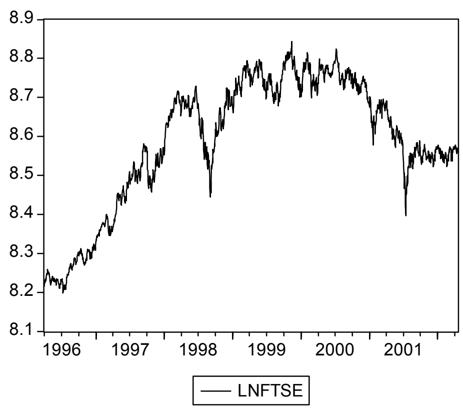

Fig. 3(a). Evolution of the FTSE100 price index

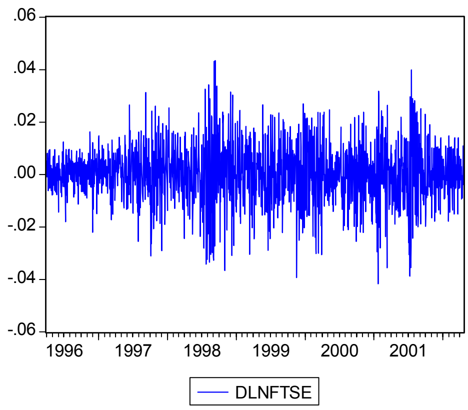

Fig. 3(b). The FTSE100 general price index returns

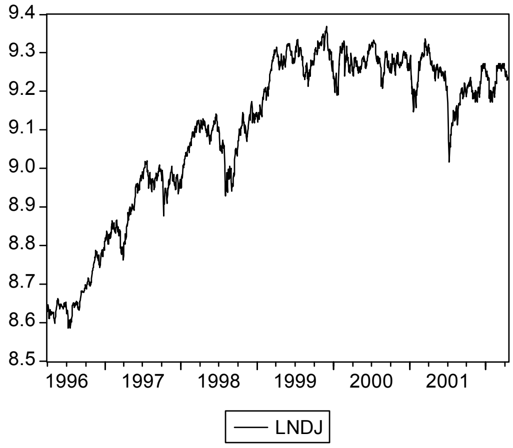

Fig.4 (a). Evolution of the DJIA price index

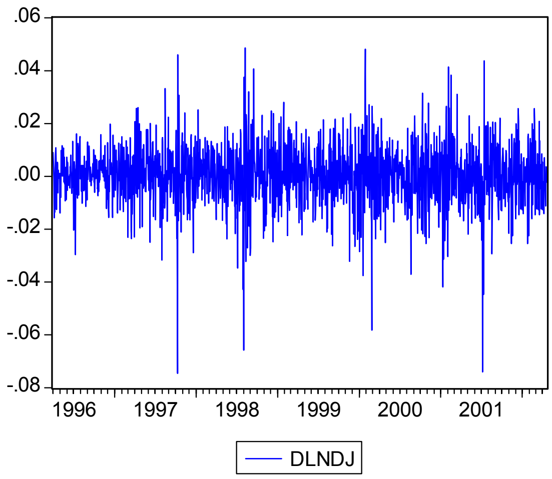

Fig. 4(b). The DJIA general price index returns