Market capitalization and efficiency. Does it matter? Evidence from the Athens Stock Exchange

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Abstract

The efficient market hypothesis (EMH) is tested in the case of the Athens Stock Exchange (ASE) after the introduction of the euro for three different indices. The underlying assumption is that stock prices would be more transparent; their performance easier to compare; the exchange rate risk eliminated and as a result we expect the new currency to strengthen the argument in favour of the EMH. The FTSE/ASE 20, which consists of "high capitalisation" companies, the FTSE/ASE Mid 40, which consists of medium sized companies and the FTSE/ASE SmallCap, which covers the next 80 companies, are used. Five statistical tests are employed to test the residuals of the random walk model: the BDS, McLeod-Li, Engle LM, Tsay and Bicovariance test. Bootstrap as well as asymptotic values of these tests are estimated. The random walk hypothesis is rejected in all three cases and alternative GARCH models are estimated.

Keywords: Non-Linearity, Market Efficiency, Random Walk, GARCH
JEL Classification: C22, C52, G10

1. INTRODUCTION

Numerous studies have investigated the validity of the weak-form efficient market hypothesis. The weak form of the EMH postulates that successive one-period stock returns are independent and identically distributed (*iid*), i.e. the price levels resemble a random walk. On the other hand, it is well known that stock returns are characterised by volatility clustering, where large returns are followed by large returns and small returns tend to be followed by small returns, leading to contiguous periods of volatility and stability. In this paper we are going to examine both hypotheses in the case of an emerging capital market which has recently joined the euro zone. We will employ three different indices from the Athens Stock Exchange (ASE), which represent different sections of the market.

There has been a limited number of studies in the literature that focus on empirical application to the ASE whilst none has investigated the three assumptions described above. Siriopoulos (1996) used monthly observations of the ASE General Index from 1974:1 to 1994:6. Using the BDS test statistic and the correlation dimension, it was concluded that a GARCH model could not explain the non-linearities of the series which might be generated by a "semi-chaotic behaviour". Barkoulas & Travlos (1998) used daily observations of the ASE30, the 30 most marketable stocks, from January 1981 to December 1990. Models including AR(*p*) and a GARCH (1,1) were employed and diagnostic tools such as BDS, correlation dimension and Kolmogorov entropy were estimated. They concluded that "*the BDS test detects remaining unspecified hidden structure in the Greek stock returns*" but " *do not find evidence in support of a chaotic structure in the Athens Stock Exchange*". More recently, Apergis & Eleptheriou (2001) examined market volatility using daily observations of the ASE General Index for the period January 1990 to July 1999. They compared different GARCH models based on the log likelihood and concluded that "*the presence of persistence in volatility clustering implies inefficiency of the ASE market*". Lastly, Siourounis (2002) employs GARCH type models and tests for their validity using a data set of daily closings of the ASE General Index for the period of 4 January 1988 until 30 October 1998. The Ljung-Box tests statistic is employed as a diagnostic tool and it was found that "*the GARCH(1,1) and LGARCH(1,1) models can explain quite satisfactory the dependencies of the first and second moments*".

The contribution of our analysis is interesting for four different reasons: i) to examine whether the new currency has strengthened the argument in favour of the EMH as expected, ii) to investigate the time series behaviour of the three main indices of the ASE while the transition -from being an Emerging Capital Market- to a Developed one takes place, iii) to test the hypothesis that capitalisation influences efficiency using indices that represent different fractions of the market and iv) robust econometric methodology is employed to test the random walk hypothesis.

2. METHODOLOGY

We start our analysis with the naive random walk, which is closely associated with the weak form EMH

$$x_t = x_{t-1} + \varepsilon_t \qquad (1)$$

where $x_t = \ln(E_t)$ represents the natural log of the original time series, E_t, and ε_t is a zero-mean pure white noise random variable. If the random walk hypothesis holds, then the series x_t will have a single unit root (i.e. will be $I(1)$) and the series Δx_t ($= x_t - x_{t-1} = \ln(E_t / E_{t-1})$) will be purely random. The series Δx_t may be examined further by estimating the equation:

$$\Delta x_t = constant + \varepsilon_t \qquad (2)$$

using ordinary least squares. Under the random walk hypothesis the constant term should be insignificantly different from zero and the resultant residuals should be uncorrelated.

Additionally, the GARCH(1,1) specification is

$$\begin{aligned} &\Delta x_t = z_t'\gamma + \varepsilon_t ; \varepsilon_t / \Omega_{t-1} \sim N(0, \sigma_t^2) \\ &\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \end{aligned} \qquad (3)$$

Many statistical tests for randomness have been proposed in the recent literature. Instead of only using a single statistical test, five different tests are considered in this exercise for testing the hypothesis that the residuals are *iid*. This will allow us on the one hand to obtain a deeper and more detailed insight into the series properties by generating useful information from the various tests and on the other hand to minimise the probability of missing something and thus drawing the wrong conclusion. If our battery of tests displays a unanimous "consensus" in favour of a specific result, we would interpret this "consensus" as strong corroboration of that outcome.

The five tests that are going to be used are the following: McLeod & Li (1983), Engle LM (1982), BDS (1996), Tsay (1986), and Hinich & Patterson (bicovariance) (1995). All these tests share the principle that once any linear structure is removed from the data, any remaining structure should be due to a non-linear data generating mechanism.

The McLeod & Li test looks at the autocorrelation function of the squares of the prewhitened data and tests whether $corr\ (e_t^2, e_{t-k}^2)$ is non-zero for some k and can be considered as an LM statistic against ARCH effects (see Granger & Terasvirta 1993, GT hereafter, and Patterson & Ashley 2000). The test suggested by Engle (1982) is an LM test, which should have considerable power against GARCH alternatives (see GT 1993; Bollerslev, 1986). The Tsay (1986) test explicitly looks for quadratic serial dependence in the data and has proven to be powerful against a TAR process. The BDS test is a nonparametric test for serial independence based on the correlation integral of the scalar series, $\{e_t\}$ (see Brock, Hsieh & LeBaron 1991 and GT 1993). The Hinich Bicovariance test assumes that $\{e_t\}$ is a realisation from a third-order stationary stochastic process and tests for serial independence using the sample bicovariances of the data. The last two tests are general linearity tests and in the case of the BDS test the alternative to linearity can be considered to be a stochastic non-linear model (GT 1993). The reader is also referred to the detailed discussion of these tests in Patterson & Ashley (2000) and Panagiotidis (2002).

In line with other studies (e.g. Brock, Hsieh and LeBaron, 1991), they conclude that the BDS test is the most powerful one. However, two simulation studies by Brooks & Heravi (1999) and Brooks & Henry (2000) revealed that the BDS test can sometimes confuse different types of non-linear structure (such as threshold autoregressive and GARCH-type models) and has small power in detecting neglected asymmetries in conditional variance models. Both problems are present when a GARCH filter is used and the data are generated from a non-linear data generating process and consequently do not affect our analysis. All the estimations in our exercise are carried out using Nonlinear Toolkit 4.6 by Patterson & Ashley (2000) and EViews 4.1.

3.DATA & UNIT ROOT TESTS

After years of adopting stabilisation policies in order to reduce inflation and achieve the other convergence criterion, Greece joined the Economic and Monetary Union. The official announcement was made on 19/6/2000 from the European Council although the decision was known in advance. The data employed in this exercise consist of three indices:

the FTSE/ASE20, the FTSE/ASE Mid 40 and the FTSE/ASE Small Cap. These indices are the performance benchmark of the Greek market and are a joint venture between FTSE and the Athens Stock Exchange. The first is a capitalisation weighted index and consists of the top 20 companies by market capitalisation (mainly the banking sector and telecommunications). The FTSE/ASE Mid 40 includes medium sized companies and measures the growth sector of the market and the FTSE/ASE Small Cap covers the next 80 companies[1].

The data statistics of the logarithmic transformation and the first differences of the series are given in Table 1[2]. Table 2 presents the results of the unit root tests. Clear evidence emerges that all series are *I*(*1*).

4. RESULTS

The corresponding random walk and GARCH (1,1) models for each index are presented in Table 3. The *t*-statistics of the estimated constant of the RW models are above the critical value of the 1% significance level, indicating that the mean of the series DLFTSE20, DLFTSE Mid 40 and DLFTSE Small Cap are significantly different from zero. This result is not consistent with the random walk hypothesis.

The diagnostic tests for all models are presented in Tables 4 and 5. Under investigation are the ordinary residuals of the RW and the standardised

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[1] For more information on the indices and their composition http://www.ase.gr and http://www.ftse.com . The data are available free from http://www.enet.gr/finance/finance.jsp .

[2] Note that fewer observations are available for the FTSE/ASE Small Cap since it started later than the other two.

residuals of the GARCH. The employed tests are, like most econometric procedures, only asymptotically justified. Given the limited sample available, the tests are estimated using both the asymptotic theory and the bootstrap. The values under "asymptotic theory" are based on the large sample distributions of the relevant test statistics. For the "Bootstrap" results, 1000 new samples are independently drawn from the empirical distribution of the pre-whitened data. Each new sample is used to calculate a value for the test statistic under the null hypothesis of serial independence. The obtained fraction of the 1000 test statistics, which exceeds the sample value of the test statistic from the original data, is then reported as the significance level at which the null hypothesis can be rejected (for a detailed discussion on the sample size, the asymptotic theory and the bootstrap see Patterson & Ashley 2000).

Clear evidence emerges across the spectrum of tests that the residuals of the RW are not *iid*. Almost all *p*-values are 0, suggesting that some kind of hidden structure exists in the data (see Table 4). The failure of the RW model to explain the behaviour of the series and consideration of the constant terms that are statistically different from zero, casts doubts on the validity of weak form efficiency. The "unanimous" verdict of the employed battery of tests, led us to conclude that capitalisation does not influence efficiency. The evidence against the EMH is clear in all of the indices.

To test for the presence of volatility clustering, we have proceeded with GARCH modelling. The results are presented in Table 3 and the diagnostics in Table 5. The 'general-to-specific' approached is followed in all cases, starting with five lagged values of the dependent variable. The variance of the series was found to be insignificant in all cases for the mean equation. The standard deviation is found to be significant in the case of the FTSE20 and the FTSE Mid 40. However, only the constant term is found significant in the FTSE Small Cap, implying that volatility clustering is not helpful in predicting the future returns (see also Millionis & Moschos, 2000).

The GARCH models produce lower SC's (Schwartz criterion) and as a result are preferred to the RW in this respect. Additionally, evidence emerges to support the hypothesis that the standardised residuals of the GARCH models are *iid*. Most of the *p*-values in Table 5 exceed the 5% benchmark. Therefore, we could accept the randomness hypothesis.

5. CONCLUSIONS

We have tried to answer three questions: i) Has new currency strengthened the argument in favour of the EMH? ii) Has the time series behaviour of the three main indices of the ASE changed, as the last moves from being an Emerging Capital Market to a Developed one? iii) Does capitalisation influence efficiency? Firstly, we were able to provide strong evidence against the random walk hypothesis after the introduction of the common currency. Secondly, the time series behaviour has not changed in the respect that the volatility clustering phenomena still seems to drive the data generating process. Thirdly, we found that the lower capitalisation fraction of the market is more "efficient", in the sense that the past volatility does not help in explaining future returns. Past volatility was found to be important for the FTSE20 and the FTSE Mid 40 but not for FTSE Small Cap. In that respect, the robust methodology followed in the study revealed useful information about three different sectors of the market.

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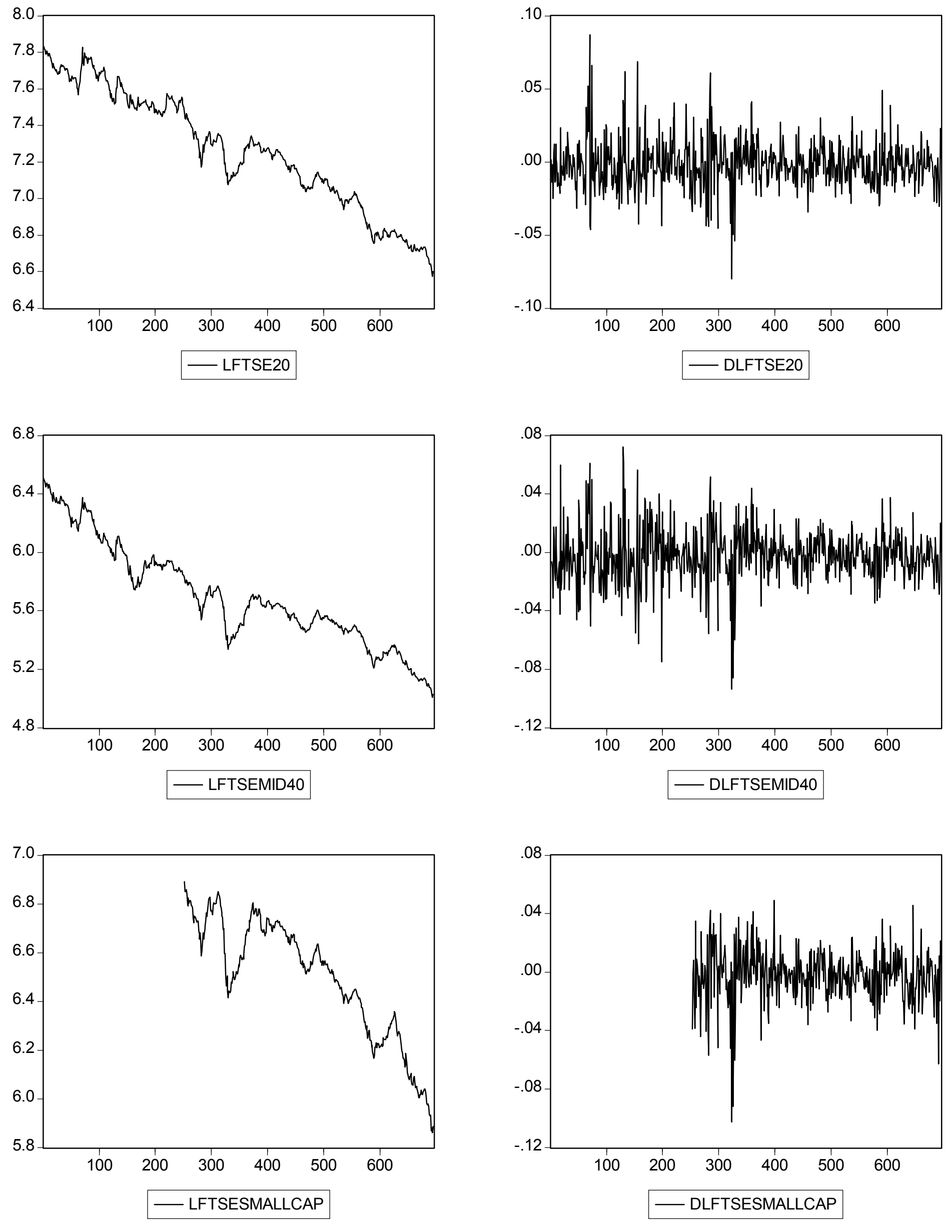
FIGURE 1


LFTSE20
DLFTSE20
LFTSEMID40
DLFTSEMID40
LFTSESMALLCAP
DLFTSESMALLCAP

APPENDIX 1

Table 1: Data Statistics Period from 1/6/00 to 14/3/03 for the FTSE20 and the FTSE Mid 40 and 1/6/01 to 14/3/03 for the FTSE Small Cap.

	LFTSE20	DLFTSE20	LFTSEMID40	DLFTSEMID40	LFTSE SmallCap	DLFTSE SmallCap
Mean	7.262261	-0.001770	5.699177	-0.002126	6.491656	-0.002264
Median	7.267791	-0.002526	5.643679	-0.002081	6.540467	-0.001489
Maximum	7.829463	0.086787	6.503929	0.071906	6.890212	0.049059
Minimum	6.574099	-0.080191	5.007564	-0.093773	5.859674	-0.102835
Std. Dev.	0.322354	0.016190	0.345319	0.018362	0.244326	0.017864
Skewness	-0.155543	0.520309	0.371905	-0.116009	-0.616700	-0.852284
Kurtosis	1.954926	6.639343	2.422366	5.776838	2.426937	6.862521
Jarque-Bera	34.43011	414.3093	25.68358	224.5282	34.21899	329.0128
Probability	0.000000	0.000000	0.000003	0.000000	0.000000	0.000000
Sum	5047.271	-1.228314	3960.928	-1.475781	2882.295	-1.003137
Sum Sq. Dev.	72.11502	0.181655	82.75618	0.233646	26.44494	0.141059
Observations	695	694	695	694	444	443

Table 2 Unit Roots

Unit Root tests	Levels	First Differences	CV 1%
		ADF	
LFTSE20	-0.35913	-23.6921	-3.43956
LFTSE Mid 40	-1.29885	-23.3435	-3.43956
LFTSE Small Cap	0.361803	-19.0743	-3.43956
		PP	
LFTSE20	-0.3647	-23.7737	-3.43956
LFTSE Mid 40	-1.34682	-23.7343	-3.43956
LFTSE Small Cap	-0.17082	-19.77	-3.43956

CV 1% is the critical value at the 1% significance level. ADF is the Augmented Dickey-Fuller and PP is the Phillips-Perron unit root tests.

Table 3: Estimated Models

Sample 1/6/00-31/12/02						
Dependent Variable	**D(LFTSE20)**		**D(LFTSE MID 40)**		**D(LFTSE SMALL CAP)**	
	RW	GARCH	RW	GARCH	RW	GARCH
Constant	-0.001770	-0.006355	-0.002126	-0.004866	-0.002264	-0.001725
	(2.88)	(2.32)	(3.05)	(2.54)	(2.67)	(2.20)
Dependent (t-1)				0.1226		0.1387
				(2.92)		(2.34)
GARCH						
SQR(GARCH)		0.314054		0.21473		
		(1.67)		(1.79)		
Variance Equation						
C		3.39E-05		7.14E-06		1.83E-05
		(3.54)		(2.33)		(2.11)
ARCH(1)		0.16374		0.122		0.1521
		(5.73)		(6.84)		(5.82)
GARCH(1)		0.70333		0.862		0.7983
		(12.88)		(46.01)		(18.78)
Adjusted R squared	0.00	-0.00367	0.00	0.007128	0.00	-0.00074
SE of regression	0.01619	0.01622	0.018362	0.018308	0.017864	0.017805
SC	-5.400813	-5.513373	-5.14912	-5.30842	-5.20052	-5.30645

Note: Numbers in ( ) are the corresponding *t* statistics, SC is the Schwartz criterion, SE is the Standard Error and RW is the random walk model. The sum of the GARCH coefficients are less but close to one in all cases, suggesting that the GARCH process is stationary. The GARCH term represents σ^2 in (3).

Table 4: Diagnostic Tools

	RW FTSE20		RW FTSE MID 40		RW FTSE SMALL CAP	
	BOOTSTRAP	ASYMPTOTIC THEORY	BOOTSTRAP	ASYMPTOTIC THEORY	BOOTSTRAP	ASYMPTOTIC THEORY
MCLEOD-LI TEST						
USING UP TO LAG 20	0.000	0.000	0.000	0.000	0.000	0.000
USING UP TO LAG 24	0.000	0.000	0.000	0.000	0.000	0.000
BICOVARIANCE TEST						
UP TO LAG 13	0.000	0.000	0.000	0.000	0.000	0.000
ENGLE TEST						
USING UP TO LAG 1	0.009	0.000	0.009	0.000	0.468	0.556
TSAY TEST	0.000	0.000	0.000	0.000	0.001	0.000

BDS										
						BOOTSTRAP				
Dimension		EPS=0.50	EPS=1.00	EPS=2.00	EPS=0.50	EPS=1.00	EPS=2.00	EPS=0.50	EPS=1.00	EPS=2.00
	2	0.000	0.000	0.000	0.000	0.000	0.000	0.127	0.033	0.054
	3	0.000	0.000	0.000	0.000	0.000	0.000	0.012	0.000	0.000
	4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
						ASYMPTOTIC THEORY				
	2	0.000	0.000	0.000	0.000	0.000	0.000	0.130	0.030	0.051
	3	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.001	0.000
	4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The residuals of the RW and the standardised residuals of the GARCH are under investigation in this part. Following de Lima (1996), the BDS test was also calculated for the squared standardised residuals. The results were not altered and are available for the author. Only *p*-values are reported.

Table 5: Diagnostic Tools

	GARCH FTSE20			GARCH FTSE MID 40			GARCH FTSE SMALL CAP		
	BOOTSTRAP	ASYMPTOTIC THEORY		BOOTSTRAP	ASYMPTOTIC THEORY		BOOTSTRAP	ASYMPTOTIC THEORY	
MCLEOD-LI TEST									
USING UP TO LAG 20	0.702	0.812		0.082	0.065		0.120	0.108	
USING UP TO LAG 24	0.793	0.884		0.133	0.142		0.196	0.215	
BICOVARIANCE TEST									
UP TO LAG 11	0.849	0.930		0.392	0.434		0.593	0.719	
ENGLE TEST									
USING UP TO LAG 1	0.201	0.244		0.665	0.670		0.056	0.086	
TSAY TEST	0.182	0.198		0.051	0.052		0.143	0.159	
BDS	BOOTSTRAP								
Dimension	EPS=0.50	EPS=1.00	EPS=2.00	EPS=0.50	EPS=1.00	EPS=2.00	EPS=0.50	EPS=1.00	EPS=2.00
2	0.751	0.764	0.740	0.603	0.514	0.581	0.997	0.995	0.984
3	0.648	0.561	0.594	0.605	0.377	0.329	0.874	0.939	0.844
4	0.531	0.579	0.500	0.624	0.259	0.157	0.838	0.769	0.593
	ASYMPTOTIC THEORY								
2	0.771	0.787	0.773	0.654	0.548	0.616	0.993	0.989	0.988
3	0.668	0.590	0.624	0.649	0.418	0.367	0.900	0.953	0.880
4	0.561	0.597	0.540	0.672	0.282	0.166	0.880	0.820	0.638