Market Efficiency and the Euro: The case of the Athens Stock Exchange

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> > March 2005 Abstract

The behaviour of an emerging market, the Athens Stock Exchange (ASE), after the introduction of the euro is investigated. 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 General ASE Composite Index and the FTSE/ASE 20, which consists of "high capitalisation" 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 and asymptotic values of these tests are estimated. Alternative models from the GARCH family (GARCH, EGARCH and TGARCH) are also presented in order to investigate the behaviour of the series. Lastly, linear, asymmetric and non-linear error correction models are estimated and compared.

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

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1. INTRODUCTION

A large body of literature has accumulated over the past three decades concerning the validity of the weak-form efficient market hypothesis (EMH) with respect to stock markets (see for instance Chappell and Eldridge 2000). 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. At the same time it is well known that stock returns are characterised by volatility clustering; the tendency for volatility to appear in bunches, as well as leverage effects, the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude (see, for instance, Bollerslev, Engle and Nelson 1994 and Engle 2002 for extensive surveys and discussion on ARCH and GARCH models). In this paper we are going to investigate both hypotheses in the case of an emerging capital market which has recently joined the euro zone. We examine how the introduction of the single European currency has affected the efficiency of a stock market in the process of becoming a developed capital market¹.

A limited number of studies have appeared in the literature providing empirical analysis of the ASE but none has investigated the introduction of the common currency. 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 "semichaotic behaviour". Barkoulas and Travlos (1998) used daily observations of the ASE30, the 30 most marketable stocks, from January 1981 to December 1990. Models including an 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". Niarchos and Alexakis (1998) followed a different methodology to test the EMH in the Athens Stock exchange. They used error correction models and compared the speed of adjustment. Their evidence rejected the EMH. More recently, Apergis and 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".

These studies, amongst others, underline the fact that there is strong evidence against the EMH. The goal of this paper is twofold. Firstly, to review weak form efficiency in the light of the introduction of the common currency. Given the evidence against the EMH found in previous studies, has the euro changed anything? Our prior is that the new currency will strengthen the case for the EMH: costs are more transparent to investors (domestic and non), the disappearance of the risks associated with exchange rates fluctuations, vanishing capital control regulations, easy and straightforward comparison of prices and evaluation of performances (to name a few). Additionally, the centre of power over interest rates moved from Athens to Frankfurt and most of the political uncertainty of the past is expected to vanish (for a description of the aging problems of the Greek economy see Alogoskoufis, 1995). Secondly, to nest and extend the methodologies used. The employed methodology includes linear and nonlinear models. The assumption of randomness, which is closely associated with the EMH, is investigated using a powerful battery of tests. Linear and non-linear models recently developed in the literature are also considered for the first time in this framework. Additionally, this exercise might be useful for the countries who are going to adopt the euro soon as well as those that are planning to do so. Should they expect any significant differences in their capital markets?

¹ In July 2000 Morgan Stanley announced the change in the classification of the MSCI Greece Index from an emerging to a developed market index with effect from the 1st of June 2001 (see http://www.msci.com/pressreleases/archive/pr000731.html).

The outline of the paper is as follows: Section 2 discusses the econometric methodology followed, and the models and the tests for non-linearity that are employed. Section 3 presents the statistical properties of the data. The empirical results are discussed in Section 4 and Section 5 concludes.

2. METHODOLOGY

We start our analysis with the naive random walk

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

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 (= $x_t - x_{t-1}$) will be purely random. The series Δx_t may be examined further by estimating the equation:

$$\Delta \mathbf{x}_t = constant + \varepsilon_t$$

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.

Secondly, an autoregressive processes (AR) is employed. The general autoregressive model of order p can be written as:

$$\Delta x_t = c + \alpha_1 \Delta x_{t-1} + \alpha_2 \Delta x_{t-2} + \dots + \alpha_p \Delta x_{t-p} + \varepsilon_t$$

Thirdly, three models from the GARCH family are considered: The GARCH(1,1) specification is

$$\Delta x_t = z'_t \gamma + \varepsilon_t;$$

$$\sigma_t^2 = \beta_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2$$

Two models that allow for asymmetric shocks to volatility, TARCH and EGARCH, are also considered.

In the exponential GARCH (EGARCH) model of Nelson (1991), σ_t^2 depends on both size and the sign of lagged residuals. The specification is:

$$\ln(\sigma_t^2) = \beta_0 + \beta_1 \ln(\sigma_{t-1}^2) + \beta_2 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

This implies that the leverage effect is exponential and its presence can be tested by the hypothesis that γ >0. The news impact is asymmetric if $\gamma \neq 0$. The TGARCH or Threshold GARCH (also known as GJR model) was introduced by Zakoian (1994) and Glosten, Jaganathan, and Runkle (1993). The specification for the conditional variance is given by

$$\sigma_t^2 = \omega + a\varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta \sigma_{t-1}^2$$

where $d_t = 1$ if $\varepsilon > 0$, and 0 otherwise. If $\gamma > 0$ the leverage effect exists and again the news impact is asymmetric if $\gamma \neq 0$ (for a discussion on the impact of news on volatility see Engle and Ng 1993).

Lastly, error correction models (ECM), asymmetric (AECM) and non-linear error correction models (NECM) are considered. If x_t , y_t are both I(1) then it is typically true that any linear combination x_t+by_t will also be I(1). However, for some pairs of I(1) series there does exist a linear combination $z_t=x_t-Ay_t$ that is I(0). When this occurs, x_t , y_t are said to be cointegrated. If x_t , y_t are cointegrated they may be considered to be generated by an error-correcting model of the form

$$\Delta x_t = \rho_1 z_{t-1} + lagged(\Delta x_t, \Delta y_t) + \varepsilon_x$$

where at least one of ρ_1, ρ_2 is non-zero and ε_{xt} , are jointly white noise.

The error corrections in the models considered above are symmetric so that the extent of the effect $|z_{t-1}|$ is the same regardless of the sign of z_{t-1} . However, when the current level of shares (or indices) is determined, it may well matter whether z_{t-1} (the disequilibria from the previous day/week) was positive or negative. To investigate these possibilities further sets of error correction models (*asymmetric error correction models*) were examined, using the notation (Granger and Lee, 1989) $z = z^+ + z^-, z^+ = \max(z, 0)$ and $z^- = \min(z, 0)$.

$$\Delta x_t = \rho_{11} z_{t-1}^+ + \rho_{12} z_{t-1}^- + lagged(\Delta x_t, \Delta y_t) + \varepsilon_{xt}$$

Lastly, we are going to briefly discuss the non-linear error correction model. This basically refers to non-linear adjustment to long-run equilibrium economic relationships. This type of non-linear adjustment allows for faster adjustment when deviations from the equilibrium level get larger. Further, it allows for the possibility of more than one equilibrium when the additional regressors, that is z_{t-1}^2 and z_{t-1}^3 , are statistically significant. In that sense, the cubic error correction model is more flexible than the Granger and Lee (1989) type of asymmetric adjustment.

Following Escribano and Granger (1998), the non-linear error correction model may be written as:

$$\Delta x_{t} = \rho_{11} z_{t-1} + \rho_{12} z_{t-1}^{2} + \rho_{13} z_{t-1}^{3} + lagged(\Delta x_{t}, \Delta y_{t}) + \varepsilon_{xt}$$

Escribano and Granger (1998) point out that "The non-linear error correction terms should be considered as local approximations to the true non-linear specifications if it occurs. In particular, if z_{t-1} enters as a cubic it would produce a non-stable difference equation for x_t , since for large values z_{t-1} the cubic polynomial is unbounded, and so would not be appropriate as this series is supposed to be I(0)".

The existence of nonlinearity in asset prices is a necessary condition for the usefulness of technical analysis (Neftci, 1991) and the latter casts doubts for the EMH. Many tests have been proposed in the literature for detecting non-linearity in the residuals. Instead of using a single statistical test, for the purposes of this paper five different tests are considered; McLeod and Li (1983), Engle LM (1982), Brock et al (1996) (BDS), Tsay (1986), and Hinich and Patterson (bicovariance) (1995). All these tests share the principle that once any (linear or non-linear) structure is removed from the data, any remaining structure should be due to an (unknown) non-linear data generating mechanism. All the procedures embody the null hypothesis that the series under consideration is an *i.i.d.* process.

The McLeod and 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 and Terasvirta 1993; Patterson and Ashley 2000). The test suggested by Engle (1982) is an LM test, which should have considerable power against GARCH alternatives (see Granger and Terasvirta 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_i } (see Brock, Hsieh and LeBaron 1991 and Granger and Terasvirta 1993). The Hinich Bicovariance test assumes that { e_i } 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 (Granger and Terasvirta 1993). The reader is also referred to the detailed discussion of these tests in Barnett et al (1997) and Patterson and Ashley (2000).

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 consists of two indices: the General Index (ASE Composite Share Index) and the FTSE/ASE20. The last is a joint venture between FTSE and the ASE and is a capitalisation weighted index. It consists of the top 20 companies by market capitalisation (mainly the banking sector and telecommunications²). This sample has been chosen for two reasons. Firstly, there is no need to replicate results that are already available in the literature (see Introduction). Secondly, this sample is "homogenous" in the sense that is the first one which allows an investor to directly compare returns

² For more information on the indices and their composition, see <u>http://www.ase.gr</u> and <u>http://www.ftse.com</u>. The data are available free from <u>http://www.enet.gr/finance/finance.jsp</u>.

of the ASE with other European stock markets of the euro zone without having to take into account exchange rate risks.

The summary statistics of the logarithmic transformation and the first differences of the series are given in Table 1. Table 2 presents the results of the unit root and cointegration tests. Clear evidence emerges that both series are I(1) and cointegrated (see Tables 3a and 3b). The cointegrating equation is:

LGeneral = 0.5177LFTSE20+0.0019Trend (0.339) (0.00053)

where *Trend* is a linear deterministic trend and std. err. in ().

4. RESULTS

In this section a number of alternative models are considered with the ASE General Index as the dependent variable (DLGeneral), where D denotes first difference. Starting with the simplest form, with no explanatory variables, Model 1 corresponds to the random walk. Secondly, an AR(p) model was considered for values from p = 0 to p = 10. The optimal lag length is chosen to minimise the Schwarz criterion (SC). Model 3 is the standard linear error correction model. The simple GARCH (1,1) and two asymmetric GARCH models (EGARCH and TGARCH) are models 4, 5 and 6 respectively. Model 7 is the simple error correction model, model 8 is the asymmetric error correction model used by Granger and Lee (1989). Model 9 introduces the non-linear adjustment used previously by Escribano and Granger (1998) and Escribano and Pfann (1998) amongst others. The FTSE 20 is used as it consists of the high capitalisation companies which usually "drive" the General Index. A dummy variable is introduced in the long-run relationship to capture the crisis that the ASE faced in September and October 2001(see Table 3). This unconventional approach is also followed by Escribano and Granger (1998) in order to explain a bubble period in the priced of gold and silver.

The general-to-specific approach was followed. In particular, in the case of the asymmetric GARCH models (EGARCH and TGARCH), we started with five lagged values of DL*General* and DL*FTSE20*. The preferred model was the one that minimised the SC. The same methodology was followed for the determination of the number of independent variables in the case of the ECM, AECM and NECM.

Table 4 summarises the results from all the models. The RW outperformed the AR, producing lower SC and is the preferred "linear " univariate model³. The constant term is negative and significant in all cases but the ECM, AECM and NECM. EGARCH has the lowest SC and the ECM and the NECM the lower standard error of regression.

The diagnostic tests for all models are presented in Tables 5 and 6. Under investigation are the ordinary residuals of the RW, ECM, ACM, NECM and the standardised residuals of the GARCH, EGARCH and TGARCH. 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 and Ashley 2000).

Firstly, we are able to reject the hypothesis that the ASE General Index follows a random walk. The *p*-values across the battery of tests employed are 0 (or very close to 0). The same conclusion can be drawn for the ECM, the AECM and NECM models suggesting that some kind of hidden structure is

³ The results of the AR are not reported here but are available from the author.

contained in the residuals. The error correction term is found insignificant in all cases (table 4, models 5,6 and 7). The non-linear error correction term (cubic) has the highest *p*-value (0.808). The NECM error corrects much faster and is particular useful in volatile periods (see first 100 observations in Figure 3). However, it is clear from Table 6 that significant nonlinearity is present in the residuals of this model.

On the other hand, we can accept the *iid* assumption in some cases for the residuals of the GARCH models. A thorough investigation of the results reveals that only in the case of the standardised residuals of the TGARCH model is there a "unanimous" acceptance of the randomness hypothesis (low *p*-values in the Engle and the Tsay test in the case of GARCH and Engle in the case of EGARCH). For both models (TGARCH and EGARCH), the coefficient estimates of the conditional mean constant are negative and statistically significant, reflecting the sustained downward sloping of the General Index over the sample period. The estimated coefficient of γ in the case of the TGARCH model is positive and statistically significant suggesting that leverage effects exist and the news impact is asymmetric. The latter is a pictorial representation of the degree of asymmetry of volatility to positive and negative shocks. The news impact curve plots the next-period volatility that would arise from various positive and negative values of lagged shock, given an estimated model. The GARCH news impact curve is symmetrical about zero, so that a shock of a given magnitude will have the same impact on the future conditional variance whatever its sign. On the other hand, TGARCH or EGARCH news impact curves are asymmetric, with negative shocks having less/more impact on future volatility than positive shocks of the same magnitude (see Figure 2).

What is the implication of our results for weak-form efficiency? Firstly, we can reject the hypothesis that the series follows a random walk. Evidence was found in favour of the TGARCH model. However, neither the variance nor the standard deviation were found to be statistically significant predictors in the mean equation. As a result, the conclusion we draw is that persistence

and volatility clustering is present in the series but this does not imply inefficiency (see also Millionis and Moschos 2000).

5. CONCLUSIONS

The weak form EMH was tested for the Athens Stock Exchange after the introduction of the common European currency. Alternative linear and nonlinear models were used to model the General Index. Simple univariate linear models (RW and AR), various conditional volatility models (GARCH, EGARCH and TGARCH) and multivariate models (ECM, ACM, NECM) were estimated. A battery of tests for randomness were estimated in each case. Bootstrap values as well as asymptotic are generated. Firstly, we were able to reject the random walk hypothesis using a robust econometric methodology that has not been used in earlier studies. Secondly, we overcame the arguments that appeared in the literature that the ASE is characterised by deterministic chaos. We have tested all the models that we used in the past. The preferred model (TGARCH) is the one that produced a unanimous verdict of iid residuals. The evidence suggests that leverage effects exist and the news impact is asymmetric. The argument in favour of time varying variance does not challenge weak form efficiency. Overall, strong efficiency gains are found to exist in the period after the introduction of the common currency.

References

Alogoskoufis, G. (1995), The two faces if Janus: Institutions, policy regimes and macroeconomic performance in Greece, *Economic Policy*, **20**, 148-192.

Apergis, N. and Eleptheriou, S. (2001), Stock Returns and Voilatility: Evidence from the Athens Stock Exchange, *Journal of Economics and Finance*, **25**, 50-61.

Barkoulas, J. and Travlos, N. (1998), Chaos in an emerging capital market? The case of the Athens Stock Exchange, *Applied Financial Economics*, **8**, 231-243.

Barnet, W.A., A.R. Gallant, M.J. Hinich, J.A. Jungeilges, D.T. Caplan, M.J. Jensen (1997), A single-blind controlled competition amongst tests for nonlinearity and chaos, *Journal of Econometrics*, **82**, 157-92.

Bollerslev, T. (1986), Generalized Autoregressive Conditional Heteroscedasticity, *Journal of Econometrics*, **31**, 307-27.

Bollerslev, T., Engle, R., and Nelson, D., (1994), ARCH models, in *Handbook of Econometrics*, IV, Eds, Engle, R. and McFadden, D.L., Chapter 49, 2959-3038, Elsevier Science.

Brock, W.A., Dechert, W., Scheinkman J. and LeBaron, B. (1996), A Test for Independence based on the Correlation Dimension, *Econometrics Reviews*, **15**, 197-235.

Brock, W.A., Hsieh, D.A., LeBaron, B. (1991), *Nonlinear Dynamics, Chaos, and Instability*, MIT Press, Cambridge, Massachusetts.

Chappell, D., Eldridge, R.M. (2000), Evidence of Market Efficiency in a war environment, *Applied Financial Economics*, **10**, 5, 489-492.

de Lima, P.J.F. (1996), Nuisance Parameter free properties of correlation integral based statistics, *Econometric Reviews*, **15**,3, 237-259.

Engle , R.F. and Ng, V.K. (1993), Measuring and Testing the impact of news on volatility, *Journal of Finance*, **48**, 1022-1082.

Engle, R.F. (1982), Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation, *Econometrica*, **50**, 987-1007.

Engle, R.F. (2002), New frontiers for ARCH models, *Journal of Applied Econometrics*, **17**, 425-446.

Escribano, A. and Granger, C.W.J. (1998), Investigating the relationship between gold and silver prices, *Journal of Forecasting*, 17, 81-107.

Escribano, A., and Pfann, G.A. (1998), Non-linear error correction, asymmetric adjustment and cointegration, *Economic Modelling*, 15, 197-216.

Glosten, L.R., R. Jaganathan, and D. Runkle (1993), On the Relation between the Expected Value and the Volatility of the Normal Excess Return on Stocks, *Journal of Finance*, **48**, 1779-1801.

Granger, C.W.J. and Lee, T.H. (1989), Investigation of Production, Sales and Inventory relationships using multicointegration and non-symmetric error correction models, *Journal of Applied Econometrics*, Vol4, S145-S159.

Granger, C.W.J. and Terasvirta, T. (1993), *Modelling Nonlinear Economic Relationships*, Oxford University Press, Oxford.

MacKinnon, J.G., Haug, A.A. and Michelis, L. (1999) "Numerical distribution functions of likelihood ratio tests for cointegration," *Journal of Applied Econometrics*, **14**, 563-577

McLeod, A.I. and Li., W.K. (1983), Diagnostic Checking ARMA Time Series Models Using Squared-Residual Autocorrelations, *Journal of Time Series Analysis*, **4**, 269-273.

Millionis, A. and Moschos, D. (2000), On the validity of the weak-form efficient market hypothesis applied to the London stock exchange: comment, *Applied Economics Letters*, **7**, 419-421.

Neftci, S.N. (1991), Naïve trading rules in Financial Markets and Wiener-Kolmogorov Prediction theory, *Journal of Business*, **64**, 4, 549-571.

Nelson, D.B. (1991), Conditional Heteroscedasticity in Asset Returns: A new approach, *Econometrica*, **59**, 347-370.

Niarchos, N. and Alexakis, C. (1998), Stock market prices, causality and efficiency: evidence from the Athens stock exchange, *Applied Financial Economics*, **8**, 167-174.

Patterson, D.M. and Ashley, R.A. (2000), A Nonlinear Time Series Workshop, Kluwer Academic, London.

Siriopoulos, C. (1996), Investigating the behaviour of mature and emerging capital markets, *Indian Journal of Quantitative Economics*, **11**, 1, 76-98.

Tsay, R.S. (1986), Nonlinearity tests for Time Series, Biometrica, 73, 461-466.

Zakoian, J. M. (1994), Threshold Heteroskedastic Models, *Journal of Economic Dynamics and Control*, **18**, 5, 931-955.



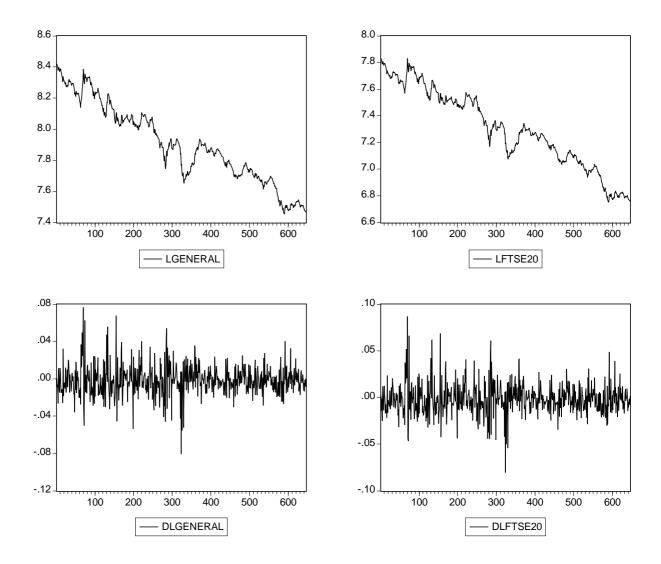
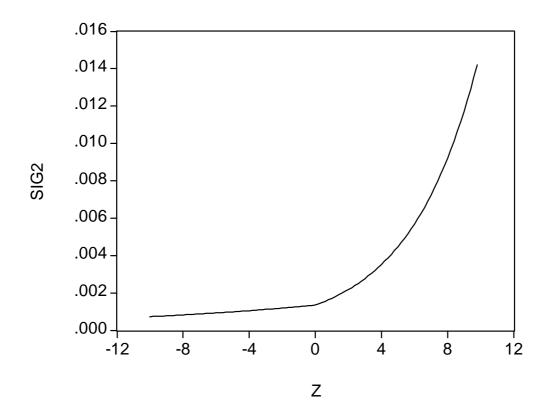


FIGURE 2: Estimated News Impact Curve from TGARCH



NOTE: The news impact curve plots the next period volatility (SIG2 on Figure 2) that would arise from various positive and negative values of the lagged shock (ε_{t-1} , Z in Figure 2), given an estimated model. The curve is drawn by using the estimated conditional variance equation for the model under consideration, with its given coefficients, and with the lagged conditional variance set to the unconditional variance. The TGARCH news impact curve is asymmetric with positive shocks having more impact on future volatility than negative shocks of the same magnitude.

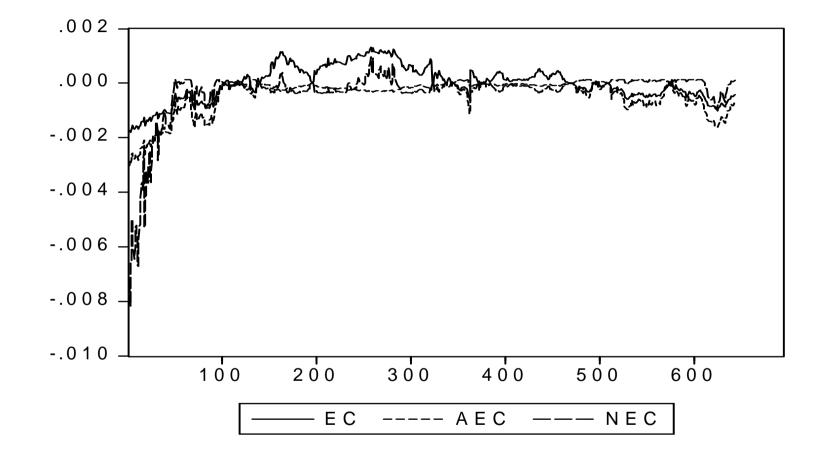


FIGURE 3: Error Correction Components, where ec=-0.025461*z, aec =-0.042425*z++0.00649*z-, and nec=0.018387*z-0.37277*z²-21.22782*z³

APPENDIX 1

Table 1: Summary Statistics The levels and the first difference of the series (period from 1/6/00 to 31/12/02, daily observations)

| | LGENERAL | LFTSE20 | DLFTSE20 | DLGENERAL |
|--------------|----------|-----------|-----------|-----------|
| Mean | 7.906188 | 7.305408 | -0.001656 | -0.00148 |
| Median | 7.880948 | 7.295308 | -0.002394 | -0.00207 |
| Maximum | 8.419543 | 7.829463 | 0.086787 | 0.076205 |
| Minimum | 7.454193 | 6.75338 | -0.080191 | -0.08059 |
| Std. Dev. | 0.250363 | 0.293077 | 0.016475 | 0.015995 |
| Skewness | 0.126852 | -0.124461 | 0.528173 | 0.330906 |
| Kurtosis | 2.047701 | 1.969053 | 6.592779 | 6.250502 |
| | | | | |
| Jarque-Bera | 26.10202 | 30.22939 | 376.3088 | 295.2675 |
| Probability | 0.000002 | 0 | 0 | 0 |
| | | | | |
| Sum | 5099.491 | 4711.988 | -1.066442 | -0.95289 |
| Sum Sq. Dev. | 40.36686 | 55.31572 | 0.174521 | 0.16451 |
| Observations | 645 | 645 | 644 | 644 |

L GENERAL is the log of the General Index; LFTSE20 is the log of the FTSE20 and LFTSE Mid 40 is the log of FTSE Mid 40 and D denotes the first difference of the series.

Table 2: Unit Root Tests

| | Levels | First Differences | Critical Values 1% |
|----------|-----------|----------------------|-----------------------|
| | A | DF with intercept | t |
| LGeneral | -1.157375 | -23.23483 | -3.44 |
| LFTSE20 | -0.718135 | -22.96417 | -3.44 |
| | | PP | |
| LGeneral | -1.221341 | -23.33435 | -3.44 |
| LFTSE20 | -0.729186 | -23.03782 | -3.44 |

ADF is the Augmented Dickey-Fuller Unit Root Test and PP is the Phillips-Perron Unit Root Test.

| Table 3a. Long-run re | elationship an | d cointegration | (Johansen) |
|-----------------------|----------------|-----------------|------------|
| | | | |

| UNRESTRICTED COINTEGRATION RANK TEST (TRACE AND MAXIMUM EIGENVALUE) | | | | | | | | | | |
|---|----------|-------|---------|--------|----------|--------|--------|--|--|--|
| Hypothesized No. Of CE Eigenvalue Trace Stat 0.05 CV Prob. Max-Eigen Stat 0.05 CV P | | | | | | | | | | |
| None | 0.029561 | 27.99 | 25.8721 | 0.0269 | 19.20418 | 19.387 | 0.0531 | | | |
| At Most 1 | 0.013635 | 8.786 | 12.518 | 0.1939 | 8.786595 | 12.518 | 0.1939 | | | |

Notes: Trace test indicates 1 cointegrating equation (CE) at the 0.05 critical value (CV) and the Max-eigenvalue test indicates 1 cointegrating equation at the 0.10 CV. Prob: MacKinnon-Haug-Michelis (1999) *p*-values. We assume linear deterministic trend.

Table 3b. Long-run relationship and cointegration (Engle and Granger)

| COINTEGRATING EQUATION (ENGLE-GRANGER APPROACH) | | | | | | |
|--|--|--|--|--|--|--|
| LGeneral=1.74+0.84*LFTSE20-0.044*D | | | | | | |
| Unit root test on the residuals of the LR relationship | | | | | | |
| ADF -2.84 (Critical Value 1% -2.56) | | | | | | |
| PP -2.79 | | | | | | |

D is a dummy variable introduced in the long run relationship and takes the value of 1 between 14/9/01 and 2/11/01.

The result of cointegration is supported by both the Engle-Granger and the Johansen methodology.

| | 1. | 2- Dependent ∨ 2 | 3 | 4 | | 5 | 6 | 7 |
|-------------------------|---------|----------------------------|----------|-----------|----------------------|----------|----------|----------|
| Models | RW | GARCH(1,1) | EGARCH | TGARCH | | ECM | AECM | NECM |
| Regressor | | | | × | Regressor | | <u>,</u> | |
| Constant | -0.0014 | -0.00145 | -0.00184 | -0.00184 | Constant | -0.00122 | -0.00075 | -0.00094 |
| | (2.34) | (2.69) | (3.32) | (3.21) | | (1.95) | (0.721) | (1.16) |
| | | | | | DLGENERAL (-5) | 0.274319 | 0.270364 | 0.263128 |
| | | | | | | (1.23) | (1.22) | (1.18) |
| | | | | | DLFTSE20(-1) | 0.092641 | 0.091901 | 0.091748 |
| | | | | | | (2.41) | (2.39) | (2.38) |
| Variance | | | | | | | | |
| Equation | | | | | DLFTSE20(-4) | 0.126621 | 0.126236 | 0.123888 |
| С | | 3.07E-05 | -0.09164 | 1.89E-05 | | (3.13) | (3.305) | (3.23) |
| | | (3.52) | (2.64) | (3.45) | DLFTSE20(-5) | -0.32322 | -0.31991 | -0.31444 |
| ARCH(1) | | 0.175279 | | 0.08929 | | (1.5) | (1.485) | (1.45) |
| | | (5.66) | | (4.46) | CV ⁺ (-1) | | -0.04243 | |
| GARCH(1) | | 0.70463 | | 0.772211 | | | (0.888) | |
| | | (12.87) | | (19.76) | CV ⁻ (-1) | | 0.00649 | |
| RES / | | | | | | | | |
| SQR[GARCH](1) | | | 0.105045 | | | | (0.129) | |
| | | | (8.33) | | CV(-1) | -0.01876 | | 0.018387 |
| RES/ | | | 0.00004 | | | (0.73) | | (0.37) |
| SQR[GARCH](1) | | | -0.08304 | | $OU(1)^2$ | | | 0 07077 |
| | | | (6.05) | | $CV(-1)^2$ | | | -0.37277 |
| EGARCH(1) | | | 0.998425 | | $OV(1)^3$ | | | (0.42) |
| | | | (229.98) | | $CV(-1)^3$ | | | -21.2278 |
| (RESID<0)* | | | | 0.151283 | | | | (0.808) |
| ARCH(1) | | | | | | | | (0.000) |
| | | | | (3.93) | I | | | |
| Adjusted R ² | 0 | -0.00469 | -0.00677 | -0.00677 | | 0.023003 | 0.021988 | 0.02207 |
| SE of regression | | 0.016033 | 0.016049 | 0.016049 | | 0.023003 | 0.021988 | 0.02207 |
| Pr (J-B stat) | 0 | 0.010033 | 0.010049 | 0.016049 | | 0.015655 | 0.015641 | 0.01564 |
| SC | -5.4245 | -5.54843 | - | -5.554214 | | -5.40227 | -5.3927 | -5.38426 |

Table 4: Estimated Models

Note: Numbers in () are the corresponding *t* statistics, SC is the Schwarz criterion and SE is the Standard Error, RW is the random walk model, ECM is the linear Error Correction model, ACM is the asymmetric Error Correction Model and NECM is the non-linear error correction model. The "general-to-specific" approach was followed. The preferred model in each case was the one that min the SC. CV is the cointegrating vector.

| | RW | | - | GA | RCH | | EGAF | RCH | | TGA | RCH | | |
|--------------------|----|----------------------|----------|----------|----------------------|----------|----------|----------------------|-------------|-----------|----------------------|----------|----------|
| | E | BOOTSTRAP ASYMPTOTIC | | ГIC | BOOTSTRAP ASYMPTOTIC | | IC | BOOTSTRAP ASYMPTOTIC | | | BOOTSTRAP ASYMPTOTIC | | |
| MCLEOD-LI TEST | | | | | | | | | | | | | |
| USING UP TO LAG 20 |) | 0.000 | 0.000 | | 0.376 | 0.477 | | 0.122 | 0.141 | | 0.32 | 3 0.388 | |
| USING UP TO LAG 24 | 1 | 0.000 | 0.000 | | 0.524 | 0.654 | | 0.159 | 0.197 | | 0.36 | 7 0.447 | |
| BICOVARIANCE TES | Т | | | | | | | | | | | | |
| UP TO LAG 11 | | 0.001 | 0.000 | | 0.710 | 0.803 | | 0.584 | 0.680 | | 0.80 | 2 0.882 | |
| ENGLE TEST | | | | | | | | | | | | | |
| USING UP TO LAG 1 | | 0.024 | 0.009 | | 0.174 | 0.194 | | 0.119 | 0.137 | | 0.30 | 3 0.304 | |
| USING UP TO LAG 2 | | 0.000 | 0.000 | | 0.066 | 0.073 | | 0.004 | 0.000 | | 0.11 | 6 0.134 | |
| USING UP TO LAG 3 | | 0.000 | 0.000 | | 0.105 | 0.137 | | 0.007 | 0.001 | | 0.19 | 6 0.222 | |
| USING UP TO LAG 4 | | 0.000 | 0.000 | | 0.058 | 0.050 | | 0.009 | 0.002 | | 0.06 | 5 0.061 | |
| TSAY TEST | | 0.000 | 0.000 | | 0.085 | 0.083 | | 0.479 | 0.494 | | 0.28 | 9 0.28 | |
| BDS | В | OOTSTRAF | þ | | | | | | | | | | |
| Dimension | Е | PS=0.50 | EPS=1.00 | EPS=2.00 | EPS=0.50 | EPS=1.00 | EPS=2.00 | EPS=0.50 | EPS=1.00 EF | PS=2.00 E | PS=0.50 | EPS=1.00 | EPS=2.00 |
| | 2 | 0.001 | 0.001 | 0.001 | 0.717 | 0.829 | 0.854 | 0.604 | 0.747 | 0.907 | 0.858 | 0.856 | 0.781 |
| : | 3 | 0.000 | 0.000 | 0.000 | 0.489 | 0.572 | 0.686 | 0.241 | 0.239 | 0.346 | 0.713 | 0.622 | 0.549 |
| | 4 | 0.000 | 0.000 | 0.000 | 0.372 | 0.472 | 0.547 | 0.072 | 0.107 | 0.241 | 0.645 | 0.531 | 0.438 |
| | А | SYMPTOTI | С | | | | | | | | | | |
| | 2 | 0.000 | 0.000 | 0.000 | 0.959 | 0.956 | 0.828 | 0.655 | 0.788 | 0.914 | 0.865 | 0.861 | 0.802 |
| : | 3 | 0.000 | 0.000 | 0.000 | 0.927 | 0.766 | 0.443 | 0.253 | 0.267 | 0.380 | 0.747 | 0.644 | 0.58 |
| | 4 | 0.000 | 0.000 | 0.000 | 0.853 | 0.676 | 0.449 | 0.045 | 0.100 | 0.259 | 0.687 | 0.57 | 0.483 |

Note: The standardised residuals of the GARCH, EGARCH and TGARCH 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 from the author. Only *p*-values are reported.

| Table 0. Diagnos | | | | | | | _ | | |
|--------------------|----------|--------------|----------|----------|------------|----------|----------|-----------|----------|
| | E | CM | | Asymme | etric ECM | | Non-Lin | ear ECM | |
| | BOOTSTRA | AP ASYMPTOTI | IC | BOOTSTRA | P ASYMPTOT | IC | BOOTSTRA | P ASYMPTO | TIC |
| 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 TES | Г | | | | | | | | |
| UP TO LAG 11 | 0.002 | 0.000 | | 0.002 | 0.000 | | 0.003 | 0.000 | |
| ENGLE TEST | | | | | | | | | |
| USING UP TO LAG 1 | 0.006 | 0.001 | | 0.006 | 0.001 | | 0.005 | 0.001 | |
| USING UP TO LAG 2 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| USING UP TO LAG 3 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| USING UP TO LAG 4 | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| TSAY TEST | 0.000 | 0.000 | | 0.000 | 0.000 | | 0.000 | 0.000 | |
| BDS | BOOTSTRA | P | | | | | | | |
| 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 0.012 | 0.000 | 0.000 | 0.014 | 0.000 | 0.000 | 0.010 | 0.000 | 0.000 |
| | 3 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 4 | 4 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | ASYMPTOT | IC | | | | | | | |
| | 2 0.009 | 0.000 | 0.000 | 0.012 | 0.000 | 0.000 | 0.007 | 0.000 | 0.000 |
| ÷ | 3 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | 4 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Table 6: Diagnostic Tests