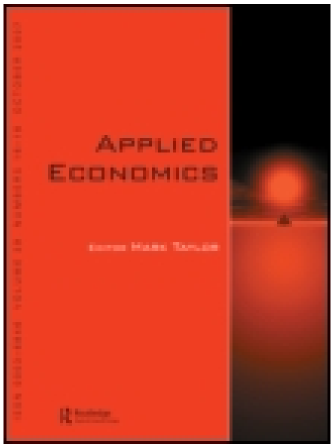

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Nonlinearities in emerging stock markets: evidence from Europe's two largest emerging markets

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Nonlinearities in emerging stock markets: evidence from Europe's two largest emerging markets

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Recent developments in time series analysis allow proper modelling of nonlinearities in economic and financial variables. A growing body of research was dedicated to investigation of potential nonlinearities in conditional mean of many economic and financial variables, mainly concentrating in developed economies. However, nonlinearities in financial variables in developing economies have not been fully examined yet. In this article we investigate potential nonlinearity and cyclical behaviour of stock returns in Europe's two largest emerging stock markets, mainly in the Greek and Turkish stock markets. Specifically, we use STAR family models, which allow to model nonlinearities in the conditional mean, for modelling monthly returns on stock exchange indices of the Athens Stock Exchange and Istanbul Stock Exchange. Although we find no nonlinearity in conditional variance, we do find strong evidence in favour of nonlinear adjustment of stock returns. It is found that allowing for nonlinearity in conditional mean results in a superior model and provides good out-of-sample forecasts, which contradicts to efficient market hypothesis.

I. Introduction

Economists nowadays generally accept that many economic variables, including financial ones, follow nonlinear processes (Granger and Teräsvirta, 1993; Campbell *et al*., 1997; Franses and van Dijk, 2000). Nonlinearity in a variable can stem from either conditional mean or conditional variance or both. If nonlinearity of a variable originates solely from conditional variance, then such processes are more aptly modelled by auto regressive conditional heteroscedasticity (ARCH) models, originally developed by Engel (1982), or their natural extensions, generalized ARCH (GARCH) models of Bollerslev (1986). The ARCH and GARCH models have extensively been used for modelling financial time series. However, lesser attention has been paid to modelling of financial time series when there is a nonlinear behaviour in the conditional mean. The nonlinearity in conditional mean should be appropriately modelled in order to avoid misspecification of the conditional variance.

Recent developments in modelling nonlinear time series in which nonlinearity stems from conditional mean allow modelling financial time series more appropriately. A growing body of research has been devoted to examination of nonlinear behaviour of financial time series, especially in the case of

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developed economies. See, for example, Hsieh (1991), Abhyankar *et al.* (1995, 1997), Schaller and Norden (1997), Pandey *et al.* (1998), Martens *et al.* (1998), Qi (1999), Perez-Quiros and Timmerman (2000), Gallagher and Taylor (2001), Kanas (2001), Sarantis (2001), Maasoumi and Racine (2002), Shively (2003), McMillan (2003, 2005), Östermark *et al.* (2004), Narayan (2005) and Chung *et al.* (2005). Although nonlinear dynamics of mature stock markets are well examined, a lesser work is done for studying nonlinear properties of emerging markets when nonlinearity stems from conditional mean. A few exceptions are Busetti and Manera (2003), Chiang and Doong (2001) and McMillan (2005).[1] Busetti and Manera (2003) have used STAR-GARCH models to examine the market interactions in the Pacific Basin Region. Chiang and Doong (2001) employed TAR-GARCH models to study stock returns in seven Asian stock markets. McMillan (2005) used smooth transition autoregressive (STAR) models to investigate nonlinear dynamics in three Asian emerging stock markets as well as in three mature markets.

Emerging markets have been attracting international investors hoping to benefit from abnormal high returns as well as portfolio risk diversification (Harvey, 1995). Despite importance of these markets for investors, possible nonlinearities in dynamics of emerging stock markets have not been investigated fully yet. The dynamics of emerging markets is quite different from mature markets. It is well known that the emerging markets are characterized by higher volatility and rapid and steep price falls when compared to mature markets (Bekaert and Harvey, 1997; De Santis and Imrohoroglu, 1997; Patel and Sarkar, 1998). In addition, it is well known that emerging markets are highly inefficient in terms of speed of information reaching all traders when compared to mature markets, and biases due to market thinness and nonsynchronous trading are more severe in the case of emerging markets (Barkoulas and Travlos, 1998). Therefore, studying possible nonlinearities in dynamics of these markets is of greater importance for both academicians and market practitioners. On the other hand, modelling nonlinearities in stock markets is crucial for determining whether the stock prices have a predictable element, discovery of which should be a violation of the efficient market hypothesis.

In this article, we examine the nonlinear properties of the stock return dynamics in Europe's two largest emerging stock markets, mainly Athens Stock Exchange (ASE) and Istanbul Stock Exchange (ISE). Both stock markets have attracted substantial interest of investors in the recent decade. In 2005 the ratio of purchases by international investors to the total traded value in ISE increased to 21.13% from 7.47% in 1997 (ISE Annual Factbook 2005). In 2005, over 50% of transactions on the ASE were carried out by international investors (PM Communications, 2006). Being largest emerging markets in the Europe, these stock markets have similarities with both mature and emerging markets elsewhere in the world (see De Santis and Imrohoroglu (1997); Vougas (2004); Kilic (2004), among others). Although some evidence is provided for nonlinearities in these markets, the nonlinear dynamics of the markets have not been investigated fully. Barkoulas and Travlos (1998) using BDS tests due to Brock *et al.* (1987) find nonlinearity in daily returns on ASE30 index. Abutaleb and Papaioannou (2000) employed a time-varying model, which allows parameters of a conventional autoregressive model to change over time, for predicting athens stock market index. Harris and Kücüközmen (2001) using daily aggregate returns of ISE found that the returns exhibit significant linear and nonlinear dependence, and concluded that nonlinearity originates from the linear dependence in conditional variance rather than nonlinear dependence in the conditional mean. Yümlü *et al.* (2005) employing neural net models for predicting ISE found that smoothed piecewise neural models are superior to feedback and global neural models as well as to conventional EGARCH models. Our methodology here to examine nonlinearities in the markets differs from previous works. In this article, we use STAR family models to examine nonlinear dynamics of the stock returns, expanding recent works of Sarantis (2001), who studied G-7 stock markets, and McMillan (2005), who compared nonlinearities in three Asian emerging markets and three mature markets. Although we find no nonlinearity in conditional variance, we do find strong evidence in favour of nonlinearity in the conditional mean. In addition to examination of nonlinear adjustment of stock returns, we also investigate cyclical behaviour of returns and compare out-of-sample forecasting performance of nonlinear models to linear alternatives.

[1] In addition, Sarno (2000), Taylor and Sarno (2001), Enders and Chumrusphonlert (2004) and Leon and Najarian (2005), among others, have employed nonlinear models to study nonlinear adjustment of exchange rates in developing countries.

The economic theory suggests a number of sources of nonlinearity in the financial data. One of the most frequently cited reasons of nonlinear adjustment is presence of market frictions and transaction costs. Existence of bid-ask spread, short selling and borrowing constraint and other transaction costs render arbitrage unprofitable for small deviations from the fundamental equilibrium. Subsequent reversion to the equilibrium, therefore, takes place only when the deviations from the equilibrium price are large, and thus arbitrage activities are profitable (He and Modest, 1995). Consequently, the dynamic behaviour of returns will differ according to the size of the deviation from equilibrium, irrespective of the sign of disequilibrium, giving rise to asymmetric dynamics for returns of differing size (Dumas, 1992, 1994; Krägler and Krugler, 1993; Obstfeld and Taylor, 1997; Shleifer, 2000; Coakley and Fuertes, 2001). In addition to transaction costs and market frictions, interaction of heterogeneous agents (Hong and Stein, 1999; Shleifer, 2000), diversity in agents' beliefs (Brock and LeBaron, 1996; Brock and Hommes, 1998) also may lead to persistent deviations from the fundamental equilibrium. On the other hand, heterogeneity in investors' objectives arising from varying investment horizons and risk profiles (Peters, 1994), herd behaviour or momentum trading (Lux, 1995) may give rise to different dynamics according to the state of the market, i.e. whether the market is rising or falling.

Because of these arguments we consider STAR models (originally proposed by Chan and Tong, 1986) as a generalization of the threshold autoregressive (TAR) model, and developed further by Teräsvirta and Anderson (1992); Granger and Teräsvirta (1993); Teräsvirta (1994) which are capable of capturing the nonlinear behaviour consistent with both market friction models, where market dynamics differ between large and small returns, and more general nonlinear behaviour perhaps arising from the state of the market (i.e. differing dynamics depending on whether the market is rising or falling). The STAR model is selected for a number of reasons. First, it is theoretically more appealing over the simple threshold models which impose an abrupt switch in parameter values. Such instantaneous changes in regimes are possible only if all traders act simultaneously and in the same direction. For the market of many traders acting at slightly different times, however, a smooth transition model is more appropriate. Second, the STAR model allows for different types of market behaviour depending on the nature of the transition function. In particular, the logistic function allows for differing behaviour depending on whether returns are positive or negative, while the exponential function allows differing behaviour to occur for large and small returns regardless of sign. The former function may be motivated by considerations of the general state of the market, while the latter function is motivated by considerations of market frictions, such as transactions costs or noise trader risk. Finally, the ability of this model to allow gradual transition between regimes of behaviour is consistent with the stylized facts of asset returns, that they exhibit momentum, or positive correlation, over a short horizon, but reversal, or negative correlation, over a longer horizon, and hence are characterized by persistence and slow reversion (Campbell *et al.*, 1997).

The remaining of the article is organized as follows. In Section II we discuss specification and estimation of STAR models. The estimates of linear and STAR models are provided in Section III. In this section we also compare in-sample fit and out-of-sample forecasting performance of the linear and STAR models. Section IV contains a brief discussion.

II. Specification and Estimation of STAR Models

A single-transition function (or two-regime) STAR model for a univariate time series y_t is given by

$$y_t = \pi_{1,0} + \pi_1' x_t + \left(\pi_{2,0} + \pi_2' x_t\right) \cdot F(s_t; \gamma, c) + u_t \tag{2.1}$$

where x_t is a vector consisting of lagged values of the endogenous variable. The disturbance u_t is white noise with zero mean, and is assumed to be homoscedastic over regimes with variance σ^2 and to be normally distributed. The transition function $F(s_t; \gamma, c)$ is a continuous function bounded between 1 and 0. Thus the STAR model can be interpreted as a regime-switching model that allows for two regimes, associated with the extreme values of the transition function, $F(s_t; \gamma, c) = 0$ and $F(s_t; \gamma, c) = 1$, whereas the transition from one regime to the other is gradual. The parameter γ determines the smoothness of the transition, and thus, the smoothness of transition from one regime to the other. The two regimes are associated with small and large values of the transition variable s_t relative to the threshold c.

Two popular choices of the transition function $F(s_t; \gamma, c)$ are the logistic function

$$F(s_t; \gamma, c) = \frac{1}{1 + \exp\left(-\gamma(s_t - c)/\sigma_{s_t}\right)} \tag{2.2}$$

and the exponential function

$$F(s_t;\gamma,c)=1-\exp\left(\frac{-\gamma(s_t-c)^2}{\sigma_{s_t}^2}\right) \quad (2.3)$$

where $\sigma_{s_t}$is sample SD of the transition variable s_t.

These yield, respectively, the logistic STAR (LSTAR) and exponential STAR (ESTAR) models. The logistic function is convenient for modelling differing dynamics depending on whether the returns take large or small value, i.e. the direction of disequilibrium. The LSTAR model may be consistent with the differing investor psychology between rising and falling markets, or the existence of market frictions whose impact differs between 'bull' and 'bear' markets. Thus, the LSTAR model can describe a situation where contractionary and expansionary periods have rather different dynamics. In contrast, the transition occurs symmetrically for s_t about threshold c if exponential function is used in (2.1). The ESTAR model implies that contractionary and expansionary periods have similar dynamics (Teräsvirta and Anderson, 1992).

An obvious extension of the single-transition function STAR model is a two-transition function STAR model (Eitrheim and Teräsvirta, 1996) given as

$$\begin{aligned} y_t = \pi_{1,0}+\pi_1'x_t+\left(\pi_{2,0}+\pi_2'x_t\right)\cdot F_1(s_{t1};\gamma_1,c_1) \\ +\left(\pi_{3,0}+\pi_3'x_t\right)\cdot F_2(s_{t2};\gamma_2,c_2)+u_t \end{aligned} \quad (2.4)$$

where F_1 and F_2 are either logistic or exponential functions as defined above. The STAR model given in (2.4) is known as a multiple regime smooth transition model (MR-STAR) and allows possibility for four regimes. For a thorough discussion of MR-STAR models see van Dijk (1999, Chapter 2).

The empirical specification procedure for STAR models consists of following steps (van Dijk, 1999: 18):

(1) Specify an appropriate linear autoregressive model for the time series under investigation.
(2) Test the null hypothesis of linearity against the alternative of STAR-type nonlinearity. If linearity is rejected, select the appropriate transition variable s_t and the form of the transition function $F(s_t;\gamma,c)$.
(3) Estimate the parameters in the selected STAR model.
(4) Evaluate the model using diagnostic tests, and modify the model if necessary.
(5) Use the model for descriptive or forecasting purposes.

Since the nonlinearity tests are sensitive to autocorrelation, the lag structure of the autoregressive model should be specified so as to capture the significant autocorrelation in the linear model. The lag structure of the model can be selected by applying conventional information criteria such as Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC) or the so-called t-significance method.

Once the appropriate linear model is defined, we carry out linearity tests against the alternative STAR-type nonlinearity. The linearity tests are complicated by the presence of unidentified nuisance parameters under the null hypothesis. This can be seen by noting that the null hypothesis of linearity may be expressed in different ways. Besides equality of the parameters in the two regimes, H_0: $\pi_1=\pi_2$, the alternative null hypothesis H_0': $\gamma=0$ also gives rise to linear model. To overcome this problem, one may replace the transition function $F(s_t;\gamma,c)$ with appropriate Taylor approximation following the suggestion of Luukkonen *et al.* (1988). For example, a third-order Taylor approximation results in the following auxiliary regression

$$\begin{aligned} y_t = \beta_{0,0}+\beta_0'x_t+\beta_{1,0}s_t+\beta_1'x_ts_t+\beta_{2,0}s_t^2+\beta_2'x_ts_t^2 \\ +\beta_{3,0}s_t^3+\beta_3'x_ts_t^3+e_t \end{aligned} \quad (2.5)$$

where $\beta_{i,0},\beta_i'$, for $i=1,2,3$ are functions of the parameters π_1,π_2,γ and c, and e_t comprises the original shocks u_t as well as the error term arising from the Taylor approximation. In (2.5) it is assumed that the transition variable s_t is not one of the elements in x_t. If this is not the case, the term $\beta_{i,0}s_t^i$ for $i=1,2,3$ should be dropped from the auxiliary regression. The null hypothesis of linearity can be expressed as $H_0'':\beta_i'=0$, $i=1,2,3$ that is, the parameters associated with the auxiliary regressors are zero. This null hypothesis can be tested by a standard variable addition test in a straightforward manner. The test statistic, to be denoted as LM, has an asymptotic χ^2 distribution with degrees of freedom $3(p+1)$, where p is the dimension of the vector x_t.

To identify the appropriate transition variable s_t, the LM statistics can be computed for several candidates, and the one for which the p-value of the test statistic is smallest can be selected. Since monthly data exhibit short-run fluctuations that do not represent changes in regimes, we carry out the linearity tests using long differences as potential transition variables, that is, $s_t = \Delta_d y_{t-1} \equiv y_{t-1} - y_{t-1-d}$.[2]

When the appropriate transition variable s_t has been selected, the next step in specification of a STAR model is to choose between logistic and exponential functions. Teräsvirta (1994) suggests using use a decision rule based on a sequence of tests in Equation 2.5. Particularly, he proposes to test the following null hypotheses

(i) H_{03}: $\beta_3 = 0$
(ii) H_{02}: $\beta_2 = 0 | \beta_3 = 0$
(iii) H_{01}: $\beta_1 = 0 | \beta_3 = \beta_2 = 0$

in (2.5) by means of LM type tests. These hypotheses are tested by ordinary F-tests, to be denoted as F_3, F_2, and F_1, respectively. The decision rule is as follows: If the p-value corresponding to F_2 is the smallest, then ESTAR model should be selected, while in all other cases LSTAR model should be preferred.

Once the transition variable and form of the transition function are selected, the STAR models can be estimated by using any conventional nonlinear optimization procedure. The burden on the optimization algorithm can be alleviated by using good starting values. For fixed values of the parameters in the transition function, γ and c, the STAR model is linear in parameters $\pi_{1,0}, \pi_1', \pi_{2,0}$ and π_2', and therefore, can be estimated by OLS. Hence, a convenient way to obtain sensible starting values for the nonlinear optimization algorithm is to perform a two-dimensional grid search over γ and c, and select those parameter estimates that minimize variance of the residual term.

After estimation, we perform diagnostic tests to evaluate the estimated STAR models. Particularly, we perform misspecification tests for skewness and kurtosis, as well as the ARCH test of Engle (1982), and the LM tests for autocorrelation, parameter constancy and additive nonlinearity, as suggested by Eitrheim and Teräsvirta (1996). If the estimated model passes all misspecification tests, then it can be used for descriptive and/or forecasting purposes.

III. Data and Empirical Results

In this article we consider monthly returns for the ASE and ISE indices, covering the period January 1988 to October 2005. The index data is taken from the Datastream. We compute the monthly returns as $y_t = \text{Ln}\,(X_t/X_{t-1})$ where X_t is composite stock price index. We use the sub-sample January 1988 to April 2002 for estimation and diagnostic checking, and leave remaining 42 observations for out-of-sample forecasting.

The linear model is initially specified with maximum lag order of 12, with intermediate lags then deleted one by one (starting with the least statistically significant according to the t-ratio) provided that such deletions reduce the AIC. The estimated linear models for monthly returns for the two markets are as follows[3]:

Linear model for the Greek stock market:

$$y_t = \underset{(0.068)}{0.046}\, y_{t-1} + \underset{(0.069)}{0.128}\, y_{t-2} + \underset{(0.068)}{0.166}\, y_{t-8} + \underset{(0.069)}{0.174}\, y_{t-10} - \underset{(0.069)}{0.143}\, y_{t-12} + \varepsilon_t$$

$\hat{\sigma}_\varepsilon^2 = 0.008$, AIC $= 43.858$, $\bar{R}^2 = 0.310$, SEE $= 0.089$, RSS $= 1.207$, DW $= 1.929$

$Q(36) = 43.231(0.190)$, ARCH(1) $= 0.839(0.360)$

Linear model for the Turkish stock market:

$$y_t = \underset{(0.012)}{0.049} + \underset{(0.088)}{0.336}\, y_{t-1} - \underset{(0.089)}{0.191}\, y_{t-2} + \underset{(0.087)}{0.149}\, y_{t-3} - \underset{(0.065)}{0.141}\, y_{t-5} - \underset{(0.071)}{0.134}\, y_{t-11} + \varepsilon_t$$

$\hat{\sigma}_\varepsilon^2 = 0.019$, AIC $= 150.173$, $\bar{R}^2 = 0.124$,

SEE $= 0.139$, RSS $= 2.957$, DW $= 2.00$,

$Q(36) = 30.829\ (0.713)$, ARCH(1) $= 2.077\ (0.15)$

The values below the parameter estimates are heteroscedasticity consistent SEs. $\hat{\sigma}_\varepsilon^2$ is the residual variance, Q is Ljung–Box Q statistic for no autocorrelation, SEE is standard error of estimate and RSS is sum of squared residuals. ARCH is Engle's (1982) test against conditional heteroscedasticity. The estimated linear model for the ISE returns does not reveal any misspecification. The ARCH test

[2] We also considered lags of the returns, that is y_{t-d}, $d = 1, \ldots, 12$, as candidate transition variables. However, linearity was never rejected when the lags of the returns were considered. Therefore, we here report results for long differences only.
[3] The linear models include dummy variables for outliers evident in the residuals. The linearity tests were also conducted using these dummy variables in order to ensure that rejection of the null of linearity is not due to presence of big outliers. We included the same dummy variables in the estimation of the nonlinear models as well.

suggests no nonlinearity in the conditional variance. On the other hand, the estimated linear model for the ASE returns display some shortcomings, namely, residuals suffer from excess kurtosis and skewness, and the ARCH tests suggest that there is nonlinearity in the conditional variance (see Table 3 further). However, as pointed out by Lundbergh and Teräsvirta (1998), mis -modelling of the conditional mean could lead to misspecification of the conditional variance. Therefore, we proceed to linearity tests to check for nonlinearities in the conditional mean of the series under consideration.

The results of the linearity tests are reported in Panel A of the Table 1. As the table reveals, the null hypotheses of linearity for both stock return series are rejected at conventional significance levels for a number of candidate transition variables. However, the *p*-values of LM-type statistics are the smallest when annual change in the returns ($\Delta_{12}y_{t-1}$) was considered as a transition variable.

Having selected the most appropriate transition variable we conduct a sequence of *F*-tests described above to determine the form of the transition function. The *p*-values of the *F*-statistics are reported in Panel B of the Table 1. Since the *p*-values of the F_2 statistic are the smallest for both time series under consideration, we select the exponential function and estimate ESTAR models. The estimated ESTAR model for ASE returns (not provided here, available upon request from authors) suggested additional nonlinearity in the conditional mean and therefore we have estimated a MR-STAR model for ASE returns.

We have estimated the models using nonlinear least squares, which is equivalent to quasi maximum likelihood based on a normal distribution. Under certain (weak) regularity conditions, which are discussed by White and Domowitz (1984) and Pötscher and Prucha (1997), among others, the NLS estimates are consistent and asymptotically normal. The exponents are divided by the sample variance of the transition variable in the exponential functions and by the SD in the logistic function in order to make γ scale-free. For obtaining initial values to facilitate the nonlinear optimization algorithm we have conducted an extensive two-dimensional grid search over γ and c, ranging γ (after scaling) from 1 to 100 by 0.01 increments and ranging c from -0.5 to 0.5 by 0.01 increments.[4] Before proceeding to estimation of the STAR models using the optimal values of the parameters γ and c obtained from the grid search, we have deleted intermediate lags one by one (starting with the least statistically significant according to the *t*-ratio), if such deletions had reduced the AIC, and conducted a new grid search.

Table 1. Linearity and model selection test results

	LM3 statistic	
Candidate transition variables	Athens stock exchange	Istanbul stock exchange
Panel A: Linearity tests against STAR-type nonlinearity		
$\Delta_1 y_{t-1}$	0.700	0.360
$\Delta_2 y_{t-1}$	0.293	0.401
$\Delta_3 y_{t-1}$	0.263	0.637
$\Delta_4 y_{t-1}$	0.367	0.898
$\Delta_5 y_{t-1}$	0.564	0.309
$\Delta_6 y_{t-1}$	0.004	0.038
$\Delta_7 y_{t-1}$	2.55×10^{-5}	0.273
$\Delta_8 y_{t-1}$	4.52×10^{-6}	0.161
$\Delta_9 y_{t-1}$	9.07×10^{-6}	0.008
$\Delta_{10} y_{t-1}$	2.63×10^{-6}	0.110
$\Delta_{11} y_{t-1}$	6.82×10^{-6}	0.001
$\Delta_{12} y_{t-1}$	3.0×10^{-7}	3.90×10^{-5}
Panel B: Model selection tests		
F_1	0.029	0.052
F_2	0.008	0.046
F_3	0.832	0.863

Notes: *F*-versions of the LM-type tests were used. *p*-values of the test statistics are reported.

The estimated nonlinear models for both stock markets are provided subsequently in Table 2.[5]

The critical parameters in the STAR models are slope coefficients, γ, and threshold values, c. Estimation of the slope coefficients is problematic (Granger and Teräsvirta, 1993; Teräsvirta, 1994; and van Dijk, 1999) and the estimate of the slope coefficient often appears to be insignificant when judged by its *t*-statistic (for a thorough discussion of this issue see van Dijk (1999: 31–32). As the above-given estimates evidence, only the slope coefficient of the ESTAR model for ISE returns is statistically significant (at 5% level) whereas the threshold parameters in all cases are statistically significant at 1% significance level. Although the estimate of the slope coefficient in a STAR model may turn to be statistically insignificant, its estimate gives some information regarding the dynamics of the model because this parameter determines the speed of transition between regimes.

[4] We have based our range for threshold value c on observed range of returns by discarding the extreme values at each end.
[5] In estimating the parameters in the STAR models, following Rothman *et al.* (2001), we have imposed restriction on the value of slope coefficients, namely $\gamma \leq 500.0$, in the transition functions. When the slope coefficient approaches infinity, the STAR model reduces to TAR model. See also van Dijk (1999:8)

Table 2. Estimated nonlinear models for the stock markets

MR-STAR model for the Greek stock market

$$y_t = \underset{(0.785)}{-2.176}y_{t-1} + \underset{(0.103)}{0.452}y_{t-2} + \underset{(0.105)}{0.509}y_{t-10} - \underset{(0.031)}{0.145}y_{t-12}$$

$$+ (\underset{(0.761)}{2.099}y_{t-1} + \underset{(0.032)}{0.181}y_{t-8}) \cdot F_1(s_{t_1}; \gamma_1, c_1) + (\underset{(0.096)}{0.203}y_{t-1} - \underset{(0.107)}{0.451}y_{t-2} - \underset{(0.127)}{0.412}y_{t-10}) \cdot F_2(s_{t_2}; \gamma_2, c_2) + \varepsilon_t$$

$$F_1(s_{t_1}; \gamma_1, c_1) = 1.0 - \exp\left(-\left(\frac{500.0}{0.025}\right) \cdot \left(\Delta_{12}y_{t-1} - \underset{(0.0002)}{0.0007}\right)^2\right)$$

$$F_2(s_{t_2}; \gamma_2, c_2) = \frac{1.0}{1.0 + \exp\left(-\underset{(43.352)}{(38.396/0.138)} \cdot \left(\Delta_2 y_{t-1} + \underset{(0.017)}{0.057}\right)\right)}$$

$\hat{\sigma}_\varepsilon^2 = 0.005$, AIC $= -9.606$, $\bar{R}^2 = 0.467$, SEE $= 0.075$, RSS $= 0.768$, DW $= 1.875$, $F_{\mathrm{AC}} = 1.974$ (0.162), $F_{\mathrm{PC}} = 1.429$ (0.131), $F_{\mathrm{NRNL}} = 1.530$ (0.144)

ESTAR model for Turkish stock market

$$y_t = \underset{(0.012)}{0.039} + \underset{(0.209)}{1.082}\, y_{t-1} - \underset{(0.191)}{0.553}\, y_{t-2} + \underset{(0.168)}{0.261}\, y_{t-3}$$

$$+ \left(\underset{(0.223)}{-0.897}\, y_{t-1} + \underset{(0.200)}{0.473}\, y_{t-2} - \underset{(0.191)}{0.266}\, y_{t-3} \underset{(0.072)}{-0.190}\, y_{t-5} - \underset{(0.080)}{0.158}\, y_{t-11}\right)$$

$$\cdot F(s_t; \gamma, c) + \varepsilon_t$$

$$F(s_t; \gamma, c) = 1.0 - \exp\left(-\left(\underset{(5.867)}{12.997/0.042}\right) \cdot \left(\Delta_{12}y_{t-1} - \underset{(0.008)}{0.170}\right)^2\right)$$

$\hat{\sigma}_\varepsilon^2 = 0.015$, AIC $= 140.663$, $\bar{R}^2 = 0.176$, SEE $= 0.128$, RSS $= 2.242$, DW $= 1.947$, $F_{\mathrm{AC}} = 2.785$ (0.097), $F_{\mathrm{PC}} = 0.785$ (0.655), $F_{\mathrm{NRNL}} = 1.122$ (0.339)

Notes: The values below the parameter estimates are heteroscedasticity consistent SEs. $\hat{\sigma}_\varepsilon^2$ is the residual variance, SEE is SEr of estimate, and RSS is sum of squared residuals, F_{AC}, F_{PC} and F_{NRNL} are Eitrheim and Teräsvirta's (1996) test against first-order serial correlation of residuals, parameter constancy and additional nonlinearity, respectively. The figures in parentheses following the test statistics are *p*-values.

The model specification tests outlined above suggest a single-transition function STAR model for the ISE returns and a two-transition function (one of logistic and the other of exponential form) STAR model for the ASE returns. A single transition function in the ESTAR model for the ISE returns suggest that there are two different regimes in the Turkish stock market, and two transition functions in the MR-STAR model for ASE returns indicate presence of four distinct regimes for the Greek stock market. The regimes in the markets are characterized by the values that the transition functions in the models take on. The plots of transition functions for ASE and ISE returns against time and transition variables are given in Figs 1 and 2, respectively.

The exponential function in the ESTAR model for ISE returns suggests presence of market imperfections and frictions, implying that the dynamic behaviour of returns differ according to the size of the deviation from the equilibrium, giving rise to asymmetric dynamics for returns of differing size. Two regimes in the ESTAR model are middle regime (i.e. when $F_{\mathrm{E}} < 1.0$) and outer regime (i.e. when $F_{\mathrm{E}} = 1.0$). As can be seen from the Fig. 2, the middle regime roughly correspond to the periods when the annual difference between (monthly) returns is within the interval from 0.0 to 0.35, and the outer regime corresponds to the periods when the difference is beyond this interval. This means that the outer regime is characterized by lesser or abnormally

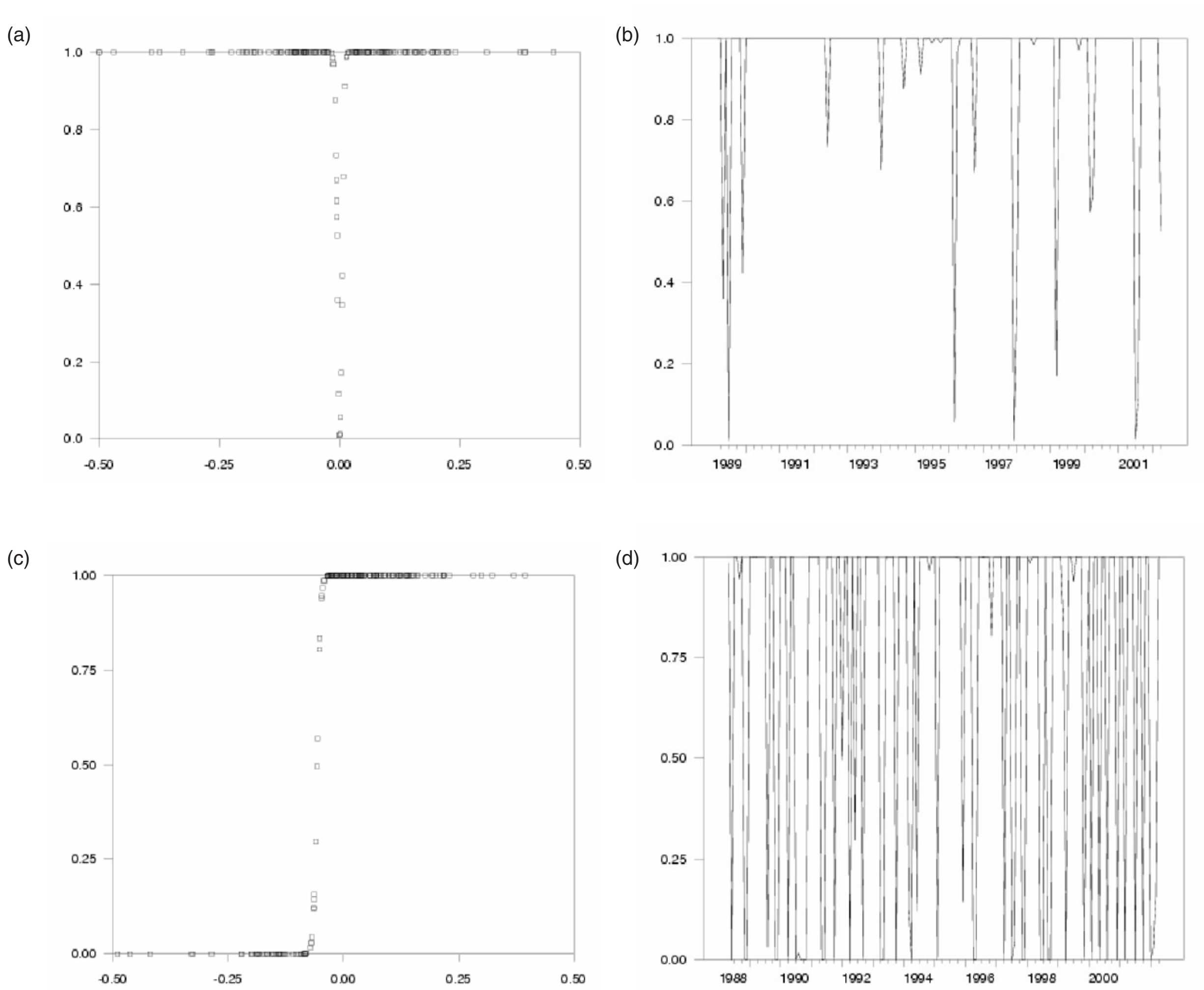

Fig. 1. Transition functions against time and transition variables in the MR-STAR model for ASE returns. Exponential function against transition variable (a) and time (b). Logistic function against transition variable (c) and time (d)

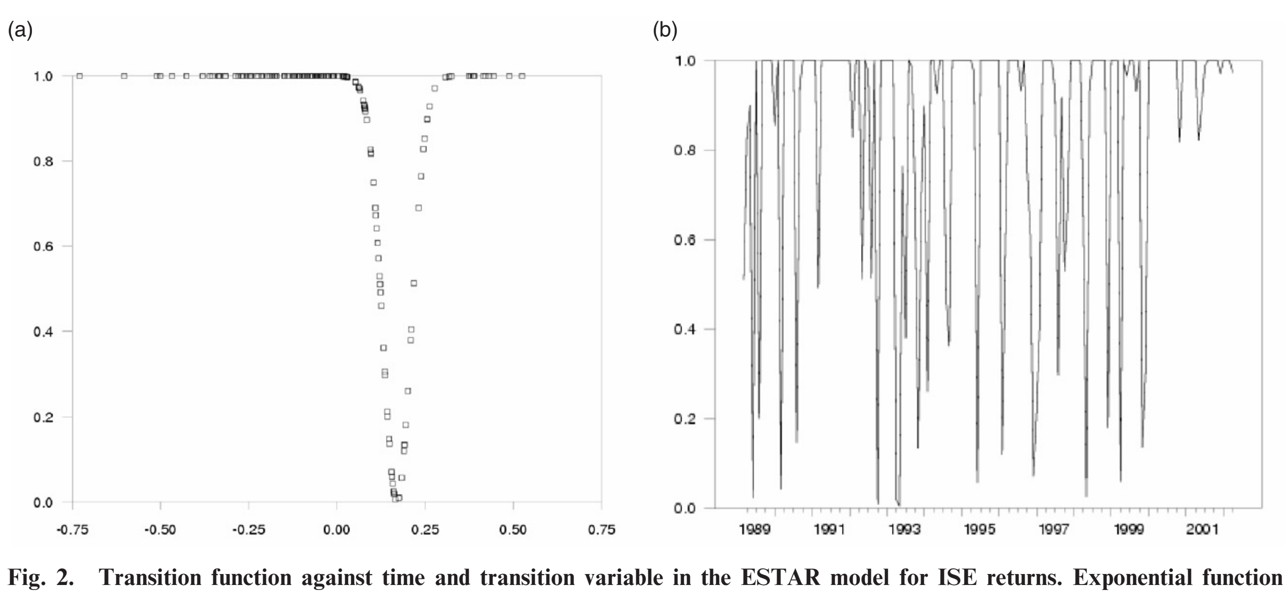

Fig. 2. Transition function against time and transition variable in the ESTAR model for ISE returns. Exponential function against transition variable (a) and time (b)

high returns compared to the previous year. Both the abnormally high return and loss periods have similar dynamics, and the path of reversion to the equilibrium in both periods is symmetric.

The estimated value of the slope coefficient γ for ISE returns is approximately equal to 13.0. This suggests that the speed of transition between regimes is moderate in line with stylized facts, contrary to the Markov regime switching and TAR models, which assume an abrupt change in regimes. A higher value of the slope coefficient implies that a fall (rise) in the returns may occur quite rapidly when the returns are initially above (below) the band around the threshold value, c. This also means that when the returns are in the middle regime, i.e. within the band, switching to the outer regime in either direction also happens rapidly.

The MR-STAR model for ASE returns includes both exponential and logarithmic transition functions. The exponential function suggests presence of market imperfections for the Greek stock market as well. The logistic function, on the other hand, suggests that the dynamics of the market differ depending upon whether the market is initially falling or rising. The four regimes governing the Greek stock market are the outer-lower regime (i.e. when the exponential function (F_E) takes value 1 and the logistic function (F_L) takes value 0), the middle-lower (i.e. when $F_E = F_L = 0$), the middle-upper (i.e. when $F_E = 0$ and $F_L = 1$) and the outer-upper regime (i.e. when $F_E = F_L = 1$). The four regimes are characterized jointly by annual and bi-monthly differences in returns. Middle regimes (whether middle-lower or middle-upper) correspond to periods when the annual differences between returns is approximately zero. That is, the outer regimes correspond to higher or lower return periods when compared to the previous year. Similarly, the lower regimes (whether middle-lower or outer-lower) correspond to lower return periods whereas the upper regimes (whether middle-upper or outer-upper) correspond to higher return periods.[6]

The estimate of the slope coefficient for the exponential function in the MR-STAR model for ASE returns is 500.0, the maximum value imposed by our estimation algorithm. It suggests that the transition from the middle regimes to the outer regimes and *vice versa* is almost instantaneous. On the other hand, the slope coefficient for the logistic function is approximately equal to 38.4, which indicates a rapid transition between the lower and upper regimes. A fast transition between the regimes implies that when the market is in recession (expansion) period, recovery (downturn) of the market happens quite rapid whereas the recession and expansion periods have quite different dynamics. That is, a fall or a rise in the market happens rapidly. This contradicts with the findings of Sarantis (2001) for developed markets, who found lower speeds of transition in regimes for G-7 stock returns. However, this result is consistent with findings of Patel and Sarkar (1998) who document that prices tend to fall more rapidly and steeply in emerging markets when compared to developed stock markets and with those of De Santis and Imrohoroglu (1997) who find that emerging markets exhibit higher probability of large price changes than mature markets.

The dynamic behaviour of the nonlinear model can be further investigated by examining the characteristic roots of the model. Following previous researchers (Teräsvirta and Anderson, 1992; Öcal, 2000; Sarantis, 2001) we compute the characteristic roots for each regime separately. The characteristic roots for each regime of both nonlinear models are shown in Table 3. All regimes for both stock markets contain pairs of complex roots implying that both markets are characterized by cyclical movements. The Greek stock market has the largest cycle around 10 months in the outer-lower regime, i.e. when the market is in recession. The middle regimes have relatively shorter cycles around five and a half months. The outer-higher regime, i.e. the expansion periods, has a relatively larger cycle around eight and half months. The Turkish stock market has a shorter cycle around 5 months in the middle regime, and relatively longer cycle of 8 months in the outer regime (i.e. when the market is falling or rising). It is interesting to note that both markets have relatively larger cycles when the market is either falling or rising. All but the outer-higher regime (expansion period) in the Greek market are dominated by unstable roots, implying that when the market is in recession it reverts to expansion period. However, the characteristic root in the outer-lower regime (recession period) is close to unity implying that recovery from contraction takes a longer period. Since the other two unstable roots (in the middle regimes) are sufficiently large, once the market

[6] The exponential function takes value less than 1 when the annual difference is in the interval from (approximately) −0.03 to 0.03. The logistic function takes value 0 when the bi-monthly difference is less than −0.12 and takes on value 1 when the difference is greater than 0.02.

Table 3. Characteristic roots of the estimated nonlinear models

Stock market	Regime	Characteristic roots	Modulus	Period
Greece	Outer-lower regime ($F_E=1$, $F_L=0$)	-1.014	1.014	
		$-0.776 \pm 0.559i$	0.956	10.073
		$-0.275 \pm 0.865i$	0.908	
		$0.265 \pm 0.867i$	0.907	
		$0.761 \pm 0.565i$	0.948	
		0.987	0.987	
		-0.510	0.510	
		0.510	0.510	
	Middle-lower regime ($F_E=0$, $F_L=0$)	-2.368	2.368	
		$-0.763 \pm 0.346i$	0.838	
		$-0.366 \pm 0.784i$	0.865	5.539
		-0.530	0.530	
		$0.189 \pm 0.841i$	0.862	
		$0.638 \pm 0.542i$	0.837	
		0.786	0.786	
		0.537	0.537	
	Middle-upper regime ($F_E=0$, $F_L=1$)	-1.974	1.974	
		-0.787	0.787	
		$-0.685 \pm 0.429i$	0.808	
		$-0.327 \pm 0.748i$	0.817	5.422
		$0.148 \pm 0.790i$	0.804	
		$0.539 \pm 0.558i$	0.776	
		$0.718 \pm 0.188i$	0.742	
	Outer-upper regime ($F_E=1$, $F_L=1$)	$0.801 \pm 0.125i$	0.810	
		$0.666 \pm 0.615i$	0.906	8.412
		$0.212 \pm 0.834i$	0.861	
		$-0.191 \pm 0.832i$	0.853	
		$-0.641 \pm 0.616i$	0.889	
		$-0.783 \pm 0.134i$	0.794	
Turkey	Middle regime ($F_E=0$)	0.799	0.799	
		$0.142 \pm 0.554i$	0.572	4.758
	Outer regime ($F_E=1$)	$0.803 \pm 0.274i$	0.849	
		$0.602 \pm 0.633i$	0.873	7.748
		$0.107 \pm 0.828i$	0.835	
		$-0.320 \pm 0.806i$	0.867	
		-0.854	0.854	
		$-0.673 \pm 0.436i$	0.801	

recovers from contraction period, it enters expansion period quite rapidly and tends to stay there. Larger roots in the middle regimes also suggest that a fall in the market happens quite rapidly as well, consistent with findings of the Patel and Sarkar (1998) for emerging markets that prices tend to fall rapidly and steeply whereas recovery from contraction periods takes a longer time. Contrary to the Greek market, both regimes in the Turkish stock market are dominated by a stable root, which implies a tendency of the returns to stay in whatever regime they are. However, since the slope coefficient is sufficiently large, once good (bad) news arrives at the market, the market recovers (turns down) from recession (high growth periods) quickly.

We compare the estimated linear and nonlinear models by using several criteria. First we check for reduction in the estimated residual variances, SE of estimate, and increase in the coefficient of determination. The results of the residual and specification tests are reported in Panel A of the Table 4. As can readily be seen from the table, the residual tests reveal no misspecification for both linear and nonlinear models for ISE. The Jarque–Bera test of normality indicates that residuals from both models are normally distributed. LB statistics are also acceptable for both residuals and squared residuals, which indicate that the residuals are white noise processes. Nor ARCH effect was found for either model. On the other hand the residuals from the linear model for ASE suffer from excess kurtosis and skewness, implying nonnormality of residuals, and there is ARCH effect in the residuals. However, allowing for nonlinearity remedies these shortcomings. In addition, allowing for nonlinearity in the conditional mean of the time series reduces SE of

Table 4. Residual and specification tests

	The Turkish stock market				Greek stock market			
	Linear model		ESTAR model		Linear model		MRSTAR model	
Panel A. Residual tests								
JB	0.075	(0.963)	2.133	(0.344)	138.174	(0.000)	1.110	(0.574)
Skewness	−0.165	(0.418)	−0.282	(0.167)	1.014	(0.000)	0.111	(0.584)
Kurtosis	−0.097	(0.814)	−0.156	(0.705)	4.103	(0.000)	−0.359	(0.381)
LB(1)	0.000	(0.995)	0.077	(0.782)	0.166	(0.684)	0.546	(0.460)
LB(12)	4.284	(0.978)	8.117	(0.776)	8.077	(0.779)	18.686	(0.096)
LB(1)-squared	2.118	(0.146)	2.078	(0.149)	0.859	(0.354)	1.720	(0.190)
LB(12)-squared	12.148	(0.434)	4.826	(0.964)	44.795	(0.000)	20.156	(0.064)
ARCH(1)	2.077	(0.150)	2.025	(0.155)	0.839	(0.360)	0.048	(0.826)
ARCH(12)	8.608	(0.736)	5.552	(0.937)	57.798	(0.000)	18.533	(0.100)
$\hat{\sigma}_{\varepsilon}^2$	0.019		0.015		0.008		0.005	
$\hat{\sigma}_S/\hat{\sigma}_L$	–		0.888*		–		0.791*	
$\bar{R}^2$	0.124		0.176*		0.310		0.467*	
SEE	0.139		0.128*		0.089		0.075*	
AIC	150.173		140.663*		43.858		−9.606*	
Panel B. Forecast performance								
ME	−0.0294		−0.0104		0.0088		0.0004	
MAE	0.0715		0.0567*		0.0560		0.0358*	
RMSE	0.0913		0.0786*		0.0673		0.0452*	
DM	–		−2.089*	(0.037)	–		−3.725*	(0.000)
D ($n=42$)	64.3%		78.6%*		47.6%		78.6%*	
$y_t>0$	100.0%*	($n=27$)	85.2%		52.0%	($n=25$)	88.0%*	
$y_t<0$	0.0%	($n=15$)	66.7%*		41.2%	($n=17$)	70.6%*	

Notes: JB is Jarque–Bera test of normality of residuals. LB is Ljung–Box statistic for residual autocorrelation. $\hat{\sigma}_{\varepsilon}^2$ denotes variance of the residuals. ARCH is Engle's (1982) test against conditional heteroscedasticity. $\hat{\sigma}_S/\hat{\sigma}_L$ is the ratio of SD of residuals from the ESTAR model to the SD of residuals from the linear model. SEE is SE of estimate. ME, MAE and RMSE are, respectively, mean error, mean absolute error and root mean squared error for one-step-ahead forecasts. DM is Diebold and Mariano's (1995) forecast comparison statistic based on absolute prediction error. The *p*-values of test statistics are reported in parenthesis. D is correct directional change index, and *n* is the number of forecasts considered. An * denotes the preferred model.

residuals, and delivers lower error of estimate and higher $\bar{R}^2$ for both nonlinear models when compared to linear models. The AIC also favours the nonlinear models.

In order to compare the estimated linear and nonlinear models further, we perform out-of-sample forecasting exercises. We compute total 42 one-step-ahead forecasts for both competing models. The models were re-estimated, but not re-specified, over every 6 months.[7] The forecast errors are reported in Panel B of the table 4. The out-of-sample forecasting performances of the models were evaluated according to root mean squared error (RMSE) and the test of equal forecast accuracy due to Mariano and Diebold (1995) based on mean-absolute error. The first prominent result of the forecasting exercises is that both the linear and nonlinear models underpredict stock returns on average for ISE whereas overpredict ASE returns. However, mean prediction errors for the nonlinear models are lower when compared to linear alternatives. The nonlinear models deliver lower absolute and mean squared errors, suggesting that taking into account of possible nonlinearities in the data does indeed improve forecast performance. The Mariano and Diebold's test of forecast accuracy indicate that the gain in forecast accuracy is statistically significant at 5% level for the ISE returns and at 1% level for ASE returns. This suggests that there is nonlinearity in terms of the predictive performance, as well.

In addition to forecast errors and forecast accuracy tests, following Öcal and Osborn (2000) and Sarantis (2001), we also compare implied directional change for both linear and nonlinear models. The implied directional change was measured by the correct directional change index computed as $D = 100/n\sum D_t$ where $D_t = 1$ if $y_t^a \cdot y_t^f > 0$ else $D_t = 0$. y_t^a is the actual value of returns and y_t^f is the

[7] The forecasts for the ESTAR model were obtained by bootstrapping with 10 000 replications. Forecasting with nonlinear models is discussed in Granger and Teräsvirta (1993, Section 8.1) and van Dijk (1999, Section 2.5), among others.

forecasted value. The correct directional change index (D) tests whether the direction of change implied by the model is the same as the actual change. As pointed out by Sarantis (2001), although RMSE and mean absolute error (MAE) criteria provide information on the size of forecast errors, they are not reliable in terms of signalling profit opportunities, which is of primary interest to investors. The most important result is that the nonlinear models perform very well in predicting the direction of the change. As regards the Turkish stock market, the ESTAR model forecasted correctly the direction of the change over 78% of the time, whereas the linear model correctly forecasted only 64% of the time. Secondly, although the linear model correctly predicted all increases in stock prices, it predicted none of the declines. On the other hand, the ESTAR model correctly predicted 2/3 of declines and 85% of the increases. The linear model for the Greek stock market forecasted correctly the direction of the change over 47% of the time, while the MR-STAR model correctly forecasted over 78% of the time. The MR-STAR model correctly predicted 88% of increases and 71% of decreases in the market. The linear model, however, correctly predicted 52% of increases and 41% of decreases. These results suggest that STAR-family models for the financial time series not only increase forecast accuracy over linear models, but also successfully signals profit opportunities for investors as well.

IV. Conclusion

In this article, we have examined potential nonlinearity in monthly stock returns for Europe's two largest emerging markets, namely for the ASE and ISE. Starting with a specification of linear models for both stock markets we proceeded to test nonlinearities in the conditional mean and conditional variance. The linear model for the Turkish stock market exhibits nonlinearities in the conditional mean whereas no nonlinearity is found for the conditional variance. The linear model for the Greek stock market, however, displays nonlinearities both in the mean and variance. However, once the nonlinearity in the mean is taken into account, no nonlinearity is found for the variance. This result once more suggests that the conditional mean should be appropriately modelled in order to avoid misspecification of the conditional variance, as pointed out by Lundbergh and Teräsvirta (1998). The model specification tests select exponential transition functions for both stock markets, which is consistent with models incorporating transaction costs and market frictions as well as with 'behavioural finance' literature. The Greek stock market exhibits multiple nonlinearity in the mean, suggesting that the dynamics of the market differ according to both the size and the sign of deviation from the equilibrium. The estimated slope coefficients imply that the transition between the regimes is moderate contrary to TAR and Markov regime switching models which assume an abrupt change in regimes. The fitted STAR models suggest that both markets are characterized by cyclical yet globally stable dynamics. Model specification tests also favour STAR models over the linear models. In addition, as the results of the out-of-sample forecasting suggest, taking account of nonlinearity in data-generating process may improve forecast performance upon the linear models. The nonlinear models provide good out-of-sample forecasts, which disagree with efficient market hypothesis. The gains in forecast accuracy attained by allowing for nonlinearity in these markets are more than those found for mature markets (Sarantis, 2001; McMillan, 2005), which is consistent with findings of McMillan (2005) who state that 'this may arise due to greater limits to arbitrage in these markets as fundamental traders knowledge about the economy and its effects on equity and other financial asset markets is still evolving'. All in all, our results provide strong evidence of nonlinearity in stock returns for developing economies as well, and suggest that potential nonlinearity in conditional mean of financial variables in emerging markets should be taken into account by investors and researchers.

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