Regime-switching behaviour in European stock markets

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ABSTRACT

This paper examines the empirical relationship between five European stock market indices and the US market in a smooth transition regression (STR) framework. Due to globalization of economies the motivation is that the New York market has exerted substantial influence on international markets in post-October 1987 period. The results show that the US market plays indeed an important role and determines stock market asymmetric behaviour in Europe, though non-linearity is not particularly strong.

Keywords: smooth transition regression models, linearity tests, stock returns.

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1. Introduction

Recently, equity markets in various European countries have been more influenced by the US market. The US influence is well documented. The global stock market totals approximately Dollars 3,000bn. Slightly less than half of that total comes from US companies, and US GDP accounts for around 30 per cent of the world total. Of course country-specific factors such as GDP play a role, but domestic GDP is linked to the US since national markets and economies have become more internationalised. This study examines empirically the relationship between stock prices in five European markets (Germany, France, Italy, Sweden and Switzerland) and the US market. The technique employed is the smooth transition regression (STR) models, which investigate non-linearities[1] in the underlying series. To exploit the above relationship, the univariate STAR specification is extended to allow for US stock prices as additional regressors.

The motivation for using STR models is the following. In recent empirical studies investigating economic time series asymmetries, three classes of regime-switching models, namely STAR SETAR and Markov-switching models, have been very prominent. The Markov-switching models assume that changes in regime are governed by the outcome of an unobserved Markov chain. A different approach is to allow the regime switch to be determined by an observable variable, as in SETAR and STAR models. The main advantage in favour of STAR models is that changes in economic aggregates are influenced by changes in the behaviour of many different agents and it is highly unlikely that all agents react simultaneously to a given economic signal. Further, investors may be prone to different degrees of institutional inertia (dependent, for example, on the efficiency of the stock markets in which they operate) and so adjust with different time lags. Markov-switching and SETAR models imply a sharp regime switch, and therefore a small number (usually two) of regimes. This assumption is too restrictive compared to the STAR models. Thus, when considering aggregate economic series, the time path of any structural change is liable to be better captured by a model whose dynamics undergo gradual, rather than instantaneous adjustment between regimes. The STAR models allow for exactly this

[1] There are many empirical studies (see, for example, Scheinkman and LeBaron, 1989; Hsieh, 1991; Abhyankar, Copeland and Wong, 1997; Ryden, Teräsvirta and Asbrink, 1998; Brooks, 1998), which have uncovered non-linearities in stock prices.

kind of gradual change whilst being flexible enough that the conventional change arises as a special case.

So far, STAR models have been mainly applied to macroeconomic time series (Teräsvirta and Anderson, 1992; Granger and Teräsvirta, 1993; Öcal and Osborn, 2000; Skalin and Teräsvirta, 1999) or exchange rates (Michael, Nobay and Peel, 1997; Taylor and Peel, 1999; Sarantis, 1999). However, there are only few applications in the stock prices literature. For example, Sarantis (2001) uses univariate STAR models to explore non-linearities in stock returns of the G-7 industrial countries (USA, Japan, Germany, UK, France, Italy and Canada). McMillan (2001) applies multivariate STR models to the US stock market and examines the non-linear relationship between stock returns and business cycle variables.

Our work continues the theme on potential asymmetric behaviour in stock markets but takes a slightly different line by examining the influence the US stock market has on five European markets. The novel finding here is that the US market exerts a significant impact on European markets and appears to play an important role in determining stock market regimes in Europe. This reflects the strong interdependence between European and US markets.

2. Definition of smooth transition regression models

The STR model is defined as,

$$y_t=\alpha_0+\sum_{i=1}^{3}\phi_{0i}y_{t-i}+\sum_{i=1}^{3}\delta_{0i}z_{t-i}+(\alpha_1+\sum_{i=1}^{3}\phi_{1i}y_{t-i}+\sum_{i=1}^{3}\delta_{1i}z_{t-i})F(s_t;\gamma,c)+u_t \qquad (1)$$

where $\{u_t\}\sim iid(0,\sigma^2)$, y_t represents log-returns on the domestic market whereas z_t log-returns on the US market, and $F(s_t;\gamma,c)$ is the transition function bounded by zero and unity and s_t is the transition variable (determined in practice). The parameter c is the threshold and gives the location of the transition function, while γ defines the slope of the transition function. In (1), $(y_{t-1},y_{t-2},y_{t-3},z_{t-1},z_{t-2},z_{t-3})$ is the vector of explanatory variables consisting of 3 lags on y_t and z_t. In the STAR model as discussed in Teräsvirta (1994), the transition variable is assumed to be a lagged dependent variable. In the present work, however, the transition variable can be either a past value of the dependent variable (domestic market) or of an "exogenous" variable (US market). One form of transition function used in the literature is, the logistic function

$$F(s_t;\gamma,c) = \left(1+\exp(-\gamma(s_t - c))\right)^{-1}, \qquad \gamma > 0 \quad (2)$$

The logistic function is monotonically increasing in s_t, with $F(s_t;\gamma,c) \to 0$ as $(s_t - c) \to -\infty$ and $F(s_t;\gamma,c) \to 1$ as $(s_t - c) \to +\infty$. In this work, the idea that there are two distinct regimes (or a continuum of states between the two extremes) in financial markets is explored, namely bull markets and bear markets. The slope parameter indicates how rapid the transition from 0 to 1 is as a function of s_t and c determines where the transition occurs. When $\gamma \to \infty$, $F(s_t;\gamma,c)$ becomes a step function and the transition between the regimes is abrupt. In that case, the model approaches a TAR model (Tong, 1990).

3. Modelling procedure

The modelling procedure for building STR models is based on the procedure proposed by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Eitrheim and Teräsvirta (1996), and consists of the following stages:

3.1 Specification of the linear model and linearity tests

Testing linearity against STR constitutes the first step of the modelling procedure. In order to test for linearity a linear model is first selected. The starting model includes 3 lags on both variables. We perform the linearity test in the spirit of Luukkonen, Saikkonen and Teräsvirta (1988). To select the switching variable, the test is carried out for all six regressors. In cases where linearity is rejected for more than one regressor, the decision rule is to choose the transition variable for which the p-value of the test is smallest, that is, strongest rejection of linearity (Teräsvirta, 1994).

3.2 Initial estimates and non-linear estimation

To find initial values, a two-dimensional grid search is carried out using at least 150 values of γ and 40 equally spaced values of c within the observed range of the transition variable. Essentially, the transition variable series is ordered by value, extremes are ignored by omitting the most extreme 15 values at each end and 40 values are specified over the range of the remaining values. This procedure attempts to guarantee that the values of the transition function contain enough sample variation for each choice of γ and c. The model with the minimum RSS value from the grid search procedure is used to provide the γ and c for an initial estimate of the transition function. Following Teräsvirta (1994) the exponent of the transition function is standardised by the sample standard deviation. This standardisation makes γ scale-free and helps in determining a useful set of grid values for this parameter.

Reducing the order of the model in the non-linear least squares (NLS) framework is obviously a computationally heavy procedure. However, there is another practical strategy one can follow. Note that giving fixed values to the parameters of the transition function makes the STR model linear in the remaining coefficients. The grid search mentioned above is used to obtain sensible initial values. Conditional on this transition function, the parameters of the STR model can be estimated by OLS and this model is called the linearised version of the STR model. To determine the order of the linear STR a general-to-specific procedure is applied where the least significant (if non-significant) variable at any lag is dropped at each stage and the reduced model is re-estimated. The selected model is based on the minimization AIC criterion. The estimated coefficients from the linear STR along with the transition function parameters from the grid search are used as initial values in the non-linear estimation in the next stage. The preferred model is re-estimated (including the transition function parameters) by NLS in RATS using the BHHH algorithm. After estimating the parameters of the STR, these are compared with those obtained from the linearised version since the latter is used for model specification.

3.3 Evaluation of ST(A)R models

The validity of the assumptions underlying the estimation must be investigated once the parameters of the STR models have been estimated. The Lagrange multiplier (LM) tests of Eitrheim and Teräsvirta (1996) are employed. As usual, the assumption of no error autocorrelation should be tested. Further, it is useful to find out whether or not there are non-linearities left in the process after fitting a STR model. That possibility is investigated by testing the hypothesis of no additive non-linearity against the alternative hypothesis that there is an additional STR component. Finally, the constancy of the parameters is tested against the hypothesis that the parameters change monotonically, non-monotonically but symmetrically and non-monotonically non-symmetrically over time. All the tests are carried out by auxiliary regressions. For details see Eitrheim and Teräsvirta (1996). Model evaluation also includes checking whether the estimates seem reasonable, and of course, checking the residuals for ARCH and normality.

4. Empirical results

The data used are monthly seasonally unadjusted. The stock price indices are as follows: Germany: DAX 100 (1988:m1-2001:m8); France: France DS market (1988:m1-2001:m8); Sweden: Sweden DS market (1988:m1-2001:m8); USA: S&P 500 (1988:m1-2001:m8); Switzerland: Swiss market (1988:m7-2001:m8); Italy: Milan MIBTEL (1993:m7-2001:m8). Unfortunately, Switzerland and especially Italy do not have long time series on their stock price indices. Note that the sample period is chosen to start after the stock market crash in autumn 1987 and to end just before the events of September the 11th in 2001. Estimation is carried out in GAUSS software.

The starting point is a fully parameterized linear model allowing for a maximum order of 3 lags on both variables[2]. Table 1 reports the estimated equations. The most striking result is that, with the exception of Switzerland, the only significant variable is dlnSP_1(positive effect), while the endogenous dynamics seem to be insignificant. This finding confirms the common belief that the US stock market is the driving force in international markets. As to the diagnostics, the models appear to pass the misspecification tests[3].

The next stage is to test linearity against STR-type non-linearity. The linearity tests are displayed in Table 2. Note that the null hypothesis of linearity is rejected at 10% level, but not very strong[4]. Further, in Germany, France and Italy linearity is rejected in one out of six cases, in Switzerland there are two rejections, while in Sweden three. Admittedly, the statistical evidence of non-linearity is not quite strong[5].

[2] We extended the lag length up to 6 in both variables, but found that lags 4-6 appear insignificant.
[3] Since it is a well established empirical phenomenon that the distribution of stock returns is highly leptokurtic, it comes as no surprise that the residuals from the German, French and Swiss markets are non-normal.
[4] In the Swedish case though, the rejection associated with dlnSP_3 is very strong.
[5] This is finding is perhaps not unexpected since it is found that the variability of economic time series has declined during the last decade compared to 1970s and early 1980s (van Dijk and Sensier, 2001). This perhaps also explains the absence of ARCH in the linear models.

Based on the decision rule of the procedure of Teräsvirta (1994), the linearity tests suggest that dlnSP_1 is the most appropriate of all potential transition variables considered in the cases of Germany, France, Switzerland and Italy, while dlnSP_3 is chosen for the Swedish market. Therefore, the US stock market appears to play an important role in determining European market regimes. This evidence is in line with Aslanidis (2002) who finds dlnSP_1 as switching variable in the London market using again STR models.

Next, the estimated STR models selected by the AIC are presented in Table 3. It turns out[6]that the estimated parameters are close to those obtained from the grid search and the linear estimation of STR. Note that all thresholds get extreme negative values implying that the non-linearity applies for only few negative observations. This is best seen from the graph of the transition functions (Figure). Most of the time, there exists some linear structure in the processes and only sufficiently large negative shocks in the US market cause a non-linear response in the domestic markets. In the second panel of the graphs where the transition functions are plotted over time, it is seen that the functions are normally one (or close to one); they move away from unity mainly for a few periods in early and late 1990s and early 2000s[7]. Note also that each lag regressor in the first part of the model has a corresponding lag regressor of the same (approximately) magnitude but opposite sign in the second part implying a behaviour close to random walk in the range where $F = 1$. In this range only dlnSP is informative, mostly after a month. Further, there are no endogenous effects in the French and Swiss stock markets in any range. More specifically, at the extremes the models imply,

Germany

$y_t = 0.010 + 0.728 y_{t-1} + 1.396 y_{t-3} + 0.092 z_{t-1} - 2.309 z_{t-2} + u_t$, when $F = 0$

$y_t = 0.010 + 0.092 z_{t-1} + u_t$, when $F = 1$

France

$y_t = 0.209 + 2.553 z_{t-1} - 1.319 z_{t-2} + u_t$, when $F = 0$

$y_t = 0.404 z_{t-1} + u_t$, when $F = 1$

Sweden

$y_t = 0.009 - 0.821 y_{t-2} + 0.670 z_{t-1} + 1.223 z_{t-3} + u_t$, when $F = 0$

$y_t = 0.009 + 0.670 z_{t-1} + u_t$, when $F = 1$

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[6] These results are not reported, but are available from the author upon request.

[7] These were turbulent periods due to the US recession in 1990-1991, Asia financial crisis in 1997 and the 1998 Russian financial crisis.

Switzerland

$y_t = 0.175 + 2.405 z_{t-1} + u_t$, when $F = 0$

$y_t = -0.008 + 0.609 z_{t-1} + u_t$, when $F = 1$

Italy

$y_t = 0.272 + 0.956 y_{t-2} + 3.893 z_{t-1} - 1.012 z_{t-2} + 0.207 z_{t-3} + u_t$, when $F = 0$

$y_t = 0.361 z_{t-1} + 0.207 z_{t-3} + u_t$, when $F = 1$

Thus, most of the time the processes support the weak form market efficiency and only very large negative shocks in the US market imply evidence against efficient markets in the weak and semi-strong forms. This pattern of results can be probably explained by the existence of a lower barrier, which causes non-linearity but then the underlying processes are mean reverting back to their (almost) random walk behaviour. Chappell et al. (1996) also find quite a similar behaviour for the French franc/Deutshmark exchange rate using univariate SETAR models. Their results imply an AR process in the range where the exchange rate rises (depreciation of the franc) more than 1.55% above its central parity, while a random walk model otherwise[8].

The estimates of γ suggest an abrupt switch between the extremes in the Swedish and Italian markets. On the other hand, the relatively small value of γ in the German, French and Swiss markets suggest a smooth transition from one extreme to the other, contrary to the Markov-switching and the TAR models which assume a sharp switch. Almost all equations contain restrictions of the form $\phi_{0i} = -\phi_{1i}$, $\delta_{0i} = -\delta_{1i}$ which are strongly suggested by the data. The models are able to explain between 14.59% (Germany) and 26.65% (Italy) of the variation in the underlying series. According to the diagnostics the STR models form statistically adequate representations of the data since there is no sign of model inadequacy. In particular, there is no evidence of autocorrelation. The additive non-linearity test results imply that the models capture all non-linearities. Further, the models pass the parameter constancy tests. Tests of no dynamic heteroskedasticity do not indicate any problem either.

[8] It should be pointed out, however, that SETAR non-linearity in this study is found to be quite strong since the threshold applies for a large range of values.

5. Conclusions

This study adopts the smooth transition regression models to examine the empirical relationship between five European stock market indices and the US market. Due to globalization of financial markets and economies our motivation is that the New York market has exerted substantial influence on International markets in the post-October 1987 period.

The first important result is that the US market can be used to forecast all five European markets. Particularly, in the linear models it appears as the most significant variable while national markets provide almost no information. We further find that the US market initiates non-linearities and asymmetries in the national markets as it acts as switching variable for no-linear processes. The other worthy result is that non-linearity is found to be mild, which is supported by both linearity tests and STR models estimated afterwards. Most of the time, there exists some linear structure in the processes and only large negative shocks in the US market cause a non-linear response in European markets. In addition, in the latter range there is evidence against efficient markets in the weak and semi-strong forms.

An extension that could build on the results of this study is the following. The STR models considered in this work are single-equation models. In principle, the idea of smooth transition can be extended to systems of equations. To date, there is yet rather little empirical experience available of vector STR models (see van Dijk, Teräsvirta and Franses (2000) and references within). In the vector STR framework, it would be interesting to examine relationships between European and US markets, but also among Latin American and US markets. We believe that developing vector STR specifications is a very important area of further research.

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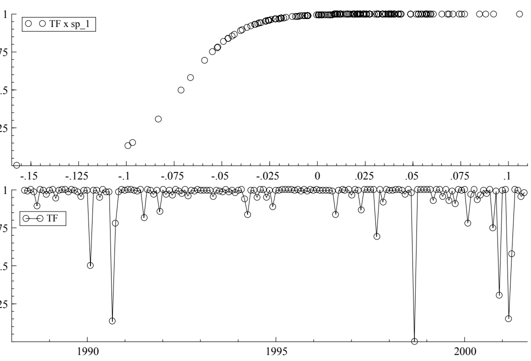
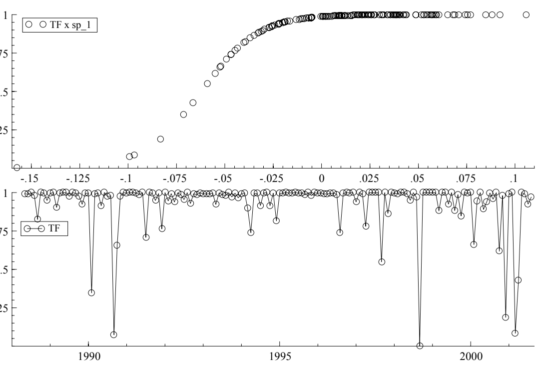
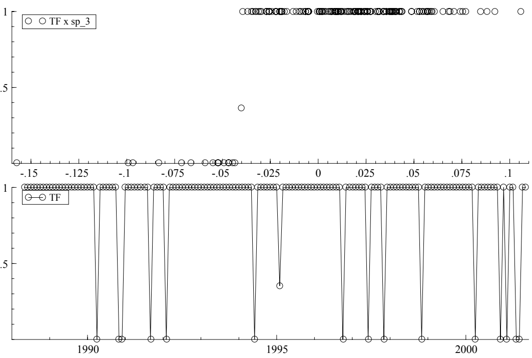


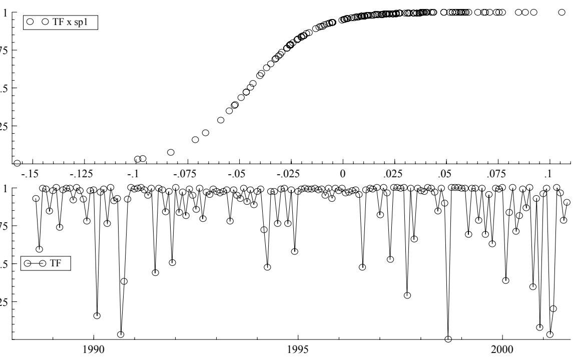
Germany



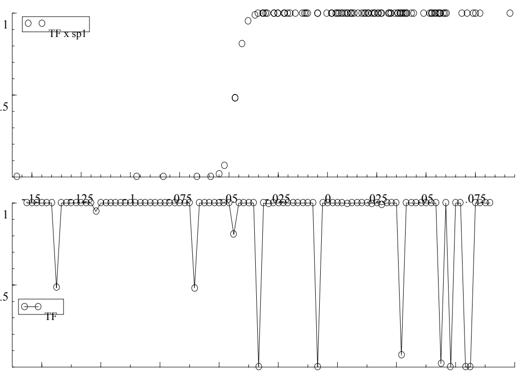
France



Sweden



Switzerland



Italy

Figure: Transition functions versus transition variables (upper panel) and over time (lower panel).

Table 1: Linear models

Coefficients	Germany	France	Sweden	Switzerland	Italy
α_0	0.004 [0.994]	0.006 [1.396]	0.002 [0.266]	0.005 [1.227]	0.001 [0.165]
ϕ_1	-0.008 [-0.094]	-0.006 [-0.064]	0.060 [0.682]	-0.110 [-1.213]	-0.089 [-0.820]
ϕ_2	-0.126 [-1.415]	-0.105 [-1.175]	-0.050 [-0.568]	-0.212 [-2.359]	-0.115 [-1.066]
ϕ_3	0.058 [0.672]	0.097 [1.176]	0.106 [1.299]	-0.029 [-0.340]	0.066 [0.628]
δ_1	0.289 [2.530]	0.356 [3.247]	0.581 [3.958]	0.447 [4.101]	0.463 [2.669]
δ_2	0.098 [0.833]	0.077 [0.660]	0.108 [0.689]	0.175 [1.487]	0.219 [1.216]
δ_3	0.107 [0.933]	-0.032 [-0.286]	0.113 [0.745]	0.156 [1.367]	0.302 [1.704]
(AIC) (SBC)	(-5.897) (-5.762)	(-5.995) (-5.860)	(-5.372) (-5.237)	(-5.994) (-5.858)	(-5.325) (-5.137)
R-sq	0.0627	0.0919	0.1355	0.1305	0.1097
Diagnostics					
Skewness	-0.714	-0.612	-0.261	-0.537	0.183
Ex kurtosis	2.141	2.760	0.068	2.266	-0.084
Normality	0.000	0.000	0.398	0.000	0.755
Autocorr(1)	0.837	0.983	0.994	0.849	0.802
Autocorr(3)	0.987	0.984	0.999	0.996	0.989
Autocorr(6)	0.708	0.954	0.999	0.049	0.859
ML(1)	0.332	0.754	0.220	0.737	0.094
ML(3)	0.667	0.893	0.119	0.981	0.007
ML(6)	0.429	0.825	0.432	0.589	0.062
ARCH(1)	0.338	0.757	0.227	0.741	0.101
ARCH(3)	0.680	0.904	0.158	0.981	0.033
ARCH(6)	0.469	0.867	0.488	0.663	0.198

Notes: t-ratios in parentheses below coefficient estimates; diagnostic tests are presented as p-values; AIC and SBC are the Akaike and Schwarz Information Criteria values based on RSS; R-sq is the usual coefficient of determination; skewness and ex. kurtosis are measured by conventional test statistics; normality refers to the test of Jarque and Bera (1980); autocorr(.) is the LM test of residual autocorrelation of Godfrey (1978); ARCH(.) is the LM test of Engle (1982); ML(.) is the test of McLeod and Li (1983).

Table 2: Linearity tests: Linear model versus STR model

Transition Variable	Germany	France	Sweden	Switzerland	Italy
y_1	0.166	0.200	0.134	0.069	0.518
y_2	0.241	0.149	0.945	0.608	0.427
y_3	0.481	0.749	0.068	0.465	0.203
z_1	**0.075**	**0.072**	0.078	**0.033**	**0.026**
z_2	0.327	0.170	0.764	0.371	0.266
z_3	0.129	0.173	**0.005**	0.271	0.394

Notes: p-values of the F-variants of the LM-tests for STR type non-linearity using the preferred linear specification as a base model.

Table 3: Smooth transition regression (STR) models

Coefficients		Germany		France		Sweden		Switzerland		Italy	
α_0	α_1	0.010 [2.386]		0.209 [1.734]	-0.209 [-1.734]	0.009 [1.740]		0.175 [1.942]	-0.183 [-1.823]	0.272 [3.381]	-0.272 [-3.381]
ϕ_{01}	ϕ_{11}	0.728 [2.153]	-0.728 [-2.153]								
ϕ_{02}	ϕ_{12}					-0.821 [-3.779]	0.821 [3.779]			0.956 [1.772]	-0.956 [-1.772]
ϕ_{03}	ϕ_{13}	1.396 [1.450]	-1.396 [-1.450]								
δ_{01}	δ_{11}	0.092 [0.820]		2.553 [2.488]	-2.149 [-2.068]	0.670 [5.266]		2.405 [3.002]	-1.796 [-2.352]	3.893 [4.066]	-3.532 [-3.655]
δ_{02}	δ_{12}	-2.309 [-1.132]	2.309 [1.132]	-1.319 [-1.105]	1.319 [1.105]					-1.012 [-1.734]	1.012 [1.734]
δ_{03}	δ_{13}					1.223 [4.173]	-1.223 [-4.173]			0.207 [1.389]	
(s_t) (γ) (c)		(z_1) (2.694) (-0.071) [1.355] [-2.371]		(z_1) (2.736) (-0.062) [1.608] [-2.422]		(z_3) (95*) (-0.040) [-15.23]		(z_1) (2.613) (-0.045) [1.332] [-2.586]		(z_1) (19.67) (-0.047) [0.440] [-17.60]	
(AIC) (SBC) (R-sq)		(-5.990) (-5.856) (0.1459)		(-6.086) (-5.970) (0.1604)		(-5.478) (-5.363) (0.2132)		(-6.072) (-5.955) (0.1854)		(-5.498) (-5.283) (0.2665)	
Diagnostics											
(Skewness) (Ex kurtosis)		(-0.907) (3.141)		(-0.776) (2.986)		(-0.140) (-0.094)		(-0.386) (2.623)		(0.053) (0.228)	
Normality		(0.000)		(0.000)		(0.749)		(0.000)		(0.882)	
Autocorr(1) (3) (6)		(0.341) (0.684) (0.532)		(0.801) (0.965) (0.834)		(0.737) (0.402) (0.726)		(0.220) (0.527) (0.058)		(0.250) (0.282) (0.563)	
Non-linearity											
(y_1) (y_2) (y_3)		(0.689) (0.698) (0.735)		(0.966) (0.390) (0.716)		(0.361) (0.897) (0.266)		(0.466) (0.486) (0.259)		(0.824) (0.402) (0.525)	
(z_1) (z_2) (z_3)		(0.750) (0.744) (0.041)		(0.769) (0.555) (0.096)		(0.158) (0.871) (0.148)		(0.437) (0.566) (0.148)		(0.759) (0.594) (0.387)	
Constancy											
All		(0.836) (0.914) (0.511)		(0.846) (0.626) (0.208)		(0.850) (0.931) (0.873)		(0.850) (0.437) (0.632)		(0.707) (0.557) (0.667)	
Intercept		(0.942) (0.996) (0.076)		(0.989) (0.885) (0.013)		(0.492) (0.775) (0.434)		(0.962) (0.122) (0.158)		(0.495) (0.430) (0.207)	
Both intercepts				(0.999) (0.969) (0.078)				(0.954) (0.370) (0.488)		(0.384) (0.317) (0.288)	
ML(1) (3) (6)		(0.876) (0.885) (0.509)		(0.307) (0.727) (0.575)		(0.172) (0.016) (0.051)		(0.509) (0.676) (0.023)		(0.283) (0.640) (0.820)	
ARCH(1) (3) (6)		(0.878) (0.887) (0.554)		(0.315) (0.736) (0.706)		(0.177) (0.015) (0.036)		(0.516) (0.698) (0.071)		(0.295) (0.638) (0.886)	

Notes: The models are estimated in RATS by BHHH algorithm; t-ratios in parentheses below coefficient estimates; * the model has been estimated using a fixed value of $\hat{\gamma}$ =95 because the algorithm does not converge otherwise, estimation tends to be problematic when $\hat{\gamma}$ is large (see Teräsvirta, 1994); diagnostic tests are the LM tests of Eitrheim and Teräsvirta (1996) and presented as p-values; non-linearity (not ignoring "holes") are the p-values for no remaining STR-type non-linearity assuming each regressor as potential switching variable in the second STR component; autocorr(.) is the LM test of residual autocorrelation; the parameter constancy tests against monotonic change(1st figure), non-monotonic symmetrical change(2nd figure) and non-monotonic non-symmetrical change(3rd figure); see Eitrheim and Teräsvirta (1996) for full details; see notes of Table 1 for information about the other statistics reported in table.