On Misspecification of Exponential Transition Models with GARCH Error Terms: The Monte Carlo Evidence

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Introduction

STAR models have been applied in econometric time series, finance and economics. The model represents quite well the two faces of market structure: bull and bear, or expansion and contraction. Therefore, it is widely known as a regime switching model. Estimation and applications of this model are seen in Luukkonen, Saikkonen and Tersvirta (1988), Granger and Tersvirta (1993), Tersvirta (1998). Recently, researchers have studied the distributional forms of STAR models based on behaviour of linear and nonlinear parameters in the model in large samples, with emphasis in models specification test (Tersvirta, 1994). Effect of outliers on specification of STAR model is considered in Escribano et al., 1998), they conclude that outliers have negative effect on the specification of the models and this leads to reduced power of the nonlinearity tests. Sensitivity of residuals of STAR model to heteroscedasticity has been studied in a Monte Carlo's experiment in Chan and McAleer, (2002); Chan and Theoharakis, (2009). So, due to the difficulty in establishing the distributional form of STAR models, the estimation of parameters in the model then poses many problems particularly when the residuals are serially correlated or not normally distributed. As part of the diagnostic checks in time series modelling, issue of serial correlation is as important as heteroscedasticity and outliers effect. All these are imbedded in financial time series. The issue serial in residuals has not been investigated in nonlinear time series. This paper then considers the effect of first order serial correlation of residuals on nonlinear time series model using the Monte Carlo's simulation method and specification procedure in Escribano and Jordá (2001).

The Smooth Transition Autoregressive (STAR) Model

A smooth transition autoregressive model of order p (STAR(p)) is given as,

$$y_t = \phi_{10} + \phi_{11} y_{t-1} + ... + \phi_{1p} y_{t-p} + (\phi_{20} + \phi_{21} y_{t-1} + ... + \phi_{2p} y_{t-p}) F(y_{t-d}; \gamma, c) + \varepsilon_t \tag{1}$$

where y_t and y_{t-d} are scalars. The time series, y_t and error term, ε_t are distributed as $y_t \sim N(\mu, \sigma^2)$ and $\varepsilon_t \sim N(0, \sigma^2)$ respectively. The error term is assumed to be serially correlated. Nonlinearity is explained by the transition function $F(y_{t-d}; \gamma, c)$ which is of two forms: the symmetric and asymmetric functions. The symmetric transition function is the exponential smooth transition autoregressive function (ESTAR) given as

$$F(y_{t-d}; \gamma, c) = 1 - \exp\left[-\gamma (y_{t-d} - c)^2\right], \gamma > 0 \tag{2}$$

and the asymmetric transition function is the logistic smooth transition autoregressive function (LSTAR) given as,

$$F(y_{t-d}; \gamma, c) = \{1 + \exp[-\gamma (y_{t-d} - c)]\}^{-1}, \gamma > 0. \tag{3}$$

The introduction of transition functions (2) and (3) in model (1) leads to ESTAR and LSTAR models respectively. In the STAR(p) model, the transition function controls nonlinearity by the transition parameters, γ and c. The parameter γ controls the degree of nonlinearity whereas the parameter c is the constant or intercept. There are occasions where $F(y_{t-d}; \gamma, c) = 0$ or $F(y_{t-d}; \gamma, c) = 1$, in that case, there is transition between two linear AR models. These are two extreme points in STAR model in which it is said to be a two-regime STAR model. Whenever $0 < F(y_{t-d}; \gamma, c) < 1$, there is nonlinearity in the relationship existing in the system and it can be said that there is smooth transitioning between the two regimes. Also, transition function uses transition variable, which is lag of the nonlinear time series and this is denoted by y_{t-d}. The specification y_{t-d} is mostly used with d as the delay parameter which satisfies$1 \leq d \leq p$. For the general specification s_t for the transition variable, we have the resulting model as smooth transition regression model.

The entire STAR(p) model then generalizes an autoregressive model which gives nonlinear realizations. In that case, at $\gamma = 0$, nonlinearity is reduced to zero and the model becomes a linear AR(p) model.

To determine nonlinearity and specify between two competing STAR(p) models, standard nonlinearity and model specification tests have been developed following Lagranges multiplier (LM) test of Luukkonen, Saikkonen and Tersvirta (1988) here after known as LST. The first considers an approximation of LSTAR function by third order Taylor's series expansion. This approximation is then substituted in the general STAR(p) model and this results to,

$$y_t = \phi_{10} + \phi_{11} y_{t-1} + ... + \phi_{1p} y_{t-p} + (\phi_{20} + \phi_{21} y_{t-1} + ... + \phi_{2p} y_{t-p}) \times \left[\frac{1}{4}\gamma\left(y_{t-d} - c\right) + \frac{1}{48}\gamma^3\left(y_{t-d} - c\right)^3\right] + \varepsilon_t \qquad (4)$$

Further simplification of approximation in (4) leads to the auxiliary regression model,

$$y_t = \beta_0 y_{t-1} + \beta_1 y_{t-1} y_{t-d} + \beta_2 y_{t-1} y_{t-d}^2 + \beta_3 y_{t-1} y_{t-d}^3 + \varepsilon_t. \qquad (5)$$

The $\beta_i\,(i = 1, 2, 3)$ are specifically the nonlinear parameters in the auxiliary regression model. In that case, the null hypothesis $H_0 : \hat{\gamma} = 0$ then corresponds to testing $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$. Under this null hypothesis, the test has asymptotically a χ^2 degree of freedom$3\,(p + 1)$. The χ^2 test may be oversized; therefore the F version is always preferred. This test is put forward as Tersvirta Procedure (TP) in selecting between LSTAR and ESTAR. This procedure is designed based on the fact that even powers of $(y_{t-d} - c)$ are missing in the approximation in (4) above, therefore, the parameter $\beta_2 = 0$ for an LSTAR model. The TP is then put forward as nested hypotheses:

$$H_{03} : \beta_3 = 0$$
$$H_{02} : \beta_2 = 0|\beta_3 = 0$$
$$H_{01} : \beta_1 = 0|\beta_2 = \beta_3 = 0 \qquad (6)$$

The original decision based on the nested hypothesis above is misleading and can lead to false specifications, therefore a way out is suggested based on the parameter β_2 above. In a situation whereby the probabilities of F-tests for H_{01}, H_{02} and H_{03} are all significant, ESTAR model is then selected when the probability of F-test for H_{02} is the smallest of H_{01} and H_{03}. Otherwise, LSTAR model is selected.

Escribano and Jordá, (2001) noticed that the nested hypothesis put forward as TP may mislead in situation where $\beta_2 \neq 0$, therefore they put forward another test which depends on the second order Taylor's series expansion of the ESTAR function:

$$y_t = \phi_{10} + \phi_{11} y_{t-1} + ... + \phi_{1p} y_{t-p} + (\phi_{20} + \phi_{21} y_{t-1} + ... + \phi_{2p} y_{t-p}) \times \left[\left(\gamma + \gamma^2\right)\left(y_{t-d} - c\right)^2 - \frac{1}{2}\gamma^2\left(y_{t-d} - c\right)^4\right] + \varepsilon_t. \qquad (7)$$

Further simplification leads to the auxiliary regression model,

$$y_t = \beta_0 y_{t-1} + \beta_1 y_{t-1} y_{t-d} + \beta_2 y_{t-1} y_{t-d}^2 + \beta_3 y_{t-1} y_{t-d}^3 + \beta_4 y_{t-1} y_{t-d}^4 + \varepsilon_t. \qquad (8)$$

So, null hypothesis of linearity is tested based on $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ and the test is asymptotically distributed as χ^2 with degree of freedom$4\,(p + 1)$. From the expansion, first and third orders of $(y_{t-d} - c)$ are missing. Escribano and Jordá (2001) test assign even orders for ESTAR model and odd orders for LSTAR model. We then test for the rejection of the hypotheses:

$$H_{0E} : \beta_2 = \beta_4 = 0$$

$$H_{0L} : \beta_1 = \beta_3 = 0 \quad (9)$$

Once H_{0E} is rejected and H_{0L} is accepted, ESTAR model is chosen. Also, once H_{0L} is rejected and H_{0E} is accepted, LSTAR is chosen. In a situation where both H_{0E} and H_{0L} are significant (or not significant) at the same level of significance, choice of model is then based on the smaller probability of rejection. This is a straight forward test and it is named after the authors as EJP. The EJP test will be used in this paper to select between the competing STAR models.

For the nonlinearity test based on the null hypotheses $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ of TP and EJP, F-tests are performed. Power of nonlinearity test is then given as the probability of detecting correctly nonlinearity of the series. So, this power is expected to increase as speed of nonlinearity, γ increases.

Serial Correlation of Residuals and Series Variance

Most of the classical assumptions in linear regression model are followed in time series. One of such assumption is that of serial correlation or autocorrelation, a phenomenon where the series or residuals are correlated. Serial correlation exists whenever there is mis-specification of models. Problem of serial correlation on some estimators of linear time series model is considered in Olaomi (2004) who indicated that ordinary least squares (OLS) estimator performs best among other estimators when a mild level of autocorrelation is allowed.

We consider a specification of STAR(p) model as,

$$y_t = \phi_{10} + \phi_{11} y_{t-1} + ... + \phi_{1p} y_{t-p} + (\phi_{20} + \phi_{21} y_{t-1} + ... + \phi_{2p} y_{t-p}) F(y_{t-d}; \gamma, c) + \varepsilon_t$$

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + ... + \rho_m \varepsilon_{t-m} + u_t \quad (10)$$

where $\rho_i, (i = 1, 2, ..., m)$ are the serial correlations in the residuals. The u_t are allowed to explain the slight random shocks in the model. $Corr(\varepsilon_t \varepsilon_{t-i}) \neq 0$ and m is the maximum lag. Then, the error term ε_t are not independently distributed across the observations. The two models in (10) are given jointly as simultaneous equations. These models still retain their individual definitions of parameters given above. The issue at hand is to study the behaviour of this joint model using data simulation approach.

Data Generating Processes and Simulation Results

For the Monte Carlo's simulation considered in this paper, our selection of data generating process (DGP) has been based on some facts: First we consider simple nonlinear time series model which will indicate clearer specification frequencies of STAR models. Unlike the model used in Tersvirta (1994), the selection frequencies for LSTAR and ESTAR are somehow close to each other. Secondly, effect of serial correlation is stronger when the model is represented with fewer parameters. Therefore, we will consider STAR(1) model with first order serial correlation as our DGP.

$$y_t = 0.25 y_{t-1} + (0.4 - 0.6 y_{t-1}) F(y_{t-1}; \gamma, c) + \varepsilon_t, \varepsilon_t = \rho_1 \varepsilon_{t-1} + u_t \quad (11)$$

and $y_t \sim N(\mu, \sigma^2)$ and the residuals from the STAR model are set as standard normal deviates, that is $\varepsilon_t \sim N(0, 1)$. The transition function is set as,

$$F(y_{t-1}; \gamma, c) = 1 - \exp\left[-\gamma (y_{t-1} - 0.2)^2\right]. \quad (12)$$

In the DGP, some of the model parameters have been fixed in order to reduce computation of too many estimates. We will consider the effect of changes in variance of the estimated residuals, $\hat{\varepsilon}_t$, therefore $\sigma = \{0.02, 0.05, 0.1, 0.15, 0.25\}$. The slope parameters $\gamma = \{1, 10, 100\}$ for the correlation set $\rho_1 = \{0, 0.25, 0.5, 0.9\}$. This experiment is then repeated over 1000 replications and the first 100 observations are discarded due to initialization errors.

Table 1: Specification of ESTAR model and Power of EJP at $\gamma = 1$

N	ρ_1	$\sigma = 0.02$		$\sigma = 0.05$		$\sigma = 0.1$		$\sigma = 0.15$		$\sigma = 0.25$	
		ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power
50	0.00	-	-	-	-	0.486	0.037	0.465	0.043	0.364	0.055
	0.25	-	-	-	-	0.333	0.036	0.318	0.044	0.254	0.063
	0.50	-	-	-	-	0.364	0.044	0.388	0.049	0.31	0.071
	0.90	-	-	0.555	0.036	0.500	0.048	0.362	0.058	0.383	0.081
200	0.00	-	-	0.419	0.055	0.298	0.084	0.222	0.126	0.092	0.282
	0.25	-	-	0.318	0.044	0.267	0.075	0.209	0.134	0.111	0.270
	0.50	-	-	0.357	0.056	0.308	0.091	0.244	0.164	0.125	0.289
	0.90	-	-	0.492	0.061	0.330	0.109	0.179	0.196	0.091	0.340
500	0.00	-	-	0.338	0.074	0.201	0.172	0.078	0.358	0.024	0.698
	0.25	-	-	0.286	0.070	0.160	0.168	0.073	0.343	0.033	0.697
	0.50	-	-	0.380	0.071	0.183	0.186	0.071	0.392	0.023	0.744
	0.90	-	-	0.343	0.070	0.114	0.280	0.062	0.520	0.025	0.826
1000	0.00	-	-	0.248	0.113	0.080	0.347	0.019	0.673	0.001	0.961
	0.25	-	-	0.273	0.121	0.099	0.343	0.020	0.696	0.010	0.967
	0.50	-	-	0.312	0.125	0.102	0.410	0.012	0.745	0.010	0.982
	0.90	0.397	0.058	0.187	0.166	0.032	0.557	0.007	0.873	0.032	0.992
3000	0.00	-	-	0.172	0.279	0.008	0.875	0.000	0.998	0.000	1.000
	0.25	0.437	0.087	0.181	0.276	0.007	0.877	0.000	1.000	0.000	1.000
	0.50	0.429	0.07	0.141	0.312	0.002	0.920	0.000	0.999	0.000	1.000
	0.90	0.372	0.086	0.078	0.485	0.000	0.986	0.000	1.000	0.000	1.000

From Table 1, nonlinear smooth transition is allowed at smaller value, $\gamma = 1$, just to make difference between the results given for the linear case in Table 3.1. GAUSS program reported more matrix inversion errors at standard deviation, $\sigma = 0.02$ for different serial correlations allowed for the residuals. The strength of non-linearity as given by the power of the test improved as standard deviation increased from 0.02 to 0.25. This improvement is seen in the estimates of powers of the test. The power of the EJP test increases as standard deviation (variance) increases and this increase tends towards 1 as sample size increases. Therefore, EJP test is consistent with sample size and this result is according to Escribano and Jordá (2001).

It is alarming to see from the results that frequency of selection of LSTAR is more than that of ESTAR even though the DGP is ESTAR. This means that when nonlinear effect is relatively small, ESTAR model closely resembles LSTAR model and therefore ESTAR model is undetectable.

Table 2: Specification of ESTAR model and Power of EJP at $\gamma = 10$

N	ρ_1	$\sigma = 0.02$		$\sigma = 0.05$		$\sigma = 0.1$		$\sigma = 0.15$		$\sigma = 0.25$	
		ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power
50	0.00	-	-	-	-	0.389	0.471	0.386	0.510	0.342	0.333
	0.25	-	-	-	-	0.404	0.468	0.376	0.484	0.306	0.310
	0.50	-	-	-	-	0.404	0.468	0.366	0.476	0.309	0.275
	0.90	-	-	0.485	0.332	0.380	0.495	0.311	0.424	0.297	0.202
200	0.00	-	-	0.435	0.874	0.323	0.995	0.215	0.999	0.136	0.985
	0.25	-	-	0.437	0.883	0.321	0.999	0.224	1.000	0.133	0.983
	0.50	-	-	0.451	0.910	0.288	0.997	0.207	0.999	0.131	0.956
	0.90	-	-	0.432	0.962	0.246	0.998	0.171	0.994	0.132	0.855
500	0.00	-	-	0.396	1.000	0.193	1.000	0.086	1.000	0.021	1.000
	0.25	-	-	0.390	0.999	0.188	1.000	0.084	1.000	0.020	1.000
	0.50	-	-	0.363	0.999	0.182	1.000	0.070	1.000	0.024	1.000
	0.90	0.468	0.848	0.334	1.000	0.117	1.000	0.042	1.000	0.028	0.999
1000	0.00	-	-	0.344	1.000	0.111	1.000	0.026	1.000	0.003	1.000
	0.25	-	-	0.335	1.000	0.097	1.000	0.018	1.000	0.002	1.000
	0.50	0.494	0.961	0.321	1.000	0.075	1.000	0.011	1.000	0.002	1.000
	0.90	0.487	0.999	0.247	1.000	0.039	1.000	0.006	1.000	0.002	1.000
3000	0.00	0.488	1.000	0.251	1.000	0.011	1.000	0.000	1.000	0.000	1.000
	0.25	0.449	1.000	0.233	1.000	0.004	1.000	0.000	1.000	0.000	1.000
	0.50	0.419	1.000	0.175	1.000	0.002	1.000	0.000	1.000	0.000	1.000
	0.90	0.388	1.000	0.111	1.000	0.001	1.000	0.000	1.000	0.000	1.000

The results presented in Table 2 shows the sensitivity of the EJP at $\gamma = 10$. There is reverse reaction in the behaviour of the model specification test as variance of the series increases. Here, the power of the test decreases as standard deviation increases from 0.02 to 0.25. This gives an indication that STAR model specification test is more sensitive and reliable at a particular value of the variance. Introduction of serial correlations at 0.25, 0.5 and 0.9 leads to decrease in the power of EJP test when standard deviation of the series is greater than 0.15. But at lower standard deviation, serial correlation increases the power of the test. At large sample size, the powers of the test converge to 1 when the standard deviation is between 0.15 and 0.25.

Higher frequencies of LSTAR model are still realised which implies that ESTAR models are still mi-specified as LSTAR at $\gamma = 10$.

Table 3 Specification of ESTAR model and Power of EJP at $\gamma = 100$

N	ρ_1	$\sigma = 0.02$		$\sigma = 0.05$		$\sigma = 0.1$		$\sigma = 0.15$		$\sigma = 0.25$	
		ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power	ESTAR	Power
50	0.00	0.996	1.000	0.951	1.000	0.883	0.994	0.768	0.695	0.592	0.179
	0.25	0.999	1.000	0.934	1.000	0.868	0.984	0.782	0.652	0.607	0.150
	0.50	0.997	1.000	0.940	1.000	0.861	0.962	0.733	0.554	0.557	0.131
	0.90	0.992	1.000	0.915	1.000	0.812	0.830	0.616	0.354	0.556	0.072
200	0.00	1.000	1.000	0.988	1.000	0.954	1.000	0.847	1.000	0.553	0.711
	0.25	1.000	1.000	0.995	1.000	0.954	1.000	0.848	0.990	0.568	0.650
	0.50	1.000	1.000	0.987	1.000	0.931	1.000	0.797	0.999	0.547	0.508
	0.90	0.999	1.000	0.981	1.000	0.901	1.000	0.695	0.963	0.484	0.250
500	0.00	1.000	1.000	0.999	1.000	0.977	1.000	0.891	1.000	0.484	0.991
	0.25	1.000	1.000	0.998	1.000	0.976	1.000	0.866	1.000	0.487	0.984
	0.50	1.000	1.000	0.997	1.000	0.964	1.000	0.820	1.000	0.480	0.929
	0.90	1.000	1.000	0.995	1.000	0.927	1.000	0.673	1.000	0.411	0.617
1000	0.00	1.000	1.000	1.000	1.000	0.981	1.000	0.907	1.000	0.447	1.000
	0.25	1.000	1.000	1.000	1.000	0.986	1.000	0.891	1.000	0.435	1.000
	0.50	1.000	1.000	1.000	1.000	0.980	1.000	0.838	1.000	0.387	0.999
	0.90	1.000	1.000	1.000	1.000	0.953	1.000	0.669	1.000	0.332	0.926
3000	0.00	1.000	1.000	1.000	1.000	1.000	1.000	0.933	1.000	0.288	1.000
	0.25	1.000	1.000	1.000	1.000	0.998	1.000	0.916	1.000	0.253	1.000
	0.50	1.000	1.000	1.000	1.000	0.996	1.000	0.867	1.000	0.203	1.000
	0.90	1.000	1.000	1.000	1.000	0.974	1.000	0.611	1.000	0.155	1.000

In Table 3, we have speed of nonlinearity $\gamma = 100$. Here, there is an improvement over the results in Table 2 as nonlinearity increased. The power of EJP test is 100% when the variation in the series is relatively small and this decreases at faster rate as standard deviation increases. Serial correlation is seen to have negative effect on the selection frequency of the ESTAR model as well as power of the test.

Conclusion

We have been able to provide additional evidence to specification of smooth transition autoregressive models. We have considered the effect of serial correlation of residuals and variance on the model specification proposed in Escribano and Jordá (1997, 2001). A simple model was considered as DGP and careful investigation of the Monte Carlo's (MC) test reveals some salient behaviours in the time series.

Firstly, at a very small standard deviation (variance), the MC test is able to recognise the ESTAR model to certain frequency of selection. Further increase in the standard deviation makes the DGP to realise series that closely resemble LSTAR model, therefore model mis-specification set in. Secondly, the DGP used gave reliable results when nonlinearity is increased (that is $\gamma \geq 50$). In that case, mis-specified results were realized when nonlinear effect is low. when nonlinearity is weak, $\gamma = 1$, serial correlation do not have any obvious effect on the EJP test but as nonlinearity is increased, serial correlation is seen to reduce frequency of selection of ESTAR model and in that case power of the test is reduced.

This paper will then serve as a guide whenever nonlinear smooth transition is being tested using Monte Carlo's or Bootstrap approach. The choice of appropriate distributional form matters particularly the value of the variance of the series. Also, unresolved serial correlation in the residuals has negative effect on the selection test.

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ABSTRACT(RÉSUMÉ)

Smooth transition models have gained popularity in modeling economic and financial series due it ability to capture the non linearity in the data sets. However, misspecification could occur for some financial and economic series when white noise process is assumed for serially correlated error terms of a nonlinear model. This paper considers the effect of a first order serial correlation of the residuals on the nonlinear time series model by specifying variants of smooth transition model using the Monte Carlo simulation method. Correct specification is examined using Escribano and Jordá (EJP) specification procedure under various levels of nonlinearity and varying degree of standard deviation of the data. It was established that the power of misspecification of non linear model is a function of serial correlation of the residuals, the sample size, degree of nonlinearity and the standard deviation of the series. Correct model is specified at moderate values of standard deviation and serial correlations. There is a swamping effect of serial correlation when the sample size is small, but appears to be masked with increase in the transition parameter especially for larger sample sizes. Great caution must be exercised in non linear model specification as high degree of serial correlations in residuals lead to inconsistencies in the estimation of power of nonlinearity test. The results will serve as guide in empirical econometric and time series modelling.