A COMPARATIVE STUDY OF STOCK PRICE FORECASTING USING NONLINEAR MODELS

Abstract:
This study compared the in-sample forecasting accuracy of three forecasting nonlinear models namely: the Smooth Transition Regression (STR) model, the Threshold Autoregressive (TAR) model and the Markov-switching Autoregressive (MS-AR) model. Data used was daily close stock prices of five banks in the South African banking sector and was obtained from the Johannesburg Stock Exchange (JSE). It covered the period from 2010 to 2012 with a total of 563 observations. Nonlinearity and nonstationarity tests used confirmed the validity of the assumptions of the study. The study used model selection criteria, SBC to select the optimal lag order and for the selection of appropriate models. The Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) served as the error measures in evaluating the forecasting ability of the models. The MS-AR models proved to perform well with lower error measures as compared to LSTR and TAR models in most cases.

Keywords:
Stock price, nonlinear time series models, error metrics

JEL Classification: C10, C32, E32
1 Introduction

In recent years, modelling economic and financial data nonlinear time series has received great attention as opposed to linear time series models. This is due to the realization that linear models fail to describe the dynamics of financial time series (Ismail and Isa, 2006). According to Maponga (2013), linear time series analysis involves simple models that describe the behaviour of time series in terms of past values. Nonlinear time series are generated by nonlinear dynamic equations which show attributes that cannot be modeled by linear time series models. These attributes are time-changing variance, asymmetric cycles, higher-moment structures, thresholds and breaks data to mention a few.

A variety of nonlinear models have been considered as alternative to standard linear models. For instance, the parametric nonlinear models such as the autoregressive conditional heteroscedasticity (ARCH) developed by Engle (1982) and the generalized autoregressive conditional heteroscedasticity (GARCH) of Bollerslev (1986) are some of the alternative linear models. Recently, the application of novel regime switching nonlinear models in financial data analysis is receiving great attention (Franses and Dijk, 2000). Most analysts of financial and economic data have effectively used these models. Commonly used among these models are the Threshold Autoregressive (TAR) of Tong (1978), Smooth Transition Regressive (STR) of Teräsvirta and Anderson (1992) and Markov-Switching Autoregressive (MS-AR) of Hamilton (1989).

These three models differ from conventional linear econometric models due to the assumption of different regimes within which the time series may exhibit different behaviour. The current study sought to explore the possibility of developing empirical models capable of describing and forecasting the South African major banks’ closing stock prices. In the main, the study intends to determine the predictive performance of each of the three models in modeling and forecasting stock prices. Forecast error metrics will be used to judge performance of the models. The study assumes that the data used satisfy the nonlinear properties so as to allow an efficient performance of the three suggested models.

The findings could empower stock market investors to make informed and accurate investment decisions. Again this may also boost the confidence of stakeholders in the financial industry to do more business with less risk exposure. Other beneficiaries of the study may be regulators and other financial institutions as well as researchers in academia.

The rest of the paper is organized as follows: Section 2 study provides a brief discussion of literature; in Section 3 study describes the methodology and results; Section 5 provides concluding remarks and recommendations.

2 Literature Review

There is much interest in modeling and forecasting the nonlinearity in a variety of macroeconomic and financial series, such as stock market, exchange rate and Gross Domestic Products (GDP). A number of nonlinear time series models have been suggested in literature, for instance the bilinear models developed by Granger and Andersen (1978), the TAR, STR and the MS-AR models. The studies reviewed herewith adopted these models.
Moolman (2004) used the idea of MS-AR model as a tool to provide evidence that the South Africa stock market returns depends on the state of the business cycle. McMillan (2005) employed the STAR model to examine nonlinear behavior in the international stock market. The study by Pérez-Rodriguez et al. (2005) concluded that the artificial neural network (ANN) and the Smooth Transition autoregressive (STAR) models in the Spanish market outperform the ARMA and the random-walk models. On the other hand, Cheung and Lam (2010) compared profitability in the US stock market using the self-exciting threshold autoregressive (SETAR) and linear models. In their studies, Ismail and Isa (2006) and Yarmohammadi et al. (2012) evaluated the performance of MS-AR model and six different time series modelling approaches to model Iranian exchange rate series. The study found MS-AR to be a useful model with the best-fit for modeling fluctuations of exchange rates.

Wasim and Band (2011) employed a two state MS-AR to identify the existence of bull and bear regimes in the Indian stock market. The model appropriately showed that Indian stock market will remain under bull regime compared to bear regime. Amiri (2012) have compared the forecasting performance of linear and nonlinear univariate time series models for GDP growth. The evaluation of the forecasting performance of their set of nonlinear models using real time data proved that the nonlinear models are able to capture the underlying processes of GDP as opposed to linear models. Cruz and Mapa (2013) also contributed to the literature by developing an early warning system for predicting the occurrence of high inflation in the Philippines with MS model. The study successfully managed to identify episodes of high and low inflation with this model.

3 Methodology and results
This section discusses the data and methods used and provide the results of the study

3.1 Preliminary analysis
The study employed the 563 daily South African stock prices collected for the period 2010-2012 from http://www.jse.com. After using purposive sampling technique, five (5) banks from a population of twenty-one (21) banks were sampled. The banks that responded were ABSA Bank (ABSA), Capitec Bank (CAPB), First National Bank (FIRB), Nedbank (NEDB) and Standard Bank (STDB). A time series plot for these stock prices is shown a Figure 1.
The results reveal that FIRB has the lowest stock prices and is estimated by an upward sloping trend. Stock prices of other banks are explained by irregular increasing patterns with ABSA and NEBD showing convergence at several stages. Given this movements by the stock prices, the data is not stationary at all levels. The series are further checked for nonlinearity by employing the nonlinear test. Since nonlinearity in time series may occur in several ways, there exists no single test that dominates others in detecting nonlinearity. Therefore the study uses the Regression Specification Error Test (RESET) by Ramsey (1969) and Brock-Dechert-Scheinkman (BDS) by Brock et al. (1996) tests for this purpose. The null hypothesis of nonlinearity is rejected if the RESET and the BDS tests are greater than the critical values at a conventional level of significance, implying that the true specification is nonlinear. To determine the stability of the models, a Cumulative Sum (CUSUM) test by Brown et al. (1975) is used. The null hypothesis is rejected if the CUSUM test exceeds the critical value. The results of the three tests are summarised in Table 1.

### Table 1: Estimated AR Models with Nonlinearity Tests

| Parameter Estimate | ABSA | CAPB | FIRB | NEDB | STDB |
|--------------------|------|------|------|------|------|
| $\alpha_0$         | 263.614 (1.8731) | 197.824 (2.001) | 2.9902 (0.3089) | 47.3057 (0.6324) | 182.023 (2.013) |
|                    | [0.0616] | [0.0459] | [0.7575] | [0.5274] | [0.0446] |
| $\alpha_1$         | 0.862676 (20.5228) | 0.9897 (187.60) | 0.9995 (237.80) | 0.8596 (20.51) | 0.9828 (114.0) |
|                    | [0.0000] | [0.0000] | [0.0000] | [0.0000] | [0.0000] |
| $\alpha_2$         | 0.119039 (2.8155) | 0.1379 (3.279) | 0.1379 (3.279) | 0.1379 (3.279) | 0.1379 (3.279) |
|                    | [0.0050] | [0.0011] | [0.0011] | [0.0011] | [0.0011] |

RESET Test for Specification

| Test Statistic | ABSA | CAPB | FIRB | NEDB | STDB |
|----------------|------|------|------|------|------|
| 4.00483 (0.0188) | 3.4352 (0.0329) | 3.6984 (0.0254) | 4.9172 (0.0076) | 8.7728 (0.0002) |

CUSUM Test for Parameter Stability

| Test Statistic (Harvey-Collier) | ABSA | CAPB | FIRB | NEDB | STDB |
|---------------------------------|------|------|------|------|------|
| 2.58915 (0.0099) | 0.6004 (0.5485) | 1.7090 (0.0880) | 2.6447 (0.0094) | 0.2375 (0.8123) |

Test for ARCH Effects

| LM | ABSA | CAPB | FIRB | NEDB | STDB |
|----|------|------|------|------|------|
| 3.1967 (0.07379) | 71.2252 (0.0000) | 3.0925 (0.0787) | 5.9051 (0.0151) | 12.1992 (0.0022) |

BDS

| z-statistics | ABSA | CAPB | FIRB | NEDB | STDB |
|--------------|------|------|------|------|------|
| 3.1967 (0.07379) | 3.1967 (0.0000) | 3.1967 (0.0000) | 3.1967 (0.0000) | 3.1967 (0.0000) |

Figures in (●) are t-statistics while figures in [●] are p-values

Results from the RESET tests of the five variables suggest that the use of a linear regression modelling technique was inappropriate. In addition, the residuals from various autoregressive (AR) models fitted to the data were found to have ARCH structures, further supporting the use of nonlinear modelling methods. There is no evidence of structural change in the data according to the BDS tests. The preliminary results proves that the data is suitable for the application of STR, TAR, MS-AR models.

**Modelling and Forecasting models**

This section presents the results of the three nonlinear time series models suggested. Note that estimation of the AR model was based on maximum lag five chosen with the aid of the Swartz Bayesian Criterion (SBC). This estimation was done to fulfil the requirements for the models.

**Threshold Autoregressive Models for Closing Stock Price**

Switches between one regime and another depend on a threshold variable and threshold value. This study followed the Hsu et al. (2010) structural break concept in selecting the thresholds.
Table 2: Estimated LSTR Models

| Variable | Coefficient | Std. Error | t-Statistic | Prob. | R-Square | Adj. R-Square |
|----------|-------------|------------|-------------|-------|----------|---------------|
| ABSA(t)  |             |            |             |       |          |               |
| C(1)     | 2372.968    | 1048.48    | 2.263247    | 0.024 | 0.94899  | 0.948254      |
| C(2)     | 0.825795    | 0.077052   | 10.71732    | 0.0000 |
| C(3)     | 2386.699    | 650.5343   | 3.668829    | 0.0003 |
| C(4)     | 0.820463    | 0.048884   | 16.78401    | 0.0000 |
| C(5)     | 3733.219    | 874.7009   | 4.257995    | 0.0000 |
| C(6)     | 0.732856    | 0.062796   | 11.67038    | 0.0000 |
| C(7)     | 1840.186    | 692.9351   | 2.65564     | 0.0081 |
| C(8)     | 0.881074    | 0.045018   | 19.57142    | 0.0000 |
| C(9)     | 1.000339    | 0.001225   | 816.4269    | 0.0000 |
| CAPB(t)  |             |            |             |       |          |               |
| C(1)     | 1.000446    | 0.001765   | 640.0509    | 0.0000 | 0.98512  | 0.984908      |
| C(2)     | 1441.481    | 636.0464   | 2.266315    | 0.0238 |
| C(3)     | 0.920211    | 0.035552   | 25.88318    | 0.0000 |
| C(4)     | 1.000821    | 0.001209   | 827.7597    | 0.0000 |
| C(5)     | 2983.457    | 824.0883   | 3.620313    | 0.0003 |
| C(6)     | 0.716250    | 0.084546   | 8.471738    | 0.0000 |
| C(7)     | 0.374637    | 0.097122   | 3.857384    | 0.0001 |
| C(8)     | 0.228059    | 0.084111   | 2.711422    | 0.0069 |
| C(9)     | 0.997983    | 0.001449   | 688.9222    | 0.0000 |
| FIRB(t)  |             |            |             |       |          |               |
| C(1)     | 0.998951    | 0.001915   | 521.575     | 0.0000 |
| C(2)     | 355.5556    | 87.66296   | 4.055939    | 0.0001 |
| C(3)     | 0.819949    | 0.044442   | 18.44991    | 0.0000 |
| C(4)     | 1.002158    | 0.001678   | 597.3176    | 0.0000 |
| C(5)     | 1.001118    | 0.00145    | 690.4768    | 0.0000 |
| C(6)     | 1.001137    | 0.00135    | 741.3204    | 0.0000 |
| NEDB(t)  |             |            |             |       |          |               |
| C(1)     | 1414.938    | 1354.395   | 1.044701    | 0.2966 |
| C(2)     | 0.892528    | 0.102173   | 8.735495    | 0.0000 |
| C(3)     | -2056.01    | 2762.216   | -7.443303   | 0.0000 |
| C(4)     | -2.562839   | 0.192509   | -13.31283   | 0.0000 |
| C(5)     | 1726.918    | 1550.095   | 1.114073    | 0.2657 |
| C(6)     | 0.876889    | 0.110954   | 7.903171    | 0.0000 |
| C(7)     | 0.717100    | 0.191316   | 3.748249    | 0.0002 |
| C(8)     | 0.284765    | 0.191779   | 1.484858    | 0.1382 |
| C(9)     | 3017.190    | 1984.132   | 1.52066     | 0.1289 |
| C(10)    | 0.832901    | 0.110225   | 7.552972    | 0.0000 |
| STDB(t)  |             |            |             |       |          |               |
| C(1)     | 1485.843    | 643.2156   | 2.310023    | 0.0213 |
| C(2)     | 0.859032    | 0.060756   | 14.13897    | 0.0000 |
| C(3)     | 1557.045    | 564.578    | 2.757982    | 0.0060 |
| C(4)     | 0.843761    | 0.056492   | 14.93596    | 0.0000 |
| C(5)     | 1771.688    | 462.4663   | 3.830956    | 0.0001 |
| C(6)     | 0.816977    | 0.047865   | 17.06845    | 0.0007 |
| C(7)     | 1384.418    | 396.2032   | 3.494212    | 0.0005 |
| C(8)     | 0.877154    | 0.035288   | 24.8571     | 0.0000 |
| C(9)     | 1.000742    | 0.001336   | 748.8949    | 0.0000 |

In particular, assuming that the numbers of thresholds are unknown, the Bai-Perron multiple breakpoint method was applied. The final estimated TAR models were obtained and the results are presented as equations below.

**Smooth Transition Regression Analysis**

This section provides the results for the STR modelling technique. Also shown are the forecasts of the model for the five variables. Table 2 presents the results from the LSTAR model.
As revealed by the results, all five variables have been have autoregressive processes since their lags are significant in both the linear and nonlinear parts. By observation the estimated models seem good judging from the high $R^2$ and $R^2_{adj}$ values. Again, the transition values (C1), for ABSA, CAPB, NEDB, and STDB suggest that closing stock price of these banks switch between two regimes. In fact, a closing stock price less than C1 are regarded as low stock yield periods for these banks. Larger closing stock price implies even higher stock prices.

**Markov-Switching AR Models for Stock Prices**

Prior to estimating the MS-AR model, the study identifies the number of regime switching models for the variables. This task is fulfilled by applying the linearity likelihood ratio (LR) test. The criterion is to reject the null hypothesis in favour of the alternative if the test is less than the conventional level of significance. Judging from the results presented in Table 3, it is clear that the LR test is in support of a two-state regime for all the five variables. These findings are in accordance with those by S by Ismail and Isa (2006).

**Table 3: Linearity LR Test of Two-Regime Switch**

| Variable | Chi-Square Test Statistic | P-value |
|----------|---------------------------|---------|
| ABSA     | 53.794                    | 0.0000  |
| CAPB     | 100.1                     | 0.0000  |
| FIRB     | 21.788                    | 0.0006  |
| NEDB     | 11.296                    | 0.0796  |
| STDB     | 12.042                    | 0.0610  |
The results for MS-AR (1) models shown in Table 4, The variances for regime 2 associated with ABSA, CAPB and FIRB the variances of Regime 2, $\sigma^2(s_i=2)$, is greater than the variance of Regime 1, $\sigma^2(s_i=1)$, suggesting that for these three closing stock prices, regime 2 is more volatile than Regime 1. In other words, regime 2 captures the behaviours in ABSA, CAPB and FIRB in an unstable manner and the opposite does not apply to regime 1. Regime 1 is reported to be stable for other banks. The findings also report that for ABSA, FIRB, NEDB and STDB, the estimated regime-dependent intercepts (expected daily increments in closing stock prices) are higher in Regime 1 than in Regime 2 while the opposite holds in the case of CAPB. In other words, changes in ABSA, FIRB, NEDB and STDB closing stock prices increases in a stable state while opposite holds for NEDB.

Table 4: Two-Regime MS-AR Modelling Results

|        | ABSA     | CAPB     | FIRB     | NEDB     | STDB     |
|--------|----------|----------|----------|----------|----------|
| $\mu(s_i=1)$ | 13749.6  | 17853.9  | 2276.56  | 15390.1  | 10507.0  |
| $\mu(s_i=2)$ | 13642.6  | 18761.8  | 2194.16  | 14488.6  | 10457.0  |
| $\phi_1(s_i=1)$ | 0.996758 | 1.00108  | 0.998810 | 0.994343 | 0.973702 |
| $\phi_1(s_i=2)$ | 0.531652 | 0.945820 | 1.259510 | 1.00960  | 1.180030 |
| $\sigma^2(s_i=1)$ | 178.457   | 201.356   | 34.4960  | 241.296  | 137.350  |
| $\sigma^2(s_i=2)$ | 241.037   | 331.188   | 116.217  | 190.232  | 18.7274  |
| $p_{11}$ | 0.989355  | 0.98621   | 0.999528 | 0.995980 | 0.94730  |
| $p_{12}$ | 0.061359  | 0.041621  | 0.999979 | 0.004151 | 0.69051  |
| $p_{21}$ | 0.010645  | 0.013793  | 0.000472 | 0.000419 | 0.052702 |
| $p_{22}$ | 0.938640  | 0.958380  | 0.000121 | 0.995850 | 0.309490 |
| $E[D(s_i=1)]$ | 16.2975   | 24.0263   | 1.0000   | 240.8884 | 1.4482   |
| $E[D(s_i=2)]$ | 93.9408   | 72.5005   | 245.5554 | 248.8181 | 18.9746  |

The results further shows that the probabilities of a closing stock price remaining in Regime 1, $p_{11}$, are smaller than the probability of a closing stock price staying in Regime 2, $p_{22}$, for all the five closing stock prices. In fact, the probabilities of a closing stock price staying in Regime 1 lie in the range of 0.947 to 0.996 with an expected duration, $E[D(s_i=1)]$, of 1 to 241 days. Similarly, the probabilities of a stock price staying in Regime 2 lie in the range 0.000 to 0.958 with an expected duration, $E[D(s_i=2)]$, of 19 to 249 days. This means that closing stock prices can stay slightly longer in Regime 2 than in Regime 1.

Model performance

This section provides the results of the forecast performance of the three models. Forecasted the future is of great importance for planing, decision-making and policy formulation. The evaluation of nonlinear models is based on the properties of resulting
residuals. Using the residuals, various tests for misspecification, including non-normality, parameter stability and autocorrelation checks were conducted. The diagnostic test statistics for these assumption (not presented here) rendered the models accurate and sufficient. On the basis of reliability, validity and wide use, the performance (error) measuring metrics are recommended for evaluating the efficiency of models in forecasting. The study uses the four error metrics such as RMSE, MAE, MAPE, and RSMPE. The model that generate the least forecast error is chosen and suggested for further analysis. Table 5 provides the results for the four error measures.

| Measure | Method | ABSA   | Capitec | FRIB   | NEDB   | STDB   |
|---------|--------|--------|---------|--------|--------|--------|
| RMSE    | LSTR   | 200.2572 | 270.9698 | 35.48659 | 219.5906 | 133.0790 |
|         | TAR    | 196.5424 | 266.1471 | 35.48629 | 210.4875 | 131.0235 |
|         | MS-AR  | 186.7458 | 217.5940 | 35.22222 | 213.6210 | 129.6859 |
| MAE     | LSTR   | 148.9502 | 189.5397 | 27.03160 | 167.8142 | 103.7542 |
|         | TAR    | 147.2353 | 186.6499 | 26.93976 | 162.2681 | 101.3549 |
|         | MS-AR  | 143.0377 | 160.6033 | 27.34744 | 157.5507 | 97.6969  |
| MAPE    | LSTR   | 0.010624 | 0.010107 | 0.011973 | 0.011023 | 0.009965 |
|         | TAR    | 0.010502 | 0.009945 | 0.011929 | 0.010853 | 0.009735 |
|         | MS-AR  | 0.010189 | 0.008897 | 0.012121 | 0.010863 | 0.009400 |
| RMSPE   | LSTR   | 0.251848 | 0.239601 | 0.283848 | 0.261327 | 0.236247 |
|         | TAR    | 0.248965 | 0.235339 | 0.282786 | 0.252104 | 0.230791 |
|         | MS-AR  | 0.241512 | 0.203568 | 0.287354 | 0.257530 | 0.228246 |

According to the results, the four error metrics select the MS-AR(1) model for ABSA, Capitec and STDB, and TAR model for NEDB accordingly. MAE, MAPE and RMSPE select the TAR model for FRIB, RMSE selects the MS-AR(1) model for FRIB. The results are in accordance with those by Dacco and Satchell (1999), whose study identified the FIRB as best modelled by the MS-AR(1).

4 Conclusion Remarks

The study explored the performance of the TAR, STAR and the MS-AR models in modelling and forecasting daily stock prices series of five banks of South Africa. The five banks considered are the ABSA, Capitec, First Rand Bank, Nedbank, and Standard Bank for the period from 2010 to 2012. The suggested models perform better when applied to nonlinear series. Appropriate test for this assumption proved that all the series are nonlinear. The estimation of the three models was based on an optimal lag five suggested by the Swartz Bayesian Criterion. The three models were successfully estimated using this lag. To evaluate the performance of the three models, the study used the four forecast error metrics which were in favour of the MS-AR model. Generally, the results proved that the MS-AR performed better in most cases compared to the LSTR and TAR models. From the discussions of the results, the following conclusions can be drawn:

- All five closing stock prices are nonlinear in nature.
- Various estimated predictive models for the five closing stock prices are robust for purposes of forecasting.

The study is recommending the used of MS-AR in modelling and forecasting the economic and financial data. This is motivation by the results of the current study.
results and the study of Ismail and Isa (2006), Wasin and Bandi (2011) and Yarmohammadi et al. (2012).

5 References

AMIRI, E. (2012) Forecasting GDP Growth rate with Nonlinear Models. 1st International Conference of Econometrics Methods and Applications. 1-18.

BOLLERSLEV, T. (1986) Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics 31 (3): 307-327.

BROCK, W. A., DECHERT, W. D., SCHEINKMAN, J. and LEBARON, B. (1996) A Test for Independence Based on the Correlation Dimension. Econometrics Reviews, 115: 197-235.

BROWN, B. L., DURBIN, J. and EVAN, J. M. (1975) Techniques for Testing the Constancy of Regression Relationships over Time. Journal of the Royal Statistical Society B, 35: 149-192.

CHONG, T. T. L. and LAM, T.H. (2010). Are Nonlinear Trading Rules Profitable in The U.S. Stock Market? Quantitative Finance 10(9), 1067-1076.

CRUZ, C. J. F. and MAPA, D. S. (2013) An Early warning system for Inflation in the Philippines using Markov-Switching and Logistic Regression Models. Theoretical and Practical Research in Economic Fields 2, 137-152.

DACCO, R. and SATCHELL, S. (1999) Why do Regime-Switching Models Forecast so Badly? Journal of Forecasting, 18: 1-16.

ENGLE, R. F. (1982) Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K. Inflation. Econometrica, 55, 987-1008.

FRANSES, P. H. and DIJK D. (2000) Non-Linear Time Series Models in Empirical Finance, Cambridge University Press, Cambridge.

HAMILTON, J. D. (1989) A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, Econometrica, 57, 357-384.

HARRIS, R. & SOLLIS, R. (2003) Applied Time Series Modelling and Forecasting, New York: John Wiley.

ISMAIL, M.T. and ISA, Z. (2007) Detecting Regime Shifts in Malaysian Exchange Rates. Journal of Fundamental Sciences, 3, 211-224.

MAPONGA, LL AND MATARISE, F. (2013) Modelling Non-Linear Time Series, A Dissertation Submitted In Partial Fulfilment Of The Requirements For The M.Sc. In Statistics in the Faculty of Science, University of Zimbabwe.

MOOLMAN, H. (2004). An Asymmetric Econometric Model of The South African Stock Market. Doctoral thesis. Pretoria: University of Pretoria.

PÉREZ-RODRÍGUEZ, J. V., TORRA, S. AND ANDRADA-FÉLIX J. (2005) STAR and ANN Models: Forecasting Performance on Spanish “Ibex-35” Stock Index. Journal of Empirical Finance 12, 490-509.

RAMSEY, J. B. 1969. Tests for Specification Errors in Classical Linear Least-Squares Regression Analysis. Journal of the Royal Statistical Society B, 31: 350-371.

SCHWARTZ, G. (1978) Estimating the Dimension of A Model. Annals of statistics, 6, 461-4.

TERÄSVIRTA, T. AND H.M. ANDERSON, H.M. (1992) Characterizing Non-Lineairities in Business Cycles Using Smooth Transition Autoregressive Models. Journal of Applied Econometrics 7, S119- S136.

TONG, H. (1978) On a Threshold Model in Pattern Recognition and Signal processing, ed. C. H. Chen, Amsterdam: Sijhoff & Noordhoff.

WASIM, A. & BANDI, K. (2011) Identifying Regime Shifts in Indian Stock Market: A Markov Switching Approach. Munich Personal RePEc Archive, 4, 1-22.