COMPARING FORECASTING PERFORMANCE OF LINEAR AND NON-LINEAR TIME SERIES MODELS

Tayyab Raza Fraz¹, Javed Iqbal² and Mudassir Uddin³

Abstract

Time series modelling and the forecasting of economic, financial time series is an active and fascinating area of research due to the presence of structural changes i.e. political regimes, business cycle variations and financial crises etc. In these cases, a careful handling is required to model time series when nonlinearity present in the data. Due to the nonlinear behavior of economic and financial time series, it is not possible to rely only on predictions from the simple estimated linear time series models. This study aims to explore and compare the forecasting performance time series models i.e. linear Autoregressive (AR) model with two nonlinear regime switching models namely Markov Regime Switching Autoregressive (MSAR) and Self-Exciting Threshold Autoregressive (SETAR). Macroeconomic variables i.e. interest rate, inflation (CPI), industrial production, GDP growth, and exchange rate from some developed and developing countries included G7 countries are chosen for this study. Quarterly based time series data from 1970 to 2016 is used. Empirically, the forecast performance of nonlinear time series model namely SETAR is found to be superior to the linear Auto Regressive model as well as nonlinear MSAR model. The results are evaluated on the basis of forecast accuracy criteria namely RMSE, MAE and MAPE.

Keywords : GDP Growth, Markov Regime Switching Autoregressive (MSAR), Self-Exciting Threshold Autoregressive (SETAR). Interest Rate, Inflation (CPI).

JEL Classification: G000

Introduction

Forecasting future path of economies is highly valuable to policy makers, government agencies, business managers, investors, and financial analysts. Many economic models stipulate

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expectation of economic variables. For example, the expectation augmented by Phillips curve employs expected future inflation in modeling current inflation. Discounted cash flow model of stock price specifies stock price as a discounted value of expected future dividends. Pricing of derivatives products requires an estimate of expected volatility over the course of its life. As future is uncertain by its very nature, it becomes arduous and challenging for researchers to conjure a satisfactory forecasting model. There is always needed an effort to secure a reliable forecasting model, however, the development continues for the superior fitting and estimating the best forecasting models. A basic cause due to which a forecasting model fails is the ignorance of the characteristics of parametric nonlinearity in economic variables. Andersen and Vahid (1998) shows that the linear forecast models do not have the ability to understand the irregular particulars of the data. Also, these traditional linear estimated models forecast the symmetric pattern of shocks (positive and negative) on the time series variable which is unreliable with the observed asymmetric outcome. An indication of successful forecast of macroeconomic variables is to deal cautiously with the nonlinearity present in the data. The overall environment of economy be determined by some of the main macroeconomic financial time series variables namely exchange rates, industrial production, gross domestic product, interest rate as well as inflation. Better modeling and forecasting techniques of these variables are the ultimately key to success in managing the macro economy. This motivates the ongoing research in macroeconomic forecasting.

The well-known linear models such as the simple autoregressive estimation are usually used to estimate the models for the economic and financial data. The famous linear time series modeling strategy i.e. the traditional Box-Jenkins approach is built on linear autoregressive integrated moving average time series model. These models are used in every field for the purpose of forecasting regardless of the nature of non-linearity inherent in data. As such these linear models may not perform satisfactorily to overcome the issue of nonlinear behavior of time series. Since the past few decades, the researchers show enormous concern in estimation and forecasting the nonlinear time series.

As Terasvirta (2002) points out there exist a large amount of nonlinear models which is impossible to review in a single study. Furthermore, since the last two decades, a good amount of research has focused on nonlinear models to augment the application of widely used linear time series models. Some nonlinear time series models are estimated mostly for the second moment forecast of conditional volatility in the data i.e. Granger and Anderson (1978) estimated the bilinear model, Engle (1982) also estimated the ARCH model while Bollerslev (1986) estimated and present the generalized ARCH (GARCH). According to Franses and Dijk (2000), nonlinear models especially regime-switching models are widely estimated and used to forecast by the researchers. They are also appreciated by many researchers and forecasters. Few years before, Clements and Smith (1997) pointed out that the linear AR model provides better out of sample and in-sample fit as compared to the any other time series model. Similarly, some researchers also studied and revealed that the non-linear time series

models are not a bench-mark for better forecasts against the linear Autoregressive time series models [For details see Diebold (1990), and De Gooijer and Kumar (1992)].

In this study, the main focus was on the forecasting performance of the nonlinear models. Considering two most famous nonlinear time series models namely MSAR and SETAR. Regime switching models are designed especially for modeling the distinct behavior of time series, which generates the data. Regime switching models permit the quick change between regimes but every regime model has a different approach to model the movements between the regimes. The main difference between MSAR models and SETAR models is actually the movement between regimes. In the MS-AR which shows no regard for its past values. While in the SETAR model the movement between regimes is related to the past values. According to Clements and Krolzig (1998), the MS-AR and SETAR models have a higher level of capability of capturing nonlinear behavior of business cycles as compared to linear models. Nevertheless, the power of forecasting of these models is not as superior as expected.

The study uses the macroeconomic data of both developed and developing countries in the analysis. Higher dependence on agriculture, underutilized natural resources, demographic characteristics, socio culture bonds, dualistic nature of economy etc., are the characteristics of developing counties which differentiate them from the developed countries. Thus the structure of macro economy in developing countries is different from the developed countries. Therefore, data of both types of countries are employed.

Quarterly data sets of five most important macroeconomic variables are used which characterize an economy namely interest rate, inflation, GDP growth, exchange rate and industrial production from 1970 to 2016. The developed countries included in analysis are four of the G7 countries Canada, Japan, United Kingdom (UK) and United States (US) and Australia while the developing countries used are the three BRICS countries i.e. Brazil, India, South Africa and Turkey. However, some series have a shorter sample range depending on availability. The parameters of the respective models are estimated and used model selection criteria for the comparison of out-of-sample fit of linear autoregressive AR models, SETAR and MSAR models.

A contribution of this study is to include some important developed countries i.e. the G7 countries and important developing countries i.e. the BRICS countries in the same analysis to evaluate the forecasting performance of linear and nonlinear time series models. Most of the earlier studies have used data from only the developed countries. Keeping in view the distinct structure of the two types of economies it is important to employ the data of both.

Forecasting Models

Linear autoregressive (AR) models

The traditional linear model i.e. AR model is considered only in this study, related to the time-series approach from Box and Jenkins (1970). Kunst (2012) revealed that the linear Autoregressive model is the common linear time series model due to its characteristics i.e. assessing and estimating the model under the assumptions of ordinary least squares regression (OLS). Following these researches, only AR model are used. A process that characterizes the AR model is the autoregressive first order process:

 $y_t = \mu + \phi_1 y_{t-1} + u_t$ (1)

The intercept parameter is " y_t " while the uncorrelated random error is presented by μ_t having mean zero and variance σ^2 . According to Akaike (1973), the order of AR lag q, is selected to minimize AIC, such that:

$$AIC(q) = \ln(\hat{\sigma}^2(q)) + 2(q+2)/T$$

Where $\hat{\sigma}^2 = \sum \hat{u}_i^2 / (T-2)$ but only considered the first four order lags. Longer lag orders never gives appropriate and better forecast [Clements and Smith (1997)]. The AR model is a special case of the more general ARMA models.

Self-exciting threshold autoregressive models

TAR model i.e. threshold autoregressive models is the simplest nonlinear threshold model that contains linear specifications separately and regime-swtiching. These tremendous procedures were firstly introduced by the renowned researcher namely Tong (1978). When w_t is taken as a lagged value itself, in time series, i.e. $w_t = y_{t_g}$ for a certain integer g > 0 then as a result, a new model is established which is SETAR model. According to Kahraman et al. (2012), nonlinear model i.e. SETAR model has always gain attention from the researchers because it contains linear function piecewise without any boundaries with respect to its applications.

If g = 1 and an autoregressive AR(1) model is assumed, a two regime SETAR model is given by: $y_t = \begin{cases} \alpha_{0,1} + \alpha_{1,1}y_{t-1} + e_t & \text{if } y_t \le c, \\ \alpha_{0,2} + \alpha_{1,2}y_{t-1} + e_t & \text{if } y_t > c, \end{cases}$ (2) where e_t are independently and identically distributed white noise sequence conditional upon the time series history π_{t-1} where $\pi_{t-1} = \{y_{t-1}, y_{t-2}, \dots, y_{1-(q-1)}, y_{1-q}\}$, so that, $E[e_t | \pi_{t-1}] = 0$ and $E[e_t^2 | \pi_{t-1}] = \sigma^2$

Equation 2 can be written by another way which is:

$$y_t = (\alpha_{0,1} + \alpha_{1,1}y_{t-1})(1 - \beta[y_{t-1} > c]) + (\alpha_{0,2} + \alpha_{1,2}y_{t-1})\beta[y_{t-1} > c] + e_t$$
(3)

Where, $\beta[I]$ is actually an indicator function such that if $\beta[I]=1$ if event I occurs while $\beta[I]=0$ otherwise.

For higher order AR models, for different regimes such as two regime case, the order of AR can be set to q1 and q2 in the lower regime and upper regime respectively. Hence, the SETAR model can be written as:

$$y_{t} = \begin{cases} \alpha_{0,1} + \alpha_{1,1}y_{t-1} + \dots + \alpha_{q1,1}y_{t-q1} + e_{t} \text{ if } y_{t-1} \leq c, \\ \alpha_{0,2} + \alpha_{1,2}y_{t-1} + \dots + \alpha_{q2,2}y_{t-q2} + e_{t} \text{ if } y_{t-1} > c, \end{cases}$$
(4)

Markov regime switching models

According to Terasvirta and Timo (2005), the Markov Regime Switching autoregressive model (MS-AR):

$$y_t = \begin{cases} \alpha_{0,1} + \alpha_{1,1}y_{t-1} + e_t \ if \ z_t = 1\\ \alpha_{0,2} + \alpha_{1,2}y_{t-1} + e_t \ if \ z_t = 2 \end{cases}$$
(5)

Hence,

$$y_t = (\alpha_{0,Zt} + \alpha_{1,Zt}y_{t-1}) + e_t$$
(6)

Where $e_t \sim \text{NID}(0,\sigma^2)$. The specification is required for process z_t for the completion of the model.

The famous Markov-Switching model (MSW) was created by Hamilton (1989) which depends on the order of four lags.

$$p(z_t = 1 | z_{t-1} = 1) = w_{11},$$

$$p(z_t = 2 | z_{t-1} = 1) = w_{12},$$

$$p(z_t = 3 | z_{t-1} = 2) = w_{21},$$

$$p(z_t = 4 | z_{t-1} = 2) = w_{22},$$

Henec, zt is the Markov Process' first order.

Therefore, w_{tj} is equal to the probability that a Markov chain moves from state *i* at time *t* -1 to state *j* at time t. i.e. $w_{11} + w_{12} = 1$ and $w_{21} + w_{22} = 1$. With finite states, an ergodic Markov chain i.e.

$$P(z_t = 1) = \frac{1 - w_{22}}{2 - w_{11} - w_{22}}$$
(7)

$$P(z_t = 2) = \frac{1 - w_{11}}{2 - w_{11} - w_{22}}$$
(8)

As pointed out by Deschamps (2008) the difference between the MSAR and the TAR model is that MSAR uses less prior information than the later model. Also the SETAR model requires the choice of a transition variable while the MSAR estimates transition function flexibly from the data.

Hsu, et al. (2010) studied the forecasting ability of traditional ARIMA model and nonlinear SETAR models. They used the data stock prices. According to Hsu, et al. (2010), the economic environment changes from time to time, therefore, the stock market often depends on change over time. They used Chow breakpoint test to choose the breakpoint for the SETAR model according to Hansen (2001). They made their results using the MSE, MAE, AMAPE, and MAPE information criteria's which strongly favored the SETAR model due to the superior forecasting ability over ARIMA model (Shin, 1992). Furthermore, he also discussed about other famous tests i.e. Phillips and Perron (1988) and ADF by Dickey and Fuller (1979) and (1981). Estimated results from these unit root tests may be biased. Perron (1989) revealed that mostly a unit root in various macroeconomic and financial variables is absent. Hence, to identify the unit root in any time series data set, the unit root breakpoint is used. Akaike criterion (AIC) and Schwarz criterion (BIC) are adopted for the matter of length of lag, two selection methods for Breakpoint test are used, one is F-statistic while the second is Schwarz (BIC) criterion.

Empirical Findings and Discussion

Breakpoint unit root test

In case of macroeconomic variable GDP growth for all the countries, break point unit root test results revealed that unit root is not present. Nevertheless, results also revealed the unit root is present in remaining macroeconomic time series for most countries i.e. inflation, industrial production, interest rate and exchange rate.

Table 1											
Break point	t unit root	test									
Economic	Break-point	Unit Root	Australia	Brazil	Canada	Canada India		South	Turkey	UK	USA
Indicators								Africa			
GDP growth	Schwarz	Level	-14.867*	-8.657*	-9.672*	-10.094*	-13.670*	-10.928*	-14.006*	-12.161*	-10.523*
	F-test		-6.949*	-7.35	-5.232**	-8.743*	-6.533*	-10.834*	-8.438*	-7.516*	-5.695**

(Table Continued.....)

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log (Exchange	Schwarz	Level	-3.80	-3.06	-2.54	-3.89	-4.88	-2.96	-2.47	-4.42	
rate)		1st diff	-12.417*	-12.796*	-10.89*	-12.360*	-6.310*	-12.015*	-12.277*	-10.827*	
-	F-test	Level	-4.03	-3.01	-3.19	-3.73	-4.96	-2.61	-3.26	- 4.74	
		1st diff	-9.192*	-11.125*	-10.535*	-6.815*	-5.751*	-5.763*	-5.111**	-9.871*	
Interest rate	Schwarz	Level	-6.354*	-7.811*	-6.064*	-4.56	-5.526**	-4.94	-14.004*	-4.18	-6.555*
		1st diff				-19.86*		-9.370*		-11.345*	
-	F-test	Level	-6.472*	6.965*	-6.064*	-4.56	-6.563*	-4.94	-3.14	-4.85	-6.555*
		1st diff				-18.06*		-6.447*	-14.90*	-6.876*	
Log (CPI)	Schwarz	Level	-6.411*	-5.659**	-5.449**	-4.18	-5.390**	-5.179**	-4.35	-4.77	-4.71
		1st diff				-8.644*			-9.987*	-8.823*	-6.974*
-	F-test	Level	-4.13	-5.681**	-5.895*	- 4.19	-7.438*	-4.95	-4.16	-3.94	-5.157**
		1st diff	-5.296*			-6.485*		-5.246**	-6.974*	-5.841*	
Log (Industrial	Schwarz	Level	-4.094	-5.487**	-5.168	-3.676	-5.608**	-3.489	-3.204	-3.568	-5.139
Production)		1st diff	-12.555*		-8.437*	- 6.641*		-14.148*	-11.251*	-12.917*	- 7.742*
-	F-test	Level	-4.094	- 5.487**	- 5.168	-3.1717	-4.664	- 4.119	-3.244	- 4.128	-4.3095
		1st diff	-8.602*			-5.474**	7.575*	-6.308*	-11.158*	-6.049*	-5.893*

* Significant at 1% and ** Significant at 5% level.

Forecast Evaluation

Table 2a and Table 2b, represent the results regarding the forecasting performance of macroeconomic variables for all the models for short term i.e. 4 quarters ahead and long term i.e. 21 quarters ahead respectively but the results do not favor a particular forecasting model. Moreover, multi-criteria (RMSE, MAE, and MAPE) are used for the comparison of forecasting ability between the models for short term and long term. The model with best forecasting performance corresponding to the linear or nonlinear model has been shown. The results are shown by each macroeconomic time series. Generally, for short-run forecasting as well as long run forecasting, SETAR model produce the lowest forecast accuracy measure in most of the cases.

Table 2a

RMSE, MAP & MAPE for one year (4-Quarters) ahead forecast

		Ex	change r	ate	G	DP grow	th		Log(CPI	.)	I	nterest Ra	ate	Lo	Log (Industrial		
]	Production)		
RM	Countr	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS	
SE	У		AR	AR		AR	AR		AR	AR		AR	AR		AR	AR	
	Australi	0.07	0.025	0.95	0.32	0.376	0.37	0.0	0.003	0.00	1.02	0.217	1.13	0.01	0.034	0.01	
	а	3		7	5		0	05		3	6		2	6		1	
	Brazil	0.71	0.782	0.68	2.01	2.178	1.95	0.0	0.019	0.07	0.25	0.035	0.16	0.08	0.117	0.68	
		3		7	4		0	38		1	5		5	2		7	
	Canada	0.05	0.072	0.05	0.34	0.247	0.29	0.0	0.003	0.35	0.73	0.209	3.01	0.00	0.003	0.21	
		4		5	1		9	15		6	1		7	6		5	
	India	0.05	0.050	0.03	0.33	0.304	0.27	0.0	0.009	0.01	0.60	0.507	0.61	0.01	0.032	0.09	
		6		5	5		2	45		5	2		5	6		4	
	Japan	0.04	0.025	0.05	0.77	0.600	0.74	0.0	0.006	0.00	0.01	0.062	0.14	0.02	0.041	0.02	
	-	2		7	8		2	06		5	0		8	9		8	
	South	2.32	4.028	2.49	0.85	0.984	0.95	0.0	0.020	0.00	0.22	0.224	0.23	0.01	0.007	0.01	
	Africa	6		5	4		3	28		6	5		0	2		9	

(Table Continued.....)

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Research

Turkey 0.3 0.03 0.01 0.222 0.17 0.0 0.025 0.02 0.00 <																	
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Turkey	0.36 8	0.003	0.38 9	0.19	0.222	0.17 5	0.0 26	0.026	0.02	0.61 4	0.182	1.45 4	0.00 7	0.009	0.01
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		UK	0.02	0.029	0.03	0.15 5	0.182	0.13 3	0.0 06	0.005	0.00 5	0.04	0.025	0.93 0	0.00 7	0.005	0.00
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		USA				0.32 7	0.338	0.33	0.0 23	0.006	0.00 7	0.41 7	0.108	0.83 2	0.00	0.004	0.01
E y AR AR <th>MA</th> <th>Countr</th> <th>AR</th> <th>SET</th> <th>MS</th>	MA	Countr	AR	SET	MS	AR	SET	MS									
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$	E	<u> </u>	0.07	AR	AR	0.00	AR	AR	0.0	AR	AR	0.00	AR	AR	0.01	AR	AR
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Australı	0.06	0.023	0.87	0.28	0.290	0.30	0.0	0.002	0.00	0.98	0.162	1.07	0.01	0.033	0.01
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		a D	0 (2	0.696	0	/	2.077	3	05	0.016	3		0.022	/	3	0.105	1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Brazii	0.63	0.686	0.60	1.93	2.077	1.87	0.0	0.016	0.06	0.23	0.033	0.14	0.07	0.105	0.60
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Canada	0.05	0.065	0.05	4	0.100	0.22	30	0.002	0.25	0.69	0.197	2 27	2	0.002	0.21
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Callada	0.05	0.005	0.05	0.25	0.190	0.23	15	0.002	6	0.08	0.167	2.57	0.00	0.003	5
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		India	0.05	0.045	0.03	0.31	0.268	0.25	0.0	0.007	0.01	0.55	0.446	0.55	0.01	0.023	0.00
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		maia	1	0.045	2	7	0.200	3	42	0.007	0.01	3	0.440	3	5	0.025	1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Japan	0.03	0.024	0.04	0.64	0.417	0.59	0.0	0.006	0.00	0.00	0.047	0.12	0.02	0.038	0.02
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Jupun	1	0.021	3	6	0.117	5	05	0.000	4	8	0.017	9	8	0.050	7
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		South	1.88	3.444	2.06	0.81	0.924	0.91	0.0	0.019	0.00	0.18	0.180	0.20	0.01	0.007	0.01
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Africa	0		0	5		0	27		5	6		3	2		9
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Turkey	0.35	0.097	0.36	0.17	0.197	0.12	0.0	0.024	0.02	0.56	0.147	1.33	0.00	0.008	0.00
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$			2		7	6		4	23		0	2		3	5		8
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		UK	0.01	0.022	0.02	0.15	0.169	0.13	0.0	0.008	0.00	0.04	0.020	0.83	0.00	0.004	0.00
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $			8		1	2		0	11		4	4		9	6		4
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		USA				0.29	0.309	0.29	0.2	0.005	0.00	0.40	0.085	0.78	0.00	0.003	0.01
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$						3		5	30		7	0		9	3		1
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	MA	Countr	AR	SET	MS	AR	SET	MS									
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	PE	<u>y</u>		AR	AR		AR	AR									
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Australı	4.79	1.708	63.8	62.7	73.37	71.9	0.0	0.050	0.05	43.7	7.135	48.2	0.30	0.693	0.23
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		a	2	10.05	42	08	0	48	96	0.214	9	94	1.650	99	/	2.267	2
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Brazii	16.9	18.25	16.0	194.	203.0	180.	0.5	0.314	1.22	11.2	1.550	0.70	1.62	2.337	16.0
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $		Canada	2 75	1 808	2.94	412	142.2	261	97	0.044	7 59	00.3	25.46	202	2	0.056	95
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Callaua	6	4.090	2.01	860	70	930	17	0.044	6	67	23.40	790	0.10	0.050	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		India	1 21	1.079	0.75	15.9	13 55	12.7	03	0.138	0.20	7.01	5 733	7.02	0.32	0.479	1 94
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		mana	4	1.075	6	80	2	54	83	0.150	7	7	0.100	1	5	0.175	1.5 1
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		Japan	0.64	0.494	0.89	149.	95.79	137.	0.1	0.125	0.08	4.86	27.88	76.1	0.61	0.838	0.58
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		· ·· [· ···	2		2	070	3	467	17		6	6	8	49	0		8
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		South	12.7	23.72	14.0	499.	583.6	566.	0.5	0.392	0.10	3.02	2.841	3.34	0.25	0.148	0.40
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Africa	85	1	76	624	10	222	51		7	4		5	7		6
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		Turkey	12.2	3.443	12.7	18.6	18.18	14.1	0.4	0.473	0.40	6.24	1.638	14.8	0.10	0.174	0.17
UK 2.60 3.176 3.11 32.1 33.56 27.1 0.2 0.171 0.07 7.94 3.517 146. 0.12 0.096 0.09 6 9 15 9 56 25 7 4 386 7 5 USA 70.4 78.37 70.6 0.4 0.113 0.14 131. 23.87 254. 0.06 0.053 0.22 79 2 62 93 4 774 0 060 0 8			60		82	30	6	70	63		3	6		15	4		1
6 9 15 9 56 25 7 4 386 7 5 USA 70.4 78.37 70.6 0.4 0.113 0.14 131. 23.87 254. 0.06 0.053 0.22 79 2 62 93 4 774 0 060 0 8		UK	2.60	3.176	3.11	32.1	33.56	27.1	0.2	0.171	0.07	7.94	3.517	146.	0.12	0.096	0.09
USA 70.4 78.37 70.6 0.4 0.113 0.14 131. 23.87 254. 0.06 0.053 0.22 79 2 62 93 4 774 0 060 0 8			6		9	15	9	56	25		7	4		386	7		5
<u>79</u> 2 62 93 4 774 0 060 0 8		USA				70.4	78.37	70.6	0.4	0.113	0.14	131.	23.87	254.	0.06	0.053	0.22
			1			79	2	62	93		4	774	0	060	0		8

Table 2b	
RMSE, MAP & MAPE for 5 year (21-Quarters) ahead forecas	t

		Exchange rate			GDP growth				Log(CPI)	I	nterest Ra	ate	Log (Industrial					
																	I	Production	n)
RM	Country	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS			
SE			AR	AR		AR	AR		AR	AR		AR	AR		AR	AR			

(Table Continued.....)

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	Australia	L 0 1	0.134	0.12	03	0.375	0.36		0.030	0.01	31	3 731	4.10		0.080	0.08
	Australia	46	0.154	4	66	0.575	3	50	0.050	0.01	67	5.751	4.10 0	94	0.000	4
	Brazil	1.1	0.652	1.11	1.2	1.322	1.25	1.3	0.081	1.87	0.7	0.063	0.35	0.0	0.059	0.07
		23		2	73		1	40		5	60		2	56		0
	Canada	0.1	0.119	0.12	0.4	0.485	0.47	0.7	0.011	0.03	3.2	1.422	3.01	0.0	0.019	0.06
		12		0	70		6	75		3	30		9	69		1
	India	0.3	0.287	0.17	0.4	0.557	0.65	0.2	0.032	0.02	2.4	2.141	2.14	0.0	0.248	0.19
		09		7	56		6	31		5	22		4	76		1
	Japan	0.1	0.138	0.10	1.2	1.254	1.20	0.0	0.016	0.03	0.0	0.889	0.83	0.0	0.895	0.03
	0 4	89	2.000	8	17	0.501	8	25	0.057	4	43	2.024	4	29	0.002	
	Africa	4.0	3.000	4.55	0.5	0.501	0.51	51	0.057	0.04	2.0	2.924	3.32 4	32	0.085	0.07
	Turkey	0.7	0.784	0.95	0.6	0 740	0.79	0.2	0.037	0.26	56	5 049	9.10	0.0	0.059	0.04
	,	53		1	92		7	79		7	49		1	41		3
	UK	0.0	0.050	0.04	0.3	0.339	0.34	0.0	0.020	0.04	0.1	0.187	4.44	0.0	0.048	0.05
		34		2	27		1	74		4	70		6	40		8
	USA				0.4	0.462	0.47	0.0	0.013	0.02	2.1	0.669	6.63	0.0	0.063	0.06
	<u> </u>		OPT	240	70	CET	8	61	OPT	3	74	CET	4	91	CET	1
MA	Country	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS
E	Australia	0.1	0.087	0.08	0.2	0.280	0.28	0.0	0.028	0.00	27	3 207	3.61	0.0	0.070	0.07
	Australia	0.1	0.087	8	89	0.289	5	42	0.028	9	76	3.291	9	83	0.070	4
	Brazil	0.8	0.421	0.83	1.0	1.076	0.99	1.0	0.067	1.35	0.7	0.143	0.32	0.0	0.053	0.04
		44		5	13		3	87		6	26		4	34		5
	Canada	0.0	0.077	0.07	0.3	0.400	0.39	0.7	0.009	0.03	2.9	1.322	2.59	0.0	0.016	0.05
		74		- 7	90	-	7	25		0	37		5	62	-	4
	India	0.2	0.258	0.15	0.2	0.345	0.43	0.1	0.026	0.01	2.1	1.891	1.89	0.0	0.214	0.16
		79		8	83		1	98		9	35		7	66		5
	Japan	0.1	0.118	0.09	0.9	0.967	0.92	0.0	0.012	0.02	0.0	0.694	0.71	0.0	0.589	0.03
	<u> </u>	58	2.102	2	39	0.410	0	18	0.051	4	41	0.555	3	23	0.075	0
	South	3.8	2.192	3.70	0.4	0.418	0.41	0.1	0.051	0.04	2.4	2.577	3.07	0.0	0.075	0.06
	Turkey	41	0.657	0.70	0.5	0.573	9	20	0.027	0.22	15	4 262	7.50	20	0.055	0.03
	Turkey	0.0	0.057	1	68	0.575	3	24	0.027	4	99	4.202	0	34	0.055	5
	UK	0.0	0.037	0.03	0.2	0.259	0.27	0.0	0.019	0.04	0.1	0.160	4.04	0.0	0.047	0.05
		25		2	55		3	69		3	39		6	37		5
	USA				0.3	0.373	0.39	0.0	0.012	0.01	1.9	0.598	3.40	0.0	0.056	0.05
					90		6	56		7	75		3	79		2
MA	Country	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS	AR	SET	MS
PE	Accetuatio	0.1	AR 7.062	AR 0.72	75	AR	AK 75.1	0.0	AR	AR 0.19	106	AR 125.7	AR 129	17	AR 1.409	AK
	Australia	8.1 73	7.065	0.75	63	/3.83	90	0.9	0.396	0.18	100	125.7	158.	63	1.498	1.58
	Brazil	30	15.01	29.9	646	671.5	620	22	1 375	22.7	38	7 824	17.6	0.7	1 1 5 5	0.99
	Diazii	33	15.01	9	.2	071.5	21	33	1.575	25	87	7.024	17.0	59	1.155	8
	Canada	6.0	6.346	6.32	268	280.9	272.	17.	0.197	0.64	294	132.0	254.	1.3	0.330	1.51
		91		4	.1		63	34		0	.9	27	8	20		4
	India	6.7	6.287	3.85	113	136.3	154.	4.0	0.527	0.37	24.	21.53	21.2	1.4	4.578	3.52
		96	0.505	9	.5	251.0	24	03	0.0/7	5	23	4	2.17	13	10.05	7
	Japan	3.3	2.535	2.00	247	251.8	235.	0.3	0.267	0.51	17.	350.6	347.	0.4	12.85	0.66
	South	34	18.60	32.0	./	147.8	156	26	1.054	0.60	13	45.78	54.0	90	1.646	1.45
	Africa	26	18.00	0	8	147.0	38	62	1.054	9	12	45.78	54.9	0.0	1.040	8
	Turkey	25.	28.65	34.4	133	134.5	132	4.5	0.553	4.55	47.	42.97	76.8	0.7	1.182	0.76
)	68		0	.4	29	12	47		4	87	5		42		1
	UK	3.8	5.716	4.96	115	118.1	124.	1.4	0.403	0.91	21.	25.67	717.	0.8	1.017	1.19
		85		0	.5	52	65	75		1	07	6	2	16		9
	USA				262	238.2	268.	1.2	0.258	0.37	110	364.6	1888	1.6	1.186	1.11
		1			1	19	85	01		3	9	54		70		4

NOTE: Forecast evaluation criteria techniques MAE, MAPE and RMSE are used.

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Exchange rate

The comparison of forecasting performance for short-run forecasting of the exchange rate is presented in Table 2a, while for long run forecasting comparison, the results are shown in Table 2b. Most of the results are in favor of nonlinear models for short-run forecasting. As the SETAR and MS-AR contains the lowest forecasting errors in five out of nine countries for the exchange rate, in which SETAR models technique have better prediction ability performance for exchange rate of Australia, Japan, and Turkey with the lowest forecasting errors. The MS-AR modeling technique is much better for developing countries such as India and Brazil as compared to the SETAR and Linear AR models. But linear AR models is also a suitable technique for the forecasting purpose for developed countries such as Canada and the UK, while it is also a better forecasting technique for South Africa which is a developing country.

For the long run forecasting, the linear AR modeling technique is a better choice for the two developed countries e.g. Canada and the UK. While the SETAR modeling technique has the best forecasting performance as compared to the AR and MS-AR models for Australia and two developing countries Brazil and South Africa. MS-AR modeling technique has the lowest forecasting error for exchange rates of India and Japan (Table 2b).

GDP growth

The Comparison of forecasting techniques for the short-run horizons also takes account for the Gross domestic product of countries, displayed in Table 2a. The best forecasting technique for theGDP growth of Brazil, India, Turkey and the UK is MS-AR technique, using the multi-comparison criteria. Furthermore, SETAR is the best forecasting model for the most developed countries named Canada and Japan. Linear AR modeling technique is better among SETAR and MS-AR for GDP growth of Australia, USA, and South Africa. For long run forecasting (Table 2b), linear AR models are superior for GDP growth of Canada, India, UK and Turkey. SETAR modeling technique is best for South Africa and the USA while the MS-AR modeling technique is far better than linear AR and SETAR for GDP growth of Australia, Brazil, and Japan.

Consumer Price Inflation

The CPI is a measure that studies the average of prices of a consumer goods and services. It is one of the most important macroeconomic variables for any country. The performance for the short-run forecasting for CPI totally supports the nonlinear regime models. The SETAR modeling technique is the best one among all the other forecasting techniques for the CPI for Australia, Brazil, Canada, India, and the USA. While the MS-AR technique is the most suitable and better forecasting modeling technique for Japan, UK, South Africa and Turkey. All the information criteria fully

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supported the results. For long run forecasting prospect, again CPI of all countries including developed countries, favors the nonlinear regime models. The SETAR modeling technique has superior forecasting ability for Brazil, Turkey, and all developed countries (included in this study) as compare to the MS-AR technique except Australia, India, and South Africa which has the lowest forecasting errors for MS-AR.

Interest rate

According to the results shown in Table 2a, for short-run forecasting prospect, the SETAR modeling technique is the most superior among the MS-AR and linear AR model for the interest rate of all countries except Japan. For long run forecasting prospect, again SETAR is the most powerful forecasting technique for Brazil, Canada, India, turkey and the USA while the MS-AR is not suitable for the interest rate time series. All in all, the SETAR modeling techniques is the most suitable forecasting technique for the interest rate.

Industrial production

Industrial or manufacturing production is the backbone of the economy of any country. The results can be seen above table for the purpose of short-run forecasting comparison. MS-AR modeling technique has the lowest forecasting error for Industrial production of Australia, Japan, and the UK while SETAR model is a suitable forecasting technique for industrial production of Canada and South Africa. The linear AR model is best among nonlinear models for the remaining four countries. According to our results, the long run forecasting outcome is the most surprising result. As the linear AR modeling technique has the superior forecasting ability for most of the countries except Australia, Canada and USA in which the SETAR and MS-AR are better forecasting techniques.

Conclusion

In this research paper, the forecast performance of two famous regime models namely Self-exciting threshold SETAR models and Markov regime switching autoregressive MSAR models is evaluated viz-a-viz the linear AR model using the data of some important macroeconomic variables namely exchange rate, consumer price inflation, gross domestic product growth, interest rate and industrial production. Quarterly data from 1960 to 2016 are employed from some important developed countries including the G7 countries and some important developing countries including the BRICS countries. The literature has presented conflicting results regarding this comparison. It is found that both the SETAR and MSAR models are empirically more powerful than the linear AR model using the three forecast evaluation criteria by means of shocks and particular characteristics. One of the main reason regarding the inability of the less satisfactory performance of the linear AR models that these generally fail to capture the stylized behavior some economic time series i.e. structural breaks and asymmetries in business cycle recessions and expansions.

In some cases, especially with industrial production, there is evidence suggesting that the forecasting power of nonlinear regime models is not much superior to linear model. In the short-run, the forecasting performance of SETAR model is better than MSAR model for the exchange rate and inflation of different countries. For interest rate variable the forecasting power of SETAR model is superior for all the developed and developing countries.

The MSAR model gives more accurate forecast for GDP growth for most of the countries. However, there is not much difference in the forecasting ability of the MSAR model for exchange rate and inflation. Empirically, the forecasting power of linear AR model is found to be better than nonlinear models in few cases of the exchange rate, GDP growth and industrial production especially for developing countries thus supporting the De-Gooijer and Kumar (1992) conclusion who also found superiority of linear mode's forecast in some cases. For the long run, the forecast performance of the SETAR model is superior to the MSAR and linear AR models for the exchange rate and interest rate and inflation for most of the countries. Overall, it is found that the nonlinear models namely the SETAR and MSAR yield better forecasts. It is also found that the forecasting performance of SETAR model is superior to the MSAR and linear AR models for both the short run and long run forecasting horizons for all the macroeconomic time series related to the developed and developing countries. Thus when nonlinearity and structural changes are present in the time series data, the linear models do not perform satisfactory as compared to the nonlinear models.

References

- Altinay, G. (2005). Structural breaks in long-term Turkish macroeconomic data, 1923-2003. Applied Econometrics and International Development, 5(4), 117-130.
- Anderson, H. M., & Vahid, F. (1998). Testing multiple equation systems for common nonlinear components. *Journal of Econometrics*, 84(1), 1-36.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of* econometrics, 31(3), 307-327.
- Clements, M. P., &Krolzig, H. M. (1998). A Comparison of the Forecast Performance of Markov switching and Threshold Autoregressive Models of US GNP. *The Econometrics Journal*, 1(1), 47-75.
- Clements, M. P., & Smith, J. (1997). The performance of alternative forecasting methods for SETAR models. *International Journal of Forecasting*, 13(4), 463-475.
- Clements, M. P., Franses, P. H., & Swanson, N. R. (2004). Forecasting economic and financial timeseries with non-linear models. *International Journal of Forecasting*, 20(2), 169-183.
- De Gooijer, J. G., & Kumar, K. (1992). Some recent developments in non-linear time series modelling, testing, and forecasting. *International Journal of Forecasting*, 8(2), 135-156.
- Deschamps, P. J. (2008). Comparing smooth transition and Markov switching autoregressive models of US unemployment. *Journal of Applied Econometrics*, 23(4), 435-462.

- Diebold, F. X., &Nason, J. A. (1990). Nonparametric exchange rate prediction?. Journal of international Economics, 28(3-4), 315-332.
- Engel, C. (1994). Can the Markov Switching Model forecast exchange rates?. Journal of International Economics, 36(1-2), 151-165.
- Feng, H., & Liu, J. (2003). A SETAR model for Canadian GDP: non-linearities and forecast comparisons. *Applied Economics*, 35(18), 1957-1964.
- Fraz, T.R, & Fatima, S. (2016). Exploring the Impact of Macro Economic Variables on Exchange Rate: A Case of some Developed and Developing Countries. *Pakistan Journal of Applied Economics, Special Issue*, 299-315.
- Glynn, J., Perera, N., Verma, R., (2007). Unit root tests and structural breaks: a survey with applications. Journal of Quantitative Methods for Economics and Business Administration, 3(1), 63–79
- Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, 357-384.
- Hsu, K. H., Li, J. F., Lin, Y. B., Hong, C. Y., & Huang, Y. C. (2010). A SETAR Model for Taiwan Stock Exchange Capitalization Weighted Stock Index: Non-linearities and Forecasting Comparisons. Finance paper series, 13(1), 74-88.
- Kosater, P., & Mosler, K. (2006). Can Markov regime-switching models improve power-price forecasts? Evidence from German daily power prices. *Applied Energy*, 83(9), 943-958.
- Kunst, R.M. (2012). Econometric Forecasting. University of Vienna & Institute for Advanced Studies Vienna, 41-75.
- Ling, T. Y., Nor, A. H. S. M., Saud, N. A., & Ahmad, Z. (2013). Testing for Unit Roots and Structural Breaks: Evidence from Selected ASEAN Macroeconomic Time Series. *International Journal* of Trade, Economics and Finance, 4(4), 230-237.
- Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of macroeconomics*, 2, 71-162.
- Swanson, N. R., & White, H. (1995). A model-selection approach to assessing the information in the term structure using linear models and artificial neural networks. *Journal of Business & Economic Statistics*, 13(3), 265-275.
- Teräsvirta, T. (2006). Forecasting economic variables with nonlinear models. *Handbook of economic forecasting*, *1*, 413-457.
- Zhou, C., Wu, Y. L., Chen, G., Feng, J., Liu, X. Q., Wang, C., ... & Lu, S. (2011). Erlotinib versus chemotherapy as first-line treatment for patients with advanced EGFR mutation-positive non-small-cell lung cancer (Optimal, Ctong-0802): a multicentre, open-label, randomised, phase 3 study. *The lancet oncology*, 12(8), 735-742.