Available online at www.sciencedirect.com

ScienceDirect

The Journal of Finance and Data Science 4 (2018) 90−100

http://www.keaipublishing.com/en/journals/jfds/

Forecasting performance of smooth transition autoregressive (STAR) model on travel and leisure stock index

Usman M. Umer [a,*], Tuba Sevil [b], Güven Sevil [c]

[a] *Graduate School of Social Sciences, Anadolu University, Eskişehir, Turkey*

[b] *Sports Science Faculty, Anadolu University, Eskişehir, Turkey*

[c] *Open Education Faculty, Anadolu University, Eskişehir, Turkey*

Received 22 September 2017; accepted 23 November 2017

Available online 26 December 2017

Abstract

Travel and leisure recorded a consecutive robust growth and become among the fastest economic sectors in the world. Various forecasting models are proposed by researchers that serve as an early recommendation for investors and policy makers. Numerous studies proposed distinct forecasting models to predict the dynamics of this sector and provide early recommendation for investors and policy makers. In this paper, we compare the performance of smooth transition autoregressive (STAR) and linear autoregressive (AR) models using monthly returns of Turkey and FTSE travel and leisure index from April 1997 to August 2016. MSCI world index used as a proxy of the overall market. The result shows that nonlinear LSTAR model cannot improve the out-of-sample forecast of linear AR model. This finding demonstrates little to be gained from using LSTAR model in the prediction of travel and leisure stock index.

Keywords: Nonlinear time-series; Out-of-sample forecasting; Smooth transition autoregressive; Travel and leisure

1. Introduction

In recent years, travel and leisure emerged to become the most important economy activity around the world. According to UN World Tourism Organization[1] travel and tourism contribute $7.2 trillion and 283.5 million job opportunities to the global economy in 2015, and leisure travel spending comprises of 76.6% of travel and tourism GDP. Especially, international tourists spending have a positive contribute to the foreign exchange earnings, balance of payment and consequently to the national economy of destination country. Given a significant role of travel and leisure in the global economy, reliable forecast of this sector is important for policy decision making and generating positive return from investment.

* Corresponding author.

E-mail address: usman_mu@anadolu.edu.tr (U.M. Umer).

Peer review under responsibility of China Science Publishing & Media Ltd.

https://doi.org/10.1016/j.jfds.2017.11.006

Despite, a wide range of techniques have been proposed by researchers to successfully forecast the dynamics in this sector, there is no conclusive model that outperform others in all forecast accuracy criteria. Earlier studies on forecasting travel and leisure used traditional linear modeling techniques such as Autoregressive Integrated Moving Average (ARIMA) specifications. Due to advancement in econometric techniques and pervasiveness of nonlinear behavior in some financial and economic time series, nonlinear techniques such as artificial neural networks (ANNs), exponential smoothing (ETS), regime switching models and fuzzy time series become widely applied to achieve higher level of forecasting accuracy.

The forecasting performance of both linear and nonlinear models investigated by numerous studies. Kulendran and Witt[2] compare the forecasting performance of ARIMA-type models against a basic structural model, a causal structural time-series model and the naive specification. Their finding shows that ARIMA models outperform others in the short-run forecasts and naïve model in the mid-run. A study of Vu and Turner[3] confirms that ARIMA model exhibit superior forecasting accuracy relative to basic structural model. Similarly, Chu[4] investigate the performance of regression models, naïve models and ARIMA specifications, and report better predictive ability of fractionalized ARIMA (ARFIMA) model in both short-run and long-run, and seasonal autoregressive integrated moving average (SARIMA) specification in the long-run. On the other hand, to uncover the most reliable forecasting technique, Hassani et al[5] evaluate nine alternative parametric and nonparametric models; and indicate the least accurate prediction of fractionalized ARIMA (ARFIMA) and neural networks specifications.

Law[6] examine the feasibility of backpropagation neural networks to forecast tourism demand, and show outstanding performance of backpropagation neural network relative to regression models and feed-forward neural networks. Xu et al[7] examine the applicability of fuzzy Takagie-Sugeno rules extracted from support vector machines (SVMs) method, and demonstrate the superiority of this method for tourism demand predictions. Furthermore, Li et al[8] proposed generalized dynamic factor model (GDFM) to forecast tourism demand. They argue that GDFM improve the forecast accuracy of traditional regression models.

Nonlinear time-series models are widely advocated to characterize the asymmetric dynamics of data. One of these models which allows regime switching is the smooth transition autoregressive (STAR) model of Luukkonen et al[9] and Teräsvirta.[10] STAR model is an extended version of the popular Autoregressive (AR) model that imply the existence of nonlinear behavior in the time series. In this model the transition between regimes exogenously determined by the transition function, which is commonly described as either logistic or exponential function. STAR model allows researchers to explain the nonlinear dynamics of financial and economic time series, although empirical studies provide mixed results in favor of STAR model.

STAR model is widely applied in macroeconomic studies. Leybourne and Mizen[11] use STAR models to investigate the disinflations in three countries, and Skalin and Teräsvirta[12] to examine the nonlinearities in Swedish business cycle. Sarantis[13] investigate real exchange rate of G-10 countries and report the absence of much difference in out-of-sample forecasting performance between STAR and linear model. Similar results are also reported by Boero and Marrocu[14] using three exchange rates. On the other hand, Bradley and Jansen[15] investigate the forecasting performance between linear and STAR models and found the superiority of STAR model against linear models to forecast industrial production. Moreover, Teräsvirta et al[16] examine the performance of STAR model using 47 macroeconomic variables of the G7 economies. The result shows that forecasting performance of STAR model outperforms linear AR models.

In the tourism sector, Claveria and Torra[17] analyze the forecasting ability of ARIMA, ANN and STAR specifications for tourism demand. They find that the forecasting accuracy of ARIMA model outperform nonlinear self-exciting threshold autoregressive (SETAR) and ANN models, especially in the short-term. On the other hand, Saayman and Botha[18] compare the ability of SARIMA, STAR, the basic structural model (BSM) and singular spectrum analysis (SSA) to forecast tourism demand by allowing structural breaks in the data. They show the superior performance of nonlinear models relative to SARIMA model.

In this paper, we employ monthly travel and leisure index from April 1997 to August 2016 to investigate whether forecasts from STAR model outperform the linear autoregressive model. In order to compare the quality of forecast between these models, we apply root mean squared forecast error (RMSE), the mean absolute forecasts errors (MAE) and the most versatile forecast accuracy tests of Diebold and Mariano (DM, 1995). The rest of the paper structured as follows: Section 2 introduces the method used to examine the forecasting ability of STAR and linear AR models. Section 3 describes the data and demonstrates the performance of travel and leisure index. Section 4 presents empirical result of the study and examine the predictive performance of models. Section 5 the conclusions.

2. Methodology

This study adopts the smooth transition autoregressive (STAR) modeling framework, which was developed by Luukkonen et al[9] and Teräsvirta,[10] to examine the dynamics in stock index of travel and leisure sector. In financial markets, stock index has been observed to exhibit different characteristics under different state of economy, for instance high volatility or lower mean values usually during recession. Therefore, adopting a model that switch smoothly from one regime to another enables to better understand the underling dynamics. Numerous empirical studies point out the nonlinearity of many economic and financial data due to structural and behavioral changes, and suggest a nonlinear model over linear models that enable to account excessive changes in economic settings. The nonlinear STAR models have been advocated for their superiority to capture a state-dependent features and allow financial trends to switch smoothly rather than discrete. Tse[19] employ STAR models to examine the reaction between cash and future markets in response to Dow Jones index futures mispricing. Moreover, the regime switch dynamics of credit default swap (CDS) has been characterized using STAR models by Huang and Hu,[20] and argues the effectiveness of these models to differentiate price regimes.

2.1. The STAR model

2.1.1. The basic framework

A basic representation of STAR model for a univariate time series can be specified as:

$$\Delta y_t = \vartheta' x_t + \vartheta' x_t G(s_t;\gamma,c) + \varepsilon_t \tag{1}$$

where, Δ is the first difference operator, y_t is the dependent variable; $x_t = (1, y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$ is a vector that represents all the right hand side explanatory variables; $\vartheta = (a, \phi_{1,}\ \phi_2, \ldots, \phi_{p-1})'$ is a vector of parameter to be estimated. $G(s_t;\gamma,c)$ is a continuous transition function, which is bounded by 0 and 1, and s_t is a transition variable. The parameter γ represents the speed and smoothness of transition, while c can be interpreted as threshold between two regimes. ε_t is the error term, such that $\varepsilon_t \sim idd(0,\sigma^2)$. This model defined as two-regime switching model, in which the transition function G allows the dynamics of model to switch between regimes in a smoothly manner.

A common specification of the generalized version of smooth transition functions is given by

$$G(s_t;\gamma,c) = \left\{1 + \exp\left[-\gamma/\sigma_{st}^k \prod_k (s_t - c_k)^k\right]\right\}^{-1} \tag{2}$$

where σ_{st} is the standard deviation of the transition variable. The two most widely adopted version of the general smooth transition functions to explain the regime switching patter in financial assets are the logistic function and the exponential functions, and the resulting logistic STAR (LSTAR) and exponential STAR (ESTAR) models.

A logistic function can be derived from the general transition functions by setting $k = 1$;

$$G(s_t;\gamma,c) = \{1 + \exp[-\gamma/\sigma_{st}(s_t - c)]\}^{-1}, \quad \gamma > 0 \tag{3}$$

On the other hand, an alternative exponential function can be represented as;

$$G(s_t;\gamma,c) = \left\{1 - \exp\left[-\gamma/\sigma_{st}^2 (s_t - c)^2\right]\right\}, \quad \gamma > 0 \tag{4}$$

If γ is large both logistic function and the exponential transition functions switch between 0 and 1 more quickly, and the reverse is true when γ is small. As shows in Fig. 1, when $\gamma \to 0$, the logistic function $G(\cdot)$ approaches the constant value and the LSTAR model reduces to a linear AR model; alternately this model converges to threshold autoregressive (TAR) model when $\gamma \to \infty$. The ESTAR model reduces to a linear AR model either $\gamma \to 0$ or $\gamma \to \infty$.

2.1.2. Nonlinearity test and estimation

Teräsvirta[10] provide detailed procedures regarding STAR modeling processes. The first step is to identify the lag length from the AR estimate; Schwartz Bayesian Criterion (SBC) or Akaike Information Criterion (AIC) can be used to determine lag length. The second step is linearity test. Testing for linearity is usually the first step towards employing non-linear model, since non-linear frameworks including STAR models should only be used if the null hypothesis of linearity is rejected; otherwise a linear model would be appropriate for modeling the underlying data. Testing linearity against STAR-type nonlinearity implies testing the null hypothesis of H_O:ϑ=0, both γ and c are nuisance parameters and would take any value as they are not identified under the null. Alternatively, if the null hypothesis was H_O: γ=0, then neither ϑ nor c would be identified. To mitigate this problem, Luukkonen et al[9] propose an auxiliary regression by replacing the transaction function $G(s_t;\gamma,c)$ with Taylor series approximation.

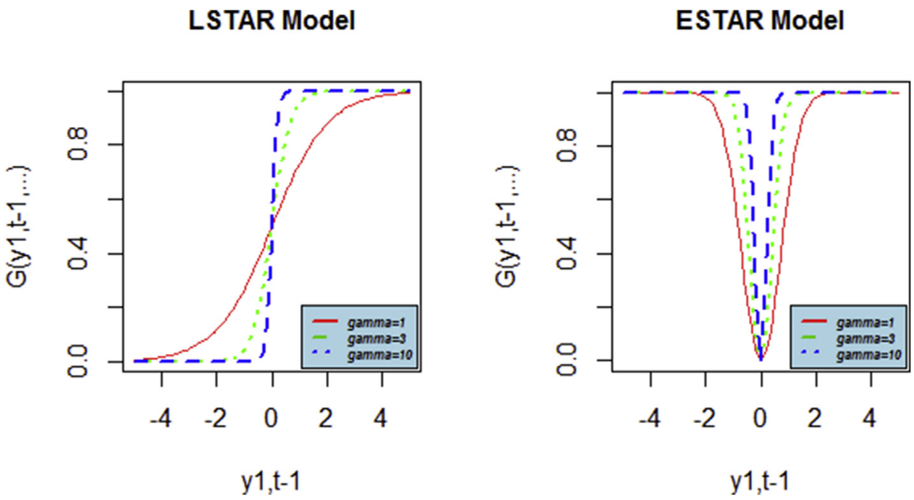

Fig. 1. Shape of logistic and exponential transition functions.

Since, using lower order power in the auxiliary regression of logistic function can make the process explosive and non-meaningful time series model, Luukkonen et al[9] suggests to include up to third order powers. Hence, when the transaction function in the LSTAR replaced by the third order Taylor series expansion, the LSTAR model can be specified as

$$\Delta y_t = \vartheta_0' x_t + \sum_{i=1}^{3} \vartheta_i' x_t s_t^i + e_t \tag{5}$$

where Δ is the first difference operator, that is $\Delta y_t = y_t - y_{t-1}$; e_t is the error term that combines the original error term ε_t, and the error resulting from the Taylor expansion. $\vartheta_i = (\vartheta_1, \vartheta_2, \vartheta_3)'$ are the vector of parameters form auxiliary regression. The null hypothesis of linearity in the above non-linear STAR models auxiliary regressions, $H_0' = \vartheta_1 = \vartheta_2 = \vartheta_3 = 0$, can be tested against the non-linear STAR models using the Lagrange multiplier (LM) test of statistics with an asymptotic χ^2 distribution.

After verifying the existence of nonlinearity in a time series, the last step is to set transition variable and select suitable form of transition function $G(s_t; \gamma, c)$ and to determine the appropriate nonlinearity STAR-type model. The specification of the STAR model can be made based on a sequence of hypothesis testes, in the context of Eq. (5),

$$H_{O,1} : \vartheta_3 = O$$

$$H_{O,2} : \vartheta_2 = O | \vartheta_3 = 0$$

$$H_{O,3} : \vartheta_1 = O | \vartheta_2 = \vartheta_3 = 0$$

The test for linearity against LSTAR model is equivalent to testing the null hypothesis of $H_{O,1}$ and $H_{O,2}$, alternatively the test against ESTAR model relies on hypothesis $H_{O,3}$. The decision rule to choose between LSTAR and ESTAR models has been proposed by Teräsvirta.[10] If $H_{O,1}$ is rejected, choose LSTAR model. On the other hand, if $H_{O,1}$ is accepted and $H_{O,2}$ rejected it can be interpreted as evidence in support of ESTAR against LSTAR model. Alternatively, if $H_{O,1}$ and $H_{O,2}$ are accepted but $H_{O,3}$ rejected, supports the choice of LSTAR model. Once the appropriate model is selected, the model can be estimation using nonlinear least square.

2.1.3. Forecasting with STAR model

Forecasting one-step and multi-steps-ahead is possible using both linear and nonlinear models. However, forecasting with a nonlinear model beyond one-step-ahead is more complex than linear model. In one-step-ahead forecast the estimate of parameters are carried out using the lagged value of some information set, however lack of information and accumulation of errors makes multi-step-ahead forecast more complicated. Therefore, selecting a proper forecasting method is crucial as length of forecast horizon increases. For instance, for a time series y_t an autoregressive (AR) model, that would be a nonlinear model with an additive error term, can be specified as

$$y_t = f(x_t; \vartheta) + \varepsilon_t \tag{6}$$

where $x_t = (y_{t-1}, y_{t-2}, \ldots, y_{t-p})'$ is a vector that represents all the right-hand side explanatory variables; $\vartheta = (a, \phi_1, \phi_2, \ldots, \phi_{p-1})'$ is a vector of parameter to be estimated. The one-step ahead forecast for y_{t+1} can be written as

$$\widehat{y}_{t+1|t} = f\left(x_{t+1};\widehat{\vartheta}_t\right) = E\left\{f\left(x_{t+1};\widehat{\vartheta}_t\right) + \varepsilon_{t+1}\right\} \tag{7}$$

where $\widehat{\vartheta}_t$ denotes the parameter estimate that are obtained using observation up to period t. The two-step ahead forecast can be constructed as

$$\widehat{y}_{t+2|t} = \int_{-\infty}^{\infty} f\left(\widehat{y}_{t+1|t} + \varepsilon_{t+1},\, x_{t+2};\widehat{\vartheta}_t\right)d\varepsilon_{t+1} = E\left\{f\left(\widehat{y}_{t+1|t} + \varepsilon_{t+1}, x_{t+2};\widehat{\vartheta}_t\right)|\Omega_t\right\} \tag{8}$$

where Ω_t represents the information set available at the time of t. As the forecast horizon increases, the dimension of integral would grow to obtaining point forecast. To avoid numerical integration in multi-step forecast and provide a good approximation of integral, simulation or bootstrap re-sampling residual procedure can be applied (see Granger and Teräsvirta,[21] Teräsvirta et al,[16] and Ubilava and Helmers[22] for more details). In this paper, we apply the bootstrap approach. For a two-step-ahead bootstrap forecast, the $\widehat{y}_{t+2t}$ constructed

$$\widehat{y}_{t+2|t} = \frac{1}{k}\sum_{i=1}^{k}\widehat{y}_{t+2|t}(i) = \frac{1}{k}\sum_{i=1}^{k} f\left(\widehat{y}_{t+1|t} + \widehat{\varepsilon}^{i}_{i+1}, x_{t+2};\widehat{\vartheta}\right) \tag{9}$$

where k is some large number and the ith value of residuals, $\widehat{\varepsilon}^{i}_{i+1}$, are independently draw with replacement from the set of residuals in the estimated model up to time t. An h-ahead forecast, $\widehat{y}_{t+h|t}$, can be constructed by following similar procedures in Eqs (8) and (9).

There are numerous literatures on forecasting accuracy test, most of which are drowns from Granger and Newbold,[23] where comparing root mean squared forecast error (RMSE) and the mean absolute forecasts errors (MAE) of pair of alternative models under when normality condition is assumed. These forecast accuracy test computed as

$$\text{RMSE} = \left(\frac{1}{P}\sum_{i=1}^{P}\left(y_{P,t+h} - \widehat{y}^{k}_{P,t+h|t}\right)^2\right)^{\frac{1}{2}}, \text{and MAE} = \frac{1}{P}\sum_{i=1}^{P}\left|y_{P,t+h} - \widehat{y}^{k}_{P,t+h|t}\right|^2 \tag{10}$$

where P denotes the forecast period. The smaller the RMSE and MAE values, the smaller the forecast errors and the better forecast performance.

The most versatile and widely used forecast accuracy tests to compare the quality of forecast between competing models in empirical studies is the Diebold and Mariano (DM)[24] test. In this test the forecast error from two models, $y^1_{t+\mathrm{h}|t}$ and $y^2_{t+\mathrm{h}|t}$ computed as $e^i_{t+\mathrm{h}|t} = y_{\,t+\mathrm{h}} - y^i_{t+\mathrm{h}|t}, i = 1, 2$. The DM statistic test written as:

$$\widehat{d}_P = P^{-1/2}\,\frac{\sum_{t=R-h+1}^{T-1}\left(f\left(\widehat{e}^1_{t+h}\right) - f\left(\widehat{e}^2_{t+h}\right)\right)}{\widehat{\sigma}_P} \tag{11}$$

where R is the estimation period, P the forecast period, f is loss function, $f(e^i_{t+\mathrm{h}|t}) = f(y_{\,t+\mathrm{h}}, y^i_{t+\mathrm{h}|t})$ $\quad i = 1, 2$ and T is the sample size. $\widehat{e}^1_{t+\mathrm{h}}$ and $\widehat{e}^2_{t+\mathrm{h}}$ are h-step ahead forecast errors for model 1 and 2. $\widehat{\sigma}^2_P$ can be specified as

$$\widehat{\sigma}^2_P = \frac{1}{P}\sum_{t=R-h+1}^{T-1}\left(f\left(\widehat{e}^1_{t+h}\right) - f\left(\widehat{e}^2_{t+h}\right)\right)^2 + \frac{2}{P}\sum_{t=R-h+1+j}^{lP} w_j\left(f\left(\widehat{e}^1_{t+h}\right) - f\left(\widehat{e}^2_{t+h}\right)\right)\left(f\left(\widehat{e}^1_{t+h-j}\right) - f\left(\widehat{e}^2_{t+h-j}\right)\right) \tag{12}$$

where $w_j = \frac{j}{lP+1}, lP = o(P^{1/4})$. The null hypothesis of equal forecasting accuracy that derived from the loss differential is

$$\mathbf{H_0} : E\left(f\left(e^1_{t+h}\right) - f\left(e^2_{t+h}\right)\right) = 0,\ \ and$$
$$\mathbf{H_1} : E\left(f\left(e^1_{t+h}\right) - f\left(e^2_{t+h}\right)\right) \neq 0$$

The DM test shows that the statistic is asymptotically distributed $N(0, 1)$. When one competing model nested another, the DM test is not applicable. A modified version of DM test proposed by Clark and McCracken (CM)[25] allows comparison of out of sample unconditional forecasting ability between nested models. Moreover, it follows a Student's t-distribution with (T − 1) degrees of freedom, instead of a standard normal distribution under the null hypothesis. The CM test statistics is defined as

$$\widehat{d}^{*}_P = (P-1)^{1/2}\frac{\overline{\omega}}{\left(P^{-1}\sum_{t=R}^{T-1}\left(\omega_{t+h} - \overline{\omega}\right)\right)^{1/2}}, \tag{13}$$

Where $\omega_{t+h} = \hat{e}^1_{t+h}(\hat{e}^1_{t+h} - \hat{e}^2_{t+h})$ and $\overline{\omega} = P^{-1}\sum_{t=R}^{T-1}\omega_{t+1}$. The hypothesis in this test is the same as DM test, except the alternative hypothesis $\mathbf{H_1} : E(f(e^1_{t+h}) - f(e^2_{t+h})) > 0$ (see Bhardwaj and Swanson,[26] and Boutahar et al[27]). However, the Diebold−Mariano forecasting accuracy test has been employed to evaluate the quality of forecasting performance.

3. Data

The dataset in this study consists of Turkey travel and leisure index, FTSE CNBC Global 300 travel and leisure index and MSCI World index for the period April 1997 to August 2016. We employ the FTSE CNBC Global 300 travel and leisure index as a broad representation of travel and leisure sector. Travel and leisure sector is one of the largest and diverse classifications of FTSE. Since adding benchmark alongside the travel and leisure monthly data is helpful for comparing returns across periods, MSCI World index used as a proxy of the overall market. These data are monthly stock indices obtained from DataStream.

Table 1 reports the basic descriptive statistics for three series. The mean and standard deviation of returns for Turkey travel and leisure monthly returns are 1.7% and 11.2%, respectively. Annualized values of these are approximately 20.4% (0.017 × 12) and 38.8% (0.112 × $\sqrt{12}$) respectively. The corresponding annualized mean and standard deviation for FTSE and MSCI returns are 7.2% and 16.3%, and 2.4% and 17%, respectively. This implies that Turkey travel and leisure stock return has higher mean and volatility than FTSE travel and leisure and MSCI. Likewise, the average return of FTSE is higher than the benchmark MSCI return with a relatively similar volatility level, this indicates Travel and Leisure industry tend to outperform the market return. The skewness statistics which measures the degree of asymmetry in return distribution shows that all series display negative skewness, it reflects a short right tail than left tail. The sample excess kurtosis values for Turkey and FTSE are 1.1 and 0.9, inclined to normal distribution, however the tails of MSCI are slightly fatter than the tails of a normal distribution. From rational investor's perspective, assets with a relatively high average return, low volatility and positive skewness are preferred to a similar asset.

Fig. 2 shows a three-panel performance summary chart to display a set of related measures together for comparison across a set of index. The first chart is a normal cumulative return that shows the cumulative performance of each series through time. The Turkey travel and leisure index tend to outperform both the FTSE travel and leisure index and MSCI world index. The second chart shows Turkey travel and leisure index monthly returns. The third panel in the series is a drawdown chart, which shows the level of loss from the last maximum cumulative return attained.

It helps to assess the loss periods and compare the level of severity. Fig. 2 shows that all three indices drawdown between 2008 and 2009, during the Global financial crisis. The Turkish index experience the next highest drawdowns between 2011 and 2012. While, Turkey travel and leisure index have higher cumulate returns, it tends to have highest drawdowns than any of the other indices.

4. Empirical results

Before proceeding to the linearity test, we examine the stationary of time series using Augmented Dickey-Fuller (ADF) and Zivot-Andrews unit root tests and the result indicates that all series are integrated of order one at 1% and 5% significance level. We use the Schwartz Information Criterion to select the optimal lag length. The next step is to assess linearity against the alternative nonlinearity embedded in the STAR model. Linearity testing is essential for two primary reasons; first non-linear model applied if only non-linearity hypothesis is rejected and linearity model is not suitable, second it allows to determine the value for the delay parameter.

The linearity tests are presented in Table 2. In employing linearity test, we consider the value for the delay parameter d range from 1 to 4, and the lag p selected by BIC. The p-value for each case calculated and the corresponding d value is chosen by the lowest p-value. As can been from Panel A of the table, the linearity is rejected for FTSE and MSCI more strongly when $d = 2$ at 5% level of significance, however linearity is not rejected for Turkey in

Table 1
Descriptive statistics.

	Mean	St.dev	Skewness	Kurtosis
Turkey	0.017	0.112	−0.137	1.082
FTSE	0.006	0.047	−0.538	0.855
MSCI	0.002	0.049	−0.689	1.505

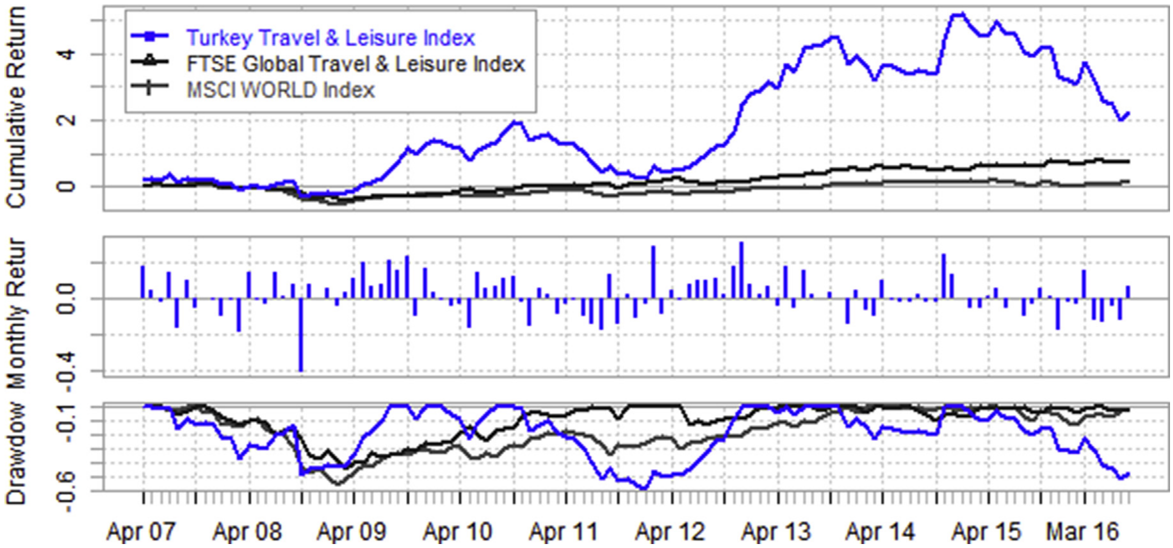

Fig. 2. Performance summary chart.

Table 2
Linearity tests.

	Panel A: p-Values of the Linearity Test for Various Values of *d*						
		d	**1**	**2**	**3**	**4**	
Turkey			0.986	0.958	0.637	0.988	
FTSE			0.153	0.013	0.016	0.285	
MSCI			0.092	0.028	0.116	0.139	
	Panel B: p-Values of the Linearity Tests						
	p	**d**	$\mathbf{H}_{0,1}$	$\mathbf{H}_{0,2}$	$\mathbf{H}_{0,3}$	$\mathbf{H}_{1,2}$	**Model**
Turkey	4	3	0.574	0.646	0.366	0.716	AR
FTSE	4	2	0.026	0.294	0.052	0.045	LSTAR
MSCI	3	2	0.003	0.338	0.574	0.009	LSTAR

The lag length in the AR model is determined according to Schwartz Bayesian Criterion (SBC). The delay parameter d is selected corresponding to the lowest *p*-value of the linearity test using the residual series of the AR process. Numbers in the column of panel B below the hypothesis are *p*-values corresponding to the test with the null of linearity.

all d values ($d \leq p$). It implies that apart from Turkey, the nonlinear model better explains the feature of FTSE and MSCI time series than a linear model. Since the equation for FTSE and MSCI can be modeled as STAR model, the next stage to specify the STAR model. A sequence of hypothesis testing undertaken based on the context of Eq. (5). The result in panel B shows the specification of appropriate nonlinearity STAR-type model through testing a sequence of hypothesis. In both FTSE and MSCI cases the nonlinearity appears to be the logistic form, which is in support of LSTAR model.

4.1. Estimates of linear AR and LSTAR models

A linear autoregressive model can be expressed as follows:

$$\Delta y_t = a_{10} + \beta'_{10} x_{t-1} + \sum_{i=1}^{p-1} \vartheta'_{1,\,i} \Delta x_{t-i} + \varepsilon_t \tag{14}$$

The nonlinear version of LSTAR model estimated as:

$$\Delta y_t = a_{10} + \beta'_{10} x_{t-1} + \sum_{i=1}^{p-1} \vartheta'_{1,i} \Delta x_{t-i} + \left(a_{20} + \beta'_2 x_{t-1} + \sum_{i=1}^{p-1} \vartheta'_{2,i} \Delta x_{t-i} \right) * G(s_t; \gamma, c) + \varepsilon_t \tag{15}$$

Estimation result of linear AR and two-regime LSTAR models are shown in Table 3. To illustrate the dynamics, column 2−4 reports the estimated parameters of linear AR model in Eq. (14) and column 5−7 presents the result of model estimation in Eq. (15). The estimated parameters of the transition function show that transition between regimes is quite different among series. The relative large value of the estimation of γ for MSCI suggests a very sharp transition from one regime to the other at 1% significance level, contrary to the estimate for Turkey which assumes a slow transition.

It is important to note that the estimation value of γ for FTSE suggests a quick transition between regimes. The estimated threshold value c for Turkey is negative and not significant. The threshold value between regimes c for FTSE and MSCI is 4.5% and −1.5% respectively. Despite the estimated coefficient vectors of α, β and ϑ for almost all series in linear AR model are significant, the coefficients corresponding to the estimate of LSTAR model are different for each series. For instance, none of the estimated coefficient of LSTAR model for Turkey is significant. The coefficient

Table 3
Estimation outcome from linear AR and LSTAR models.

	AR			LSTAR		
	Turkey	FTSE	MSCI	Turkey	FTSE	MSCI
a_{10}	−0.015**	−0.006*	−0.002	0.091	0.000	−0.044*
	(0.006)	(0.002)	(0.002)	(0.229)	(0.005)	(0.013)
$\beta_{1,0}$	0.904*	0.995*	0.897*	−0.454	−0.945*	−0.989*
	(0.054)	(0.045)	(0.061)	(1.164)	(0.236)	(0.217)
$\vartheta_{1,1}$	−0.776*	−0.756*	−0.626*	−0.114	−0.088	0.344***
	(0.050)	(0.037)	(0.051)	(1.383)	(0.205)	(0.207)
$\vartheta_{1,2}$	−0.505*	0.502*	−0.369*	−0.086	−0.343**	−0.586*
	(0.061)	(0.042)	(0.051)	(1.097)	(0.167)	(0.147)
$\vartheta_{1,3}$	−0.244*	−0.246*		0.646	−0.234**	
	(0.050)	(0.038)		(2.409)	(0.110)	
a_{20}				−0.139	0.102***	0.043*
				(0.364)	(0.058)	(0.014)
$\beta_{2,0}$				−0.167	−1.692	0.229
				(1.817)	(1.166)	(0.344)
$\vartheta_{2,1}$				−0.466	1.728***	−0.405
				(2.150)	(0.989)	(0.314)
$\vartheta_{2,2}$				−0.224	0.739**	0.594*
				(1.741)	(0.359)	(0.190)
$\vartheta_{2,3}$				−1.294	−0.004	
				(3.798)	(0.270)	
γ				5.045	648.020	4045.968*
				(15.482)	(3801.815)	(0.000)
c				−0.069	0.045*	−0.015*
				(0.460)	(0.014)	(0.000)
R^2	0.848	0.905	0.769	0.537	0.588	0.547
DW	0.529	0.492	0.781	1.978	2.096	2.138
JB	2.803	13.360*	54.544*	4.234	4.783***	0.315
Q(4)	113.895*	119.518*	65.465*	0.347	0.464	3.375
Q(12)	130.020*	137.255*	80.743*	12.206	7.981	8.865
ARCH(p)	8.834*	19.030*	13.501*	1.508	0.729	0.303

Note: The standard error values are in parentheses. *, **, *** shows significant at the 1, 5 and 10 percent level respectively. DW is the Durbin−Watson statistics tests the presence of autocorrelation. As a rule of thumb the DW d value between 1.5 and 2.5 show the absence of autocorrelation in the data. JB is the Jarque and Bera test of normality of residuals; Q(p) is the Ljung−Box test for residual autocorrelation up to order p; ARCH(p) is the LM test of no autoregressive conditional heteroscedasticity or ARCH effects up to order p.

Table 4
Point forecast evaluation: RMSE, MAE and Diebold−Mariano statistics.

	AR												
	h	1	2	3	4	5	6	7	8	9	10	11	**12**
Turkey	RMSE	0.159	0.153	0.144	0.150	0.152	0.143	0.144	0.143	0.142	0.143	0.143	0.143
	MAE	0.128	0.121	0.109	0.111	0.111	0.104	0.105	0.105	0.103	0.104	0.105	0.105
FTSE	RMSE	0.065	0.065	0.061	0.061	0.061	0.061	0.061	0.061	0.062	0.061	0.062	0.062
	MAE	0.053	0.053	0.047	0.047	0.047	0.047	0.047	0.047	0.048	0.048	0.048	0.048
MSCI	RMSE	0.055	0.053	0.044	0.043	0.046	0.046	0.045	0.045	0.045	0.044	0.045	0.045
	MAE	0.048	0.046	0.037	0.038	0.040	0.040	0.039	0.038	0.039	0.038	0.038	0.039
	LSTAR												
Turkey	RMSE	0.204	0.199	0.193	0.187	0.197	0.214	0.202	0.175	0.343	0.320	0.202	0.194
	MAE	0.150	0.142	0.138	0.142	0.139	0.148	0.151	0.137	0.184	0.189	0.161	0.158
FTSE	RMSE	1.580	15.5	13	1580	932	163000	95900	1.6e+07	9.8e+06	1.7e+09	1.0e+09	1.7e+11
	MAE	0.767	4.70	5.710	360	239	37000	23000	3.8e+06	2.3e+06	3.9e+08	2.4e+08	4.0e+10
MSCI	RMSE	0.077	0.082	0.065	0.058	0.060	0.066	0.070	0.065	0.055	0.065	0.058	0.054
	MAE	0.059	0.061	0.050	0.048	0.046	0.053	0.054	0.054	0.048	0.054	0.044	0.042
	Diebold−Mariano: AR and LSTAR												
Turkey		−0.468	−1.08	0	0	−0.995	−0.446	0	0	−0.517	−0.907	0	0
FTSE		−1	−0.92	−0.845	−0.775	−0.707	−0.642	−0.577	−0.513	−0.447	−0.378	−0.301	0
MSCI		−3.38*	0	−3.09**	−4.13*	−2.64**	0	−2.35**	−4.46*	0	−2.1***	0	0

*, **, *** indicates significant at the 1, 5 and 10 percent level respectively.

of $\beta_{1,0}$ for FTSE and MSCI is close to one and significant, which suggests the lag value of FTSE and MSCI has a larger effect on these series.

4.2. Forecasting performance comparison

To evaluate the forecasting performance of the estimated linear AR and LSTAR models, we compute 1−12 step-ahead out-of-sample forecasts for each series from both linear and nonlinear models. We use the bootstrap method to obtain the forecast from LSTAR model. Then the forecasts, which obtained using estimated parameters and residuals in the models, are evaluated in relation to the actual values. Table 4 reports the result of forecasting performance. The forecast produced by linear AR and LSTAR model are compared based on forecast performance. The forecast accuracy of these models evaluated using the root mean squared forecast error (RMSE) and the mean absolute forecasts errors (MAE) for each series and forecast horizon. The smaller the RMSE and MAE values indicates the smaller the forecast errors and the better forecast performance.

Interestingly, the result from forecast evaluation in Table 4 shows that the forecast obtained by linear AR model for three series have a smaller forecasting error compared to the forecasts generated by LSTAR model. This implies that nonlinear LSTAR model do not improve the forecasting performance of linear AR model for travel and leisure index, which is consistent with the result obtained by Sarantis[13] and Boero and Marrocu[14] for exchange rates.

Furthermore, to evaluate the accuracy of forecast obtained from the two models, we apply the pairwise Diebold and Mariano test with the null hypothesis of equal forecast accuracy of linear AR and LSTAR model. The result show that LSTAR model forecast for Turkey and FTSE are not significantly different from linear AR specification, while the statistical significance of test statistics in some forecast horizons of MSCI indicate significance difference in the forecast accuracy of both specifications.

5. Conclusion

Travel and leisure become an important economic activity and major source of income for most countries. International tourist arrivals have surged 1235 million in 2016 from a mere 527 million in 1996, and recorded an average consecutive robust growth of 3.9% since the 2009 global financial crisis according to UN World Tourism Organization.[1] This makes travel and leisure industry growing as faster as other significant sector such as financial services, automotive and health care.

This study compares the forecast of monthly travel and leisure index generated from linear and smooth transition autoregressive (STAR) models. Out-of-sample forecasting performance of these models examined using root mean squared forecast error measures, mean absolute forecasts errors measures and Diebold−Mariano test statistics. The result shows that nonlinear LSTAR model do not improve the forecasting accuracy of linear AR model for travel and leisure index, which is consistent with the findings reported by Sarantis[13] and Boero and Marrocu[14] for exchange rates. Hence, STAR model does not offer an improved out-of-sample fit as compared to its counterpart linear AR specification.

The finds of this study are important for short-term investment strategy of economic agent and policy makers to choose the most fit model to forecast travel and leisure sector. Furthermore, it open avenue for further research to investigate whether other models such as, ARIMA, artificial neural networks (ANNs) or exponential smoothing (ETS) can provide better forecast accuracy of travel and leisure index.

References

1. UNWTO. World tourism barometer. *World Tour Barom*; 2017;15 January. http://mkt.unwto.org/barometer/january-2017-volume-15-advance-release.
2. Kulendran N, Witt SF. Forecasting the demand for International Business Tourism. *J Travel Res*. 2003;41(3):265−271. https://doi.org/10.1177/0047287502239034.
3. Vu J, Turner L. Regional data forecasting accuracy: the case of Thailand. *J Travel Res*. 2006;45(2):186−193. http://journals.sagepub.com/doi/abs/10.1177/0047287506291600. Accessed September 22, 2017.
4. Chu F. A fractionally integrated autoregressive moving average approach to forecasting tourism demand. *Tour Manag*. 2008;29(1):79−88. http://www.sciencedirect.com/science/article/pii/S0261517707000970. Accessed September 22, 2017.
5. Hassani H, Silva E, Antonakakis N, Filis G. Forecasting accuracy evaluation of tourist arrivals. *Tour Res*. 2017;63:112−127. http://www.sciencedirect.com/science/article/pii/S0160738317300117. Accessed September 22, 2017.
6. Law R. Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting. *Tour Manag*. 2000;21(4):331−340. http://www.sciencedirect.com/science/article/pii/S0261517799000679. Accessed September 22, 2017.
7. Xu X, Law R, Chen W, Tang L. Forecasting tourism demand by extracting fuzzy Takagi−Sugeno rules from trained SVMs. *CAAI Trans Intell*. 2016;1:30−42. http://www.sciencedirect.com/science/article/pii/S2468232216000056. Accessed September 22, 2017.
8. Li X, Pan B, Law R, Huang X. Forecasting tourism demand with composite search index. *Tour Manag*. 2017;59:57−66. http://www.sciencedirect.com/science/article/pii/S0261517716301133. Accessed September 22, 2017.
9. Luukkonen R, Saikkonen P, Teräsvirta T. Testing linearity against smooth transition autoregressive models. *Biometrika*. 1988;75(3):491−499. https://academic.oup.com/biomet/article-abstract/75/3/491/234926. Accessed September 22, 2017.
10. Teräsvirta T. Specification, estimation, and evaluation of smooth transition autoregressive models. *J Am Stat Assoc*. 1994;89(425):208−218. https://doi.org/10.1080/01621459.1994.10476462.
11. Leybourne S, Mizen P. Understanding the disinflations in Australia, Canada and New Zealand using evidence from smooth transition analysis. *J Int Money Financ*. 1999;18:799−816. http://www.sciencedirect.com/science/article/pii/S0261560699000327. Accessed September 22, 2017.
12. Skalin J, Teräsvirta T. Another look at Swedish business cycles, 1861−1988. *J Appl Econom*. 1999;14(4):359−378. https://doi.org/10.1002/(SICI)1099-1255(199907/08)14, 4<359::AID-JAE517>3.0.CO;2−1.
13. Sarantis N. Modeling non-linearities in real effective exchange rates. *J Int money Financ*. 1999;18:27−45. http://www.sciencedirect.com/science/article/pii/S026156069800045X. Accessed September 22, 2017.
14. Boero G, Marrocu E. The performance of non-linear exchange rate models: a forecasting comparison. *J Forecast*. 2002;21:513−542. http://onlinelibrary.wiley.com/doi/10.1002/for.837/full. Accessed September 22, 2017.
15. Bradley M, Jansen D. Forecasting with a nonlinear dynamic model of stock returns and industrial production. *Int J Forecast*. 2004;20:321−342. http://www.sciencedirect.com/science/article/pii/S0169207003001055. Accessed September 22, 2017.
16. Teräsvirta T, Van Dijk D, Medeiros M. Linear models, smooth transition autoregressions, and neural networks for forecasting macroeconomic time series: A re-examination. *Int J Forecast*. 2005;21:755−774. http://www.sciencedirect.com/science/article/pii/S0169207005000464. Accessed September 22, 2017.
17. Claveria O, Torra S. Forecasting tourism demand to Catalonia: neural networks vs. time series models. *Econ Model*. 2014;36:220−228. http://www.sciencedirect.com/science/article/pii/S0264999313003842. Accessed September 22, 2017.
18. Saayman A, Botha I. Non-linear models for tourism demand forecasting. *Tour Econ*. 2017;23(3):594−613. http://journals.sagepub.com/doi/abs/10.5367/te.2015.0532. Accessed September 22, 2017.
19. Tse Y. Index arbitrage with heterogeneous investors: a smooth transition error correction analysis. *J Bank Financ*. 2001;25:1829−1855. http://www.sciencedirect.com/science/article/pii/S037842660000162X. Accessed September 22, 2017.
20. Huang AY, Hu W-C. Regime switching dynamics in credit default swaps: evidence from smooth transition autoregressive model. *Phys A Stat Mech its Appl*. 2012;391(4):1497−1508. https://doi.org/10.1016/j.physa.2011.08.008.
21. Granger C, Teräsvirta T. *Modelling Non-linear Economic Relationships*. Oxford Oxford Univ Press; 1993. https://ideas.repec.org/b/oxp/obooks/9780198773207.html. Accessed September 22, 2017.

22. Ubilava D, Helmers C. Forecasting ENSO with a smooth transition autoregressive model. *Environ Model Softw*. 2013;40:181−190. http://www.sciencedirect.com/science/article/pii/S136481521200240X. Accessed September 22, 2017.
23. Granger CWJ, Newbold P. *Forecasting Economic Time Series*. Academic Press; 1986. http://econpapers.repec.org/bookchap/eeemonogr/9780122951831.htm. Accessed September 22, 2017.
24. Diebold F, Mariano R. Comparing predictive accuracy. *J Bus Econ*. 2002;20(1):134−144. http://amstat.tandfonline.com/doi/abs/10.1198/073500102753410444. Accessed September 22, 2017.
25. Clark T, McCracken M. Tests of equal forecast accuracy and encompassing for nested models. *J Econom*. 2001;105:85−110. http://www.sciencedirect.com/science/article/pii/S0304407601000719. Accessed September 22, 2017.
26. Bhardwaj G, Swanson N. A predictive comparison of some simple long-and short memory models of daily US stock returns, with emphasis on business cycle effects. *Contrib Econ Anal.* 2006:379−405. http://www.sciencedirect.com/science/article/pii/S0573855505760144. Accessed September 22, 2017.
27. Boutahar M, Mootamri I, Péguin-Feissolle A. A fractionally integrated exponential STAR model applied to the US real effective exchange rate. *Econ Model*. 2009;26:335−341. http://www.sciencedirect.com/science/article/pii/S0264999308001028. Accessed September 22, 2017.