MODELLING AND FORECASTING TOURIST FLOWS TO BARBADOS USING STRUCTURAL TIME SERIES MODELS

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ABSTRACT

This paper updates the work of Greenidge (2001), employing structural time series models (STSM) to explain and forecast quarterly tourist flows from Barbados' primary source markets – the USA, the UK, Canada and CARICOM – for the period 1966:1-2007:4. Our main goal is to determine if inferences made in 2001 still hold. Results show that the structure and nature of the tourist arrivals series have evolved somewhat since the work of Greenidge (2001). Of particular interest, arrivals from the main source markets appear to be less income sensitive. The study also investigates the predictive power of STSM. A seasonal naïve model is used for benchmark comparison purposes. We find that STSM outperform the seasonal naïve model in its both multivariate and univariate form.

Keywords: Tourism Modelling, Forecasting, Structural Time Series, Barbados

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1. Introduction

The need for accurate forecasts of tourism demand to aid decision at all levels (from government to a single tourist business) has well been recognised in the tourism literature (see Archer, 1987; Witt and Witt, 1995; Wang and Lim, 2005; Kim and Moosa; 2005). Strategic planning is imperative due to the perishable nature of the tourism product: tourism products, such as plane seats, hotel rooms etc. cannot be inventoried. Hence, the importance of tourism forecasting lies in the ability to limit the losses caused by discrepancies between its supply and demand. This is particularly true for Barbados, where the economic fortunes of the country are closely tied to its tourism industry.

The importance of tourism to Barbados is made clear by examining those variables where shocks to monthly international tourist arrivals can have the most acute impacts. Receipts from tourism have a direct impact on the balance of payments, accounting for over 60% of the country's total foreign exchange receipts on average. Thus, positive shocks to international tourist arrivals will improve the current account and strengthen financial reserves. The multiplier effect of tourism also boosts other sectors of the economy, such as the transportation, agriculture, entertainment and the food and drinks sectors that can help to service the tourism industry. Tourism also plays a key role in job creation, employing over 10% of the labour force on average. In fact, tourism often provides employment to low-skilled labour (Culpan, 1987), women (Cukier-Snow and Wall, 1993) and students and young adults (Mathieson and Wall, 1982) who generally have higher unemployment rates than other segments of the labour force. Against this backdrop, it is clear that the forecast of tourism is a leading component in predicting Barbados' economic performance. Hence, there is a crucial need for accurate tourism forecasts.

Despite the importance of tourism to Barbados, there is relatively little literature on forecasting its tourist arrivals. Among the few studies that exist is Worrell *et. al* 1997, who utilise seemingly unrelated regression techniques to model both the supply and demand for tourism. However, the problem with econometric studies is the difficulty or disregard for modelling the underlying time series components. Instead, other authors have opted to utilise univariate time series models. Dharmaratne (1995) and Dalrymple and Greenidge (1999) both use ARIMA modelling to forecast Barbados' tourism demand, while Lorde and Jackman (2009) used the Naïve Trend and Seasonal Model, Winter's 3-parameter Exponential Model, Time Series Decomposition and SARIMA modelling to forecast the tourist arrival series. However, the main argument against univariate models is that it is impossible to perform any causal analysis. Furthermore, the individual components of these models have little economic meaning.

One way of dealing with these issues is to employ a structural time series approach (STSM). This allows the researcher to simultaneously model the effects of exogenous macroeconomic variables on a series as well as the unobserved time series components, such as stochastic seasonality trends and cycles, all of which have direct interpretations. Hence, STSM permit the extraction of the main elements of the series, which help to identify important aspects of its evolution, along with information on how the series responds to changes in particular variables. Within the context of tourism forecasting, the multivariate or general structural model (GSM) has generally outperformed other causal models (see Gonzalez and Moral, 1995). Furthermore, the basic structural model (BSM), which focuses on the time series components alone, has been shown to generate more accurate forecasts than the univariate ARIMA model (Turner et al., 1997).

Greenidge (2001), to the authors' knowledge, is the only study, which employed an STSM approach to forecasting tourism demand in the Caribbean. Using quarterly data from 1968-1997, Greenidge modelled tourist arrivals to Barbados from the US, UK, Canada and Other source markets.[1] His findings suggest that income in the origin is the only significant factor in explaining tourism demand. In addition, the BSM outperformed the GSM in terms of forecasting accuracy.

[1] The main tourist source markets to Barbados are the US, the UK, Canada and CARICOM; the remaining source markets are too small relative to the main markets and are hence placed in the category called OTHER.

Building on the work of Greenidge (2001), this paper provides further quantitative analysis of international tourism demand for Barbados. We do not attempt to duplicate the efforts made by Greenidge, but rather provide an update on the recent tourism trends in Barbados.

Over the last ten years, the industry has significantly evolved, for instance the UK rather than the US, now dominates tourist arrivals and CARICOM's share of total arrivals has risen markedly (from 13.5% in 1997 to 20.9% in 2006). There have also been several shocks to the system, for example the 9/11 event and World Cup 2007, which may have altered the dynamic properties of the series.

In this study, we attempt to once again utilise an STSM approach to modelling tourist arrivals to Barbados, this time around focusing on the US, UK, Canada and CARICOM source markets. Our main goal is to determine if inferences made in 2001 still hold. Secondly, the forecasting accuracy of the new STSM is examined within the context of international tourism demand by comparing it to another forecasting technique, the seasonal naïve model. Several researchers have shown that the simple naïve model, in which future forecasts are taken directly from past values, have performed better or on par with more formal forecasting models (Witt and Witt, 1995). Hence, this model serves as a baseline in the evaluation of forecasting models. If the naïve process produces more accurate forecasts than the STSMs, it does not follow that tourism demand has not changed but simply that the anticipated change generated by the formal model produces a less accurate forecast than assuming no change (Turner and Witt, 2001).

The remainder of this paper is structured as follows. Section 2 provides a brief review of the related literature and section 3 describes the data and econometric methodology employed. Section 4 presents the results of estimations along with an analysis of the forecasting performance of the estimated STSM, and finally, Section 5 concludes.

2. Brief Review of the Related Forecasting Literature

Tourism demand forecasting has emerged as the most important areas of tourism research. According to Li et al (2005), 420 studies on tourism forecasting were published between 1960-2002 alone. Logically, to exhaustively survey this body of literature in any single undertaking is virtually impossible. In fact, such an exercise is far beyond the scope of our study. Against this backdrop, the presentation in this section of our study borrows from Li et al. (2005) and Li and Song (2008), who provide comprehensive reviews of the recent developments in tourism modelling and forecasting.

According to these reviews, two main forecasting approaches has dominated the tourism literature: causal/econometric models and time series models. Li and Song (2008) note that modern econometric techniques such as error correction models, vector autoregressive models and time varying parameter models have emerged as the main econometric forecasting methods in the post-2000 period. With respect to univariate models, the authors note that different versions of the ARIMA models have been applied to over two-thirds of the post-200 studies that utilise time-series forecasting techniques.

Despite the large body of literature on forecasting tourism demand, the main question still remains: which model works best – univariate or multivariate? As far as the forecasting accuracy is concerned, both Li et al (2005) and Li and Song (2008) conclude that there is no single approach that consistently outperforms the alternatives in all cases. Hence, the choice between these two approaches tends to depend on the objective and/or resources of the research. Under econometric approaches, one is able to analyse the causal relations between tourism demand and its influencing factors. However, the main limitation of econometric approaches is data unavailability or data of poor quality. On the other hand, with univariate models particular attention is paid to exploring historic trends and patterns, which are usually ignored in a causal framework. In addition, these models only require historical observations of the variable being forecasted and therefore, are less costly in terms of data collection and model estimation. However, with univariate models, it is impossible to perform any causal analysis

In an attempt to improve forecasting accuracy and combine the advantages of both methodologies, researches have recently introduced time series techniques into the causal regression dimension. The most notable example is structural time series models (STSMs). These models are able to include explanatory variables along with stochastic trend, seasonal and cyclical components that capture the effects of all the variables that are not observable.

Gonzalez and Moral (1995) are the first researchers to introduce the idea of multivariate STSM within the context of forecasting tourism. Their results indicate that the estimated multivariate structural model compares well with other sophisticated econometric forecasting techniques, namely, the transfer function and error correction models. Since the pioneering work of Gonzalez and Moral (1995), other researchers have opted to use STSM: Greenidge (2001) used STSM to predict quarterly tourist flows to Barbados from four major tourist markets, Turner and Witt (2001) – to forecast tourism demand for New Zealand, Witt and Turner (2002) – tourism demand for China, Du Preez and Witt (2003) and Kulderan and Witt (2003a) – for Australia and Blake et al (2006) – for Scotland. These studies show that multivariate STSM perform consistently well, thereby lending support to the idea that models which encompass both time series components and exogenous macroeconomic variables can improve forecasting accuracy.

3. Forecasting Tourism Demand

Economic theory ensures that any demand function should consist of at least two variables: an income variable and a price variable. In general, income in the tourism-generating country seems to offer a robust explanation of the variation in Caribbean arrivals (see Clarke et al, 1986; Belchere, 1988; Metzgen-Quemarez, 1990; and Carey, 1991) with elasticities that vary from destination to destination. However, evidence about the effects of relative prices in the Caribbean is inconclusive. Rosensweig (1988) finds some evidence at a very aggregated level for the Caribbean region as a whole, but the results at the national level are mixed. Although other factors such as the distance from major markets and airfares may have an effect, these results are not particularly robust.

3.1 An STSM of Tourism Arrivals and Data

The multivariate STSM to be tested is

$$InARR_i = f\left(InY_i, InP_i, Trend, Seasonal, Cycle\right) \quad (1)$$

where ARR_i denotes arrivals to Barbados from source market *i*, Y_i is income in source market *i* and P_i is the relative destination price.

The income variable is the real Gross Domestic Product (GDP) in the origin country. The relative destination price is calculated as the Barbadian consumer price index (CPI) divided by the origin country (CPI) and then multiplied by the exchange rate between the Barbadian and origin country currency. The data on exchange rates, CPI and real GDP are obtained from the International Monetary Fund IFS CD-ROM, while data on arrivals are obtained from the Central Bank of Barbados Statistical Digest.

3.2 Econometrics Methodology

The inclusion of time-varying components in the regression Equation 1 allows one capture movement in arrivals that is not explained by the two explanatory variables included and would otherwise be left in the residuals. This would enhance the predictive powers of the model. The econometrics methodology discussed below is basically taken from Greenidge (2001).

Trend: The trend component in Equation 1 is modelled as

$$\left(level\right)\ \mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \quad \eta_t \ \ NID\left(0, \sigma_\eta^2\right) \quad (2)$$

$$\left(slope\right)\ \beta = \beta_{t-1} + \xi_t \ \ \xi_t \ NID\left(0, \sigma_\xi^2\right) \quad (3)$$

where η_t and ξ_t are the level and slope disturbances, respectively, and are mutually uncorrelated.

NID $\left(0,\ \sigma^2\right)$ denoted normally and independently distributed with mean zero and variance σ^2. μ_t and β_t represent the level and slope of the trend, respectively. From this general formation the trend can take on various allowable forms. The simplest would be a random walk. This can be achieved by setting β_t equal to zero. It can further be restricted for setting σ_η^2 to zero. Retaining β_t, but setting σ_ξ^2 to zero, allows for a fixed slope.

How is the form of the trend determined? The estimation procedure is done by casting the model in state space form and applying Kalman Filtering (Harvey 1989), and the extent to which the level and slope change over time is governed by the hyperparameters, $q_\eta^2 = \sigma_\eta^2 / \sigma_\varepsilon^2$ and $q_\xi^2 = \sigma_\xi^2 / \sigma_\varepsilon^2$, where σ_ε^2 is the variance of the residuals for Equation 1 (of course the outcome must be consistent with prior knowledge). The stochastic form is first specified. A value for any hyperparameter of zero would indicate that the corresponding component is deterministic and the model can be rectified with that particular component fixed, and tested to see if it is significantly different from zero.

Seasonal: The seasonal component of Equation 1, γ_t, is modelled as:

$$\gamma_t = \gamma_{t-1} + \ldots + \gamma_{t-s+1} + \omega_t; \quad \omega_t \approx NID \left(0, \sigma_\omega^2\right) \tag{4}$$

Without the disturbance term, ω_t, one has the deterministic case and the seasonal components sum to zero over the previous year. This is the dummy variable form of stochastic seasonality. The trigonometric form of stochastic seasonality may be written as:

$$\gamma_t = \sum_{j=1}^{[s/2]} \gamma_{j,t} \tag{5}$$

where each $\gamma_{j,t}$ is generated by

$$\gamma_{j,t} = \gamma_{j,t-1} \cos\lambda_j + \gamma^*_{j,t-1} \sin\lambda_j + \omega_{jt} \tag{6}$$

$$\gamma^*_{j,t} = -\gamma_{j,t-1} \sin\lambda_j + \gamma^*_{j,t-1} \cos\lambda_j + \omega^*_{jt} \qquad \forall j = 1, \ \ldots, \ [s/2] \tag{7}$$

where ω_{jt} and ω^*_{jt} are zero mean white-noise processes which are uncorrelated with each other with a common variance σ_j^2 are $j = 1, \ldots, [s/2]$. Again one can use the hyperparameter estimates of σ_ω^2 to determine whether seasonality of deterministic or stochastic form should be modelled.

<u>Cycle:</u> The cycle component of Equation 1, ψ_t, is modelled as:

$$\begin{pmatrix} \psi_t \\ \psi_t^* \end{pmatrix} = \rho \begin{pmatrix} \cos\lambda_c & \sin\lambda_c \\ -\sin\lambda_c & \cos\lambda_c \end{pmatrix} \begin{pmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{pmatrix} + \begin{pmatrix} \mathrm{K}_t \\ \mathrm{K}_t^* \end{pmatrix}, \ t = 1, \ldots, T \tag{8}$$

where λ_c is the frequency, in radians, in the range $0 \le \lambda_c \le \pi$, and ρ is the damping factor such that $0 < \rho \le 1$. K_t and K_t^* are two white-noise disturbances which are mutually uncorrelated with zero mean and common variance σ_k^2. Upon estimation, the hyperparameter which is shown is for the variance of the cycle itself, σ_ψ^2, rather than σ_k^2. Note that in the limiting case, as $\rho \to 1$, Equation 6 reduces to the deterministic but stationary cycle (Harvey 1995).

3.3 Procedure

The procedure consists of two phases. First, equation 1 is estimated excluding any explanatory variables and with the trend, seasonal, and cycle components modelled as specified by Equation 2, 4, and 6, respectively. Following Harvey, this was referred to as the Basic Structural Model (BSM). The dataset is of quarterly frequency and spans from 1968 to 2007. The estimation period is 1966:1 to 2005:4, and the last two years are reserved to produce out-of-sample forecasts. The next phase of the analysis is to re-estimate the model and include the explanatory variable of Equation 1. This is referred to in the results section as the General Structural Model (GSM).

4. Empirical Results

4.1 Model Estimation

These results are summarised in Tables 1 (BSM) and 2 (GSM). For US arrivals, the BSM model differed slightly from that reported by Greenidge (2001) where all the individual components are stochastic. Instead, the estimated BSM here contains a stochastic trend, one stochastic cycle, seasonal dummies and an irregular component. The diagnostic tests suggest that the model is relatively well behaved: the errors appear to be normally distributed, stable and non-heteroscedastic. However, as indicated by the Q statistic, the model displays a small degree of serial correlation. While it is plausible to include lagged arrivals as an independent variable to correct for autocorrelation, this approach restricts the study to one-step-ahead predictions or to conditional forecasts based on replacing the lagged variable with its predictions. Since the magnitude of autocorrelation appears small, the authors opt to retain forecasting freedom.

Figure 2 plots the individual components of the BSM. The first graph shows the trend of US arrivals. While this market exhibits a general upward movement over the period, we find three main downturns in arrivals that appear to correspond to the two oil shocks in the mid 1970s and early 1980s and to the gulf war in 1991, and by extension, economic recessions in the US. An examination of the top right graph, which shows the annualised growth rate of the trend, confirms our previous inferences. This provides some preliminary evidence that US tourism demand is indeed responsive to conditions in the origin country.

The graph in the lower left corner displays the seasonal component. Of particular interest, the graph implies that the amplitude of the seasonal fluctuations has been decreasing over time. This may be due to promotional efforts of local tourism authorities to reduce seasonal variations. A joint test of significance[2] confirms that seasonality is indeed a key component of US arrivals. On average, arrivals are 7.2% above its underlying trend in the first quarter, fall below in the second and third quarters and are about 1.5% above the trend level in the final quarter. Overall, arrivals tend to peak in the winter months. With respect to the cyclical component, the BSM suggests that US arrivals have a cycle length of about 5.3 years, with amplitude of about 0.007.

In terms of the GSM for the US market, our initial model appears to have a non-normality problem. An inspection of the residual series reveals very large values for two observations – quarters one and two of 1983. To correct this problem, the model is re-estimated with two observation-specific dummy variables for the first and second quarters of 1983. Unlike Greenidge, where income was the only significant explanatory variable with an elasticity of 2.26, both relative prices and real GDP are statistically significant (as shown in Table 2). The coefficients suggest that a one percentage point increase in real income in the US results in a 1.45% increase in arrivals from the US, while a one percentage point increase in relative prices reduces tourism demand by 0.90%. Moreover, the only remaining significant variable of the BSM are the seasonal components suggesting that the included explanatory variables do in fact capture a large portion of the data generating process. Interestingly, the inclusion of the explanatory variable resulted in slight increase in both the cycle length (5.43 years) and the amplitude (0.023) and also changed the direction of the trend component (Figure 3). As in the case of the BSM, the GSM model performs well in terms of diagnostic testing.

For the UK BSM, the hyperparameters suggest that the slope and seasonal dynamics are non-stochastic and that the irregular component is irrelevant. Hence, the model given in Table 1 contains a trend (stochastic level and fixed slope), one stochastic cycle and

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[2] The seasonal dynamics are jointly test for significance using a chi-square test. Seasonal χ^2 test statistic is 6.522 [p-value: 0.09].

dummy seasonality and differs slightly from Greenidge's specification, which contained two stochastic cycles. With the exception of a bit of autocorrelation, this model appears to be well behaved. An inspection of the individual time-varying components reveals an almost perfect 12-year cycle with amplitude of 0.054 and a generally upward sloping trend. The seasonal patterns are significant and similar to that of the US[3]: on average, arrivals for the UK are 10.7% and 7.7% above trend in quarters 1 and 4, respectively and 4.9% and 13.4% below trend in quarters 2 and 3, respectively.

Of key note, when the explanatory variables are added to the mix, the hyperparameters suggest that the remaining trend is deterministic. Moreover the cycle length is reduced to 11.5 years and now accounts for 13.9% of the trend. We can therefore conclude that the explanatory variables are fairly successful in explaining UK arrivals. On the other hand, the seasonal patterns remained roughly on par with that of the BSM. Unlike the US market, real GDP is the only significant explanatory variable. It should be noted that the income elasticity of demand is well below that of Greenidge (2001), (just 0.53 compared to 1.51).

The BSM fitted for the Canadian market mirrored that of Greenidge and contains a stochastic trend, seasonality and irregular components. The model is well fitted and passed all diagnostic tests. For this market, seasonality plays a major role in explaining arrivals, evidenced by a seasonal chi-squared test statistic of 87.372 [p-value: 0.00]. While the seasonal behaviour of Canadian arrivals is quite similar to that of the US and UK arrivals, its multiplicative effect on the trend is much more dramatic; Canadian arrivals are 12.8% and 56.6% above trend in the autumn and winter quarters, respectively and 22.5% and 46.9% below trend in spring and summer, respectively.

As in the case of the UK, the inclusion of explanatory variables changes the time varying components; the hyperparameters now indicate that the remaining trend is deterministic. The seasonal dynamics are altered a bit, but their multiplicative effect on the trend

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[3] Seasonal χ^2 test statistic is 12.656 [p-value0.005].

remained roughly the same[4]. Of the explanatory variables only real GDP is significant with an elasticity of 1.27. This is well below the 3.13 reported in 2001 by Greenidge.

The estimated BSM for CARICOM arrivals includes a trend (stochastic level and fixed slope), stochastic seasonality and an irregular component. However, an inspection of the residuals revealed a normality issue. As such, observation-specific dummies were once again incorporated into the model. A look at the individual time-varying components imply that the CARICOM market also displays a high degree of seasonality, but its pattern contrasts that of the Canadian, US and UK markets. In the first and fourth quarters, CARICOM arrivals are 17.1% and 9.4% below trend respectively, while in summer and autumn they are 11.6% and 25.3% above the trend respectively, that is, arrivals tend to peak in the third quarter each year. This quarter corresponds to the summer months, when the island holds its largest national festival, Crop Over, which lasts for a month beginning in July. For the GSM, since most of the CARICOM arrivals originate from Trinidad and Tobago (T&T), we assume that the growth performance of CARICOM source countries converges on T&T's growth.

Upon inclusion of the explanatory variables, the univariate components drastically change; the hyperparameters imply that the slope should be excluded and arrivals in quarter two are now only 0.42% above trend. There is also a significant difference in the trend component. In the BSM, the trend was generally upward sloping while in the GSM, there is no general direction, i.e., its movements appear randomised. As in the case of the UK and Canada, only income seems to influence tourism demand from CARICOM.

4.2 Forecasting performance of the model

The strength of any forecasting model lies in its predictive powers. In this section, the out-of-sample forecasting accuracy of the STSM models is evaluated. The actual and fitted values of tourist arrivals from each market are plotted for the period 2006(1) to

[4]It should be noted that our initial GSM had a non-normality problem. Hence, two observation dummy variables were included to correct this issue.

2007(4) for each model[5]. This gives an indication of the extent to which the model is picking up turning points. For the US and UK markets, all data points of the actual series lie within the prediction interval (set at two root mean square errors, [RMSE]). However, some of the out-of-sample forecasts for Canadian and CARICOM arrivals are somewhat off, with the actual lying outside the prediction interval for two of the eight quarters. Of key interest, there is a bit of a problem picking up the turning point in the second quarter of 2007 for the US, UK and Canada, with the forecast being significantly below the actual for both markets. This underestimation of tourist arrivals can be associated with the influx of tourists for Cricket World Cup 2007, held in April 2007.

To further evaluate out-of-sample forecast performance of STSM models, 1-step, 4-step and 8-step-ahead forecasts, which represent the short-term, the medium-term and the long term, respectively, are generated. These forecasts are evaluated using the Mean Absolute Percentage Error (MAPE) for each forecast horizon (Table 3)[6]. The MAPE is used to penalise the size of the errors and is computed as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|Y_t - \hat{Y}_t|}{Y_t} \times 100 \tag{9}$$

Table 3 presents the MAPE for the various forecast horizons. Overall, the BSM outperforms the GSM for the US, UK and Canadian markets, with the superior performance of the BSM occurring in each forecasting horizon for the UK and Canada. In contrast, the GSM performed best for CARICOM on average. To some extent, model performance for this market appears to depend on the length of the forecast horizon. However, the error difference between the GSM and BSM was not statistically significant at the 10% level.

We also compare the models to a seasonal Naïve model, which serves as a baseline in the evaluation of forecasting methods. Under this method, the 1-period-ahead forecast is

[5] Figures are available on request from the authors

[6] For CARICOM, we only evaluate the 1-step and 4-step-ahead forecasts. Data on Real GDP for Trinidad and Tobago was only available up to 2006. Hence, for the GSM, the period is 2006 alone

given by the actual value in the corresponding period in the previous year. In general, both structural time series models outperform the seasonal naïve process. The only exception is the UK GSM. Of particular interest, the overall error difference for between the naïve model and both the GSM and BSM was statistically significant at the 5% level. Hence, it is certain that both the GSM and BSM outperform the seasonal naïve process.

Finally, we compare the forecasts of our STSM to those of Greenidge 2001[7]. The model proposed by Greenidge (2001) is re-estimated and forecasts for the period 2006(1) to 2007(4) are developed and evaluated using the MAPE. In each individual case, our model outperforms that of Greenidge (2001) [8]. In fact, with a t-values of 3.12 for the BSM and 2.59 for the GSM, the average error difference is significant at the 5% level thereby justifying an update of this model.

5. Concluding Remarks

This paper updates the work of Greenidge (2001), employing structural time series models to evaluate and forecast tourist arrivals to Barbados from the UK, US, Canada and CARICOM. Since the work of Greenidge (2001), the industry has significantly evolved. There have also been several shocks to the system, for example the 9/11 event and World Cup 2007, which may have altered the dynamic properties of the series. Hence, this study provides an update on the recent tourism trends in Barbados.

Consistent with the findings of Greenidge, income in the source country is the most significant factor influencing tourism demand. What is particularly interesting, however, is that arrivals from each source market appear to be less sensitive to changes in GDP, evidenced by smaller income elasticities. One possible explanation could be that there is a "better value for money" compared to ten years ago, i.e. the prices of goods and services offered by Barbados are more comparable to prices in other destinations and/or

[7] We do this for the Canadian, US and UK markets as Greenidge's study did not include CARICOM.
[8] Results not shown here but are available on request.

their home country. Alternatively, it could be that Barbados is offering more goods and services that are more essential for tourist experience than it did ten year ago.

We also find differences in the properties of univariate components relative to those of Greenidge (2001). This points to a need for constant updates of the tourism forecasting models to incorporate the developments in the industry over time. A disregard for changes in the industry can certainly reduce the quality of tourism forecasts, and by extension, increase the negative externalities caused by discrepancies between its supply and demand. In Barbados, where tourism acts as a catalyst for economic growth, such an incident can have grave repercussions on the economy.

Among our key findings is that no one STSM has the same components. Rather, the trends in the individual market segments are diverse, reinforcing the importance of customised modelling. For instance, relative prices are only relevant in the US market and seasonality is the most dominant feature of the Canadian market. It is then plausible to assume that the behaviour of tourists varies from market to market and therefore, marketing strategies should also vary accordingly. Information provided in this study – regarding the differing degrees of responses to particular variables as well as the disparities in the time series components – can therefore assist policy makers in tailoring their marketing strategies towards the different source markets.

This study also investigates the predictive power of STSM. As is well known, the seasonal naïve model has proven reliable in many forecasting contexts and hence, is used as a benchmark for forecasting accuracy in this paper. Our results suggest that structural time series models are capable of producing accurate forecasts in both its multivariate and univariate form; overall, both structural time series models outperform the seasonal naïve process. Therefore, we provide evidence that tourism forecasting accuracy can be improved by employing STSM. The use of STSM when forecasting tourism demand for Barbados is likely to have a positive effect on the quality of decisions made by individuals at all levels in the industry.

References

Archer, B.H. (1987) Demand Forecasting and Estimation, in Ritchie J.R.B. and Goeldner C.R. (eds) Travel, Tourism and Hospitality Research. Wiley, New York, pp. 77-85.

Blake, A., Durbaryy, R., Eugenio-Martin, J., Gooroochurn, N., Hay, B., Lennon, J., Hay, B., Lennon, J., Sinclair, M., Sugiyarto, G. and Yeoman, I. (2006) 'Integrating forecasting and CGE models: The Case of Tourism in Scotland', Tourism Management, 27, 2, 292-305.

Belchere, W. (1988) The Impact of Tourism on the Economy of the Bahamas. Eddystone, PA: WEFA Group.

Clarke C., Wood, C. and Worrell D. (1986) 'Prices, Incomes and the Growth of Tourism', Central Bank of Barbados Economic Review, 13, 1, 10-45.

Carey, K. (1991) 'Estimation of Caribbean Tourism Demand', Atlantic Economic Journal, 19,3, 32-40.

Cukier-Snow, J., and Wall, G. (1993) 'Tourism Employment: Perspectives from Bali', Tourism Management, 14,3, 195-201.

Culpan, R. (1987) 'International Tourism Model for Developing Countries', Annals of Tourism Research, 14,4, 541-552.

Dharmaratne, G. (1995) 'Forecasting Tourist Arrivals in Barbados', Annals of Tourism Research, 22,4, 804-818.

Dalrymple, K., and Greenidge K. (1999) 'Forecasting Arrivals to Barbados', Annals of Tourism Research, 26,1, 188-218.

Gonzalez, P. and Moral, P. (1995) ‘An Analysis of the International Tourism Demand in Spain’, International Journal of Forecasting, 11,2, 233-251.

Greenidge, K. (2001) ‘Forecasting Tourism Demand: An STSM Aapproach’, Annals of Tourism Research, 28,1, 98-112.

Kim, J.H. and Moosa, I.A. (2005) ‘Forecasting International Tourist Flows to Australia: A Comparison between the Direct and Indirect Methods’, Tourism Management, 26,1, 69-78.

Kulderan, N. and Witt, S. (2003) ‘Forecasting the Demand for International Business Tourism’ Journal of Travel Research, 41, 3, 265-271.

Harvey, A.C. (1989) Forecasting Structural Time Series Models and the Kalman filter, Cambridge University Press, Cambridge.

Harvey, A.C. (1995) STAMP 5.0: Tutorial Guide, Chapman and Hall, London.

Kulendran N., and King, M. (1997) ‘Forecasting International Quarterly Tourist Flows Using Error-Correction and Time Series Models’, International Journal of Forecasting, 13, 319-327.

Li, G., Song, H. and Witt S. (2005) ‘Recent Developments in Econometric Modeling and Forecasting’, Journal of Travel Research, 44, 1, 82-99.

Li, G., and Song, H. (2008) ‘Tourism Demand Modelling and Forecasting – A Review of Recent Research’, Tourism Management, 29, 203-220.

Lorde T. and Jackman M. (2009) ‘Modelling and Forecasting Tourist Flows to Barbados’, Mimeo.

Mathieson, A., and Wall, G. (1982) Tourism: Economic, Physical and Social Impacts, Longman, London.

Metzgen-Quemarez, Y. (1990) Estimating the Demand for International Tourist Services: the USA and the Caribbea,. Princeton University Press, Princeton.

Turner, L.W., Kulderan, N. and Fernando, H. (1997) 'Univariate Modelling using Periodic and Non-periodic Analysis: Inbound Tourism to Japan, Australia and New Zealand compared', Tourism Economics, 3,1, 39-56.

Turner, L.W. and Witt, S.F. (2001) 'Forecasting Tourism using Multivariate and Univariate Structural Time Series Models', Tourism Economics, 7,2, 135-147.

Rosenweig J. (1988) 'Elasticities of substitution in Caribbean tourism', Journal of Development Economics, 29,1, 89-100.

Wang, Y. and Lim. C. (2005) Using Time Series Models to Forecast Tourist Flows. Proceeding of the 2005 International Conference on Simulation Modelling. In V. Kachitvichyanukul, U. Purintrapiban, P. Utayopas Eds.

Witt, S.F. and Turner, L. (2002) 'Trends and Forecasts for Inbound Tourism to China', Journal of Travel and Tourism Marketing, 13, 1, 97-107.

Witt, S.F. and Witt, C.A. (1995) 'Forecasting Tourism Demand: A Review of Empirical Research', International Journal of Forecasting, 11,3, 447-475.

Worrell, D., K. Greenidge, D. Downes, and K. Dalrymple (1997) 'Forecasting Tourism Demand in Barbados' in Central Bank of Barbados Working Papers, Vol. II. Central Bank of Barbados, Bridgetown, Barbados.

Figure 1: Model Components of the BSM (US Arrivals)

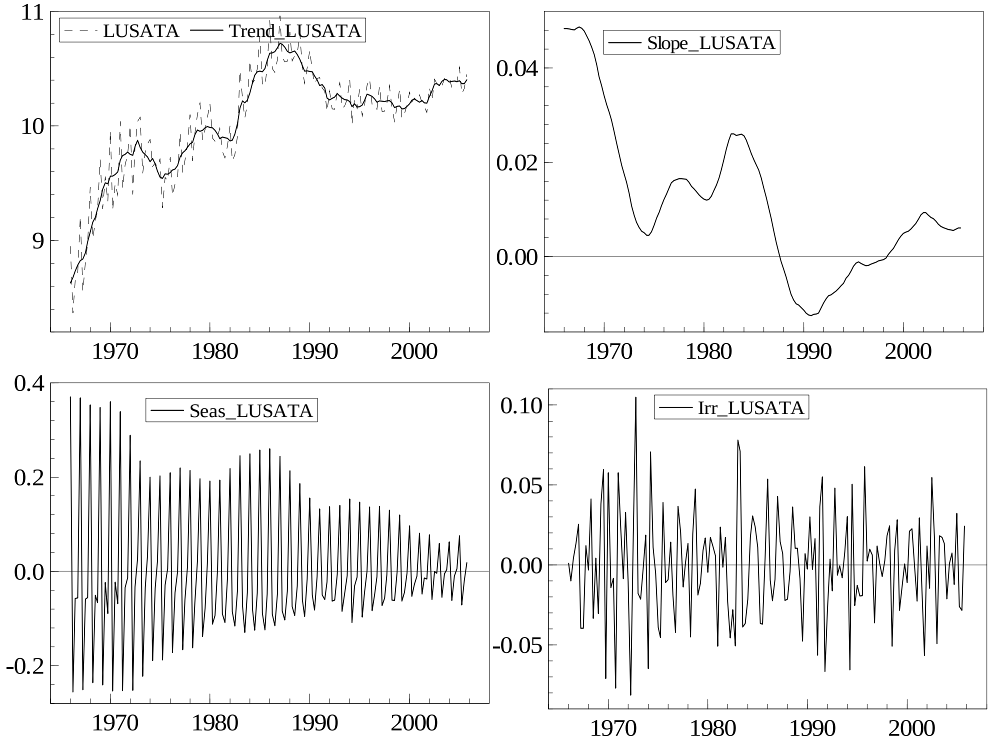

Figure 2: Model Components of the GSM (US Arrivals)

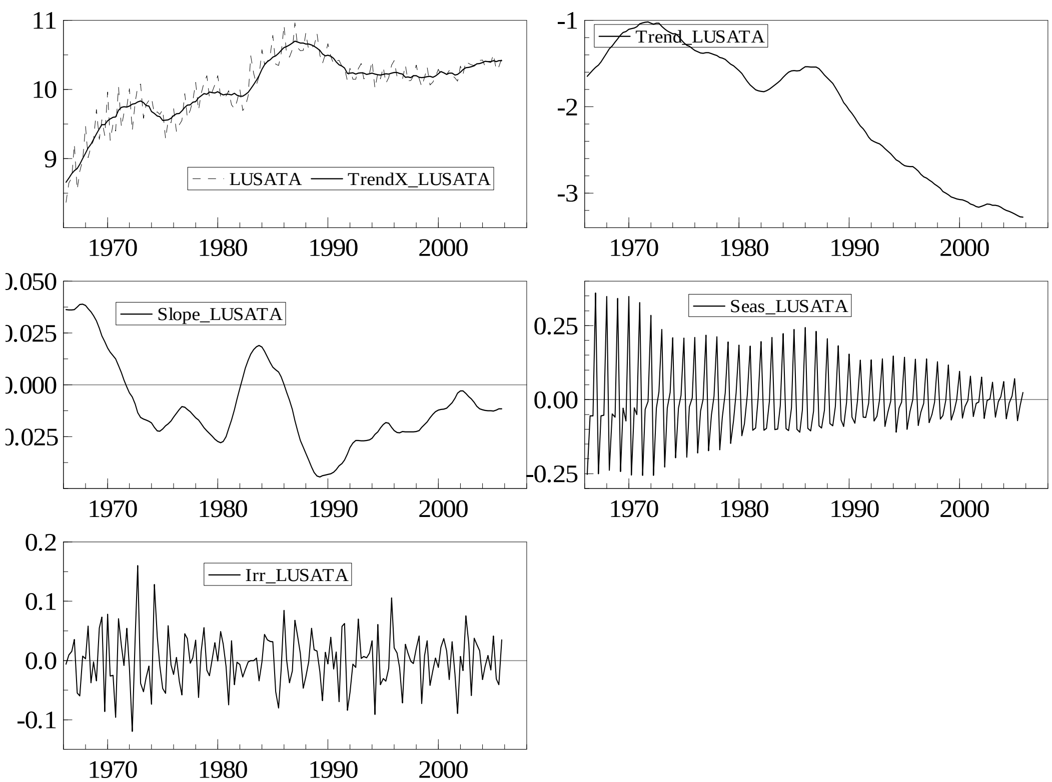

Table 1: Basic Structural Time Series Model

	US		UK		CANADA		CARICOM	
Estimation								
Variable	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Level	10.402***	0.000	10.909***	0.000	9.343***	0.000	10.271***	0.000
Slope	0.006	0.322	0.021***	0.000	-0.003	0.870	0.011**	0.012
Cycle _1	0.006	-	-0.057	-	-	-	-	-
Cycle _2	-0.006	-	-0.010	-	-	-	-	-
Season 1	0.019	0.631	0.0767	0.193	0.177**	0.014	-0.053**	0.036
Season 2	-0.019	0.584	-0.134	0.004	0.517***	0.000	-0.211***	0.000
Season 3	-0.071**	0.045	-0.049	0.272	-0.049***	0.000	-0.041**	0.038
Seasonal Index								
Q1	0.072		0.106		0.566		-0.171	
Q2	-0.071		-0.049		-0.225		0.116	
Q3	-0.019		-0.134		-0.469		0.253	
Q4	0.015		0.077		0.128		-0.094	
Summary Statistics								
Normality	0.307		2.460		3.547		2.416	
H (51)	0.444		0.440		0.411		0.416	
DW	1.881		1.857		1.979		1.987	
Q	20.064 (12,6)		19.852 (11,7)		5.311 (12,6)		14.758 (11,6)	
R^2	0.416		0.502		0.461		0.355	

Table 2: General Structural Time Series Model

	US		UK		CANADA		CARICOM	
Estimation								
Variable	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Level	-3.277	0.650	7.984***	0.000	0.156	0.972	9.247***	0.000
Slope	-0.012	0.606	0.009*	0.064	-0.021	0.068	-	-
Cycle _1	-0.023	-	-0.199	-	0.0035	-	-	-
Cycle _2	0.003	-	0.009	-	-0.000	-	-	-
Season 1	0.024	0.509	0.067	0.245	0.144***	0.001	-0.047*	0.059
Season 2	-0.021	0.548	-0.136***	0.002	-0.460***	0.000	-0.220***	0.000
Season 3	-0.071**	0.038	-0.048	0.258	-0.234***	0.000	-0.043**	0.031
GDP	1.449*	0.015	0.534**	0.012	1.266**	0.038	0.316***	0.002
Relative Prices	-0.901**	0.015	0.435	0.360	0.292	0.511	-0.003	0.992
Seasonal Index								
Q1	0.067		0.118		0.549		-0.177	
Q2	-0.071		-0.049		-0.234		0.004	
Q3	-0.021		-0.136		-0.459		0.262	
Q4	0.024		0.068		0.144		-0.090	
Summary Statistic								
Normality	0.508		3.214		0.740		4.559	
H (51)	0.509		0.460		0.411		0.445	
DW	1.884		1.851		1.844		2.032	
Q	14.662 (12,6)		20.033 (11,8)		11.306 (11,7)		14.660 (11, 6)	
R^2	0.489		0.542		0.461		0.366	

Table 3: Forecasting performance of BSM and GSM

Origin Country	Forecast Horizon (Quarters)				
	MAPE (%)	**1**	**4**	**8**	**Average**
US	BSM	0.033	0.353	0.542	0.309
	GSM	0.168	0.339	0.511	0.339
	Naïve	0.246	0.667	0.645	0.519
	MAPE (%)	**1**	**4**	**8**	**Average**
UK	BSM	0.123	0.197	0.426	0.249
	GSM	0.494	0.510	0.625	0.543
	Naïve	0.136	0.494	0.630	0.420
	MAPE (%)	**1**	**4**	**8**	**Average**
Canada	BSM	0.250	1.833	2.201	1.428
	GSM	0.261	1.821	2.308	1.463
	Naïve	0.817	1.911	2.048	1.592
	MAPE (%)	**1**	**4**	**8**	**Average**
CARICOM	BSM	0.400	1.110	N.A.	0.755
	GSM	0.117	1.314	N.A.	0.716
	Naïve	0.614	1.323	N.A.	0.969