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PREDICTING TOURIST ARRIVALS DURING DOWNTURNS

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Predicting Tourist Arrivals During Downturns

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Abstract

Many small island developing states in the Caribbean tend to depend on tourist arrivals as a main engine of economic growth, foreign exchange and job creation. International tourist arrivals are quite sensitive to news and the general economic cycle. Ideally, tourism planners in these small states would like to anticipate downturns in order to formulate and implement timely policy responses. This paper provides an assessment of the various approaches to forecasting tourist arrivals during a crisis using data from the tourism dependent island of Barbados. The results presented in the study suggest that structural time series models and regime switching models produce forecasts that are relatively unbiased. In general, however, relatively simple models (AR models) tend to produce more accurate forecasts (albeit biased) over the various downturns examined in the study.

Keywords: Economic Shocks; Prediction; Tourist Arrivals

1 Introduction

The decision to travel, like most other economic decisions, is affected by not only the relative characteristics of the good but also those of the individual. As a result, changes in the economic fortunes of the source market, natural disasters, ethnic conflicts, crime, terrorist incidents, and other exogenous factors can result in significant deviations of the trend growth in tourist arrivals (Crouch, 1994). These fluctuations can and do have a significant impact on the solvency of hotels, employment in the industry and overall economic activity. It is therefore imperative that tourism planners and policymakers have models that can explain and forecast tourist arrivals not only relatively stable periods, but also periods characterised by falling demand.

Song and Li (2008) provide a useful survey of recent modelling and forecasting approaches applied to the issue of forecasting tourism demand. The authors segment these studies along two lines: (1) studies that use quantitative techniques; and, (2) those that use qualitative approaches. Despite the large number of studies and various empirical approaches, Song and Li note that very few studies look at the issue of tourism cycles and turning points. Notable exceptions included Gouveira and Rodrigues (2005), Witt et al. (2003) and Patsouratis et al. (2005) who all attempted to look at the issue of tourism cycles. Gouveira and Rodrigues (2005) using information on monthly tourist bed-nights and non-parametric modelling techniques report that visitor arrival cycles tend to lag overall economic cycles. Witt et al. (2003) and Patsouratis et al. (2005) report that time varying parameter models as well as technical analysis techniques are better able to pickup these turning points in the visitor arrival cycle.

Prideaux et al. (2003) identify some strategies that can be used to improve the accuracy of various forecasting approaches after a shock occurs. The authors note that all shocks have three main elements: (1) the cause of the shock; (2) the magnitude of the shock; and, (3) a time element. Given that no two shocks are alike, Prideaux et al. (2003) suggest that forecasters may want to supplement their quantitative tools with qualitative methods. For example, one may develop a series of scenarios, perhaps through Delphi techniques, assign them weights and adjust the forecasts obtained from the quantitative approaches. The outcome of this process would be a series of scenarios based on a set of possible adverse or favourable outcomes, which could occur with some probability.

In contrast, Gounopoulos et al (2012) uses time series models to assess the relative forecasting performance of these models to predict tourist arrivals to Greece during the period of the Great Recession. Two time series models were considered: (1) autoregressive integrated moving average models, and; (2) exponential smoothing techniques. The results from this analysis suggest that while an ARIMA (1,1,1) model outperformed other models in terms of predicting the directional impacts, exponential smoothing models offered more accurate forecasts on average. However, most models performed poorly in relation to point forecasting accuracy. The authors also report that macroeconomic variables in the source markets did provide some indication of the direction and potential magnitude of shocks to tourist arrivals.

Despite the importance of forecasting tourist arrivals during periods of economic volatility or downturns, most of the previous studies have employed relatively simple approaches to forecast arrivals during periods of economic decline. There have been some recent attempts, however, to explicitly model these cyclical changes in tourist arrivals using Markov-switching models (Moore & Whitehall, 2005) and identifying the duration of shocks affecting Caribbean states (Browne & Moore, 2012). This study contributes to the literature, however, by evaluating the forecasting accuracy of these Markov-switching models to forecast tourist arrivals during periods of decline in tourist arrivals relative to other models previously used in the literature.

There is good reason to think that Markov-switching models should be superior to other techniques used by previous authors. The main reason stems from the models' flexibility to model downturns by allowing the mean, coefficients or variance of the model to switch from one regime to the next. The approach also uses information from previous downturns to inform predictions of future declines. By doing so, the model can provide policymakers with a 'best guest' of the likely magnitude of the downturn given historical experiences.

The remainder of this paper is structured as follows. Following the introduction, Section 2 summaries the key statistical characteristics of downturns in tourist arrivals using the case of long-stay inbound arrivals to Barbados. Section 3 of the paper outlines the forecasting approaches applied in the study while Section 4 provides an evaluation of the forecasting accuracy of these models. Section 5 concludes with key findings in relation to the accuracy of the forecasting models considered.

2 Data

Over the sample period used in this period, growth in total long-stay tourist arrivals to Barbados has generally been steady, with relatively short periods of negative growth. On average, arrivals rose by approximately 2.2 percent per quarter between 1976 and 2013. The UK market, which is also the largest in terms of total number of tourist received, had the fastest rate of quarterly growth of approximately 5 percent per quarter, with most of the other markets growing by about 2 percent per quarter.

Table 1: Descriptive Statistics for Inbound Tourist Arrivals for Barbados

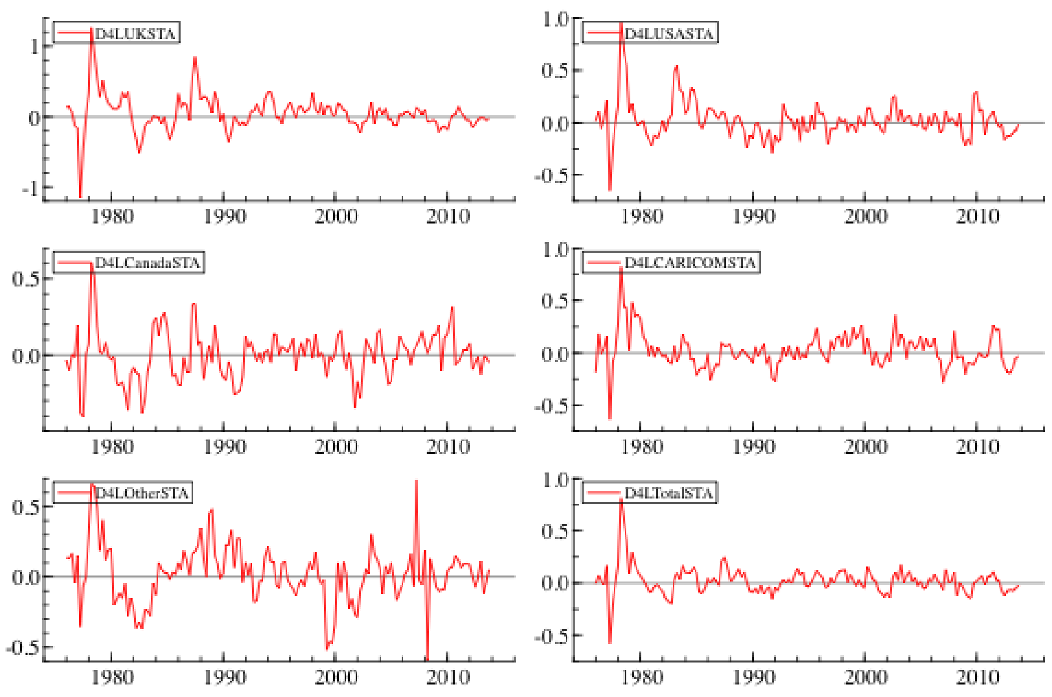
	UK	USA	Canada	CARICOM	Other	Total
Mean	0.050	0.021	-0.002	0.022	0.021	0.022
Std. Dev.	0.247	0.177	0.155	0.165	0.203	0.132
Skewness	0.523	1.390	0.307	0.746	0.191	1.488
Excess Kurtosis	7.392	6.860	1.767	4.411	1.742	11.900
Minimum	-1.152	-0.651	-0.404	-0.637	-0.593	-0.576
Maximum	1.266	0.959	0.605	0.821	0.691	0.813
Normality Test	118.760 [0.000]	43.698 [0.000]	17.010 [0.000]	45.606 [0.000]	17.768 [0.000]	104.480 [0.000]

Note: Year-on-year natural log change is used in all calculations.

The growth in tourist arrivals deviated from a normal distributions. Tests for normality rejected the null of normality for total arrivals as well as for each individual market. The growth in the arrivals series was also positively skewed, suggestive that most values tended to be in the right tail of the distribution. The relatively large values for positive excess kurtosis also suggests that the distribution of year-on-year changes in tourist arrivals was leptokurtic, indicating that most of the values for the series was tightly packed within a narrow band, with long fat tails.

In general, growth normally fluctuated around the mean for each market interrupted by periods of large negative shocks to each market. Figure 1 plots the logged year-on-year difference of arrivals for each country. Six periods were identified for total tourist arrivals, these were 1982-1983, 1986, 1989-1992, 2001 and 2009, 2012-2013.

Figure 1: Year-on-Year Growth in Tourist Arrivals to Barbados by Market



There is a link between the tourist arrivals from each market, with the correlation ratio above 30 percent for most bi-variate pairs, however, the ratio was relatively small.[2]

2

	D4LUKSTA	D4LUSASTA	D4LCanadaS	LCARICOMST	D4LOtherST/	D4LTotalSTA
D4LUKSTA	1.000	0.434	0.473	0.574	0.480	0.821
D4LUSASTA	0.434	1.000	0.505	0.528	0.299	0.776
D4LCanadaS	0.473	0.505	1.000	0.382	0.396	0.700
D4LCARICON	0.574	0.528	0.382	1.000	0.320	0.729
D4LOtherST/	0.480	0.299	0.396	0.320	1.000	0.611
D4LTotalSTA	0.821	0.776	0.700	0.729	0.611	1.000

Downturns in tourist arrivals are relatively similar in size across the various markets. On average, during a typical downturn tourist arrivals fall by approximately 4.5 percent per quarter (Table 2). The Canadian and CARICOM markets had the largest average quarterly declines during downturns of between 7 and 8 percent. During the most recent downturn, however, had the largest quarterly decrease of approximately 8.3 percent followed by the UK and CARICOM at approximately 6 and 6.7 percent, respectively.

Table 2: Year-on-Year in Tourist Arrivals During Downturns

	UK	USA	Canada	CARICOM	Other	Total Arrivals
1982(q1)-1983(q4)	-0.205	0.209	-0.117	-0.011	-0.259	-0.036
1986(q1)-1986(q4)	0.202	0.114	-0.129	-0.137	0.112	0.027
1989(q1)-1992(q4)	-0.029	-0.108	-0.059	-0.047	0.134	-0.039
2001(q1)-2001(q4)	-0.042	-0.052	-0.134	-0.080	-0.156	-0.074
2009(q1)-2009(q4)	-0.148	-0.078	0.084	-0.128	-0.088	-0.093
2012(q1)-2013(q4)	-0.060	-0.083	-0.036	-0.067	0.000	-0.057
Average	-0.047	0.000	-0.065	-0.078	-0.043	-0.045

3 Methodological Approach

To provide forecasts of tourist arrivals, five time series forecasting approaches are considered. The first approach is the autoregressive integrated moving average ($ARIMA$) model. $ARIMA$ models do not assume knowledge of the underlying structural relationships (i.e. between tourist arrivals and other macroeconomic series). Tourist arrivals are assumed to be functions of past values of the series as well as previous errors. It is a relatively useful approach to use as a baseline forecast since only the data on series of interest is required.

Estimation of the model is done in three stages: (1) identification of the order of differencing; (2) identification of the appropriate ARMA specification and diagnostic checking; and, (3) estimation. The natural logarithm of tourist arrivals is used in all regressions. Rather than imposing I, the order of integration, on the data, it is left as part of the estimation process. The seasonal AR and MA terms are set to zero and non-stochastic seasonal dummy variables are instead included in the model.

The $ARIMA$ model is just a restricted version of a more general structural time series (STS) model (Harvey, 1989). The stochastic formulation of the general STS model assumes that the trend and cycle in tourist arrivals follows a stochastic process, with an irregular component ε_t, which are all assumed to be stochastic. The seasonal (cyclical) component in trigonometric form may be expressed as follows:

$$\phi_t = \sum_{i=1}^{s/2} \phi_{jt} \tag{1}$$

with ϕ_{jt} determined by:

$$\begin{bmatrix} \phi_{jt} \\ \phi_{jt}^{*} \end{bmatrix} = \rho \begin{bmatrix} cos\lambda_j & sin\lambda_j \\ -sin\lambda_j & cos\lambda_j \end{bmatrix} \begin{bmatrix} \phi_{jt-1} \\ \phi_{jt-1}^{*} \end{bmatrix} + \begin{bmatrix} \omega_{jt} \\ \omega_{jt}^{*} \end{bmatrix} \tag{2}$$

where $\lambda_j = 2\pi j/s$ is the frequency in radians and ρ is the damping factor ($0 < \rho \leq 1$).

To allow for non-linearity in tourist arrivals a non-linear approach can also be employed. The stochastic process of the series of interest is modelled using the following autoregressive specification of order *k*:

$$\Delta_k y_t = v(s_t) + \sum_{i=1}^{k} \phi \Delta_k y_{t-i} + \varepsilon_t \tag{3}$$

where v is the regime-dependent intercept, s_t is the regime index, ϕ are the coefficients on the autoregressive terms, and ε_t is a sequence of *i.i.d* $N(0,1)$ random variables. By allowing the intercept to depend on the regime, the model implicitly assumes a smooth transition from one state to the next.

Following Hamilton (1989), the state variable, s_t, is represented as an unobserved discrete-time, discrete-state Markov process. The transition probability matrix is such that:

$$P_{ij} = \Pr[s_t = j \mid s_{t-1} = i] \quad with \sum_{j=0}^{N} P_{ij} = 1 \; for \; all \; i \, . \tag{4}$$

Maximum likelihood estimation of the framework given in Equation (3) is undertaken using the Expectation Maximization algorithm. The two-regime and three-regime versions of that given in Equation (4) are applied to monthly tourist arrivals. A two-regime approach allows for a period of decline and growth, while the three-regime specification can be interpreted as periods of decline, slow growth and rapid growth.

This study employs the Davies (1987) upper bound test statistic and the Akaike information criterion to choose the optimal number of regimes. Davies' test statistic calculates the upper bound for the significance level of the likelihood ratio to identify the optimal number of regimes. Let L_1 represent the log-likelihood ratio under the alternative, L_0, the log-likelihood under the null, q, the difference in the number of parameters under the alternative and the null and, M, the standard likelihood ratio test statistic, calculated as $M = 2(L_1 - L_0)$. If one assumes that the likelihood ratio has just one peak, the upper bound for the significance level of M can be derived from:

$$\Pr[\chi_q^2 > M] + 2(M/2)^{q/2}\exp(-M/2)/\Gamma(q/2) \qquad (5)$$

where $\Gamma(.)$ is the gamma function. The upper bound given in Equation (5) implies that for a given lag length, testing the null of $n-1$ states against the alternative of $n(n>1)$ at the 5% level of significance has a critical value of 10.95. The maximum number of regimes considered was limited to three, since a larger number of regimes would be conceptually difficult to analyse. In addition to the four models identified above a random walk with drift model (RW-drift) was also estimated.

All models are estimated using Oxmetrics 6.2 (Doornik, 2009). In relation to the model selection procedures, the lag lengths are selected based on misspecification tests, parameter constancy tests, encompassing tests and information criteria. The observations used in the study cover the period 1976Q1 to 2013Q4 and the holdout sample periods are the downturns in the Barbados tourist market identified by Browne and Moore (2012) was used to conduct the out-of-sample evaluations.

To evaluate the out-of-sample forecast accuracy of each model, the test statistic presented is the relative root mean squared error (RMSE), where the benchmark model is the naïve model. The relative RMSE (compared to the benchmark model) is used to provide a forecast evaluation statistic that is scale independent. For the naïve model, the relative RMSE statistic equals one. Of course the random walk is not a trivial rival, particularly in many financial and economic series; therefore, a value of one or close to one is not necessarily an indication of bad forecasting performance. The advantage of the relative RMSE statistic is that it is independent of the scale of the variables. This method is preferred when comparing the utility of different forecasting models across data sets that have dissimilar scales (Armstrong & Collopy, 1992).

4 Results

In order to first evaluate the predictive accuracy of the forecasts from the various models evaluated, the Diebold and Mariano (1995) tests of predictive accuracy is employed. The test provides a statistical assessment of the predictive accuracy of the forecasts from the various models. The null hypothesis of the tests is that the forecast errors are equal to zero. Therefore, if the test rejects the null hypothesis, this suggests that the forecasts obtained from the given model generate series that are statistically different from the actual out-of-sample observations.

For the five markets considered, as well as the forecasts for overall arrivals, in general the structural time series models normally provide forecasts that are not statistically different from the distribution of the actual tourist arrivals series during downturns (Table 3). For the three largest market segments (UK, USA and Canada), the null of mean zero forecast errors from the structural time series model could not be rejected. In comparison, null of mean zero forecast errors could only be not rejected for the UK and USA market while for the AR model with Monte Carlo sampling from previous estimation errors, this was only the case for the forecasts from the UK. These three models were also able to provide reasonably accurate forecasts for the residual or other markets.

For the CARICOM market and overall tourist arrivals, the relatively simpler models produced relatively unbiased forecasts. In the case of the CARICOM market, the forecasts errors of the naïve model, as well as that of the AR model with Monte Carlo sampling of errors, produced forecast errors that were insignificantly different from zero. Similarly, for overall tourist arrivals the simple AR model was the only one to produced unbiased forecasts.

Table 3: Diebold-Mariano Tests of Predictive Accuracy (All Downturns)

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Model
UK	5.210 (0.000)	-0.233 (0.817)	1.130 (0.263)	-0.066 (0.948)	-2.570 (0.014)
USA	-3.990 (0.000)	2.30 (0.027)	0.923 (0.361)	-0.716 (0.477)	2.180 (0.035)
Canada	-2.130 (0.039)	-5.010 (0.000)	2.390 (0.021)	-0.594 (0.556)	4.350 (0.000)
CARICOM	-4.210 (0.000)	0.136 (0.892)	-3.020 (0.004)	6.550 (0.000)	0.879 (0.384)
Other	-5.960 (0.000)	0.108 (0.914)	1.880 (0.067)	-1.380 (0.176)	4.370 (0.001)
Total	-1.100 (0.277)	3.360 (0.002)	-3.860 (0.000)	-0.021 (0.983)	-7.260 (0.000)

In addition to the statistical tests of forecasting accuracy over the various downturns, Tables 4-10 provide the RMSE as well as the relative RMSE for the various models estimated over each of the downturns occurring within the sample period. In general, the forecasts from the various models have relatively small forecast errors, in line with the findings from the tests of predictive accuracy reported earlier and also suggestive that it is possible to obtain reasonably accurate predictions of tourist arrivals during downturns, once suitable models are employed. Looking first at the

Table 4: Forecast Evaluation Statistics for the Various Models of UK Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.37	0.39	0.45	0.43	0.37
1986(q1)-1986(q4)	0.20	0.29	0.26	0.14	0.20
1989(q1)-1992(q4)	0.21	0.21	0.77	0.41	0.21
2001(q1)-2001(q4)	0.14	0.14	0.25	0.23	0.14
2009(q1)-2009(q4)	0.21	0.21	0.12	0.09	0.21
2012(q1)-2013(q4)	0.13	0.13	0.12	0.13	0.12
Relative RMSE					
1982(q1)-1983(q4)	1.000	1.050	1.646	1.499	1.000
1986(q1)-1986(q4)	0.999	1.435	4.201	1.324	1.000
1989(q1)-1992(q4)	0.999	1.011	3.371	1.717	1.000
2001(q1)-2001(q4)	0.999	0.997	2.694	2.560	1.000
2009(q1)-2009(q4)	1.004	1.005	0.616	0.460	1.000
2012(q1)-2013(q4)	1.005	1.036	1.005	1.091	1.000

UK market, the largest market segment of tourist arrivals, the RMSE is less than 1 for all the models considered and over the six downturns identified. Moreover, the relatively simple models, AR and Naïve models seem to do a relatively better job of forecasting arrivals during these periods. This was also the case for the residual other markets. This is somewhat surprising as these models do not utilise information from any other economic variables, for example source market income, only past information on the dynamics of tourist arrivals form the UK. Only in the wake of the downturn in tourist arrivals that occurred in 2009, due to onset of the global financial crisis, did the regime switching and the structural time series model perform better than these simple models.

In the case of the Canadian and CARICOM markets, however, the structural time series model and to some extent the AR model with estimation error sampling as well as the regime switching models provided forecasts that were just as good or better than the naïve model. In particular, using the case of the downturn that occurred in 2001, the regime-switching model produced forecasts that were 80 percent more accurate than those from the naïve model. For the more recent downturns, 2009 and 2012-2013, the AR models with sampling from estimation errors were superior. For the Canadian market, similar results were obtained. In general, the naïve model produced forecasts with a smaller RMSE, however, during the most recent downturn the regime switching and structural time series models performed best, with gains in predictive accuracy of 40-70 percent.

Table 5: Forecast Evaluation Statistics for the Various Models of USA Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.27	0.29	0.39	0.51	0.27

1986(q1)-1986(q4)	0.06	0.11	0.18	0.07	0.06
1989(q1)-1992(q4)	0.23	0.24	0.16	0.61	0.23
2001(q1)-2001(q4)	0.09	0.09	0.05	0.10	0.09
2009(q1)-2009(q4)	0.19	0.19	0.18	0.15	0.19
2012(q1)-2013(q4)	0.12	0.12	0.29	0.22	0.12
Relative RMSE					
1982(q1)-1983(q4)	1.000	1.052	1.994	2.068	1.000
1986(q1)-1986(q4)	1.000	1.748	1.720	0.686	1.000
1989(q1)-1992(q4)	1.000	1.045	1.134	4.175	1.000
2001(q1)-2001(q4)	1.000	0.967	0.275	0.517	1.000
2009(q1)-2009(q4)	1.000	1.013	1.217	0.991	1.000
2012(q1)-2013(q4)	1.001	0.988	5.614	4.164	1.000

Table 6: Forecast Evaluation Statistics for the Various Models of Canadian Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.19	0.24	0.58	0.20	0.19
1986(q1)-1986(q4)	0.10	0.11	0.07	0.19	0.10

1989(q1)-1992(q4)	0.15	0.15	0.28	0.16	0.15
2001(q1)-2001(q4)	0.19	0.20	0.17	0.16	0.19
2009(q1)-2009(q4)	0.15	0.15	0.20	0.23	0.14
2012(q1)-2013(q4)	0.05	0.05	0.05	0.11	0.05
Relative RMSE					
1982(q1)-1983(q4)	1.000	1.259	4.440	1.252	1.000
1986(q1)-1986(q4)	1.004	1.040	0.493	1.218	1.000
1989(q1)-1992(q4)	1.002	1.004	2.224	1.233	1.000
2001(q1)-2001(q4)	1.002	1.028	1.866	1.816	1.000
2009(q1)-2009(q4)	1.047	1.068	1.448	1.599	1.000
2012(q1)-2013(q4)	0.998	1.020	0.284	0.601	1.000

Table 7: Forecast Evaluation Statistics for the Various Models of CARICOM Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.13	0.16	0.14	0.71	0.13
1986(q1)-	0.14	0.16	0.09	0.16	0.14

1986(q4)					
1989(q1)-1992(q4)	0.13	0.13	0.18	0.26	0.12
2001(q1)-2001(q4)	0.09	0.09	0.12	0.11	0.09
2009(q1)-2009(q4)	0.14	0.14	0.10	0.05	0.14
2012(q1)-2013(q4)	0.18	0.18	0.12	0.15	0.18
Relative RMSE					
1982(q1)-1983(q4)	1.009	1.271	0.571	2.845	1.000
1986(q1)-1986(q4)	1.006	1.145	0.835	1.025	1.000
1989(q1)-1992(q4)	1.008	1.015	1.159	1.554	1.000
2001(q1)-2001(q4)	1.009	0.965	0.513	0.480	1.000
2009(q1)-2009(q4)	1.006	1.041	0.849	0.421	1.000
2012(q1)-2013(q4)	1.004	0.980	1.430	1.739	1.000

Table 8: Forecast Evaluation Statistics for the Various Models of Other Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.24	0.25	0.81	0.50	0.24

1986(q1)-1986(q4)	0.11	0.15	0.10	0.42	0.11
1989(q1)-1992(q4)	0.15	0.17	0.17	0.18	0.15
2001(q1)-2001(q4)	0.24	0.24	0.17	0.31	0.24
2009(q1)-2009(q4)	0.11	0.11	0.12	0.06	0.11
2012(q1)-2013(q4)	0.09	0.09	0.15	0.18	0.09
Relative RMSE					
1982(q1)-1983(q4)	1.005	1.046	5.707	2.912	1.000
1986(q1)-1986(q4)	0.995	1.409	3.338	4.657	1.000
1989(q1)-1992(q4)	0.999	1.109	1.502	1.497	1.000
2001(q1)-2001(q4)	1.000	0.981	1.361	2.521	1.000
2009(q1)-2009(q4)	1.001	0.993	1.020	0.452	1.000
2012(q1)-2013(q4)	1.000	0.987	1.501	1.771	1.000

In the case of total tourist arrivals, however, the regime-switching model outperformed all the other models considered. For the last four downturns in tourist

Table 9: Forecast Evaluation Statistics for the Various Models of Total Tourist Arrivals to Barbados

	AR Model	AR Model with Monte	Regime Switching	Structural Time Series	Naïve Forecast

		Carlo			
RMSE					
1982(q1)-1983(q4)	0.14	0.17	0.28	0.13	0.14
1986(q1)-1986(q4)	0.03	0.09	0.10	0.08	0.03
1989(q1)-1992(q4)	0.11	0.12	0.10	0.18	0.11
2001(q1)-2001(q4)	0.12	0.12	0.06	0.15	0.12
2009(q1)-2009(q4)	0.12	0.12	0.09	0.06	0.12
2012(q1)-2013(q4)	0.10	0.10	0.05	0.10	0.10
Relative RMSE					
1982(q1)-1983(q4)	1.001	1.202	2.069	0.793	1.000
1986(q1)-1986(q4)	0.998	3.159	3.590	1.018	1.000
1989(q1)-1992(q4)	1.004	1.043	0.820	1.386	1.000
2001(q1)-2001(q4)	1.007	1.002	0.504	1.264	1.000
2009(q1)-2009(q4)	1.008	1.024	0.779	0.526	1.000
2012(q1)-2013(q4)	1.012	1.030	0.522	1.098	1.000

The study also provided an assessment of the potential benefits of forecasting disaggregated tourist arrivals rather than the aggregated series for all markets. In this instance, rather than comparing the results to the naïve model, the relative RMSE is calculated relative to the RMSE for models estimated using data on total tourist arrivals compared to the combination forecasts from previously estimated models. The results suggested that significant gains in forecasting accuracy can be obtained by predicting the individual markets and then aggregating the results, i.e. most of the relative RMSE ratios were less than one.

Table 10: Forecast Evaluation Statistics for Combination Forecasts of Total Tourist Arrivals to Barbados

	AR Model	AR Model with Monte Carlo	Regime Switching	Structural Time Series	Naïve Forecast
RMSE					
1982(q1)-1983(q4)	0.14	0.17	0.08	0.14	0.14
1986(q1)-1986(q4)	0.03	0.08	0.11	0.05	0.03
1989(q1)-1992(q4)	0.13	0.13	0.23	0.29	0.13
2001(q1)-2001(q4)	0.12	0.12	0.11	0.13	0.12
2009(q1)-2009(q4)	0.11	0.11	0.08	0.04	0.11
2012(q1)-2013(q4)	0.10	0.09	0.11	0.14	0.10
Relative RMSE					
1982(q1)-1983(q4)	0.964	0.967	0.276	1.037	0.963
1986(q1)-1986(q4)	1.006	0.862	1.058	0.613	1.011
1989(q1)-1992(q4)	1.133	1.125	2.210	1.564	1.135
2001(q1)-2001(q4)	0.978	0.974	1.797	0.881	0.985
2009(q1)-2009(q4)	0.896	0.885	0.970	0.693	0.913
2012(q1)-2013(q4)	0.963	0.939	2.148	1.381	0.978

5 Conclusions

Despite the importance of the issue of forecasting tourist arrivals during periods of economic volatility or downturns, there are relatively few studies that have attempted to model and forecast cyclical downturns. This study evaluates the forecasting accuracy of various models of tourist arrivals: AR, AR with random sampling from estimation errors, regime switching models as well as structural time series models. Obtaining forecast of tourist arrivals during periods of relatively slow or negative growth in tourist arrivals could help tourism planners identify lagging markets and quickly implement contingency plans to help support these markets.

The results provided in the paper suggest that models, which account for cyclical features of tourist arrivals (e.g. regime switching and structural time series models), produce forecast errors that are insignificantly different from zero. However, the relative RMSE was only slightly better than relatively simple or naïve models during most of the downturns evaluated in the study, with this finding holding across the various markets. For the most recent downturns, however, the models that explicitly account for cycles in tourist arrivals (structural time series as well as regime switching) did yield some gains in terms of forecasting accuracy relative to simple time series models.

The study also provided an assessment of the relatively accuracy of forecasting overall tourist arrivals or forecasting each marking and then producing a combination forecast. While the forecast errors from both approaches were relatively small, in general, the combination forecasts produced better results than the models of aggregate tourist arrivals. These gains in forecasting accuracy even occurred across the simple time series models considered.

The results provided in the study therefore suggest that while the forecasts from relatively simple models are not unbiased, they can produced relatively accurate forecasts during periods of economic downturns. Future research should extend the suite of simple models considered to look at the possibility of using simple moving averages and other smoothing techniques.

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