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Editorial

Tourism forecasting: An introduction

Tourism modeling and forecasting has been a very important area of research over the past five decades. According to Li, Song, and Witt (2005), over 420 studies were published over the period 1960–2000, while in a subsequent review, Song and Li (2008) identified another 121 articles which were published on this topic during the period 2000–2007. A recent literature search by the editors of this special issue indicates that more than 50 studies have been added to the publication list since 2007. There are three main reasons for this impressive increase in the number of published studies in the area of tourism demand modeling and forecasting. First, world tourism has grown from a mere 69.3 million international tourist arrivals in 1960 to 935 million in 2010, with an average growth rate of 5.3% per year; this has undoubtedly generated a considerable degree of research interest from academics and practitioners who want to understand both the determinants of this phenomenal growth and its future trends. Second, forecasting forms an important part of the tourism business planning process, and accurate forecasts of future tourism demand have a direct effect on the growth strategies of tourism businesses. Third, accurate demand forecasting at the destination level also helps the destination governments to formulate appropriate strategies and policies, with a view to generating sustainable tourism development, as tourism is an important source of foreign exchange income and a major generator of employment for many countries.

The studies published between the 1960s and the 1980s focused mainly on forecasting tourism demand using traditional modeling techniques, such as static regression methods and ARIMA time series models. Since the 1990s, however, more advanced modeling techniques have started to appear in the tourism forecasting literature. For example, following the works of Kulendran (1996) and Kulendran and King (1997), cointegration and error correction models have now become standard techniques in tourism forecasting research, although these models were initially developed in the late 1980s (see for example Engle & Granger, 1987). Time varying parameter (TVP) models (Riddington, 1999; Song & Wong, 2003), almost ideal demand system (AIDS) models (Li, Song, & Witt, 2004), structural equation models (SEM) (Turner & Witt, 2001), and vector autoregressive (VAR) models (Song & Witt, 2006) have also been used frequently in tourism forecasting research. In addition to the above-mentioned econometric models, quantitative methods such as artificial neural network (ANN), support vector machine (SVM) and rough set (RS) models (see for example Burger, Dohnal, Kathrada, & Law, 2001; Kon & Turner, 2005; Law, 2000; Law & Au, 1999), which are known as artificial intelligence (AI) methods, have also been implemented in tourism forecasting by researchers with backgrounds in computing science and statistics. The published studies on AI modeling, however, have been outnumbered by those on econometric and time series methods. Time series models have mainly been used for benchmarking purposes in tourism forecasting, though some studies, such as those of Cho (2003), Goh and Law (2002) and Smeral and Wüger (2005), use pure time series as the main tools for generating forecasts. A recent trend in the tourism forecasting literature has been a focus on forecasting competitions, and the combination

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and integration of forecasts (see Oh & Morzuch, 2005; Shen, Li, & Song, 2010; Wong, Song, Witt, & Wu, 2007).

This special issue of the IJF is yet another important milestone for tourism forecasting research, as it collects the latest writings of key researchers in tourism forecasting. This is the second special issue to focus primarily on tourism forecasting, after the *Journal of Travel and Tourism Marketing* published the first special issue on tourism forecasting and marketing in 2003.

The first article, by Athanasopoulos, Hyndman, Song and Wu, presents the results of a major tourism forecasting competition conducted by researchers from Australia and Hong Kong. The paper evaluates the forecasting performances of a wide range of forecasting techniques using tourism data which were contributed by various researchers who have published in tourism forecasting over the past 20 years, and by a number of national tourism organizations. A total of 1311 tourism time series were made available for the forecasting competition. This study differs from previous forecasting competitions in several important ways: first, the competition looks at tourism demand (arrivals or expenditure) only; second, both causal and non-causal forecasting models are included in the competition; third, both interval and point forecasts are assessed; fourth, the effect on the forecasting performance of aggregating the forecasts of higher frequency data to give lower frequency data is examined; and finally, an alternative error measure, the mean scaled error, is used to assess the forecasting performances, in addition to the commonly used error measures from other forecasting competition exercises. The results of the competition suggest that non-causal time series models tend to outperform causal models, although among the causal models, the TVP models generally perform better than the other causal models, such as the autoregressive distributed lag model (ADLM) and VAR models.

The main contributions of this study are two-fold. First, the study has added new dimensions to the existing forecasting competition literature in terms of the competition design and the scope of the models used. In particular, the inclusion of causal models in the exercise has important implications for practitioners, as tourism decision-makers are interested in both forecast accuracy and policy evaluation. The results of this study suggest that there is a trade-off between the forecasting accuracy and the inclusion of explanatory variables. Therefore, practitioners can decide whether to use causal or non-causal time series models, depending on the task at hand. Second, this study sets a benchmark for future tourism forecasting research, as the forecasting performance evaluation in this study involves experts in all of the forecasting techniques used. In previous tourism forecasting studies, researchers who are good at using certain forecasting methods may have outperformed their opponents by misspecifying the alternative models. In this research, however, both the time series and econometric experts have expertise in their respective fields, so that they have all tried their utmost to come up with the best model specifications. Thus, the competition is both fair and reliable.

Another interesting feature of this competition was that it was opened up to any contributors via an online prediction platform. The extended competition is described by Athanasopoulos and Hyndman, with descriptions of the winning methods contributed by Baker, Howard and Brierley. The online forecasting competition was designed to provide instant feedback to the competitors, who could then revise their forecasts based on the feedback received. The findings suggest that such feedback can significantly improve the forecasting performance. This conclusion challenges the literature on traditional forecasting competition designs, and also has important implications for practitioners in terms of continuously monitoring and revising their business forecasts, based on the feedback received.

Song, Li, Witt and Athanasopoulos compare the forecasting performance of the TVP structural time series model (TVP-STSM) with the performances of the seven competing time series and econometric models. The rationale for using TVP-STSM to account for the seasonal tourism demand is that the seasonal patterns and the effects of the influencing factors on tourism demand tend to vary over time. In order to generate accurate forecasts of the future tourism demand, the time varying nature of the demand models needs to be reflected in the specifications of the models. This is the first attempt to combine the TVP model and STSM for forecasting tourism demand, and the test of the effectiveness of the TVP-STSM in modeling the seasonal tourism demand is carried out based on international tourist arrivals to Hong Kong from four source markets: China, Korea, the UK and the USA. The empirical results suggest that the TVP-STSM outperforms all seven competing models for one- to four-quarter-ahead *ex post* forecasts and one-quarter-ahead *ex ante* forecasts. However, it is worth noting that this study does not include as many time series models as that of Athanasopoulos et al. (this issue), and therefore the superiority of the econometric models, and especially that of TVP-STSM, may be biased against the time series models. Further research is therefore needed in order to include such forecasting techniques as ETS, Forecast Pro, Theta and Damped Trend ETS in the forecasting comparison set.

The combination of long term and short term forecasts is the main concern of the paper by Andrawis, Atiya and El-Shishiny. The idea is to create annual series from monthly data and then forecast both series using appropriate time series techniques. The forecasts of the two series are then combined. The accuracy of combining the forecasts produced for different frequencies is compared with that of the directly combined forecasts from individual forecasts at the same frequencies. This combination strategy is then applied to Egyptian inbound tourism data, and the results suggest that this forecast combination method generally produces reliable and accurate forecasts. The contribution of this paper is that it adds a new dimension of forecast combination to tourism forecasting literature, as previous studies have mainly focused on the combination of forecasts generated for series at the same frequencies.

The majority of published articles in the tourism forecasting literature report only point forecasts. One of the problems with point forecasts is that practitioners face a much greater risk in their decision-making process when working with point forecasts. Kim, Wong, Athanasopoulos and Shen look at the accuracy of prediction intervals in the context of forecasting the demand for Hong Kong tourism. The time series models considered in the study include the AR, bias-corrected AR and innovations state space models, as well as the basic structural time series model and the seasonal ARIMA. The authors employed an automatic forecasting approach in which the interval forecasts were produced from the above mentioned time series models with specifications which are automatically determined by a fully data-dependent procedure. The results suggest that the bias-corrected bootstrap interval forecasts are much tighter than those generated by the other models, and also produced accurate coverage values. The innovations state space exponential smoothing and basic structural time series models also perform reasonably well, as measured by the probability coverage properties, but the accuracy decreases with the increasing forecasting horizon.

The study by Fildes, Wei and Ismail evaluates the performances of econometric models in predicting the air traffic flows between the UK and five selected countries. The air passenger flows tend to be highly correlated with international tourist flows. The econometric models included in this study are an autoregressive distributed lag model (ADLM), a TVP model, an automated econometric model, a VAR, and a number of time series models for benchmarking purposes. The empirical results show that the "pooled" ADLM that incorporates the "world trade" variable generally outperforms the alterative models, especially the time series models. This conclusion is in line with that of the paper by Song, Li, and Witt, namely that econometric models are more accurate than pure time series models. Another conclusion which is drawn from this study is that the forecasting performance of the automated econometric model could be improved if judgmental intervention is involved. Based on the empirical results, the authors make an important recommendation: when evaluating the forecasting performances of different models, a range of error measures which incorporate natural metrics which fit the decision problem and the associated loss function should be reported. Another interesting finding is that the TVP specification does not help with the forecasting accuracy, despite the structural beaks exhibited in the models. This contradicts the research finding of Song, Witt, and Jensen (2003).

Carson, Cenesizoglu and Parker's interest is in seeing whether it is better to forecast the demand for commercial air travel in the USA using the aggregate data or the airport specific data. The methods compared are: the econometric models used by the US Federal Aviation Administration, which forecast the aggregate using macroeconomic variables, the aggregating individual market (AIM) approach, and a quasi-AIM model, which restricts the coefficients of the models to be homogeneous across all airports. The empirical results suggest that the disaggregate forecasting approaches (both AIM and quasi-AIM) outperform the macroeconometric approach in terms of the MAPE and RMSE of the out-of-sample forecasts at different forecasting horizons. Although the authors found that the heterogeneous AIM gives more precise estimates of the model at the airport level, they still suffer from uncertainty due to the number of parameters estimated in the airport specific models. The homogenous AIM or quasi-AIM in fact reduces the uncertainty in model estimation, and hence generates more accurate forecasts. The paper also concludes that additional effort is needed to introduce more variants of the structural AIM so that the forecasting performance of the demand for commercial air travel can be further improved.

The last paper in this special issue is related to forecasting hotel reservations. Haensel and Koole first decomposed the historical booking data using a singular value decomposition method, then dynamically adjusted the booking data and the expected number of reservations for each day in the booking horizon to the earlier decomposed data using the penalized least squares and historical proportion methods. The updating/adjustment procedure is tested using the real hotel reservation data, and these adjustment procedures improve the forecasting accuracy significantly relative to the alternative models without updating/adjustment.

In summary, the tourism forecasting articles in this special issue have addressed such issues as forecasting competition, forecast combination, and forecast integration. The demand variables predicted include tourism arrivals, tourist expenditure, hotel reservations and air passenger flows between the UK and a number of countries and among different airports within the USA. The causal methods used in these studies include ADLM, Pooled ADLM, AIM and quasi-AIM, TVP, STSM, TVP-STSM, and VAR. Non-causal models such as Box-Jenkins (AR, ARIMA and SARIMA), Theta, state space exponential smoothing, and bias-corrected bootstrap AR models are also used.

According to Athanasopoulos et al. (this issue), non-causal time series models generally outperform causal regression models, no matter how the causal models are specified. This conclusion confirmed the results of some previous studies. However, the articles by Song et al. (this issue) and Fildes et al. (this issue) suggest that the reverse is true when more sophisticated causal models, such as TVP-STSTM and the pooled ADLM, are used to forecast the quarterly demand for tourism and air passenger flows. The research finding of Song et al. suggests that the TVP-STSM can improve on the forecasting performance of pure time series models by large margins across all forecasting horizons where *ex post* forecasting is concerned, and it also improves on the forecasting performances of time series models by a relatively large margin where ex ante one-period-ahead forecasts are concerned. These conflicting results warrant further studies, and in particular, more time series models should be included in the comparison set when econometric forecasts are evaluated.

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