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Forecasting turning points in tourism growth☆

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ABSTRACT

Tourism demand exhibits growth cycles, and it is important to forecast turning points in these growth cycles to minimise risks to destination management. This study estimates logistic models of Hong Kong tourism demand, which are then used to generate both short- and long-term forecasts of tourism growth. The performance of the models is evaluated using the quadratic probability score and hit rates. The results show that the ways in which this information is used are crucial to the models' predictive power. Further, we investigate whether combining probability forecasts can improve predictive accuracy, and find that combination approaches, especially nonlinear combination approaches, are sensitive to the quality of forecasts in the pool. In addition, model screening can improve forecasting performance.

Introduction

Tourism has shown sustainable growth over the last few decades, leading to the development of multiple tourism-related industries. Accurate forecasts of tourism demand are crucial to decision making on tourism. In a recent review of the literature, Wu, Song and Shen (2017) find that non-causal time series models, causal econometric models and artificial intelligence (AI) based models are the most commonly used approaches to forecasting tourism demand in both research and practice. For example, Hassani, Webster, Silva and Heravi (2015) develop a singular spectrum analysis framework, a non-causal time series model, for forecasting tourist arrivals; and Yang, Pan and Song (2014), among others, use panel data to extend causal models identifying key determinants of hotel demand. The rapid development of AI and machine learning has also had an impact on the tourism literature. For instance, support vector regression (Cang, 2014; Chen and Wang, 2007), artificial neural networks (Claveria, Monte and Torra, 2015) and fuzzy systems (Hadavandi, Ghanbari, Shahanaghi, and Abbasian-Naghneh, 2011) are now used to forecast tourist arrival. Although the literature is rich in methodologies for forecasting tourism demand growth, few studies predict turning points using probability forecasting. Yet the latter may be more useful than level forecasting, as emphasised in a review article by Witt and Witt (1995), because tourism demand exhibits growth cycles over time. Butler (1980) categorises each cycle into six phases: exploration, involvement, development, consolidation, stagnation and either decline or rejuvenation. The differences between these phases fundamentally alter the key factors determining business success and the effectiveness of government policies, forcing businesses and governments to think and act very differently when developing investment strategies and establishing regulations. Therefore, accurate forecasts of phases of tourism demand are as important as accurate forecasts of tourism demand itself.

Another reason why probability forecasting is as important as level forecasting is that forecasts come with uncertainty. Even if forecasts are positive, tourism demand may turn out to be negative. Therefore, forecasting phases in terms of their probability has

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significant benefits for stakeholders. Such a probability not only indicates the chance of the occurrence of a particular scenario, but also reflects the forecaster's confidence in his/her estimates. Suppose that two analysts with equal prediction accuracy are asked to assess the probability of tourism growth in the next period. The first analyst opines that tourism demand in the next period has a 90% chance of being positive, whereas the second provides an estimate of 60%. Although both forecasts suggest that demand will be positive, the first analyst is more confident and more informative than the second. Probability forecasts also play an essential role in risk management. Investors and government officials can combine the probabilities assigned to different states with business knowledge about the costs and benefits of each scenario to calculate the expected profits and take action accordingly.

Given the importance of tourism demand growth cycles and the useful information gained through probabilistic assessment of each phase, more and more probability forecasts are being published and probability forecasting models being built for major economic and financial indicators. For example, the Survey of Professional Forecasts in the US is a survey of macroeconomic forecasts undertaken quarterly since 1968. The survey presents forecasters' estimates of the probability that the growth of a particular variable will fall into a certain range. The Monetary Authority of Singapore has also published quarterly probability forecasts of key macroeconomic variables since 1999. Probability forecasts not only have a high practical value, but have been shown to be theoretically important. In earlier studies, Witt and Witt (1989, 1991) forecast both directional change in tourism demand and its turning points by origin, and evaluate the resulting forecasts by the percentage of correct predictions. However, they find that forecasting accuracy varies considerably with origin and that none of the models outperform the no-change model, also called the naïve model, except in two of the origin countries. These studies have spawned a series of efforts to build forecasting models for turning points, such as Rossello-Nadal (2001) and Kulendran and Wong (2009), and research evaluating their performance, such as Witt, Song and Louvieris (2003). In general, these researchers find that models using leading indicators generally outperform univariate time series models in forecasting directional change or growth rate cycles. Kulendran and Wong (2011) make a first attempt to predict expansion and contraction periods using logit and probit models, and evaluate the predictive power of various leading indicators using the quadratic probability score (QPS), an analogue of mean squared forecasting error. They find that real income changes are the most important factor determining turning points.

Although the QPS scores for most of the models used by Kulendran and Wong (2011) are less than 0.55, the threshold below which a model can be said to have predictive power, as suggested by Chen (2009), the issues of real-time forecasting, long-horizon forecasting, instability in tourism demand growth and performance measurement have not been fully addressed. Therefore, in the following sections, we discuss the challenges involved in characterising phases in tourism demand growth, namely the information lag problem and variance in states. As the states of a time series are not observable, they can be defined in many ways. For example, the state at time t can be defined using two-sided averages. Therefore, the state at time t depends not only on past values, but also on future values. To avoid the information lag problem, we focus on predicting directional changes in real time rather than trends based on two-sided averages. In addition, the magnitude of the variance in states can have a huge impact on predictability. As we show later, variance in states is a component of the QPS. The chosen definition of states must account for this.

Second, as investment plans or policies are usually implemented over several quarters, it is best to produce both short- and long-term forecasts. We propose nine models that differ in their methods of information combination and in the leading indicators used, and evaluate their predictive ability over both horizons. Third, during the period under study, tourism growth in Hong Kong fluctuated considerably due to local and global crises and policy changes. To accommodate instability in the series, therefore, all of the models are estimated in a rolling framework, allowing the parameters to adjust to the recent economic environment in a timely manner. Fourth, although the QPS is widely used to measure the performance of probability forecasts, it can at best provide a coarse summary of out-of-sample predictability. To understand why one model outperforms another, it is best to break the QPS into separate components and examine them closely. Hence, in the evaluation section, QPS is decomposed into three components, namely calibration, sharpness and uncertainty, as proposed by Murphy (1973). As these components represent three dimensions of performance, they offer a more comprehensive understanding of why one model is better than another.

Forecast combination is a burgeoning field of tourism research. Chan, Witt, Lee and Song (2010) and Shen, Li and Song (2011) consider several linear combination methods, and Cang (2011) examines a nonlinear combination approach. They find that combined forecasts generally outperform the best individual forecast. However, the performance of combined probability forecasts has never been studied in the tourism context. In practice, forecasters often hold different or even opposing views on future states. For example, Moutinho and Witt (1995) report on a group discussion in which they invited a panel of tourism experts to give their opinions on the probabilities of various possible directions for tourism development, such as the use of AI for tourism programme design, underwater hotels and space travel, and to summarise their opinions to reach a consensus. However, from the perspective of forecast users, it is difficult if not impossible to gather experts and derive a consensus from their opinions. In this study, we introduce several combination approaches to forecasting turning points in tourism growth, and thus offer practitioners a new means of summarising opinions.

The paper is structured as follows. In Section "Econometric methods", we briefly discuss the procedures for estimating individual probability forecasting models, describe the possible combination approaches associated with these models and define the performance measurements. Section "Data and Empirical Results" describes the data used in the study and discusses the issues involved in characterising different states of tourism growth rate. The estimation results and empirical analysis are also presented. Section "Concluding Remarks" summarises our findings and provides recommendations for further research.

Econometric methods

First, we assume that y_t is a binary variable defining two states of growth, such as expansion and contraction or positive and negative growth. It takes a value of 1 when the tourism market is in the first state and 0 otherwise. Due to the latent nature of growth