Tourism Management 30 (2009) 495–511

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Combining volatility and smoothing forecasts of UK demand for international tourism

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ARTICLE INFO

Article history:
Received 17 April 2008
Accepted 5 October 2008

Keywords:
Volatility
GARCH
EGARCH
Shock
Forecast combination
Bias

ABSTRACT

Univariate volatility models are applied to UK tourism demand to the country's most popular international destinations. Volatility is a concept borrowed from Finance. The fact that significant volatility models are found for ten of the twelve destinations examined shows that the volatility concept has relevance to tourism demand. Volatility models are able to quantify the impacts of positive and negative shocks on tourism demand. The impacts of negative shocks vary in magnitude and duration according to the destination involved and the nature of the shock. The forecasting capability of these models has never been assessed in the tourism field. They are shown to generate highly accurate forecasts, but become optimal when combined with forecasts obtained from exponential smoothing models. Two methods of combining individual forecasts are considered. Bias in individual volatility and smoothing models and in combinations of them is examined.

1. Introduction

The last thirty years have seen many studies of international tourism demand forecasting by both tourism researchers and practitioners. Reliable forecasting underpins rational planning in tourism and related industries. It acts as a basis for the development of supply-side facilities including urban and rural transportation, heritage sites, hospitality and catering, promotion of attractions, retail, entertainment and other support services. It is also an aspect of pricing policies related to international transport, airport taxes, urban congestion charging and environmental quality. In that tourism makes a major contribution to nations' trade performances, economic development and prosperity, reliable forecasting is needed to assist decision makers plan effectively and resourcefully. Forecasts of tourism volume are a prime requirement for destinations to foresee infrastructure and superstructure development needs (Sheldon, 1993).

Quantitative approaches to tourism forecasting fall into two groups – causal econometric models and time series models. The former models select explanatory variables on the basis of economic theory. The most recent developments in this field include combinations of time varying parameter models (TVP), the linear almost ideal systems approach (LAIDS) and cointegration/error correction models (ECM), particularly TVP–ECM (Li, Wong, Song, & Witt, 2006) and TVP–LAIDS (Li, Song, & Witt, 2006).

The focus in this paper is on the second group of models of tourism demand. Time series methods require only historical data related to the subject matter at hand. Foremost among this class of models is the well-documented univariate ARIMA approach, typically applied to long-haul travel movement (Chu, 2008; Kim, 1999; Kim & Moosa, 2001; Kulendran & Witt, 2003; Lim & McAleer, 2000a, 2000b; du Preez & Witt, 2003). The popularity of ARIMA models reflects their general ability to produce accurate forecasts (Chu, 1998a; Lim & McAleer, 2002).

In a study of inbound tourism to Korea, recent research has extended the ARIMA approach by incorporating the concept of 'volatility' (Kim & Wong, 2006). This is referred to as 'ARIMA-volatility' modelling throughout this paper. The underlying premise is that international tourism demand is susceptible to the impact of shocks to the industry that lead to periods of relatively large upturns and downturns in activity, i.e. volatile behaviour. The concept of volatility is borrowed from Finance, motivated by the observation that large market returns (of either sign) tend to follow large returns, and small returns (of either sign) tend to follow small returns (Brooks, 2004). Clusters of volatile behaviour become evident over time. Negative shocks (or 'bad news shocks' in the parlance of Finance) that have the potential to generate volatile behaviour in tourism demand are well-documented in the literature. They include political instability (Gartner & Shen, 1992), terrorism (Bhattarai, Conway, & Shrestha, 2005; Coshall, 2003; Wahab, 1996), crime and violence (Tynon & Chavez, 2006), disease (Huan, Beaman, & Shelby, 2004), natural disasters (Milo & Yoder, 1991) and war (Ryan, 1991). Of these, terrorism has become the

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doi:10.1016/j.tourman.2008.10.010

most significant threat to the tourism and hospitality industries in recent years (Israeli & Reichel, 2003). Examples of positive (or 'good news') shocks to tourism flows would be injections of capital investment at a destination or a marked increase in marketing activity. In Finance, there is evidence in several contexts that negative shocks are associated with greater volatility than are positive shocks of the same magnitude. Although this latter concept is most rarely studied in the tourism field, one study produced contrary findings to the effect that the impacts of positive and negative shocks on monthly inbound tourist arrivals to the Maldives are much the same (Shareef & McAleer, 2007).

There have been very few applications of univariate volatility models in the tourism field, yet these models have the potential to assist policy formulation either before or at the moment of a shock. The industry needs to be able to quantify the likely impact of shocks to the demand system and have in place contingency plans to adapt to the impact of a volatile market. In this respect, Kim and Wong (2006) mention that incorporation of volatility into the modelling process may well lead to more accurate forecasts of international tourism demand. This paper is the first to formally test this notion and generally evaluates the volatility concept in the context of UK demand for international tourism to 12 destinations. The differential impacts of negative and positive shocks on volatility are also examined.

Less frequently applied in the tourism demand literature are exponential smoothing time series models, despite evidence that they often provide adequate forecasts of directional and trend changes in tourism demand (Cho, 2003; Saunders, Sharp, & Witt, 1987; Witt, Newbould, & Watkins, 1992; Witt & Witt, 1991). The inherent rationale is that smoothing models incorporate parameters reflecting any trend and/or seasonality that is present. The parameters control how rapidly the model reacts to changes in the process that generates the time series (Gardner, 1985). Smoothing models have ready application for forecasting tourism demand, since they can react quickly to changes in economic conditions and recent observations tend to be assigned larger weights in the forecasting process. Naïve models may also be included under the time series heading (Chan, 1993; Coshall, 2006). In particular, a Naïve 2 process assumes that the growth rate in tourism demand at one particular time period equals the growth rate observed at the previous, equivalent time period. This model is often used as a standard for comparing the forecasting accuracy of competing models. However, it is worthy of note that Naïve models can sometimes outperform more formal forecasting methods when applied to tourism demand (Turner & Witt, 2001).

ARIMA-volatility models are here compared with exponential smoothing models and Naïve 2 in terms of their forecasting accuracy for the most popular destinations for UK international tourism and over different forecasting horizons. Incorporation of the concept of volatility and the rapid reaction to changes in data patterns respectively justify the potential for the ARIMA-volatility and exponential smoothing approaches to forecasting international tourism demand. The question therefore arises as to whether the advantages of both methods can be pooled to generate combined forecasts that are significantly superior to those generated by the individual models. Application of combination forecasts in tourism is rare (Chu, 1998b; Li, 2007; Oh & Morzuch, 2005; Wong, Song, Witt, & Wu, 2007). While the study of Li (2007) concludes that combination forecasts are superior to individual forecasts in terms of accuracy, that of Wong et al. (2007) suggests that the relative performance of the methods varies according to the combination procedure used and the origin country or region studied. This paper adopts two commonly employed combination methods to pool ARIMA-volatility and exponential smoothing forecasts.

A final consideration is that most empirical studies of international tourism demand concentrate on the identification of models with minimum forecasting error. Such models implicitly assume that the obtained forecasts are unbiased, yet evidence suggests that this assumption is often invalid (Witt, Song, & Louvieris, 2003). It is argued that part of the model evaluation process should involve examination for bias in forecasts. Tests of forecasting bias are conducted for the individual and combined models used in this study. All evaluations are both model specific and destination specific.

2. Models and methodology

This section explains the logic underlying the ARIMA-volatility models and describes application of exponential smoothing models. An important aspect of combining forecasts is to perform encompassing tests. Such tests examine whether competing forecasts may be combined in order to generate a forecast that is superior to the individual forecasts. Two methods for combining forecasts are described. Measures of forecasting accuracy used to compare competing models are presented. A test for forecasting bias is introduced.

2.1. Volatility models

Although uncommon in tourism studies, volatility models have been very popular in empirical research in Finance and Econometrics since the early 1990s. The models are based on influential papers by Engle (1982) and Bollerslev (1986). All volatility models start off with a 'mean equation', which is commonly a standard ARIMA (as here) or regression model. Whichever is used, it contains error or residual term over time, e_t. At the root of volatility modelling is the distinction between conditional (stochastic) and unconditional (constant) errors. The conditional variance of the error terms is denoted by σ_t^2 and is time varying. Volatility modelling involves adding a 'variance equation' to the original mean equation and which in turn models the conditional variance.

One of the most widely used volatility models goes under the name of a 'generalised autoregressive conditional heteroscedasticity' GARCH scheme and was developed by Bollerslev (1986). The conditional variance is modelled as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{1}$$

where $\alpha_0 > 0$ and α_i and $\beta_j \geq 0$ to eliminate the possibility of a negative variance. However, it has been argued that in practice, this constraint may be over-restrictive (Nelson & Cao, 1992; Tsai & Chan, 2008). The specification in (1) allows for the conditional variance to be dependent on past information. It is explained by past short-run shocks represented by the lag of the squared residuals (e_i^2) obtained from the mean equation and by past longer-run conditional variances (σ_j^2). Eq. (1) is referred to as a GARCH(p,q) process. In GARCH models, $\sum\alpha_i + \sum\beta_j$ should be less than unity to satisfy stationarity conditions. If the β_j are all zero, Eq. (1) reduces to what is called an ARCH(q) process, which is the earliest form of volatility model developed by Engle (1982). It is rare for the order (p,q) of a GARCH model to be high; indeed the literature suggests that the parsimonious GARCH(1,1) is often adequate for capturing volatility in financial data (see, for example, Chen & Lian, 2005).

A potential problem with applying the model of Eq. (1) to tourism demand data is that it presumes that the impacts of positive and negative shocks are the same or 'symmetric'. This is because the conditional variance in these equations depends on the magnitude of the lagged residuals, not their sign. The possibility that a negative shock to tourism movement causes volatility to rise by more than would a positive shock of the same magnitude remains worthy of analysis. Such a consideration led to the development of 'asymmetric' volatility models, specifically the threshold GARCH (TGARCH) (Glosten, Jaganathan, & Runkle, 1993; Zakoïan, 1994) and the exponential GARCH (EGARCH) (Nelson, 1991).