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BEFORE AND AFTER THE INCLUSION OF INTERVENTION EVENTS: AN EVALUATION OF ALTERNATIVE FORECASTING METHODS FOR TOURIST FLOWS

RACHEL J. C. CHEN

Department of Retail, Hospitality, and Tourism Management, University of Tennessee, Knoxville, TN, USA

This article investigates the intervention impacts on tourist flows and evaluates the accuracy of various forecasting techniques to predict travel demand before and after the inclusion of intervention events. The forecasting methods used in this study include (1) Naïve 1, (2) Naïve 2, (3) Holt-Winter's model, (4) Seasonal Autoregressive Integrated Moving Average (SARIMA) model, and (5) Artificial Neural Networks (ANN). The Holt Winter's and Naïve models are included for comparison purposes to ensure that minimum performance standards are being met. Data on air transport passengers including international arrivals and domestic air transport flows of the US (from January 1990 to June 2003) were obtained from the US Bureau of Transportation Statistics. This study focuses firstly on the importance for forecasting accuracy of allowing for intervention events in the modeling process. SARIMA models are therefore estimated both with and without intervention effects (the September 11th events). These models are used to generate forecasts for 2002 and the first part of 2003, and forecast accuracy is assessed using mean absolute percentage error and root mean square percentage error. The second focus of the study is to examine the impacts on tourism demand of the major crises that occurred during the period 2001–2003.

Key words: Intervention impacts; SARIMA models; Air transport; Tourism demand

Introduction

The Federal Bureau of Investigation defines terrorism as "the unlawful use of force or violence against persons or property to intimidate or coerce a Government, the civilian population, or any segment thereof, in furtherance of political or social objectives" (Carmen, 2003, pp. 3–4). The Defense Intelligence Agency defines terrorism as "premeditated, political violence perpetrated against noncombatant targets by sub-national groups or clandestine state agents, usually to influence an audience" (Carmen, 2003, p. 4).

Overview of Previous Studies Related to the Events of September 11, 2001

The terrorist attack in the US, September 11, 2001, has proven to be the largest human-made disaster in the US since the Civil War. The most

Address correspondence to Professor Rachel J. C. Chen, Ph.D., Department of Retail, Hospitality, and Tourism Management, University of Tennessee, 247 Jessie Harris Bldg., Knoxville, TN 37996-1911, USA. Tel: 1-865-974-0505; Fax: 1-865-974-5236; E-mail: rchen@utk.edu

noticeable change in travel is the new security deployment in hotels and restaurants, entertainment centers, airports, seaports, bus stations, train stations, sports stadiums, and other large commercial complexes. Most Americans maintained their regular activities, except for traveling by air. After the events of September 11th, airlines suffered more than a 50% decline in passenger load in October 2001 (Chen & Chen, 2003), 20,000 pilots were laid off, and over 100,000 airline employees lost their jobs (Santomero, 2002); hotels have also encountered an unexpected slump in occupancy rates (Olsen, 2002). It is also important to keep the effects of the attacks in perspective with regards to the economy. The insurance and air travel industries have been faced with huge losses, but the security and defense industries as well as the telecommunications industry have benefited (Eboch, 2001).

A survey conducted by Traveler Associates included 800 respondents, 400 that traveled for pleasure and 400 that fit the profile for business travelers. This survey showed that 79% of travelers felt another terrorist attack is likely, and 58% have traveled less as a result of September 11 (Vlahov et al., 2002). People felt they were more likely to visit friends and family and were more likely to stay there for longer periods of time. People seemed to have largely got over their fear of flying, with 78% saying the attacks would not affect their travel plans (Chen & Noriega, 2003; Chura, 2002).

Studies in Projecting Tourist Flows

Forecasting demand has attracted considerable interest. Studies that have documented the visitation forecasts are numerous and include Barry and O'Hagan (1972), Geurts (1982), Van Doorn (1984), Uysal and Crompton (1985), Summary (1987), Sheldon (1993), Archer (1994), Gonzalez and Moral (1995), Lim (1999), and Chen, Bloomfield, and Fu (2003). Several recent publications on new developments in forecasting applications used various techniques including cointegration analysis, error correction model (Kulendran & Wilson, 2000), and vector autoregressive model (Fernando & Ramos, 2003).

Classifications and some of the techniques of forecasting methods were discussed in Uysal and Crompton (1985) and Archer (1994). In general, quantitative and qualitative approaches are two major types of forecasting methods. Qualitative methods are also called "judgmental methods." Qualitative approaches, such as the Delphi method, allow the expert opinions of selected participants to be expressed under certain specified conditions. The assumptions, advantages, and limitations underlying the use of qualitative methods were reported in Moeller and Shafer (1994).

Quantitative forecasting methods can be classified into two categories: causal methods and time series methods (e.g., basic, intermediate, and advanced extrapolative methods). Causal methods, including regression analysis and structural models, establish methodologies for identifying relationships between dependent and independent variables. However, the most common difficulty of applying the causal methods is how to statistically determining the independent variables that affect the forecast variables. Thus, the reliability of final forecast outputs will depend on the quality of other variables (Uysal & Crompton, 1985). Furthermore, those independent variables themselves must typically be forecast to estimate the forecast for the relevant dependent variable. This is often difficult at best (Chen et al., 2003).

This study focuses on noncausal quantitative forecasting methods. Although there is an extensive literature on the implementation of forecasting models, most of these models are applied to international arrivals at a destination country, excluding the impact of sudden environmental changes (i.e., terrorist attacks and wars). Studies concerned with forecasting the trends integrated with the intervention events are rare in the literature. This study focuses firstly on the importance for forecasting accuracy of allowing for intervention events in the modeling process. The second focus of the study is to examine the impacts on tourism demand of the major crises that occurred during the period 2001–2003. Data on air transport passengers including international arrivals and domestic air transport flows of the US (from January 1990 to June 2003) were obtained from the US Bureau of Transportation Statistics.

Methods

The forecasting methods used in this study include (1) Naïve 1, (2) Naïve 2, (3) Holt Winter's seasonal double exponential smoothing model, (4) Seasonal Autoregressive Integrated Moving Average (SARIMA) model, and (5) Artificial Neural Networks (ANN) (Table 1). The Holt Winter's and Naïve models are included for comparison purposes to ensure that minimum performance standards are being met. The US air transport passenger data sets used in this study refer to monthly and quarterly visitation figures (from January 1990 to June 2003).

This study focuses firstly on the importance for forecasting accuracy of allowing for intervention events in the modeling process. Seasonal autoregressive integrated moving average (SARIMA) models are therefore estimated both with and without intervention effects (the September 11th events). The second focus of the study is to examine the impacts on tourism demand of the major crises that occurred during the period 2001–2003. Two estimation periods were (1) January 1990–June 2001, and (2) January 1991–June 2002.

Each of the two periods consisted of 11 years of monthly and quarterly US air passenger flows. Forecasts were then generated for the following 12 months (4 quarters), and forecast accuracy was assessed using mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) (Table 2). Tourist flows exhibited a consistent seasonal pattern, peaking in the months of June to August (Fig. 1). Both first differencing and 12th differencing procedures were employed for the monthly data sets, and both first differencing and fourth differencing procedures were employed for the quarterly data sets to obtain stationary, nonseasonal time series.

Specifications of Forecasting Models

Naïve 1. The Naïve 1 forecasting method simply states that the forecast value for this period (t) is equal to the observed value for the last period ($t - 1$) (Makridakis, Wheelwright, & Hyndman, 1998).

Naïve 2. The Naïve 2 forecast for period t is obtained by multiplying the current visitor numbers with the growth rate between the previous visitation in time period, $t - 1$, and the current visitation figures in time period, t (Newbold & Bos, 1994).

Holt-Winter's Method. Holt-Winter's three-parameter linear seasonal double exponential smoothing model is widely used for its easy use and ability to generate fair forecast (Winters, 1960).

Seasonal Autoregressive Integrated Moving Average (SARIMA). The SARIMA model examines the year-to-year relationships for each month or quarter (Box, Jenkins, & Reinsel, 1994). For example, seasonal relationships are between observations for the same month (V_t and V_{t-12}) or for the same quarter (V_t and V_{t-4}) in successive years. When an external intervention impinges on the time series at time t, then its impact breaks the series into two segments: preintervention and postintervention. The form of an intervention model indicates that N_t (noise component) represents the SARIMA component of a model. The error terms, e_t, associated with N_t are assumed to have a zero mean, constant variance, and to be serially independent. When the error terms possess these properties, then the e_t sequence is a white noise process.

Artificial Neural Network (ANN). The ANN model is a recurrent network. The reaction of the network to the new input is a function of both the new input and the preceding context. The input to the network at time t is from the activations in the hidden layer at time $t - 1$. And a compressed trace of all preceding inputs influences each succeeding input (Elman, 1990; Jhee & Lee, 1996).

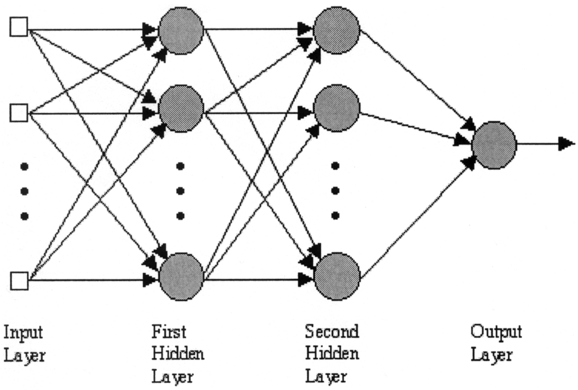
Forecasting Performance: Implication of MAPE and RMSPE

Both MAPE and RMSPE were calculated from one-step out-of-sample forecast errors to evaluate the performance of forecasting methods. The results of MAPE and RMSPE show the performances of the various forecasting methods for 1-year-ahead forecasting horizons with and without intervention events.

Table 1
Equations of Time Series Forecasting Methods

Method/Equations	Definition
(1) Naïve 1	
$F_t = A_{t-1}$	F_t = forecast visitation at time t; A_{t-1} = actual visitor number at time $t - 1$.
(2) Naïve 2	
$F_t = A_{t-1}[1 + (A_{t-1} - A_{t-2})/A_{t-2}]$	F_t = forecast visitation at time t; A_{t-1} = actual visitor number at time $t - 1$.
(3) Holt-Winter's Method	
(a) $V_t = \alpha \dfrac{Y_t}{S_{t-L}} + (1 - \alpha)(V_{t-1} + T_{t-1})$	V_t = new smoothed value in period t;
(b) $T_t = \beta(V_t - V_{t-1}) + (1 - \beta)T_{t-1}$	α = smoothing constant ($0 < \alpha < 1$);
(c) $S_t = \gamma \dfrac{Y_t}{V_t} + (1 - \gamma)S_{t-L}$	Y_t = new observation or actual value of series in period t;
(d) $F_{t+h} = (V_t - hT_t)S_{t-L+h}$	β = smoothing constant for trend estimate ($0 < \beta < 1$); T_t = trend estimate in period t; γ = smoothing constant for seasonality estimate ($0 < \gamma < 1$); S_t = seasonal estimate in period t; h = periods to be forecast into future; L = length of seasonality; F_{t+h} = forecast for h periods into the future.
(4) Seasonal Autoregressive Integrated Moving Average (SARIMA)	
$\Phi_p(B)\varphi_P(B^S)\nabla^d\nabla_s^D V_t = \Theta_q(B)\Psi_Q(B^S)\varepsilon_t$	V_t = dependent variable (e.g., number of visitors in time t); Φ_p = regression coefficients; B = the backshift operator; S = time period (i.e., when analyzing monthly data $S = 12$); ∇_s^D = seasonal differencing operator, where $\nabla_s^D = (1 - B^S)^D$; D = degree of seasonal differencing; Θ_q = coefficient, or called weights; $\varphi_P(B^S)$ and $\Psi_Q(B^S)$ = polynomials in B^S in degrees of P and Q; ε_t = error with white noise ~ iid $N(0, \sigma^2)$.

(5) Artificial Neural Network (ANN)



Findings

US domestic and international tourist flows for which seasonal data are available over the period 1990–2003 were considered. The SARIMA and ANN forecasts were compared with forecasts generated by the much simpler automatic Holt-Winter's seasonal double exponential smoothing model as well as the Naïve no change model to ensure that minimum performance standards are being met. The total impacts of intervention events on US domestic tourist flows since September 11th 2001

Table 2
Equations of Error Magnitude Measurement

Method/Equations	Definition
(6) Forecast Error	
$\varepsilon_t = A_t - F_t$	ε = the forecast error; A_t = the actual number of visitors in period t; F_t = the forecast value in time period t.
(7) Mean Absolute Percentage Error (MAPE)	
$\text{MAPE} = \frac{1}{n} * \sum_{t=1}^{n} \left(\frac{\lvert e_t \rvert}{A_t}\right) * 100$	n = number of time periods; e_t = forecast error in time period t; A_t = actual number of visitors in time period t.
(8) Root Mean Square Percentage Error (RMSPE)	
$\text{RMSPE} = \sqrt{\frac{\sum_{t=1}^{n} \left(\frac{e_t}{A_t}\right)^2}{n}} * 100$	n = number of time periods; e_t = forecast error in time period t; A_t = actual number of visitors in time period t.

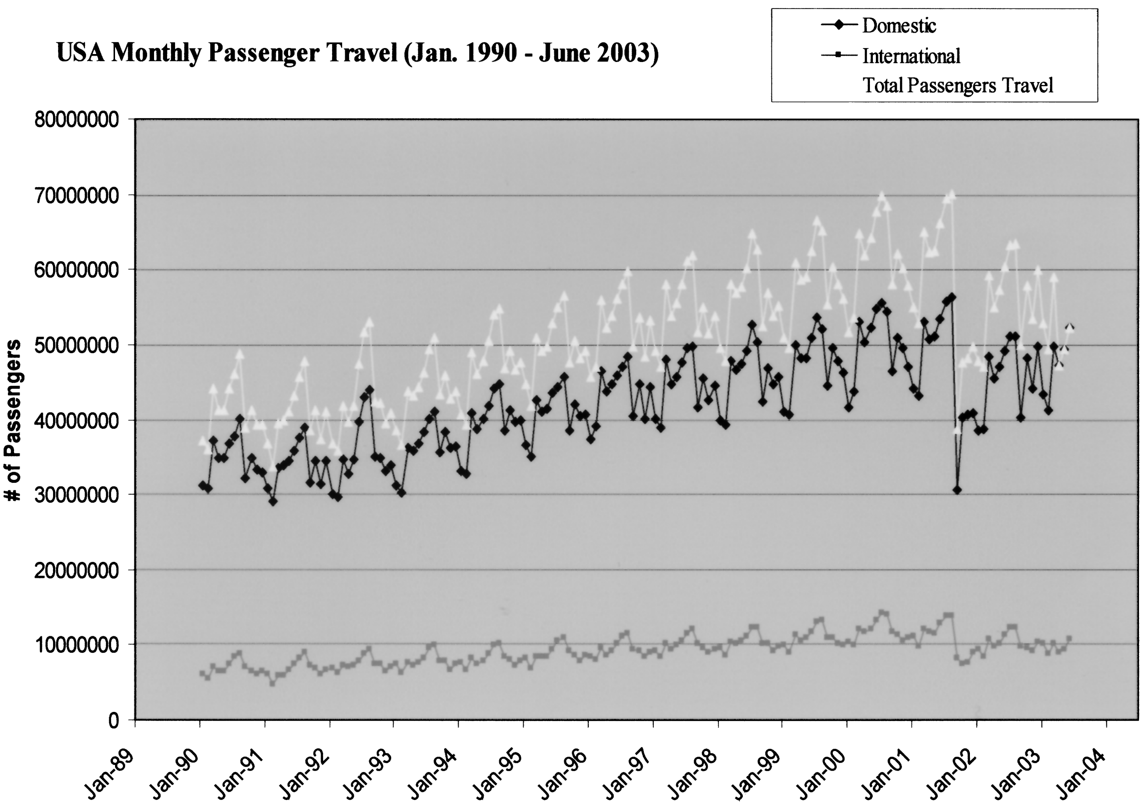


Figure 1. US monthly passenger travel (January 1990–June 2003).

showed that demand decreased by approximately 61,488,520 in terms of the number of airline seats and international passenger demand decreased by approximately 5,890,595 in terms of the number of airline seats.

In the case of the monthly international arrivals, the MAPE and RMSPE values revealed that SARIMA was the best among all the techniques when the intervention events were estimated. The MAPE and RMSPE values of the Holt-Winter's and ANN methods were also small. The Naïve 2 model performed worst. When intervention events were not considered, the Naïve 1 model performed best for the monthly international arrivals, while the ANN and Naïve 2 were the worst. In the case of the quarterly international arrivals with and without intervention events, the Naïve 1 was the best among the listed techniques. The ANN model performed worst.

In the case of the monthly domestic flows, ex-

Table 3
Evaluations of Forecasting Performances

	MAPE		RMSPE	
Model/{Estimation Period}: Forecasting Period	D	I	D	I
(1) Naïve 1				
Monthly				
{Jan. 1990–June 2001}: July 2001–June 2002	15.31(1)	17.88(1)	20.08(1)	24.50(1)
{Jan. 1991–June 2002}: July 2002–June 2003	10.04(2)	13.42(4)	11.80(2)	14.54(4)
Quarterly				
{Q1 1990–Q2 2001}: Q3 2001–Q2 2002	4.34(1)	5.52(1)	8.01(1)	11.91(1)
{Q1 1991–Q2 2002}: Q3 2002–Q2 2003	2.16(1)	3.61(1)	4.78(1)	7.06(1)
(2) Naïve 2				
Monthly				
{Jan. 1990–June 2001}: July 2001–June 2002	16.85(3)	25.59(4)	22.68(4)	30.37(3)
{Jan. 1991–June 2002}: July 2002–June 2003	20.83(5)	20.53(5)	23.78(5)	25.23(5)
Quarterly				
{Q1 1990–Q2 2001}: Q3 2001–Q2 2002	5.58(2)	6.72(2)	10.13(2)	13.86(2)
{Q1 1991–Q2 2002}: Q3 2002–Q2 2003	5.12(2)	9.79(2)	9.08(3)	17.23(4)
(3) Holt Winter's Method				
Monthly				
{Jan. 1990–Jun 2001}: July 2001–June 2002	17.90(4)	23.72(3)	22.51(3)	30.39(4)
{Jan. 1991–June 2002}: July 2002–June 2003	11.82(4)	8.45(2)	12.52(4)	9.97(2)
Quarterly				
{Q1 1990–Q2 2001}: Q3 2001–Q2 2002	18.41(5)	23.11(4)	18.95(5)	27.37(5)
{Q1 1991–Q2 2002}: Q3 2002–Q2 2003	6.81(3)	14.22(4)	8.12(2)	15.17(3)
4) SARIMA with Intervention Analysis				
Monthly				
{Jan. 1990–June 2001}: July 2001–June 2002	16.52(2)	20.11(2)	20.91(2)	26.99(2)
{Jan. 1991–June 2002}: July 2002–June 2003	9.03(1)	6.13(1)	10.41(1)	7.31(1)
Quarterly				
{Q1 1990–Q2 2001}: Q3 2001–Q2 2002	15.57(3)	20.96(3)	16.21(3)	25.12(3)
{Q1 1991–Q2 2002}: Q3 2002–Q2 2003	8.56(4)	10.51(3)	9.93(4)	13.85(2)
(5) Artificial Neural Network (ANN)				
Monthly				
{Jan. 1990–June 2001}: July 2001–June 2002	19.20(5)	28.43(5)	25.09(5)	31.39(5)
{Jan. 1991–June 2002}: Jul. 2002–June 2003	10.12(3)	10.07(3)	12.41(3)	11.91(3)
Quarterly				
{Q1 1990–Q2 2001}: Q3 2001–Q2 2002	16.28(4)	24.64(5)	17.16(4)	27.02(4)
{Q1 1991–Q2 2002}: Q3 2002–Q2 2003	15.75(5)	23.93(5)	16.11(5)	24.88(5)

Note. D = domestic passengers travel and I = international passengers travel. Figures in parentheses denote rankings. For example, based on the examination of the MAPE and RMSPE values, SARIMA (ranked 1) was the best and Naïve 2 (ranked 5) performed worst, when the intervention event was included and the next 12-month forecasts were calculated.

amination of the MAPE and RMSPE values revealed that SARIMA was the best among all the techniques when the intervention events were estimated. The MAPE and RMSPE values of the Naïve 1 and ANN methods were also small. The Naïve 2 model performed worst. When intervention events were not considered, the Naïve 1 model performed best for the monthly domestic flows, while the ANN was the worst. In the case of the quarterly domestic flows with and without intervention events, the Naïve 1 was the best among the listed techniques. When intervention events were not considered, the Holt-Winter's model performed worst. When intervention events were considered, the ANN model performed worst (Table 3).

Application of Results and Conclusions

SARIMA had the lowest forecasting error and Naïve 2 had the highest error for both monthly international arrival and domestic flow forecasts when intervention events were considered. When intervention events were excluded the Naïve 1 model generated the most accurate forecasts. The Naïve 1 procedure had the lowest forecasting error and ANN and Holt-Winter's model had the highest error for quarterly data sets with and without intervention events.

For future studies, analysts are encouraged to add other intervention events among various countries to investigate the demand changes, including financial crises (Asian crisis, July 1997), terrorist attacks (Bali, October 2002), adverse weather conditions (Guam, December 2002), wars (Iraq, March 2003), and health scares (SARS, April 2003). As Chen et al. (2003) noted, tourism planners need short- and medium-term forecasts to establish their strategic marketing plans. Such forecasts can provide valuable information for pricing, facility monitoring, seasonal employment, and short-term budgeting. With respect to developing long-term plans and protecting the existing natural resources, forecasts can determine future infrastructure needs, new facilities and utilities, and future staffing (e.g., security guards at certain airports).

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