Forecasting tourism demand using consumer expectations

Research paper

Purpose

To fill the gap due to the lack of studies on tourism demand forecasting that use non-linear models. The aim of the paper is to introduce consumer expectations in time-series models in order to analyze their usefulness to forecast tourism demand. This is the first study on tourism demand forecasting for Catalonia.

Design/methodology/approach

The paper focuses on forecasting tourism demand in Catalonia for the four main visitor markets (France, the United Kingdom, Germany and Italy) combining qualitative information with quantitative models: autoregressive (AR), autoregressive integrated moving average (ARIMA), self-exciting threshold autoregressions (SETAR) and Markov switching regime (MKTAR) models. The forecasting performance of the different models is evaluated for different time horizons (1, 2, 3, 6 and 12 months).

Findings

Although some differences are found between the results obtained for the different countries, when comparing the forecasting accuracy of the different techniques, ARIMA and Markov switching regime models outperform the rest of the models. In all cases, forecasts of arrivals show lower root mean square errors (RMSE) than forecasts of overnight stays. We have found that models with consumer expectations do not outperform benchmark models. These results are extensive to all time horizons analyzed.

Research limitations/implications

This study encourages the use of qualitative information and more advanced econometric techniques in order to improve tourism demand forecasting.

Originality/value

To date, there have been no studies on tourism demand forecasting that use non-linear models such as self-exciting threshold autoregressions (SETAR) and Markov switching regime (MKTAR) models. This paper fulfils this gap and analyzes their forecasting performance at a regional level.

Key words: tourism demand, forecasting, consumer expectations, time-series models

1. INTRODUCTION

Catalonia is one of the seventeen autonomous communities in Spain. It is located in the north-east and its capital is Barcelona. Its population (over seven million inhabitants) represents 16% of the total population of Spain. Catalonia is a tourist region: over 14 million foreign visitors come to Catalonia every year, leading to 111 million overnight stays and tourism accounts for 12% of GDP and provides employment for around 19% of the working population in the service sector. The study of aggregate tourism demand helps the making of business decisions and tourist policies and provides in-depth information about tourist flows. Although studies have been undertaken for other countries, to date, there has not been any analyses of tourism demand forecasting in Catalonia.

Consumer surveys have become an essential tool for gathering information about different economic variables (Ludvigson, 2004, Garrett et al, 2004, Howrey, 2001). Their results are weighted percentages of respondents expecting an economic variable to increase, decrease or remain constant. Therefore, the information refers to the direction of change but not to its magnitude. As pointed out by Pesaran (1987), this type of data are less likely to be susceptible to sampling and measurement errors than surveys that require respondents to give point forecasts. Statistical information from consumer surveys is available much more in advance to quantitative statistics and is related with agents' expectations. The fast availability of the results and the wide range of variables covered make them very useful for monitoring the current status of the economy, but there is no consensus on their utility for forecasting macroeconomic developments.

The objective of the paper is to analyse the possibility of improving the forecasts for tourist demand in Catalonia using the information provided by consumer surveys. As expansions are more prolonged over time than recessions (Hansen, 1997), in the behaviour of most economic variables there seems to be a cyclical asymmetry that linear models are not able to capture. To overcome this issue, four different sets of models have been considered in the paper: autoregressive (AR), autoregressive integrated moving average (ARIMA), self-exciting threshold autoregressions (SETAR) and Markov switching regime (MKTAR) models. Then the Root Mean Square Error (RMSE) has been computed for different forecast horizons (1, 2, 3, 6 and 12 months).

In order to test if survey results provide useful information to improve forecasts of the tourism demand in Catalonia we have considered the consumer confidence indicator (CCI) for the four main visitor markets (France, the United Kingdom, Germany and Italy) from January 2002 to June 2008 and we have introduced as explanatory variable in autoregressive (AR) and Markov switching regime (MKTAR) models, where the probability of changing regime depends on the information of the qualitative indicators rather than on the own evolution of the series. The comparison of these values with the ones obtained with models where information from business and consumer would permit to assess whether these indicators permit to improve the forecasts or not.

The structure of the paper is as follows. In the next section our methodological approach is described, including both benchmark models and models where consumer surveys information is included. Next, results of the forecasting competition are discussed in Section 3. Last, conclusions are given in Section 4.

2. METHODOLOGY

2.1. Benchmark models

A variety of time-series models have been used and compared to estimate and forecast tourism demand. The most commonly used being exponential smoothing and autoregressive integrated moving average (ARIMA) models (Li, Song and Witt, 2005; Witt and Witt, 1995). In this work four different models (AR, ARIMA, SETAR and MKTAR models) have been proposed to obtain forecasts for the quantitative variables expressed as year-on-year growth rates. As there are few attempts in the literature to incorporate qualitative information in quantitative forecasting models (Lee, Song & Mjelde, 2008), AR models have also been applied including qualitative survey data.

2.1.1. Autoregressions (AR)

Autoregressions explain the behaviour of the endogenous variable as a linear combination of its own past values:

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + \ldots + \phi_p x_{t-p} + \varepsilon_t \tag{1}$$

In order to determine the number of lags that should be included in the model, we have selected the model with the lowest value of the Akaike Information Criteria (AIC) considering models with a minimum number of 1 lag up to a maximum of 24 (including all the intermediate lags).

2.1.2. Autoregressive integrated moving average models (ARIMA)

The general expression of an ARIMA model (Box and Jenkins, 1970) is the following:

$$x_t^{\lambda} = \frac{\Theta_s\left(L^s\right)\theta(L)}{\Phi_s\left(L^s\right)\phi(L)\Delta_s^D \Delta^d}\,\varepsilon_t \tag{2}$$

where $\Theta_s\left(L^s\right) = \left(1 - \Theta_s L^s - \Theta_{2s} L^{2s} - \ldots - \Theta_{Qs} L^{Qs}\right)$ is a seasonal moving average polynomial, $\Phi_s\left(L^s\right) = \left(1 - \Phi_s L^s - \Phi_{2s} L^{2s} - \ldots - \Phi_{Ps} L^{Ps}\right)$ is a seasonal autoregressive polynomial,

$\theta(L)=\left(1-\theta_1 L^1-\theta_2 L^2-\ldots-\theta_q L^q\right)$ is a regular moving average polynomial, and $\phi(L)=\left(1-\phi_1 L^1-\phi_2 L^2-\ldots-\phi_p L^p\right)$ is a regular autoregressive polynomial, λ is the value of the Box-Cox (1964) transformation, Δ_s^D is the seasonal difference operator, Δ^d is the regular difference operator, *S* is the periodicity of the considered time series, and ε_t is the innovation which is assumed to behave as a white noise. In order to use this kind of models with forecasting purposes we have considered models with up to 12 AR and MA terms selecting the model with the lowest value of the AIC.

2.1.3. Self-exciting threshold autoregressions models (SETAR)

A Self-Excited Threshold Autoregressive (SETAR) model (Hansen, 1997) for the time series x_t can be summarised as follows:

$$x_t = B(L)\cdot x_t + u_t \text{ if } x_{t-k} \leq \gamma \quad (3)$$

$$x_t = \zeta(L)\cdot x_t + v_t \text{ if } x_{t-k} > \gamma \quad (4)$$

where u_t and v_t are white noises, $B(L)$ and $\zeta(L)$ are autoregressive polynomials, the value k is known as delay and the value γ is known as threshold. This two-regime self-exciting threshold autoregressive process is estimated and a Monte Carlo procedure is used to generate multi-step forecasts. The selected values of the delay are those minimising the sum of squared errors among values between 1 and 12. The values of the threshold are given by the variation of the analysed variable.

2.1.4. Markov switching regime models (MKTAR)

As an alternative to SETAR models, time series regime-switching models assume that the distribution of the variable is known conditional on a particular regime or state occurring. Hamilton (1989) presented the Markov regime-switching model in which the unobserved regime evolves over time as a first order Markov process. In this analysis, we use a Markov-switching threshold autoregressive model (MKTAR) allowing for different regime-dependent intercepts, autoregressive parameters, and variances. Once we have estimated the probabilities of expansion and recession using the Hamilton filter together with the smoothing filter of Kim (1994), we construct the following model for the time series x_t using the estimated probabilities of changing regime:

$$x_t = B(L)\cdot x_t + u_t \text{ if } P\left[Expansion / x_{t-k}\right] \leq P \quad (5)$$

$$x_t = \zeta(L)\cdot x_t + v_t \text{ if } P\left[Expansion / x_{t-k}\right] > P \quad (6)$$

where, u_t and v_t are white noises, $B(L)$ and $\zeta(L)$ are autoregressive polynomials, k is the value minimizing the sum of squared errors among 1 and 12 and the value P, known as threshold, is given by the variation of the probability.

2.2. Models where consumer surveys information is incorporated

One way to use the qualitative information of survey data on the direction of change in order to improve the forecasts of the quantitative variables consists in introducing selected indicators as explanatory variables in autoregressions. Several recent works have estimated autoregressive models for some target variable adding current and lagged values of a consumer confidence index in order to test its significance and consider the extent of its effects (Claveria, Pons and Ramos, 2007; Easaw and Heravi, 2004; Vuchelen, 2004). We have followed the same approach by incorporating the consumer confidence indicator (CCI) to autoregressive (AR) models. We have excluded the rest of the benchmark models due to the available data set.

The consumer confidence indicator (CCI) was designed by the European Commission in order to summarise the results of the consumer surveys. This indicator is obtained as an arithmetic mean of the answers (seasonal adjusted balances) to four questions:

$$CCI = (Q_1 + Q_2 + Q_3 + Q_4)/4 \tag{7}$$

where Q_1 refers to the financial situation over the next 12 months, Q_2 to the general economic situation over the next 12 months, Q_3 to the unemployment expectations over the next 12 months and Q_4 to the savings over the next 12 months.

3. RESULTS

Tourist data in this paper was obtained from *Turisme de Catalunya* and the Statistical Institute of Catalonia (IDESCAT), as well as Frontur data from the Institute of Tourism Studies (IET), while survey data from the European Commission. A descriptive analysis of this data set can be found in Claveria and Datzira (2009).

In order to evaluate the relative forecasting accuracy, all models were estimated from January 2002 to June 2007 and forecasts for 1,2,3,6 and 12 months ahead were computed. The specifications of the models are based on information up to that date and, then re-estimated each month for forecasts to be computed. Given the availability of actual values until June 2008, forecast errors can be computed in a recursive way (i.e., for the 1 month forecast horizon, 12 forecast errors can be computed). All calculations are performed with Gauss for Windows 6.0.

To summarise this information, the Root Mean Squared Error (RMSE) has been computed so methods can be ranked according to their values. It is worth mentioning that in all cases we have assumed that the information of business and consumer surveys is known in advance, which is not a strong assumption for shorter forecasting horizons but it could be for longer ones.

The results of our forecasting competition are shown in tables 1 to 4. These tables present the values of the Root of the Mean Squared Error (RMSE) obtained from recursive forecasts for 1,2,3,6 and 12 months during the period 2007.06-2008.06 for both, the benchmark models and the models including information from surveys. Each table shows the average RMSE for each country for both the number of arrivals and the overnight stays.

Table 1. Average RMSE – France

			Arrivals		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	6.66	13.44	16.60	18.29	21.17
ARIMA	*2.56**	4.66	5.82	8.31	10.66
SETAR	4.56	6.40	7.36	12.71	25.30
MKTAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	5.59	8.02	8.71	11.04	14.91
			Overnight stays		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	17.12	18.14	17.44	20.21	*6.04**
ARIMA	7.95	7.58	7.76	10.73	7.45
SETAR	12.16	15.04	15.75	17.28	17.08
MKTAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	24.37	26.05	25.59	36.48	47.94

Italics: best model without survey information
* Best model
- Matrix singular or not positive definite

Table 2. Average RMSE – UK

			Arrivals		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	12.23	13.15	12.79	11.05	31.46
ARIMA	*4.44**	5.49	7.22	11.08	14.35
SETAR	12.10	24.22	39.85	51.89	74.87
MKTAR	7.52	8.08	10.43	4.75	5.18
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	9.91	13.61	16.52	21.81	16.26
			Overnight stays		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	12.42	13.43	14.38	16.23	*5.04**
ARIMA	7.29	8.46	8.87	11.36	26.05
SETAR	248.71	641.07	2 507	19 252	19 629 900
MKTAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	13.78	13.71	18.25	25.46	21.52

Italics: best model without survey information
* Best model
- Matrix singular or not positive definite

Table 3. Average RMSE – Germany

			Arrivals		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	3.78	4.55	4.98	5.97	9.47
ARIMA	*1.88**	2.55	2.56	3.82	9.23
SETAR	11.62	11.79	14.83	139.95	3 913.97
MKTAR	2.59	4.33	5.77	8.65	4.56
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	6.53	9.09	10.20	10.29	11.38
			Overnight stays		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	4.23	4.58	4.72	5.43	*3.52**
ARIMA	4.15	5.78	6.85	8.53	12.13
SETAR	16.75	17.62	19.27	18.25	9.95
MKTAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	13.78	13.71	18.25	25.46	21.52

Italics: best model without survey information
* Best model
\- Matrix singular or not positive definite

Table 4. Average RMSE – Italy

			Arrivals		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	21.44	25.50	28.43	27.81	38.44
ARIMA	8.64	9.15	*7.69**	8.59	23.46
SETAR	15.13	28.59	44.57	99.76	271.31
MKTAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	20.98	25.94	29.62	39.64	60.18
			Overnight stays		
Benchmark models	1 month	2 months	3 months	6 months	12 months
AR	70.84	85.77	81.26	77.14	102.83
ARIMA	63.05	64.17	65.11	76.35	*47.57**
SETAR	261.77	519.24	2 400.41	67 696.97	572.31
MK-TAR	-	-	-	-	-
Models with survey information	1 month	2 months	3 months	6 months	12 months
AR	55.86	63.72	65.82	63.52	99.80

Italics: best model without survey information
* Best model
\- Matrix singular or not positive definite

The obtained results permit to conclude that, as expected, forecasts errors increase for longer horizons in most cases. Regarding the forecast accuracy of the different methods, in most cases ARIMA models are not outperformed by the rest of the methods, being the SETAR models the ones usually displaying the highest RMSE values. MKTAR models usually show lower RMSE values than other methods, although they do not always converge due to the available data. When information from consumer surveys is incorporated, AR models do not seem to obtain lower RMSE than benchmark models.

In table 5 we present the results for one moth ahead by country. In this case, ARIMA models display the lowest RMSE values. While Germany is the country with lowest RMSE values for all models except for SETAR models, Italy shows very high RMSE values. Summarising, the comparison of the forecasting performance of the two sets of models permit to conclude that in most cases, models that include information from the survey do not obtain lower RMSE than the corresponding benchmark model without survey information.

Table 5. Summary of results by country – Average RMSE for 1 month ahead

		Arrivals		
Benchmark models	France	UK	Germany	Italy
AR	6.66	12.23	3.78	21.44
ARIMA	2.56	4.44	*1.88**	8.64
SETAR	4.56	12.10	11.62	15.13
MKTAR	-	7.52	2.59	-
Models with survey information	France	UK	Germany	Italy
AR	5.59	9.91	6.53	20.98
		Overnight stays		
Benchmark models	France	UK	Germany	Italy
AR	17.12	12.42	4.23	70.84
ARIMA	7.95	7.29	*4.15**	63.05
SETAR	12.16	248.71	16.75	261.77
MKTAR	-	-	-	-
Models with survey information	France	UK	Germany	Italy
AR	24.37	13.78	9.95	55.86

Italics: best model without survey information
* Best model. The estimation results of the models are reported in the annex.
- Matrix singular or not positive definite

4. CONCLUSIONS AND DISCUSSION

Forecasting tourist demand using both quantitative forecasting models and qualitative techniques has received limited attention in the literature. There is also a lack of studies on tourism demand in Catalonia. Thus, the objective of the paper is to analyse the possibility of improving the forecasts for tourist demand for Catalonia using the information provided by consumer surveys.

Consumer surveys provide detailed information about agents' expectations. The fact that survey results are based on the knowledge of respondents operating in the market, and the rapid availability of the results, make them very useful for monitoring the current state of the economy. Therefore consumers expectations have become an essential tool for the making of business decisions and the drawing up of tourist policies in periods of high uncertainty as the present.

Taking into account that expansions are more prolonged over time than recessions, most economic variables show a cyclical asymmetry that linear models are not able to capture. To overcame this issue, four different sets of models have been considered in the paper: autoregressive (AR), autoregressive integrated moving average (ARIMA), self-exciting threshold autoregressions (SETAR) and Markov switching regime (MKTAR) models. While ARIMA models have been widely used in the tourism literature, non-linear models such as SETAR and MKTAR are used for the first time to forecast tourist demand.

In order to test if survey results provide useful information to improve forecasts of the tourism demand in Catalonia, the number of tourists and overnight stays has been forecasted for the four main visitor markets (France, the United Kingdom, Germany and Italy), with and without considering survey results. This forecasting competition has extended previous research that has considered information from business and consumer surveys to explain the behaviour of macroeconomic variables (Claveria, Pons and Ramos, 2007; Vuchelen, 2004) to the tourist demand literature.

When comparing the forecasting accuracy of the different techniques, ARIMA and Markov switching regime models outperform the rest of the models. Forecasts of arrivals show lower RMSEs than forecasts of overnight stays. To our surprise, the obtained results allow us to conclude that only in a limited number of cases the consideration of information from consumer surveys has improved the forecasting performance of the different models.

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ANNEX. ESTIMATION RESULTS

The estimation results of the best models used for forecasting tourism demand in Catalonia for one month ahead, corresponding to Germany for both arrivals and overnight stays, are reported in Tables A.1 to A.12.

Table A.1. Estimation results for 1 month ahead (Germany) – Estimation until 2007:06

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 78	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.256	4.198	0.061	0.952
AR(2)	-0.325	2.850	-0.114	0.909
AR(3)	0.622	3.068	0.203	0.840
AR(4)	-0.145	4.468	-0.032	0.974
AR(5)	0.299	3.012	0.099	0.921
AR(6)	-0.131	3.160	-0.042	0.967
AR(7)	0.049	2.437	0.020	0.984
AR(8)	0.332	1.860	0.179	0.859
MA(1)	0.931	.	.	.
MA(2)	-0.477	.	.	.
MA(3)	0.868	.	.	.
MA(4)	-0.566	.	.	.
MA(5)	0.281	.	.	.
MA(6)	-0.315	.	.	.
MA(7)	0.060	.	.	.
MA(8)	0.403	.	.	.
MA(9)	-0.185	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 78	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.282	9.014	0.031	0.975
AR(2)	-0.794	1.838	-0.432	0.668
AR(3)	0.111	7.471	0.015	0.988
AR(4)	-0.517	0.536	-0.965	0.338
AR(5)	0.402	4.807	0.084	0.934
AR(6)	-0.610	3.126	-0.195	0.846
AR(7)	0.429	5.397	0.079	0.937
AR(8)	0.006	3.521	0.002	0.999
MA(1)	0.823	.	.	.
MA(2)	-0.774	.	.	.
MA(3)	0.461	.	.	.
MA(4)	-0.243	.	.	.
MA(5)	0.584	.	.	.
MA(6)	-0.550	.	.	.
MA(7)	0.753	.	.	.
MA(8)	-0.010	.	.	.
MA(9)	-0.043	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.2. Estimation results for 1 month ahead (Germany) – Estimation until 2007:07

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 79	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-1.382	0.472	-2.926	0.005
AR(2)	-0.545	2.491	-0.219	0.827
AR(3)	0.200	3.693	0.054	0.957
AR(4)	-0.328	3.012	-0.109	0.914
AR(5)	-0.870	1.026	-0.848	0.400
AR(6)	-0.019	2.248	-0.008	0.993
AR(7)	0.509	2.846	0.179	0.859
AR(8)	0.349	1.836	0.190	0.850
MA(1)	-0.724	.	.	.
MA(2)	0.400	.	.	.
MA(3)	0.629	.	.	.
MA(4)	-0.420	.	.	.
MA(5)	-0.760	.	.	.
MA(6)	0.436	.	.	.
MA(7)	0.466	.	.	.
MA(8)	0.007	.	.	.
MA(9)	-0.189	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 79	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.234	0.768	-0.305	0.761
AR(2)	-0.998	0.470	-2.123	0.038
AR(3)	0.086	0.976	0.088	0.930
AR(4)	-0.727	0.434	-1.674	0.099
AR(5)	0.237	0.713	0.332	0.741
AR(6)	-0.259	0.406	-0.639	0.525
AR(7)	0.264	0.340	0.774	0.442
AR(8)	-0.406	0.441	-0.920	0.361
MA(1)	0.326	.	.	.
MA(2)	-0.696	.	.	.
MA(3)	0.665	.	.	.
MA(4)	-0.433	.	.	.
MA(5)	0.658	.	.	.
MA(6)	-0.028	.	.	.
MA(7)	0.495	.	.	.
MA(8)	-0.332	.	.	.
MA(9)	0.342	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.3. Estimation results for 1 month ahead (Germany) – Estimation until 2007:08

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 80	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-1.387	3.022	-0.459	0.648
AR(2)	-0.995	3.767	-0.264	0.792
AR(3)	-0.090	3.950	-0.023	0.982
AR(4)	-0.897	3.146	-0.285	0.777
AR(5)	-1.177	3.324	-0.354	0.725
AR(6)	-0.518	3.842	-0.135	0.893
AR(7)	0.402	3.363	0.120	0.905
AR(8)	0.276	2.469	0.112	0.911
MA(1)	-0.704	.	.	.
MA(2)	-0.029	.	.	.
MA(3)	0.630	.	.	.
MA(4)	-0.812	.	.	.
MA(5)	-0.653	.	.	.
MA(6)	0.205	.	.	.
MA(7)	0.691	.	.	.
MA(8)	-0.026	.	.	.
MA(9)	-0.228	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 80	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.437	7.443	0.059	0.953
AR(2)	-0.804	1.940	-0.415	0.680
AR(3)	0.184	6.096	0.030	0.976
AR(4)	-0.577	0.927	-0.623	0.536
AR(5)	0.491	4.016	0.122	0.903
AR(6)	-0.507	2.817	-0.180	0.858
AR(7)	0.407	3.358	0.121	0.904
AR(8)	-0.006	2.509	-0.002	0.998
MA(1)	0.920	.	.	.
MA(2)	-0.804	.	.	.
MA(3)	0.504	.	.	.
MA(4)	-0.297	.	.	.
MA(5)	0.619	.	.	.
MA(6)	-0.446	.	.	.
MA(7)	0.571	.	.	.
MA(8)	-0.010	.	.	.
MA(9)	-0.057	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.4. Estimation results for 1 month ahead (Germany) – Estimation until 2007:09

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 81	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.581	3.850	-0.151	0.880
AR(2)	-0.737	5.238	-0.141	0.889
AR(3)	0.071	6.404	0.011	0.991
AR(4)	-0.406	4.772	-0.085	0.933
AR(5)	-0.514	4.620	-0.111	0.912
AR(6)	-0.237	5.532	-0.043	0.966
AR(7)	0.099	4.667	0.021	0.983
AR(8)	0.563	3.284	0.172	0.864
MA(1)	0.081	.	.	.
MA(2)	-0.353	.	.	.
MA(3)	0.594	.	.	.
MA(4)	-0.458	.	.	.
MA(5)	-0.328	.	.	.
MA(6)	0.045	.	.	.
MA(7)	0.168	.	.	.
MA(8)	0.561	.	.	.
MA(9)	-0.361	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 81	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.394	11.039	0.036	0.972
AR(2)	-0.853	2.452	-0.348	0.729
AR(3)	0.183	9.379	0.020	0.985
AR(4)	-0.548	0.814	-0.674	0.503
AR(5)	0.428	5.866	0.073	0.942
AR(6)	-0.446	3.500	-0.127	0.899
AR(7)	0.441	4.450	0.099	0.921
AR(8)	-0.036	4.191	-0.009	0.993
MA(1)	0.884	.	.	.
MA(2)	-0.843	.	.	.
MA(3)	0.530	.	.	.
MA(4)	-0.258	.	.	.
MA(5)	0.536	.	.	.
MA(6)	-0.334	.	.	.
MA(7)	0.574	.	.	.
MA(8)	-0.057	.	.	.
MA(9)	-0.033	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.5. Estimation results for 1 month ahead (Germany) – Estimation until 2007:10

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 82	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.776	21.478	-0.036	0.971
AR(2)	-0.766	31.160	-0.025	0.980
AR(3)	-0.034	36.995	-0.001	0.999
AR(4)	-0.197	25.394	-0.008	0.994
AR(5)	-0.536	20.667	-0.026	0.979
AR(6)	-0.253	25.272	-0.010	0.992
AR(7)	-0.057	22.091	-0.003	0.998
AR(8)	0.495	16.080	0.031	0.976
MA(1)	-0.117	.	.	.
MA(2)	-0.260	.	.	.
MA(3)	0.521	.	.	.
MA(4)	-0.144	.	.	.
MA(5)	-0.484	.	.	.
MA(6)	0.017	.	.	.
MA(7)	0.009	.	.	.
MA(8)	0.558	.	.	.
MA(9)	-0.274	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 82	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.181	11.150	0.016	0.987
AR(2)	-0.728	1.758	-0.414	0.680
AR(3)	0.061	8.570	0.007	0.994
AR(4)	-0.475	0.615	-0.773	0.443
AR(5)	0.377	5.401	0.070	0.945
AR(6)	-0.463	3.949	-0.117	0.907
AR(7)	0.415	5.156	0.081	0.936
AR(8)	0.018	4.608	0.004	0.997
MA(1)	0.697	.	.	.
MA(2)	-0.654	.	.	.
MA(3)	0.371	.	.	.
MA(4)	-0.183	.	.	.
MA(5)	0.538	.	.	.
MA(6)	-0.402	.	.	.
MA(7)	0.672	.	.	.
MA(8)	-0.007	.	.	.
MA(9)	-0.032	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.6. Estimation results for 1 month ahead (Germany) – Estimation until 2007:11

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 83	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.026	5.986	-0.004	0.997
AR(2)	0.093	3.009	0.031	0.976
AR(3)	0.534	1.892	0.282	0.779
AR(4)	-0.121	3.485	-0.035	0.972
AR(5)	0.023	3.506	0.007	0.995
AR(6)	0.127	2.142	0.059	0.953
AR(7)	0.094	1.571	0.060	0.952
AR(8)	0.256	1.529	0.168	0.867
MA(1)	0.637	.	.	.
MA(2)	0.137	.	.	.
MA(3)	0.486	.	.	.
MA(4)	-0.462	.	.	.
MA(5)	-0.040	.	.	.
MA(6)	0.107	.	.	.
MA(7)	-0.034	.	.	.
MA(8)	0.278	.	.	.
MA(9)	-0.108	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 83	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.519	3.776	0.137	0.891
AR(2)	-0.895	1.646	-0.544	0.588
AR(3)	0.237	3.763	0.063	0.950
AR(4)	-0.558	0.743	-0.751	0.456
AR(5)	0.519	2.051	0.253	0.801
AR(6)	-0.420	1.416	-0.297	0.767
AR(7)	0.425	1.607	0.265	0.792
AR(8)	0.015	1.614	0.009	0.993
MA(1)	1.007	.	.	.
MA(2)	-0.962	.	.	.
MA(3)	0.569	.	.	.
MA(4)	-0.298	.	.	.
MA(5)	0.592	.	.	.
MA(6)	-0.334	.	.	.
MA(7)	0.513	.	.	.
MA(8)	0.003	.	.	.
MA(9)	-0.090	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.7. Estimation results for 1 month ahead (Germany) – Estimation until 2007:12

		Arrivals		
Benchmark models ARIMA (8,1,9) Estimation until observation 84	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.248	4.460	0.056	0.956
AR(2)	-0.764	1.969	-0.388	0.699
AR(3)	-0.201	3.650	-0.055	0.956
AR(4)	-0.806	3.513	-0.229	0.819
AR(5)	0.047	4.411	0.011	0.991
AR(6)	-0.389	2.732	-0.142	0.887
AR(7)	-0.317	2.438	-0.130	0.897
AR(8)	0.199	3.149	0.063	0.950
MA(1)	0.917	.	.	.
MA(2)	-0.930	.	.	.
MA(3)	0.310	.	.	.
MA(4)	-0.653	.	.	.
MA(5)	0.473	.	.	.
MA(6)	-0.349	.	.	.
MA(7)	-0.161	.	.	.
MA(8)	0.485	.	.	.
MA(9)	-0.175	.	.	.
		Overnight stays		
Benchmark models ARIMA (8,1,9) Estimation until observation 84	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.317	0.890	-0.356	0.723
AR(2)	-1.105	0.549	-2.013	0.048
AR(3)	-0.090	1.124	-0.080	0.936
AR(4)	-0.694	0.465	-1.491	0.141
AR(5)	0.342	0.676	0.506	0.615
AR(6)	-0.170	0.528	-0.321	0.749
AR(7)	0.442	0.310	1.427	0.159
AR(8)	-0.320	0.633	-0.505	0.615
MA(1)	0.228	.	.	.
MA(2)	-0.767	.	.	.
MA(3)	0.505	.	.	.
MA(4)	-0.322	.	.	.
MA(5)	0.810	.	.	.
MA(6)	-0.040	.	.	.
MA(7)	0.659	.	.	.
MA(8)	-0.372	.	.	.
MA(9)	0.298	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.8. Estimation results for 1 month ahead (Germany) – Estimation until 2008:01

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 85	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.178	2.002	-0.089	0.929
AR(2)	-0.800	2.025	-0.395	0.694
AR(3)	-0.124	2.555	-0.049	0.961
AR(4)	-0.739	2.217	-0.333	0.740
AR(5)	-0.327	2.286	-0.143	0.887
AR(6)	-0.347	2.428	-0.143	0.887
AR(7)	-0.187	2.019	-0.092	0.927
AR(8)	0.337	1.828	0.184	0.854
MA(1)	0.497	.	.	.
MA(2)	-0.674	.	.	.
MA(3)	0.408	.	.	.
MA(4)	-0.674	.	.	.
MA(5)	0.071	.	.	.
MA(6)	-0.104	.	.	.
MA(7)	-0.066	.	.	.
MA(8)	0.530	.	.	.
MA(9)	-0.278	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 85	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.184	0.903	-0.204	0.839
AR(2)	-1.041	0.479	-2.175	0.033
AR(3)	0.186	1.192	0.156	0.876
AR(4)	-0.734	0.445	-1.652	0.103
AR(5)	0.371	0.804	0.461	0.646
AR(6)	-0.202	0.488	-0.414	0.680
AR(7)	0.299	0.332	0.899	0.372
AR(8)	-0.368	0.499	-0.737	0.464
MA(1)	0.344	.	.	.
MA(2)	-0.816	.	.	.
MA(3)	0.740	.	.	.
MA(4)	-0.531	.	.	.
MA(5)	0.738	.	.	.
MA(6)	-0.043	.	.	.
MA(7)	0.429	.	.	.
MA(8)	-0.297	.	.	.
MA(9)	0.275	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.9. Estimation results for 1 month ahead (Germany) – Estimation until 2008:02

		Arrivals		
Benchmark models ARIMA (8,1,9) Estimation until observation 86	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.288	1.068	-0.270	0.788
AR(2)	-0.522	0.892	-0.585	0.561
AR(3)	0.415	1.120	0.371	0.712
AR(4)	-0.329	1.255	-0.262	0.794
AR(5)	-0.273	1.221	-0.223	0.824
AR(6)	-0.015	1.072	-0.014	0.989
AR(7)	0.384	0.833	0.461	0.646
AR(8)	0.675	0.950	0.711	0.480
MA(1)	0.381	.	.	.
MA(2)	-0.322	.	.	.
MA(3)	0.771	.	.	.
MA(4)	-0.611	.	.	.
MA(5)	-0.153	.	.	.
MA(6)	0.173	.	.	.
MA(7)	0.317	.	.	.
MA(8)	0.501	.	.	.
MA(9)	-0.471	.	.	.
		Overnight stays		
Benchmark models ARIMA (8,1,9) Estimation until observation 86	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.125	0.872	-0.144	0.886
AR(2)	-1.024	0.493	-2.079	0.041
AR(3)	0.151	1.066	0.142	0.888
AR(4)	-0.644	0.425	-1.517	0.134
AR(5)	0.404	0.726	0.556	0.580
AR(6)	-0.242	0.446	-0.542	0.590
AR(7)	0.365	0.285	1.283	0.204
AR(8)	-0.357	0.498	-0.718	0.476
MA(1)	0.447	.	.	.
MA(2)	-0.776	.	.	.
MA(3)	0.657	.	.	.
MA(4)	-0.400	.	.	.
MA(5)	0.771	.	.	.
MA(6)	-0.181	.	.	.
MA(7)	0.559	.	.	.
MA(8)	-0.354	.	.	.
MA(9)	0.277	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.10. Estimation results for 1 month ahead (Germany) – Estimation until 2008:03

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 87	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.229	1.640	-0.139	0.890
AR(2)	-0.617	1.552	-0.398	0.692
AR(3)	0.149	1.848	0.080	0.936
AR(4)	-0.211	1.842	-0.115	0.909
AR(5)	-0.104	1.355	-0.077	0.939
AR(6)	-0.112	1.303	-0.086	0.932
AR(7)	0.109	1.063	0.103	0.918
AR(8)	0.490	1.089	0.450	0.654
MA(1)	0.433	.	.	.
MA(2)	-0.456	.	.	.
MA(3)	0.580	.	.	.
MA(4)	-0.281	.	.	.
MA(5)	-0.074	.	.	.
MA(6)	-0.050	.	.	.
MA(7)	0.060	.	.	.
MA(8)	0.454	.	.	.
MA(9)	-0.307	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 87	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.456	0.850	-0.536	0.594
AR(2)	-1.074	0.683	-1.573	0.120
AR(3)	-0.139	1.095	-0.127	0.899
AR(4)	-0.689	0.475	-1.451	0.151
AR(5)	0.349	0.632	0.553	0.582
AR(6)	-0.066	0.535	-0.123	0.903
AR(7)	0.459	0.393	1.167	0.247
AR(8)	-0.308	0.680	-0.453	0.652
MA(1)	0.067	.	.	.
MA(2)	-0.709	.	.	.
MA(3)	0.509	.	.	.
MA(4)	-0.353	.	.	.
MA(5)	0.856	.	.	.
MA(6)	0.030	.	.	.
MA(7)	0.685	.	.	.
MA(8)	-0.438	.	.	.
MA(9)	0.322	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.11. Estimation results for 1 month ahead (Germany) – Estimation until 2008:04

	Coefficients	Std. Prob.	Errors	t-ratio
Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 88	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.207	2.533	0.082	0.935
AR(2)	-0.440	1.966	-0.224	0.824
AR(3)	0.404	1.474	0.274	0.785
AR(4)	-0.557	1.815	-0.307	0.760
AR(5)	0.140	2.155	0.065	0.948
AR(6)	0.010	1.601	0.006	0.995
AR(7)	0.292	1.616	0.181	0.857
AR(8)	0.396	1.892	0.209	0.835
MA(1)	0.890	.	.	.
MA(2)	-0.578	.	.	.
MA(3)	0.684	.	.	.
MA(4)	-0.838	.	.	.
MA(5)	0.399	.	.	.
MA(6)	-0.021	.	.	.
MA(7)	0.191	.	.	.
MA(8)	0.294	.	.	.
MA(9)	-0.309	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 88	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.468	0.822	-0.570	0.571
AR(2)	-1.065	0.644	-1.653	0.103
AR(3)	-0.185	1.024	-0.181	0.857
AR(4)	-0.699	0.452	-1.546	0.127
AR(5)	0.274	0.608	0.451	0.654
AR(6)	-0.068	0.504	-0.135	0.893
AR(7)	0.444	0.363	1.223	0.225
AR(8)	-0.277	0.647	-0.429	0.669
MA(1)	0.048	.	.	.
MA(2)	-0.688	.	.	.
MA(3)	0.456	.	.	.
MA(4)	-0.337	.	.	.
MA(5)	0.767	.	.	.
MA(6)	0.077	.	.	.
MA(7)	0.681	.	.	.
MA(8)	-0.386	.	.	.
MA(9)	0.314	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid

Table A.12. Estimation results for 1 month ahead (Germany) – Estimation until 2008:05

Arrivals				
Benchmark models ARIMA (8,1,9) Estimation until observation 89	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	0.050	1.392	0.036	0.972
AR(2)	-0.739	1.301	-0.568	0.572
AR(3)	0.127	1.401	0.090	0.928
AR(4)	-0.665	1.457	-0.457	0.649
AR(5)	-0.048	1.509	-0.032	0.975
AR(6)	-0.275	1.388	-0.198	0.844
AR(7)	0.057	1.163	0.049	0.961
AR(8)	0.388	1.199	0.324	0.747
MA(1)	0.736	.	.	.
MA(2)	-0.781	.	.	.
MA(3)	0.604	.	.	.
MA(4)	-0.770	.	.	.
MA(5)	0.287	.	.	.
MA(6)	-0.203	.	.	.
MA(7)	0.112	.	.	.
MA(8)	0.416	.	.	.
MA(9)	-0.328	.	.	.
Overnight stays				
Benchmark models ARIMA (8,1,9) Estimation until observation 89	Coefficients	Std. Prob.	Errors	t-ratio
AR(1)	-0.415	0.807	-0.514	0.609
AR(2)	-1.023	0.689	-1.484	0.142
AR(3)	-0.089	1.045	-0.085	0.932
AR(4)	-0.650	0.493	-1.319	0.191
AR(5)	0.386	0.605	0.637	0.526
AR(6)	-0.080	0.499	-0.161	0.873
AR(7)	0.420	0.376	1.117	0.268
AR(8)	-0.383	0.619	-0.618	0.539
MA(1)	0.101	.	.	.
MA(2)	-0.690	.	.	.
MA(3)	0.500	.	.	.
MA(4)	-0.361	.	.	.
MA(5)	0.886	.	.	.
MA(6)	-0.028	.	.	.
MA(7)	0.651	.	.	.
MA(8)	-0.533	.	.	.
MA(9)	0.364	.	.	.

The standard errors for the MA parameters are not reported because there is a MA root on the boundary. The parameter estimates remain valid