

## Tourism demand for Italy and the business cycle

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### ABSTRACT

This study provides a strategy for modelling the effect of the business cycle on tourism demand under the rationale that tourism cycles are heavily influenced by lagged effects of the overall business cycle. Using quarterly data on overnight stays in Italian hotels, both domestic and inbound between 1985 and 2004, we adopt a structural time series approach to evaluate two alternative models, the first with a latent cycle component (LCC) and the second based on specific economic explanatory variables (XCV). The two models are compared in terms of explanatory power, best-fit, residual diagnostics and forecasting ability. The results show similar performances. The policy implication is that the XCV model can be used for calibrating countercyclical interventions in tourism policy.

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### 1. Introduction

The relevance of irregular trends and cyclical patterns in tourism demand has been long recognized and research has been targeted at effective modelling and forecasting strategy. While major business cycle fluctuations strongly influence consumer demand for goods and services, such as in times of economic recession and boom, the response of tourism demand is not necessarily immediate and straightforward because of substitution effects between types of destinations and lags between decision making and the actual holiday. The business cycle factor has been emphasized in some studies (see e.g. Wong, 1997), but has been implicitly accounted for in tourism demand models through explanatory variables subject to fluctuations, such as prices and disposable income. However, little attention has been devoted to modelling the long-term relationship and lag structure between tourism demand and the business cycle (see e.g. Gouveia & Rodrigues, 2005). Explicit modelling of cyclical components can be effectively pursued through Harvey's structural time series approach (STS, see Harvey, 1989), which has progressively gained in popularity and exemplified by its application in González and Moral (1995, 1996), Greenidge (2001), Turner and Witt (2001), Kim and Moosa (2005) and Vu and Turner (2006) among others. However, none of these papers has explicitly focused on the dynamic specification and understanding of the cyclical component.

Thus, the key question posed in this paper is whether and to what extent tourism cycles can be regarded as a direct consequence of business cycles. This would mean that cyclical movements in tourism demand may be simply explained by the delayed effect of the economic cycle. In order to address this question, we compare and assess two alternative routes to the specification of the cycle component within STS models, one based on the standard stochastic specification, and the other relating cyclical movements to the overall economic dynamics as proxied by economic explanatory variables.

If a relationship between the tourism cycle and the overall business cycle can be shown, then tourism policy could take advantage of the delay between the two cycles by adopting countercyclical measures to soften the impact of adverse economic conditions.

The application of this study explores the evolution and cyclical behaviour of tourism demand in Italy measured by nights spent in tourism accommodation structures. Italy is one of the world's leading countries for tourism earnings and tourism is a key sector in the Italian economy (World Tourism and Travel Council, 2007). By separating domestic tourism from inbound tourism, we account for differences and delays in international economic cycles. Quarterly data cover the period from 1985 to 2004, which includes important cyclical events (such as the 1992–1993 recession), major events like the Football World Cup in 1990, the Roman Catholic Jubilee in 2000 and the introduction of the Euro in January 2002. The STS specification allows for a stochastic trend to capture structural changes and breaks, such as those potentially induced by the above events, and the sample is of sufficient duration to detect modifications in seasonal patterns.

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The paper is structured as follows. Section 2 reviews the literature on the impact of the business cycle on tourism demand and on the relevant econometric specifications, with an emphasis on STS models. The methodology adopted in this study is described in detail in Section 3. Section 4 illustrates the data and results of the application as regards tourism demand for Italy. Finally, Section 5 summarizes the main findings and draws some conclusions.

## 2. Literature review

The presence of cyclical movements in tourism demand has been accounted for in many empirical studies, although only a few of these have explicitly isolated this component and even fewer studies have attempted a business cycle interpretation. In a recent review of tourism demand models, [Song and Li \(2008\)](#) underline the scarcity of literature looking at tourism cycles, turning points and directional changes. Furthermore, the literature on the relation between the tourism and the business cycle shows a wide variety of methodological approaches to elicit cyclical movements.

In most tourism demand studies, the effect of the business cycle enters models through a set of economic explanatory variables. A list of economic determinants which have been exploited to explain tourism demand can be found in the meta-analysis by [Crouch \(1996\)](#) or the reviews by [Witt and Witt \(1995\)](#) or [Lim \(1997\)](#).

The detection of tourism cycles is complicated by many confounding factors which generate irregular patterns and structural changes in tourism demand. Firstly, seasonal patterns may evolve over time as a consequence of income growth and the modification of working hours and holiday entitlements. Secondly, structural changes are accelerated by technological progress and trends in the travel sector, for example the exponential increase in the availability of low cost flights. Thirdly, major events and fashions can determine short or long-term modifications in tourist flows, for example sporting events such as the Olympics or religious events such as the Jubilee year (see e.g. [Kim, Gursoy, & Lee, 2006](#)). While these three factors are sufficient to raise concerns about the variety of tourism determinants, a further element of variability stems from the cyclical patterns of the economy, which feed into the time path of tourism demand ([Wong, 1997](#)). A complication in understanding the relationship between the business cycle and tourism demand derives from the fact that the former can affect tourist choices in either direction, as a general recession may favour cheaper destinations over those more expensive. Furthermore, the evaluation of relative prices between alternative destinations is generally based on expected fares at the time of holiday planning, which explains the existence of lags between the business cycle and the tourist cycle. Finally, the economic cycle has also been shown to influence the tourism sector through the supply side, such as the dependence of performance of tourism firms on business conditions ([Chen, 2007](#)).

### 2.1. Tourism demand and the business cycle

After accounting for the economic determinants of demand, cyclic patterns in tourism time series have been generally imputed to the life-cycle hypothesis for a tourist destination. A vast literature covers this research area (see [Butler, 1980, 2006](#)), although this pattern is more likely to emerge in longer time spans than those affected by the business cycle. For example, [Formica and Uysal \(1996\)](#) consider a complete life-cycle of more than two centuries for Italy (between 1760 and the early 21st Century). They recognize an interaction between life-cycle and business cycle, and argue that the 1992 economic recession in Italy and subsequent inflation in hotel prices has exacerbated a decline stage.

The influence of the business cycle has been shown to be especially relevant for international tourism, which is more income-elastic. [Wong \(1997\)](#) finds that accounting for a sine-wave cyclical component enables improved forecasts of international tourist arrivals to Hong Kong and suggests that a business cycle component should be explicitly accounted for in econometric models. A follow-up of this study is found in [Song, Wong, and Chon \(2003\)](#), where an autoregressive distributed lag (ARDL) approach is adopted to explore the relationship between Hong Kong international tourist arrivals and a set of economic variables, but only a single (annual) lag is considered.

Most econometric models do implicitly account for business cycles by including on the right-hand side disposable income or other economic variables which reflect cyclical movements in the economy. For example, [Collins and Tisdell \(2004\)](#) provide evidence of a long-term positive relationship between Australian outbound business travel and business returns and show that the latter are a better predictor of international business travel than Gross Domestic Product (GDP). Other works (eg see [Lim & McAleer, 2002](#)) found significant links between tourism demand and macroeconomic variables at various lags by using dynamic models which allow for endogenous relationships, such as co-integration techniques.

One of the few studies which look at the synchronization between tourism demand and business cycles is the one by [Gouveia and Rodrigues \(2005\)](#). They use a non-parametric approach developed by [Harding and Pagan \(2003\)](#) and based on the Hodrick–Prescott filter to detect cycle turning points in foreign tourism stays in Algarve hotels, as well as cyclical movements in the industrial production index of the countries of origin. Their pioneering study shows a relatively constant time lag between the economic and tourism cycles.

An alternative approach to extrapolate cyclical movements is the application of unobserved components decomposition techniques, which assume that a time series is a multiplicative or additive combination of a trend component, a cyclical component, a seasonal component and an irregular component. [Koc and Altinay \(2007\)](#) apply the TRAMO/SEATS and X-12 ARIMA model to international tourist spending in Turkey, although they only refer to a joint trend/cycle component. [Brännäs, Hellström, and Nordström \(2002\)](#) explore the patterns in a time series of nights stayed in Swedish hotels by Norwegian visitors, using an ARIMA-based time series model which assumes cross-sectional and time series aggregation of individual hotel overnight stays data. They find a cycle pattern which tracks the business cycles of the destination and origin countries. The unobserved component specification is also the foundation of structural time series models.

Spectral analysis has also been applied to model seasonality and cyclical movement. The conclusions drawn by [Coshall \(2000\)](#) based on air and sea travel data for various origins and destinations sharply contrast with the rest of the literature, as a spectral analysis only highlights seasonal patterns, but not longer-term cyclical fluctuations. Coshall argues that international tourism flows are not subject to the business cycle, although he finds a relationship between the Sterling exchange rate and UK passenger flows. As discussed in Section 3, this result might be due to the choice of travel data rather than expenditure or length-of-stay data.

Finally, it is important to underline one of the limitations which affects most empirical studies on cycles listed above. With ARIMA models, spectral analysis and other sine-wave specifications, the cyclical component is assumed to be deterministic and stable over time. This may be an unnecessary constraint, especially with extremely long time series, which is overcome by structural time series models.

## 2.2. Structural time series models

There is evidence (see the review by Li, Song, & Witt, 2005) that STS models perform consistently well in forecasting. In their forecast assessments, Kulendran and Witt (2003) and Turner and Witt (2001) also conclude that the basic structural model without any additional explanatory variable (the simplest form of STS models) is sufficient to produce good short-term forecasts. They also argue that the inclusion of economic variables on the right-hand side of STS models does not seem to improve the performance. Our argument in this study goes a step further, as we evaluate the explicative power of STS models with (lagged) explanatory variables compared to basic STS models with a trigonometric cyclical component. On the forecasting front, the issue of the performance of alternative specifications has been widely treated in the literature. In their extensive review, Li et al. (2005) count 23 studies targeted at comparing forecasts (see in particular Cho, 2003; Chu, 1998; Martin & Witt, 1989; Song & Witt, 2006; Witt, Song, & Louvieris, 2003 and references therein). Although comparisons are usually limited to complex models, it has been shown that naïve models usually produce better forecasts for longer time horizons (see Kulendran & Witt, 2001, 2003) and need to be taken into account for a correct assessment of the trade-off between complexity and predictive power.

To our knowledge, González and Moral (1996) are the first to exploit the STS latent cyclical component to model expansion and recession patterns in international tourism demand for Spain. Their analysis extends a previous article (González & Moral, 1995), where no cyclical component appears, but irregular trends in demand patterns are modelled through a set of economic explanatory variables. Our study merges, compares and extends these two perspectives, with an emphasis on cycle modelling. Using the same data as González and Moral (1995), García-Ferrer and Queralto (1997) also estimate an STS model where prices and incomes appear on the right-hand side of the equation and test for their significance at different lags. While they find a good short-term forecasting performance of the STS model, they also claim that (a) the specification search process should be made transparent; (b) explanatory variables do not seem to enhance the forecasting performance (see also Kulendran & Witt, 2003); and (c) a more rigorous approach to forecast evaluation should be used. Furthermore, as also emphasized by Kulendran and Witt (2003), forecasting performances should be evaluated on both medium and long time horizons.

Greenidge (2001) adopts an STS specification with a trigonometric stochastic cycle to model tourist arrivals to Barbados, together with contemporaneous real GDP and price variables on the right-hand side of the equation. With a 30-year data-set (1968–1997), two significant cyclical components (of 1.73 and 7 years, respectively) are found for arrivals from the UK, but not for US or Canadian tourists. When the GDP appears on the right-hand side, the cyclical component disappears, but no exploration for lagged impacts is carried out. An STS model with a trigonometric cycle is also estimated in Kim and Moosa (2005), although the final objective of this study is to compare direct and indirect forecasts (i.e. on aggregate versus composite time series) of tourism flows to Australia and no estimation result is reported. Turner and Witt (2001) estimate three separate STS models for tourist arrivals to New Zealand from Australia, the US and the United Kingdom. A cyclical component is included, but no discussion is provided on its specification and interpretation.

## 3. Methodology

We adopt a three-step strategy based on STS models to explore the relationship and the delay between the business cycle and the

tourism cycle. Firstly, we model time series of tourist nights as a basic structural model (BSM), where they are simply explained by a stochastic trend, a seasonal term, an irregular component and a cyclical one. The latter component follows a given trigonometric specification, but the amplitude of the cycle is allowed to vary over time. As a second step, after purging the time series of tourist nights from the seasonal and trend components, we model the residual trend-cycle series as a function of a selection of macroeconomic indicators, deemed as relevant to explain short-term tourism response and subject to the overall business cycle. We allow for lags in the transmission of effects. Finally, in step three we apply the STS method again, this time taking into explicit account the macroeconomic determinants identified in step two and omitting the cyclical components. Based on residual and predictive diagnostics, we provide a comparative evaluation of two structural time series models: (a) the latent cyclical component model (LCC); and (b) the explicit modelling of cycles through explanatory variables (XCV).

This three-step approach allows the exploration the relative performance of the trigonometric cycle as compared to the use of exogenous economic variables. By assessing the forecasting performances of these two competing models, we contribute to the literature on tourism forecasting models (see Li et al., 2005, Song, Witt, & Jensen, 2003 among others). Under our research hypothesis, if the XCV performs satisfactorily in explaining and predicting tourist nights as compared to the LCC, then cyclical behaviour in tourism is explained by the overall economic cycle. Otherwise, failure to explain tourist nights with (lagged) economic explanatory variables would highlight the presence of a tourism-specific cycle.

The first step requires estimation of the basic STS model with a latent cyclical component (the LCC model), specified as:

$$y_t = \mu_t + \phi_t + \psi_t + \varepsilon_t \quad (1)$$

where  $y_t$  are the tourist nights,  $\mu_t$  is the local linear trend component,  $\phi_t$  is the seasonal component,  $\psi_t$  is the cycle and  $\varepsilon_t$  is the irregular component (stochastic error). The local linear trend is specified as a random walk with a stochastic random walk drift ( $\delta_t$ ):

$$\begin{cases} \mu_t = \mu_{t-1} + \delta_{t-1} + v_t \\ \delta_t = \delta_{t-1} + \zeta_t \end{cases} \quad (2)$$

where  $v_t$  and  $\zeta_t$  are independent white-noise Gaussian errors. This specification is the same as in previous studies (see e.g. González & Moral, 1995 or Kim & Moosa, 2005), although in our study the seasonal component is assumed to follow a stochastic dummy specification as in Vu and Turner (2006) instead of a trigonometric specification (the two alternatives are shown in Greenidge, 2001):

$$\phi_t = - \sum_{j=1}^{s-1} \phi_{t-j} + \omega_t \quad (3)$$

where  $s$  depends on the data periodicity (for quarterly data,  $s = 4$ ) and  $\omega_t$  is also a white-noise Gaussian error. Finally, the cyclical component is defined as in the trigonometric specification explained in Harvey and Jaeger (1993) and adopted by Kim and Moosa (2005) and Greenidge (2001):

$$\begin{cases} \psi_t = \rho \cos \lambda_c \psi_{t-1} + \rho \sin \lambda_c \psi_{t-1} + \kappa_t \\ \psi_t^* = -\rho \sin \lambda_c \psi_{t-1} + \rho \cos \lambda_c \psi_{t-1}^* + \kappa_t^* \end{cases} \quad (4)$$

where  $\rho$  is a damping factor between 0 and 1,  $\lambda_c$  is the frequency of the cycle (in radians) and the errors  $\kappa_t$  and  $\kappa_t^*$  are white noise Gaussian errors. All errors in the LCC model are assumed to be independent of each other.

Maximum likelihood estimation of (1) is achieved by rewriting the model in the state-space form and applying an optimisation

algorithm like the EM algorithm or the BHHH procedure by Berndt, Hall, Hall, and Hausman (1974), see Harvey (1989) for technical details. The damping factor and the frequency of the cycle are parameters to be estimated. Since their final estimate may be sensitive to the initial values needed to start the algorithm, it is advisable to check for the robustness of the results by estimating the model on different sets of starting values.

Once the components have been estimated, it is possible to explore the relationship between the smoothed estimate of the cyclical component and a set of economic variables, similar to those in González and Moral (1995). Since we expect to observe delays in the relationship, an appropriate choice of the relevant explanatory variables and lags can be based on an iterative stepwise distributed lag selection on the following regression model:

$$\psi_t + \varepsilon_t = \sum_{i=1}^k \sum_{j=0}^l \beta_{ij} x_{i,t-j} + \eta_t \quad (5)$$

where  $k$  is the number of explanatory variables under consideration and  $l$  the maximum lag.

The variables considered here are those most frequently employed in tourism demand functions (see e.g. Lim, 1997), those being income, consumer prices for tourist goods and services and exchange rates, as detailed in Section 4.

After selection of the relevant variables and lags, the third step requires modification of (1) to include weakly exogenous variables, as a replacement for the cyclical component. The model (termed here as XCV) follows the specification adopted in González and Moral (1995):

$$y_t = \mu_t + \phi_t + z_t' \beta + \varepsilon_t \quad (6)$$

where  $z_t$  is a vector containing the explanatory variables selected in the previous step, which are expected to influence tourist stays at time  $t$ . This means that  $z_t$  may contain both contemporaneous and lagged values, depending on the outcome of the previous step. While our specification closely follows the standard BSM employed in the tourism literature, it should be emphasized that all variables in (1), (5) and (6) are taken in first logarithmic differences, so that they represent percentage changes. This transformation has three advantages: (a) a scale reduction, which is desirable due to the large absolute values and the scale differences across variables; (b) the long-term component which might characterise the series is filtered out, so that explanatory variables reflect cyclical dynamics, as required by this study; (c) the coefficients represent short-run tourism demand elasticity.

The adequacy of the relationship portrayed in the XCV model in (6) can be assessed by looking at the sample residual diagnostics and forecasting performance of the model, with the LCC model in (1) as the benchmark. Residual diagnostics include the usual goodness-of-fit statistics for structural time series model ( $R^2_D$  and  $R^2_S$ ) and information criteria (Akaike and Schwartz Information Criteria or AIC and SIC, respectively), which enable us to compare non-nested models with a different number of regressors. Finally, a test for serial correlation in the residuals is based on the Ljung-Box Q statistic. The  $R^2_D$  and  $R^2_S$  values measure the goodness-of-fit of the equations (Harvey, 1989, p. 268), with a simple random walk plus drift (RWD) model and an RWD model in first differences around the seasonal means as benchmarks, respectively.

While a good within-sample performance could render the explanatory power of the XCV model reassuring, the out-of-sample forecasting performance is a key evaluation criterion. This is not a trivial point, because there is empirical evidence which indicates that basic time series models or even more naïve predictive models are often preferred in forecasting tourism and travel demand (see Kulendran & Witt, 2001, 2003). Among these naïve specifications, we consider the following three models:

$$y_t = \beta_1 y_{t-4} + \varepsilon_t \quad (7)$$

$$y_t = \beta_0 + \beta_1 y_{t-4} + \varepsilon_t \quad (8)$$

$$y_t = \sum_{j=1}^4 \beta_j D_j + \beta_5 \text{trend} + \beta_6 y_{t-1} + \varepsilon_t \quad (9)$$

where  $D_j$  is a seasonal dummy variable (for quarterly data) and  $trend$  is a linear trend variable. While the above models account for trend and seasonality, they ignore further explanatory variables. More specifically, models (7) and (8) are seasonal autoregressive models without and with drift, respectively. On the other hand, model (9) is an AR(1) model with linear trend and seasonal dummies. In almost all published works, forecasting performances are assessed through the loss functions computed on ex-post predictions for alternative specifications. This comparison is often limited to a given prediction step, although there is evidence that the forecasting performance may change considerably according to the horizon being considered (Kulendran & Witt, 2003). Thus, this work extends the evaluation of different model specifications to consider multi-step forecasts. The choice of the time horizon which is relevant to forecasting mainly depends on the delay in accessing official data on tourism demand. For the Italian case, data for year  $t$  is generally published between the third and the last quarter of the year  $t+1$ , which means that one-year and two-year forecast windows should be considered.

The evaluation of forecasts is based on a cost function of the prediction error. The cost function which appears most frequently in tourism studies is the mean absolute percentage error (MAPE) (see Li et al., 2005). Alternative error measures include: the root mean square percentage error, the mean absolute error, and Theil U statistic (see Cho, 2003; Goh & Law, 2002, among others). However, the MAPE does not depend on the magnitude of the forecast variables, a desirable characteristic for evaluating the forecasting performance of models with seasonality.

The MAPE index provides a descriptive evaluation, to which we add two inferential assessment methods. The first is a bias test based on the regression of the prediction errors on the constant term only (see Witt et al., 2003 for a previous application to tourism). If the estimated regression coefficient is significantly different from zero, then the null hypothesis that predictions are unbiased is rejected. The second method is a non-parametric accuracy test corresponding to the Wilcoxon signed rank test for paired samples, implemented on the differences between the absolute errors of two rival models (say  $M1$  and  $M2$ ):

$$TW = \sum_{i=1}^N I_+ \cdot \text{rank}(|e_{M1,i}| - |e_{M2,i}|) \quad (10)$$

where  $I_+$  is an indicator function which is 1 when the error of  $M1$  is larger than the error of  $M2$  and 0 otherwise. This test produces the TW statistic by calculating the differences on the paired MAPEs and adding all the ranks associated with positive differences. The null hypothesis being tested is that the rank sum for positive differences is equal to the rank sum for negative differences, hence the similarity of the forecasting performance of the two models being compared.

#### 4. Results and discussion

The 2007 WTTC simulations (World Tourism and Travel Council, 2007) estimate that the tourism industry accounts for 4.2% of Italy's Gross Domestic Product (GDP) and about 1 million jobs, for a monetary value of EUR64.9 billion. The latter figure ranks Italy eighth out of the 176 countries included in the simulation.

However, in terms of expected growth, Italy is at the bottom of the ranking (173rd). The country has a strong resort-based tourism vocation, currently in a decline stage of the tourism life-cycle, hence exposed to the competition of new destinations (Formica & Uysal, 1996).

The World Tourism Organisation (2007) ranks Italy in the top 5 destinations in terms of tourist arrivals (4.5% of world tourism flows) and in the top 4 countries in terms of international tourist receipts (with a world market share of 5.2%). The country is characterized by one of the highest average durations of overnight stays in Europe with 3.6 days, preceded by Slovenia only (data source: Eurostat REGIO, 2005). However, this figure has fallen from 3.9 in the mid-Nineties, a trend which is observed in most European destinations. Tourism demand for Italy is especially directed to private accommodation, which in 2004 represented about 58% of stays. Unfortunately, figures for this item are available for the most recent years only. Considering commercial accommodation, hotels account for 29% of total stays, while the remaining 13% is the share of complementary accommodation sites (room rentals, B&B, agri-tourism sites, etc). While these latter components have been rapidly growing over the last decade, time series data which is homogeneous and comparable in terms of collection method and statistical definitions is only accessible for the hotel segment.

Table 1 shows the main dynamics of hotel overnight stays over the sample period, split into 3-year windows. Overnight stays increase by about 30% over the period covered by the data and the only reduction is observed after the Jubilee year. If one considers the distinction between domestic and inbound tourism, where the former refers to resident visitors within the economic territory of the country of reference and the latter to non-resident visitors, inbound demand emerges as more volatile, because of a larger sensitivity to the economic conjuncture and to changes in international competitiveness. The sample period is especially informative, as it includes the 1990–1995 economic recession (followed by a growth period) and another economic slowdown after 2000. Exceptional events can be found across the sample, notable ones are the mucilage crisis which affected sea shores on the Northern Adriatic Sea in 1989–1990, the 1990 Football World Cup and the year 2000 Jubilee. The 28.3% increase of inbound overnight stays over the period 1994–1996 stands out. This figure is explained by several factors: (a) a reprise after the weak dynamics of the previous periods compared to domestic overnight stays; (b) the positive effects of currency depreciation; (c) the expansion of European economies after 1993; and (d) additional flows which can be imputed to the war in Croatia and Bosnia. These dynamics are well summarized in Fig. 1, which also shows the trend for internal tourism, intended as the sum of domestic and inbound overnight stays, and outbound tourism, that is tourism by Italian residents outside the Italian economic territory.

Another key feature of the domestic time series is a seasonal pattern among the highest in Europe. An explorative analysis, based on seasonality ratios (Shareef & McAleer, 2007), suggests that non-deterministic seasonal specifications like those employed in

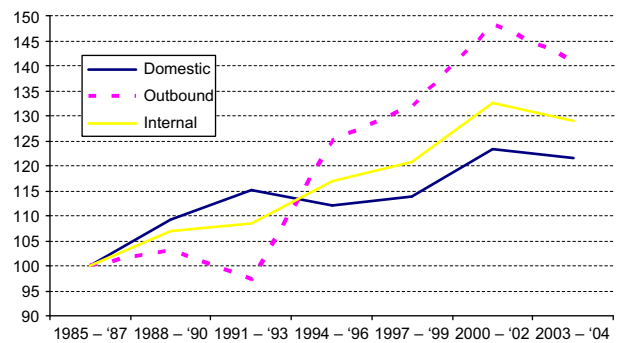


Fig. 1. Patterns in domestic, outbound and internal overnight stays. Source: National Institute of Statistics (ISTAT), various years.

this study are more appropriate, since seasonal effects decrease with variable rates of change (Table 2). This effect is especially relevant for the third quarter, which traditionally includes long holiday breaks. These dynamics suggests a potential way out from the decline stage, since it creates the conditions necessary for developing new products aimed at reviving the tourism life-cycle.

Like seasonality, the time trend also shows a monotone pattern with non-constant rates, which are unlikely to be captured by deterministic specifications. Instead, data is compatible with a theoretical framework allowing for socio-cultural changes (population and migration dynamics, leisure time availability, pollution and congestion in art cities) which affect both the potential tourism demand and the intensity and frequency of consumption. While time series models with non-observable components such as those proposed in this study fit the above seasonal and trend patterns, our objective is also to explore how the business cycle effect can be singled out through the cyclical component. The characteristics of the Italian tourism sector and the call for new strategies make it essential to have effective models for short-term forecasting and policy simulation.

#### 4.1. Data

The business cycle acts in different dimensions. Firstly, and most importantly, it is likely to affect per-capita tourism expenditure level. This relationship is relatively straightforward, especially for international tourism which is recognized as a luxury product. Secondly, it influences travel and length-of-stay decisions. The direction of this impact is more complicated, as economic recession and booms also lead to substitutions between destinations.

The relevant macro-output for a country's economy is clearly the overall level of tourism expenditure in the national territory. However, obtaining an accurate time series for this variable it is a quite complex process and Italy lacks adequate official statistics. While accommodation and holiday package expenditure is recorded for residential households through consumer surveys, the

Table 1  
Overnight stays in Italy 1985–2002. Average data for three-year periods.

Period	Domestic tourism		Inbound tourism		Internal tourism	
	Nights	% change	Nights	% change	Nights	% change
1985–1987	110,382,512	–	66,440,795	–	176,823,307	–
1988–1990	120,486,414	9.2%	68,425,869	3.0%	188,912,282	6.8%
1991–1993	127,095,693	5.5%	64,610,909	–5.6%	191,706,602	1.5%
1994–1996	123,775,986	–2.6%	82,881,204	28.3%	206,657,190	7.8%
1997–1999	125,764,996	1.6%	87,640,435	5.7%	213,405,431	3.3%
2000–2002	136,210,232	8.3%	98,406,097	12.3%	234,616,329	9.9%

Source: National Institute of Statistics (ISTAT), various years.

**Table 2**  
Seasonal patterns in Italian overnight stays (seasonality ratios, average value per period).

	1985–1987	1988–1990	1991–1993	1994–1996	1997–1999	2000–2002	2003–2004
Domestic tourism							
I_Q	64.3%	64.9%	66.7%	66.0%	66.0%	65.8%	65.8%
II_Q	87.8%	87.1%	86.1%	87.6%	89.5%	93.4%	96.6%
III_Q	191.9%	190.7%	192.4%	192.0%	190.2%	183.3%	181.5%
IV_Q	56.0%	57.3%	54.8%	54.3%	54.3%	57.5%	56.1%
Inbound tourism							
I_Q	49.4%	54.0%	54.8%	59.0%	62.4%	62.6%	64.9%
II_Q	115.8%	118.9%	124.4%	123.9%	123.3%	123.3%	123.0%
III_Q	183.9%	166.7%	158.5%	155.6%	151.6%	149.8%	147.9%
IV_Q	50.9%	60.4%	62.2%	61.6%	62.8%	64.2%	64.2%

same data is not collected for inbound tourism. This is due to the difficulties in obtaining representative data, given the variability in the typology, duration and seasonality of tourism flows to Italy, which is a “multi-opportunity tourism destination” (Formica & Uysal, 1996). Thus, the physical measurement of tourism demand has been limited as the National Statistical Institute (ISTAT) publishes time series data on tourist arrivals and hotel overnight stays, while expenditure is recorded for domestic tourism only.

The choice between arrivals and stays data to explore the aggregate impact of the business cycle on tourism demand is a complex one and the literature is mixed in this respect (see Alegre & Pou, 2006). The comprehensive but dated review by Lim (1997) finds 10 studies which use length of stay or number of nights spent at tourist accommodations versus 51 studies using tourist arrivals or departures, but it is argued that the number of nights provides a better proxy for tourism demand. A discussion is provided in Bakka (1991), where the number of nights spent in different types of accommodation is chosen over tourist arrivals for two reasons. Firstly, it is more closely related to actual tourist expenditure, since it accounts for length of stay and excludes nights spent with friends or relatives, which would lead to an overestimate of expenditure. Secondly, it overcomes an intrinsic problem of tourist arrivals in tourism demand functions, because the travel decision at the individual level is a binary one (going or not going), based on threshold levels for economic conditions (prices and income). Thus, aggregate data on tourist stays reflect the larger flexibility in individual decisions on length of stay compared to the binary choice on travel, which makes them a more accurate variable to proxy elasticities of tourist expenditure. The superiority of overnight stays as a dependent variable versus tourist arrivals is also claimed in Garin Munoz (2007) and an increasing number of studies make this choice (see e.g. Choyakh, 2008; Fernandez-Morales & Mayorga-Toledano, 2008; Song, Witt, & Jensen, 2003). For a study which intends to capture the effects of the business cycle such as the present one, in absence of tourist expenditure data, the number of nights seems to be the most natural proxy for tourism demand, as in Brännäs et al. (2002) or Gouveia and Rodrigues (2005). While the model was also run on the tourist arrivals variable, it failed to detect a cyclical pattern.

Thus, both for theoretical and empirical reasons, the present case study is based on quarterly data on hotel overnight stays in Italy over the period 1985–2004, distinguishing between domestic and inbound tourism. This variable guarantees the required homogeneity over the time span and a higher statistical reliability.

Data on tourist overnight stays are provided by the National Institute of Statistics (ISTAT, various years) and is made up of census figures collected monthly through hotels. Quarterly data is computed by summing monthly observations to ensure consistency with the frequency of the explanatory variables. These are proxies for discretionary income, tourism prices and exchange rates. More specifically we consider:

- Gross Domestic Product (GDP\_IT)
- Industrial production (excluding the building sector) for Italy (IP\_IT) and the EU-11 (IP\_EU)
- Consumer price indices for Italy (CPI\_IT), France (CPI\_FR), Spain (CPI\_SP) and Greece (CPI\_GR), adjusted by the respective exchange rates
- The aggregate Datastream Price Index for the EU-11 (CPI\_EU)
- The US Dollar/Euro exchange rate (expressed as \$/€)

The choice of using GDP and industrial production as proxies of the discretionary income is common in the literature (see González & Moral, 1996; Greenidge, 2001).

We refer to the European Union with 11 countries (about 70% of inbound tourist flows to Italy), as this enables an adequately long time series. The price variables reflect Italian prices, prices in the countries of origin (EU-11) and prices for the destinations identified as the main competitors of Italy (France, Spain and Greece). Adjustment for the exchange rate guarantees that purchasing powers are taken into account. We consider the Dollar/Euro exchange rate, a choice based on the wide range of holiday destinations that can be purchased with US currency.

As previously discussed, the assumption that these variables are meaningful determinants of the cyclical component of tourism demand suggests that they be considered as yearly changes ( $\Delta X_t = X_t - X_{t-4}$ ). The data source for the explanatory variables is Datastream and the sample starts in the first quarter of 1984, so that the inclusion of lagged variables does not imply any loss of observations. The lag specification cannot rely simply on economic theories. Given the adequate availability of data, we adopt a stepwise iterative general-to-specific approach to determine the optimal lags. This approach starts by considering all variables with a maximum lag, then the stepwise procedure selects those that are significant. In the subsequent step, all the excluded variables are reintroduced one by one into the model, together with the inflation differential usually employed in tourism modelling (among others Dritsakis, 2004). This allows collinearity problems to be overcome when simultaneously considering price levels and differences.

#### 4.2. Latent cyclical component model (LCC)

The exploration of cyclical patterns starts with the estimation of the LCC model described in Eqs. (1)–(4). Both models for domestic and inbound overnight stays are estimated (using the software STAMP) for different starting values of  $\rho$  (0, 0.1, 0.2, ..., 0.9 and 0.95) and  $\lambda$  (12, 16 and 20). The models appear to be robust to changes in the initial values and return a cycle component which is significantly different from 0. The model which displays the best fit to the data, according to all diagnostics, has a damping factor  $\rho$  very close to 1 and a cycle variance close to 0, which suggests a stationary deterministic cycle over the time span of the analysis (see Harvey, 2004), a result which should be expected given that data only

covers 20 years. The estimate  $\lambda = 43.43$  implies a cycle running for about 43 quarters (10 years and 9 months). The optimal LCC model for inbound tourist tourism demand also returns a damping factor close to unity, an extremely low cycle variance and a period of 24.95 (about 6 years and one quarter). The final estimates of the LCC models are shown below in Table 3.

Both models show a better goodness-of-fit than the benchmark models based on first differences and differences around a seasonal mean. The values of  $R^2_D$  and  $R^2_S$  are remarkably higher than those found in the tourism STS literature (compare González & Moral, 1996; Greenidge, 2001; Kim & Moosa, 2005). The model residuals are also well-behaved, with no evidence of serial correlation.

#### 4.3. Selection of explanatory variables

Based on the smoothed estimates of the cyclical and irregular component of the LCC model, we explore the determinants of the cycle. The first step consists of a stepwise regression where the dependent variable is the sum of the cyclical and irregular components extracted from the LCC model in (1). In turn, model (5) is estimated for Italian domestic and inbound tourism ( $i = 1$  and  $i = 2$ , respectively):

$$\psi_{i,t} + \varepsilon_{i,t} = \sum_{k=1}^{K_1} \sum_{j=0}^4 \beta_{kj} \cdot i^j X_{k,t-j} + \eta_{i,t} \quad i = 1, 2 \quad (11)$$

where  $j$  runs from 0 to 4, to enable the consideration of both the current values and the lags up to four quarters, as in the general-to-specific search discussed in Song and Witt (2003). The  $K_1 = 8$  exogenous variables considered for the domestic tourism equation are lags of the differenced variables  $\Delta_4 \ln(\text{GDP\_IT})_t$ ,  $\Delta_4 \ln(\text{IP\_IT})_t$ ,  $\Delta_4 \ln(\text{CPI\_IT})_t$ ,  $\Delta_4 \ln(\text{CPI\_SP})_t$ ,  $\Delta_4 \ln(\text{CPI\_FR})_t$ ,  $\Delta_4 \ln(\text{CPI\_GR})_t$ ,  $\Delta_4 \ln(\text{CPI\_EU})_t$ ,  $\Delta_4 \ln(\text{DOL\_EU})_t$ . The  $K_2 = 7$  exogenous variables for the inbound tourism equation are the same for prices and exchange rates, while income variation for foreign tourist is modelled through the proxy  $\Delta_4 \ln(\text{IP\_EU})_t$ .

The regression in (11) has an exploratory role, with the specific objective of detecting time lags between the cycle and its determinants. The adopted criteria must be conservative, to avoid the exclusion – based on purely statistical rules – of relevant delays. Thus, we based our specification search on three criteria: (a) we fix a significance level of 20% as the threshold for dropping regressors;

(b) we check for consistency of the coefficients with the economic theory, which requires a positive coefficient for income and competing destination prices, negative for own-destination prices and the Dollar/Euro exchange rate, because of its impact on the competitiveness of outbound versus internal demand (the former are reduced in favour of the latter); and finally, (c) we check for the stability of coefficients, since we expect their sign not to change when the estimation sample is reduced to 15 and 10 years.

Results shown in Table 4 highlight some economic issues and go beyond a mere descriptive analysis, focusing on strategic and forecasting implications. For domestic tourist overnight stays, the key lag is the fourth one, which is likely to depend on both the word-of-mouth process and a strong seasonality of demand. Instead, for inbound tourism, lags can be explained by the printing time of the advertising brochures, generally 2 or 3 quarters before the holiday period.

Spain emerges as the main competitor for Italy as an inbound tourism destination as well as a substitute destination for domestic tourism. To our knowledge, this is a somewhat new result in the literature on demand analysis for Italian tourism. Existing studies strongly differ in the composition of the demand models, data periods, definition of variables and estimation methods and lead to inconsistent findings. Among the few results that are consistent across studies (mainly focusing on tourists from the UK), Greece and Italy are generally regarded as complementary destinations (see Li, Song, & Witt, 2004; Lyssiotou, 2000; Papatheodorou, 1999), while Spain does not emerge as a relevant alternative. Our study also shows that prices are key factors. A strategic implication could be to benchmark Spanish price strategies or to follow strategies based on Italian peculiarities, which would allow product differentiation and a full exploitation of Italy's competitive advantages.

The estimated price elasticity is negative and greater than one, although it must be considered that this result may be over-emphasized because of specification effects, as price elasticities of overnights tend to be higher when a trend is included (Crouch, 1996). At any rate, suppliers need to take into account the strong impact of prices to support competitiveness of their products. Instead, the Dollar/Euro exchange rate results as significant for inbound demand only. This finding is consistent with the fact that the main outbound destination for Italian tourists is the Euro area (a market share of 57%).

#### 4.4. Explanatory variables model (XCV)

The selection of explanatory variables allows an explicit modelling of the cyclical component within the STS framework, through the XCV model described in (6). Final estimates are shown in Table 5 below.

By substituting the stochastic cycle specification with a set of explanatory variables, we find that the competing models show negligible differences in terms of goodness-of-fit, whether comparison is based on  $R^2_D$  and  $R^2_S$  indicators or by using information criteria. This means that the explanatory variables are an adequate replacement for the cycle component and can be exploited to explain the tourism cycle determinants, opening the way to policy considerations. The estimated coefficients show the expected signs and are consistent with the estimates obtained in the selection stage, although there is a loss of efficiency. This presumably due to the presence of the stochastic local linear trend in the XCV specification, which captures some of the cyclical variability.

In tourism research, there are conflicting findings about the relative performance of STS models versus co-integration and vector error correction approaches. Kulendran and Witt (2003) support the choice of co-integration and error correction models, but in their comparison they only consider STS models with

**Table 3**  
Parameter estimates for the latent cycle component (LCC) model.

		LCC model			
		Italian		Inbound	
Final state (last quarter of 2004)					
	<i>Parameter</i>	<i>Est.</i>	<i>(s.e.)</i>	<i>Est.</i>	<i>(s.e.)</i>
$\mu$	Intercept	17.21**	(0.020)	16.94**	(0.028)
$\delta$	Drift	0.00	(0.002)	0.01*	(0.003)
$\psi$	Cycle term	-0.01	(0.014)	-0.04	(0.014)
$\varphi$	Seasonal term	-0.46**	(0.013)	-0.38**	(0.027)
Cycle analysis					
$\rho$	Damping factor	1.00		1.00	
$\lambda$	Period (years)	10.86		6.25	
	Cycle $\chi^2$ test	7.14**		10.56**	
Diagnostics					
$R^2_D$	Goodness-of-fit 1	0.99		0.99	
$R^2_S$	Goodness-of-fit 2	0.58		0.70	
AIC	Akaike i.c.	-6.67		-5.26	
BIC	Schwartz i.c.	-6.34		-4.93	
DW	Durbin-Watson	1.98		1.96	
Q(12)	Ljung-Box	14.36		15.79	

Note: values between brackets are root mean standard errors; \* indicates a 0.05 significance level, \*\* a 0.01 significance level.

**Table 4**  
Stepwise general-to-specific regression and selection of explanatory variables for the cyclical component.

Domestic cycle				Inbound cycle			
Dependent variable: $\psi_{1,t}$				Dependent variable: $\psi_{2,t}$			
Sample(adjusted): 1986:1 2004:4				Sample(adjusted): 1985:4 2004:4			
76 observations after adjusting endpoints				77 observations after adjusting endpoints			
	$\beta$	t-value	Prob.		$\beta$	t-value	Prob.
$\Delta_4 \ln(GDP\_IT)_{t-4}$	0.52	3.00	0.00	$\Delta_4 \ln(CPI\_SP)_{t-3}$	0.21	2.69	0.01
$\Delta_4 \ln(CPI\_IT)_{t-4}$	-2.14	-6.64	0.00	$\Delta_4 \ln(DOL\_EU)_{t-2}$	-0.05	-1.33	0.19
$\Delta_4 \ln(CPI\_SP)_{t-4}$	0.16	3.17	0.00	$Dl_{t-3}$	0.93	2.48	0.01
$\Delta_4 \ln(CPI\_EU)_{t-4}$	2.93	6.17	0.00	$\Delta_4 \ln(IP\_EU)_{t-2}$	0.29	2.22	0.03
R-squared	0.39			R-squared	0.17		
Mean( $\epsilon_{1,t}$ )	0.004			Mean( $\epsilon_{2,t}$ )	-0.001		
Adjusted R-sq.	0.36			Adjusted R-sq.	0.14		
Akaike IC	-4.795			Akaike IC	-3.948		
Log likelihood	186			Log likelihood	156		
Schwarz IC	-4.672			Schwarz IC	-3.826		

Note:  $Dl_t = \Delta_4 \ln(CPI\_EU)_t - \Delta_4 \ln(CPI\_IT)_t$ .

contemporaneous explanatory variables. On the other hand, **González and Moral (1995)** include lagged explanatory variables and show better results for the STS specification. While a comparison with co-integration models goes beyond our scopes, a thorough comparison should use the dynamic STS approach suggested in this study as an appropriate benchmark.

4.5. Trends, exceptional events and seasonality

Once the economic determinants are accounted for in the XCV model, the smoothed estimates of the local linear trends allow for an evaluation of the existing patterns and the effect of exceptional events, while the evolution of seasonal patterns is captured by the stochastic seasonal component. **Fig. 2** below shows the smoothed estimates of the local linear trend from the domestic and inbound equations.

Some care is needed in interpreting the patterns, because they may also embody some “leftover” variability not fully captured by the explanatory variables, for example the effects of the devaluation of the Italian lira in 1992 and the following economic recession, whose influence is quite evident in both graphs.

However, most of the movements and reversals in the trend components can be associated with specific events. Among these, the graphs highlight the impact of the severe mucilage crisis in Northern Adriatic (Summers of 1989, 1990 and 1998) – relevant to both domestic and inbound overnight stays – the 1990 Football World Cup in Italy (for inbound tourism demand), the increased

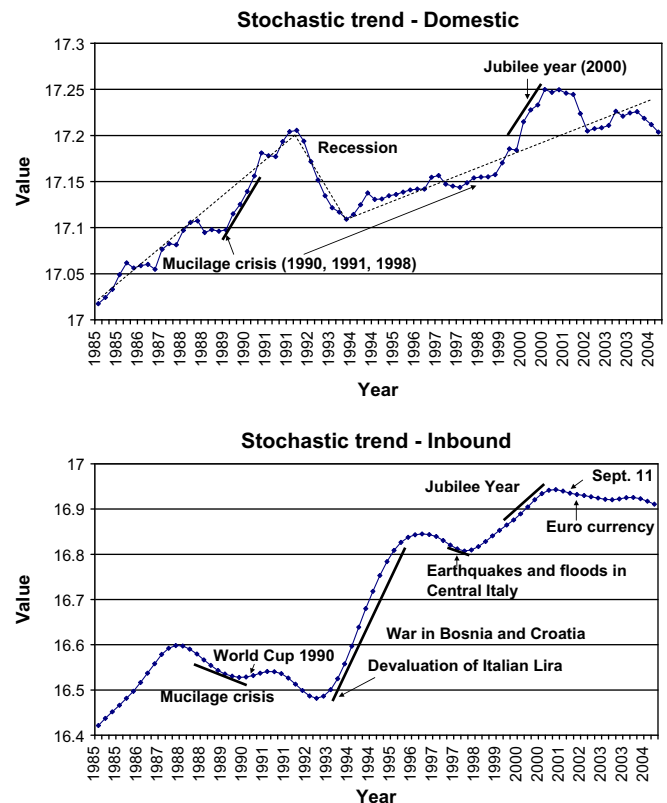
number of tourists (especially from Germany) due to the war in Croatia in the first half of the Nineties (together with the above mentioned devaluation of the Italian lira), the negative effect on inbound flows of the earthquake in Umbria and Marche in 1997 (see also **Mazzocchi & Montini, 2001**) and severe floods on the Tuscan coasts in the same period, the 2000 Jubilee year and the consequences on tourism of the 11 September 2001 terror attack. The impact of the introduction of the single currency on January 2002 on inbound overnight stays is less evident and the trend in **Fig. 2** is expected to reflect only those effects not captured by the exchange rate variable. In general, the pattern over the last 3-year window (2002–2004) looks relatively stable compared to previous periods.

Instead, **Fig. 3** shows the evolution of seasonal patterns, which open the way to some considerations. Firstly, the reduction in seasonal effects is much larger for inbound demand. Secondly,

**Table 5**  
Estimates of the XCV models.

XCV model		Italian		Inbound	
Final state (last quarter of 2004)					
Parameter	Est.	(s.e.)	Parameter	Est.	(s.e.)
$\delta$ Drift	0.00	(0.002)	-0.01	(0.016)	
$\phi$ Seasonal term	-0.47**	(0.013)	-0.38**	(0.024)	
Explanatory variables					
$\beta_1$	$\Delta_4 \ln(GDP\_IT)_{t-4}$	0.08	(0.308)	$\Delta_4 \ln(CPI\_SP)_{t-3}$	-0.13* (0.053)
$\beta_2$	$\Delta_4 \ln(CPI\_IT)_{t-4}$	-1.87*	(0.888)	$\Delta_4 \ln(DOL\_EU)_{t-2}$	0.30** (0.106)
$\beta_3$	$\Delta_4 \ln(CPI\_SP)_{t-4}$	0.16*	(0.070)	$Dl_{t-3}$	0.12 (0.240)
$\beta_4$	$\Delta_4 \ln(CPI\_EU)_{t-4}$	2.10	(1.211)	$\Delta_4 \ln(IP\_EU)_{t-2}$	1.65 (1.359)
Diagnostics					
$R^2_D$	Goodness-of-fit 1	0.99		0.99	
$R^2_S$	Goodness-of-fit 2	0.59		0.71	
AIC	Akaike i.c.	-6.67		-5.26	
BIC	Schwartz i.c.	-6.31		-4.9	
DW	Durbin-Watson	2.10		1.96	
Q(9)	Ljung-Box	8.56		11.78	

Note: values between brackets are root mean standard errors; \* indicates a 0.05 significance level, \*\* a 0.01 significance level.



**Fig. 2.** Local linear trends ( $\mu$ ) from the XCV models.



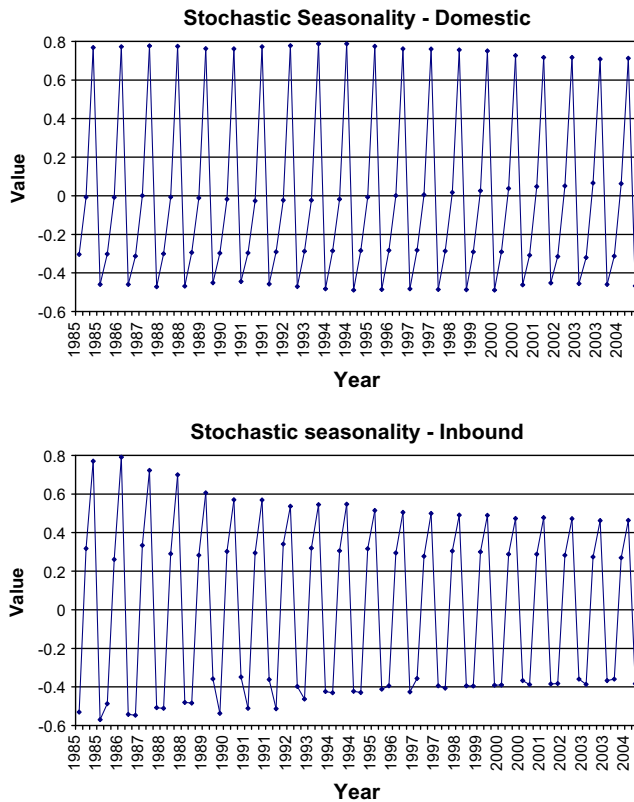


Fig. 3. Seasonal patterns ( $\phi$ ) from the XCV model.

domestic demand shows a small reduction in the Summer peak, compensated by a minor upward trend in the second (Spring) quarter, but Italian domestic overnight stays maintain a strong seasonal pattern concentrated in the Summer months. In contrast, the reduction in seasonality for inbound demand is rapid and continuing with a reduction of Summer overnight stays compensated by an increase in both Spring and Winter.

#### 4.6. Forecasting performances

Finally, we evaluate the effects of including explanatory variables for modelling the tourism cycle in terms of a rigorous assessment of the forecasting performance. As discussed in Section 2, it is advisable to compare the out-of-sample forecasting performance of the STS models with some naïve specifications as those described in Eqs. (7)–(9), as these are often found to provide acceptable forecasting error levels. Tables 6 and 7 summarize the forecast comparisons among the LCC and XCV models, together with the most informative model (according to the Akaike Information criterion) among the three naïve specifications considered here.

Table 6 reports the synthetic forecasting performance indicators, that is, bias as measured by the mean forecasting error (MFE)

and accuracy as quantified by the mean absolute percentage error (MAPE) index (Li et al., 2005; Witt et al., 2003). Besides these descriptive values, we report in Table 7 the output of the TW non-parametric statistical test – as described in Eq. (10) – to evaluate the significance of differences in accuracies. This is a useful extension, because only few studies in the literature (Chen & Wang, 2007) assess the forecasting performance with anything other than descriptive indicators, which are very sensitive to the chosen out-of-sample time span and to the specific data-set. Two sets of out-of-sample forecast results are produced, one based on a one-year ahead forecast window, the other on two-year ahead forecasts. This is consistent with the usual delay in obtaining official figures on tourist stays. Different forecast windows are built using data from 2001 to 2004 and estimation samples vary accordingly. For each set of forecasts, four different estimation samples and forecast windows are considered. For example, two-year ahead forecasts are built using estimation samples up to 1999, 2000, 2001 and 2002 and yearly forecast windows for 2001, 2002, 2003 and 2004, respectively. This means that, with quarterly data, each of our forecast evaluations is based on 16 observations.

One-year ahead forecasts show that both STS specifications (LCC and XCV) perform better than the chosen naïve specification in terms of accuracy, although the differences are only significant for inbound overnight stays. This result is consistent with the fact that international tourism is more sensitive to the economic cycle, due to a higher elasticity in price and income. This effect is captured by both the LCC and XCV models. Consistent with previous findings (see e.g. Kulendran & Witt, 2003), when a two-year ahead time horizon is considered, the above result no longer holds and the naïve models produce better forecasts. This time, differences are only significant for domestic tourism demand. Again, this confirms that taking the cycle into account is more effective when looking at inbound demand. This result also suggests that parsimony is more desirable as forecasting uncertainty and time span increase. Next, we compare the LCC model with the XCV specification. The latter always produces better forecasts, but there are no significant differences. This final finding confirms that the two specifications are relatively interchangeable as already established by looking at in-sample diagnostics. Depending on the research objectives (interpretation versus parsimonious forecasting), either specification can be chosen.

## 5. Summary and conclusions

This study provides an innovative insight on modelling the effects of the business cycle on domestic and inbound tourism demand. The rationale of the proposed approach is that cycles in tourism are mainly determined by the delayed effects of the overall business cycle.

To prove this, we first estimate a model with a stochastic cyclical component as in the structural time series approach. After extracting the cyclical component, we identify the economic determinants of the cycle, allowing for lags through a stepwise dynamic regression approach. Then, a second structural time series model is estimated, where the cyclical component is substituted by

Table 6

Forecasting performance, bias and accuracy measures: mean forecasting error (MFE) and mean absolute percentage error (MAPE).

model	Domestic overnights				Inbound overnights			
	MFE 1 year ahead	MFE 2 years ahead	MAPE 1 year ahead	MAPE 2 years ahead	MFE 1 year ahead	MFE 2 years ahead	MAPE 1 year ahead	MAPE 2 years ahead
Naïve <sup>a</sup>	0.1%*	–2.0%	4.7%	5.0%	2.9%	–0.4%*	6.5%	8.1%
XCV	2.8%	3.7%	3.7%	7.3%	2.8%	9.6%	4.5%	9.7%
LCC	3.3%	3.7%	4.2%	7.8%	3.9%	9.9%	5.0%	10.1%

Note: \* indicates a 0.05 significance level, \*\* a 0.01 significance level.

<sup>a</sup> The “winning” naïve specification for domestic demand is the model in Eq. (7), while (8) performs best for inbound demand.

**Table 7**

Statistical comparison of forecasting accuracy between competing models: Wilcoxon signed rank test (Eq. (10)).

	Domestic overnights				Inbound overnights			
	1 year ahead		2 years ahead		1 year ahead		2 years ahead	
	TW test	Prob.	TW test	Prob.	TW test	Prob.	TW test	Prob.
naïve vs XCV	49	0.163	99	0.054	<b>31</b>	<b>0.028</b>	56	0.267
naïve vs LCC	73	0.398	<b>116</b>	<b>0.007</b>	<b>36</b>	<b>0.049</b>	79	0.285
XCV vs LCC	84	0.204	85	0.190	79	0.285	71	0.438

Note: Prob. indicates the probability to fail rejecting the hypothesis that the two rival models have the same forecasting performance (see Section 3). Values in bold indicate rejection of the null hypothesis at the 95% confidence level.

the explicit explanatory variables identified in the previous step. Using data on overnight stays in Italian hotels by domestic and inbound tourists, we evaluate the relative performance of the two alternative STS specifications in terms of goodness-of-fit, residual diagnostics, economic interpretation and forecasting performance.

The results led to three main conclusions: (1) our study confirms that tourism demand responds to the business cycle with some delay; (2) the model with explicit economic explanatory variables (XCV) performs as well as the basic STS model with cycle (LCC) and they can both be employed in tourism demand analysis; (3) STS models with cycle show a better forecasting performance than naïve models in the short-term (one-year ahead), but they fail to outperform basic stochastic specifications in the longer term.

These results confirm and extend evidence from previous studies. As in Kulendran and Witt (2003) or Garcia-Ferrer and Queralto (1997), we find no evidence that STS models with explanatory variables provide a better forecast than basic univariate STS models. However, we claim that their inclusion can be quite useful for policy planning in the presence of relevant cyclical movements and show that the two alternatives can be compared. We also confirm previous results (Kulendran & Witt, 2003) that as the time horizon increases, a naïve model provides valid alternatives in forecasting.

The above results also have important policy implications. The existence of cycles suggest that the inclusion of a cyclical element in STS models (preferably the parsimonious trigonometric specification of LCC) is effective for short-term forecasting purposes, which confirms results already acknowledged in the literature. When the objective is the adoption of countercyclical policy interventions to safeguard the tourism sector (e.g. price interventions), the XCV modelling approach opens the way to identifying the specific impacts of economic policy instruments on tourism dynamics. Among these instruments, the VAT rate for overnight stays might play a relevant role. Italy's VAT is 10% compared to 7% of Spain, 5.5% of France and 8% of Greece. As our model shows, this price differential has a significant and large influence on demand. A policy decision towards the harmonization of VAT rates with the main competitors would be very effective, as well as being in line with the rationale of the EU single market. Furthermore, the positive reaction of internal demand could offset the loss resulting from lower taxation.

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