UNIVERSITÀ DELLA CALABRIA

Dipartimento di Economia e Statistica
Ponte Pietro Bucci, Cubo 0/C
87036 Arcavacata di Rende (Cosenza)
Italy
http://www.ecostat.unical.it/

Working Paper n. 20 - 2010

SEARCH COST REDUCTION INCREASES VARIATION IN HOTELS OCCUPANCY RATE: A THEORETICAL AND EMPIRICAL ANALYSIS

Marianna Succurro
Dipartimento di Economia e Statistica
Università della Calabria
Ponte Pietro Bucci, Cubo 0/C
Tel.: +39 0984 492443
Fax: +39 0984 492421
e-mail: m.succurro@unical.it

Federico Boffa
Dip.to di Studi Giuridici ed Economici
Università degli Studi di Macerata
Jesi branch - Via Angeloni, 3

e-mail: federico.boffa@unimc.it

Novembre 2010

SEARCH COST REDUCTION INCREASES VARIATION IN HOTELS OCCUPANCY RATE: A THEORETICAL AND EMPIRICAL ANALYSIS

Marianna Succurro
Department of Economics and Statistics
University of Calabria
87036 Rende (CS), Italy
m.succurro@unical.it

Federico Boffa
Department of Legal and Economic Studies
University of Macerata
Jesi branch
Via Angeloni, 3
60035 Jesi (AN) Italy
federico.boffa@unimc.it

Abstract

This study explores how direct online booking affects the variation in hotel bed-places occupancy rate between peak and off-peak periods, thereby contributing to three strands of literature, respectively the determinants of seasonality, the tourist information acquisition process and the impact of the internet on tourism. The empirical analysis, covering 18 countries over the 1997-2007 period, investigates the impact of an increase in the use of the internet by consumers on the seasonal variation in the occupancy rate. We find that internet actually increases the variation in occupancy. We contribute to reduce the lack of a theoretical framework in this field by developing a formal model to illustrate why and how the reduction in search cost entailed by the use of the internet can indeed lead to a higher seasonality.

Keywords: Internet, Search Costs, Net Occupancy Rate of bed-places

JEL Classifications: D40; D83; L11

Introduction

This paper studies the relation between the reduction in tourist's search costs due to direct online booking and the variation in bed-places net utilization between peak and off-peak periods. Search costs and direct online organization of the trip are two prominent aspects of the tourism industry that have been deeply affected by recent technological advances.
The tourism industry features a remarkably high degree of product differentiation. Understanding tourists' process of search and information acquisition is therefore key to gaining

a deeper knowledge of the industrial dynamics. Technology has modified the nature of tourists' search process in at least two directions. First, it has expanded consumption opportunities (by decreasing, for example through low-cost flights, the cost of reaching relatively far destination), thereby increasing the set of available alternatives; we may think this would tend to make direct search more valuable. Second, technological progress has directly decreased the costs of direct search, for example through the availability of faster and more reliable search tools, thanks to the Internet. Combining the two effects, it is reasonable to think that technology has made the direct online search process less time-consuming and more valuable, hence more productive.

Our paper aims at investigating the impact of such fundamental changes in the tourists' search process on the seasonal variation in the occupancy rate in hotels. We find that the reduction in the costs of direct search, proxied by the amount of direct reservations over the Internet, in fact increases the variation in bed-places net occupancy rate between peak and off-peak periods. We then model the tourist search process, and we illustrate, within a search framework, a channel through which search cost reduction for direct booking increases the variation in bed-places net occupancy rate: an improvement in the search technology decreases the cost associated to subsequent rounds of search; therefore, it can be thought of as decreasing search cost. A decrease in search cost induces consumers to search more, and, ceteris paribus, to decrease their reservation values. This, in turn, increases the elasticity of each firm's individual demand, thereby displaying an effect analogous to an increase in competitive pressure. In a two-period framework, where willingness to pay differs across periods, the variation in bed-places net occupancy rate increases with the decrease in search cost as long as an increase in competition increases the difference in output between the peak and the off-peak period.

Observe that the same result holds even when we allow for agency intermediation. The decline in search costs provides potential tourists with an incentive to undertake a longer search for the most convenient intermediary. This has an effect analogous to an increase in competitive pressure among intermediaries, with the resulting impact on the variation in bed-places net occupancy rate equivalent to the case of direct search.

The rest of the paper is organized as follows. Section 2 provides a literature review, in Section 3 we present the methodology and the data, Section 4 details the empirical results, Section 5 illustrates the formal model, while Section 6 concludes.

Literature review

Our paper relates to three separate strands of literature, respectively the capacity management issue under time-varying demand (i.e, the seasonality issue), the tourist information acquisition process and, finally, the impact of ICT on tourism.

Tourism seasonality is an interesting and multifaceted subject area which has received a great deal of attention in both academic research, in policymaking and management, especially in recent years. Amongst the various aspects considered are the definitions and approaches to measuring seasonality, its causes and impacts, policy-related issues and studies into consumer behaviour.

The concepts, theory and definitions, as well as the impacts and perceptions of seasonality, are explored by Hinch and Jackson (2000), Butler and Mao (1996), Butler (1994); links between demand fluctuations and tourist motivations are studied by Calantone and Johar (1984), Manning and Powers (1984), Spotts and Mahoney (1993). Overviews of different methods for quantifying seasonal variations are presented by Drakatos (1987), Lundtorp (2001), Koenig and

Bischoff (2003), and quantitative techniques to investigate demand variations in the accommodation sector are applied by Jeffrey and Barden (1999) and Sørensen (1999).
Causes and forms of seasonality have been identified in several studies (Cuccia and Rizzo 2010, Capò Parrilla et al. 2006, Frechtling 1996, Butler 1994, BarOn 1975). These authors distinguish different causes of seasonality in tourism. The natural causes relate to regular temporal variations in natural phenomena, particularly those associated with climate and the period of the year. Tourists have specific preferences, which make it necessary to distinguish between different purposes of tourism (such as sun and sea, hiking, ski vacations, and conferences). Natural causes are beyond the control of decision-makers. The institutional causes depend on social factors and policies concerning specific customs and legislated holidays. They include school schedules, industrial and public holidays, festivals (religious and cultural), and other events that, even today, are usually based on historic conventions.
The empirical literature on the economic determinants of tourism seasonality looks at both the demand and the supply side. The research on the seasonal variation of tourism demand focuses on tourists' income, relative price, exchange rate and substitutes prices (Rossellò-Nadal et al., 2004), consumer demographic characteristics and preferences, social and cultural interests (Cellini and Cuccia 2007, Spencer and Holecek 2007, Fernandez-Morales and Mayorga-Toledano 2008, Jang, 2004). The empirical research on the seasonal variation of tourism supply focuses on the characteristics of accommodation facilities (Capò Parrilla et al. 2006; Koenig-Lewis and Bischoff 2004). These researches find that the high quality of tourism services and the location in the historical centre lessen the seasonal variation in the occupancy rate.
Published research on seasonality impacts is also extensive. Some studies focus attention on private costs. Private producers suffer from declining returns on investment, a high level of under-exploited capacity and fixed costs in the off-seasons (Cuccia and Rizzo 2010, Bar-On 1993, 1999; Sutcliffe and Sinclair 1980). The final consumers of the destination pay higher prices in the peak-season. The workers of the tourism sector typically accept seasonal jobs, without the usual protection required by labor contracts, and long periods of unemployment (Ashworth and Thomas 1999; Bar-On 1993, 1999; Krakover 2000). Other studies focus attention on negative externalities, therefore on social costs of seasonality that concern local public utilities, the management of public goods and services such as infrastructures, public safety, public health (Murphy 1985), and natural resources (Manning and Powers 1984). Capò-Parrilla et al. (2006) argue that when the number of tourists exceeds the capacities at accommodation and facilities, a reduction in the quality of the services can occur owing to congestion, overbooking, or saturation with subsequent reduced satisfaction level. Cuccia and Rizzo (2010) sustain that seasonality has economic effects in terms of private and social costs that usually largely exceed the few benefits.
Several studies concern solutions to seasonality and policy implications. From a demand perspective, Capò-Parrilla et al.(2006) distinguish between policies designed to lessen seasonality and policies designed to reduce their negative effects. To lessen seasonality, policy-makers might encourage tourism in off-season, designing strategies to capture the differentiation in tourism demand (based on cultural, religious, sports, business tourism). Events and festivals are the most common strategies to increase demand outside the peak season (Higham and Hinch 2002, Baum and Hagen 1999; Getz 1991, 1997) as well as attracting business tourists and the identification of new market segments (Baum and Hagen1999, McEnnif 1992). Another popular strategy has been the contra-seasonal pricing policy (Weaver and Oppermann 2000, Butler and Mao 1997, O'Driscoll 1985). To reduce the negative effects of seasonality and in the interest of future generations, policy-makers should determine the optimal degree of seasonality, that depends on the carrying capacity of each destination (Capò-Parrilla et al. 2006). In the interest

of the present generation, different tools can be used, from direct monetary instruments, such as the introduction of a tourism tax on arrivals or presence, to non-monetary ones, such as the regulation of tourism flows (rationing) in very extreme cases of fragile heritage and natural sites (Cuccia and Rizzo, 2010). From a supply perspective, strategies for reducing seasonality are more limited and focused exclusively on policies oriented to reducing negative effects, such as expanding current capacity, creating new facilities or utilizing external resources (Capò-Parrilla et al. 2006).

As has been illustrated, tourism seasonality has received great attention in recent years. For the accommodation sector, in particular, the relatively high fixed costs make seasonality a particularly important issue. Low variability and an extended main season are generally regarded as desirable goals. However, there is a lack of knowledge of the factors that explain yearly demand fluctuations beyond the climatic or institutional and social ones. As Koenig-Lewis and Bischoff (2005), Lundtorp (2001), Hinch and Jackson (2000) point out, tourism seasonality research lacks a sound theoretical framework and adopting a more exacting quantitative perspective might facilitate and accelerate progress in this field. This paper, based both on empirical and theoretical analysis, contributes to fill the gaps that still exist in seasonality research. More specifically, this paper aims at investigating the determinants of seasonality different from the well known natural and institutional ones.

Our paper contributes also to the research concerning the tourist information acquisition process and the impact of ICT on tourist search. It is widely recognized that understanding search behaviour of leisure tourists is as vital to both tourism scholars and practitioners (Snepenger *et al*., 1990). Gursoy and Chen (2000) show that, given the high uncertainty and dynamics of the tourist market, understanding how tourists acquire knowledge is important for marketing and management decisions, the design of effective communication campaigns, and service delivery.

The dynamic consumer decision making process[2] has been extensively analyzed, both before the trip and while at the destination. Several studies investigate the factors which may lead to either more or less information search, underlying the role of several aspects of the environment[3] and situational variables [4] (Gursoy and McClearly, 2004; Jeng and Fesenmaier, 2002; Fesenmaier and Jeng, 2000; Gursory and Chen, 2000; Fodness and Murray, 1997, 1998, 1999; Sirakaya and Woodside, 1990; Moutinho, 1987; Van Raaij, 1986). The literature has emphasized essentially three major factors influencing tourist information search: motives (McIntosh and Goeldner, 1990; Raitz and Dakhil, 1989), determinants (Snepenger *et al*., 1990; Engel *et al.*, 1991; Van Raaij, 1986) and sources (Engel *et al*., 1995). With respect to information sources, one fundamental classification is internal vs. external search. Internal search is essentially based on the retrieval of knowledge from memory, while external search consists of collecting information from the marketplace. As reported in Fodness and Murray (1997) and Gursoy and McClearly (2004), search may take place, and almost always does initially, internally [5], such as when past experiences are used as the basis for planning a repeat visit to a destination. If the contents of memory are not sufficient for decision making, however, search activities extend out into the external environment. In the case of vacation travel, the search is often predominantly external, involving considerable effort and a variety of information sources; that’s the reason why our paper focuses on external search.

The tourist has a wide choice of external sources (Engel *et al.*, 1995) that can be used prior to departure, in transit and once at the destination (DiPietro et al., 2007) for core, secondary and en route decisions (Fesenmaier and Jeng, 2000; Hwang and Fesenmaier, 2004). Core decisions (such as primary destination, length of stay, lodging and travel budget) are significant in terms of scope and risks involved, and are thought to be made well in advance of the trip. Secondary decisions (such as entertainment and dining experiences) are considered before the trip but they are more flexible in their execution. En route decisions are defined as not being considered before the trip and are typically made on the spur of the moment during travel (e.g. shopping).

Travellers are posited to be highly involved in the decision-making process, and this is, at the least, partially due to the high costs and uncertainty associated with the services to be received. Tourism is an experience good and, as it emerges from the economics of information theory (Stigler, 1961), tourists are likely to search as long as they believe that the benefits of acquiring information outweigh the costs. The total cost of a given search strategy can be partitioned into three separate components: time spent, financial cost and effort required (Gursory and McClearly, 2004; Vogt and Fesenmaier, 1998). Time spent in search, which is more valuable for people with a higher opportunity cost of time, is considered the most important component of external search cost, followed by the monetary costs of the search (phone calls, transportation, fax, online connection, etc.). Contemporary internet technologies have provided an additional channel through which bookings can be made with minimal effort (Hyde, 2008).

Over the last 20 years, in fact, the internet has changed various facets of social life, creating many social concerns (Kim, 2010). An appropriate diffusion of the ICTs in the tourism sector improves the social and economic impacts, from which many consumers and organizations can benefit (Minghetti and Buhalis, 2010). Indeed, the internet has grown to be one of the most effective means for tourists to seek information and purchase tourism-related products (Pan and Fesenmaier, 2006).

Some recent studies explore how visitor demographic and trip purpose characteristics influence decision-making strategies for travel (Hyde, 2008; DiPietro *et al*., 2007; Pearce and Schott, 2005; Woo and Dong, 2004; Schmidt and Spreng, 1996). They find that factors influencing tourist search include specific characteristics of the vacation – vacation length, travelling distance, number of destinations visited, purpose of the trip – and characteristics of the vacationer – age, income and motivational factors, such as need for novelty versus need for relaxation. Other studies analyse the relation between the use of internet and the characteristics of the vacation and the vacationer. In these researches, consumers who book travel online have been identified as those with a higher education, who undertake more frequent international travel, visit travel websites and general websites more often, and have more positive attitudes towards use of the Internet (Morrison, Jing, O'Leary, and Cai 2001). Even amongst well-traveled consumers, there exists a group who do not book online; these non-users of Internet booking tend to be aged 60 plus years, people who seldom shop electronically, and seldom shop from the home or office (Card, Chen, and Cole 2003).

As far as the impact of ICT on tourism is concerned, it is recognized that Internet is an important external source since more and more consumers use online information for their decisions at a relatively low search cost. Although it is easy to gather information about a destination or a specific product/service from the Internet, consumers still have to spend time, pay for internet service or booking, and invest a significant amount of effort in processing what they find. It is likely that, because of low cost and ease of retrieving the information from online sources, more and more consumers will make more external effort (Gursoy and McCleary, 2004). That is the reason why the goal of the destination managers and marketers is to make external search as inexpensive and time efficient as possible by avoiding websites that are difficult to navigate, are linked to empty sites and have incomplete information. Some researches explicitly aimed to examine consumers' perspectives of the information role of the Destination marketing organisations (DMOs) (Choi et al., 2007); other studies have been conducted to measure the effectiveness of destination Marketing Organizations' websites (Li and Wang, 2010).

Given the increasing use of technology by the travellers, the DMOs and the services suppliers, it is interesting to investigate the impact of new technology sources on search costs. The industrial organization theory on consumer search under asymmetric information is widely developed. Two contributions are worth mentioning. Stiglitz (1989) provides a comprehensive overview, where he shows that an equilibrium may fail to exist in perfect competition models under search costs. He also illustrates that, under a framework of imperfect competition, search costs increase firms' rent. Bakos (1997) finds that the reduction in search cost improves allocative efficiency, by increasing the competitive pressure. Bakos' results represent the driving force behind the results of our formal model.

As it is known, sources of tourism information can be classified in terms of whether the source is commercial or non-commercial (*source of information*) and received from personal or impersonal communication (*type of information*) (Fodness and Murray, 1997). A multiplicity of information sources and decision strategies are available to the contemporary traveller. This study explores, in particular, the effects of specific impersonal online tourism information sources - both commercial and non-commercial, public or private – on search costs and occupancy rates. More specifically, the purpose of the research is to check how new technology and direct online booking affect the difference between peak and off-peak occupancy rate of bed-places in hotels and similar establishments. This article also develops a theoretical model that attempts to provide a possible explanation for the results we obtain, thereby offering a contribute to the lack of theoretical framework on the possible determinants of seasonality.

Methodology and data

The empirical analysis investigates the determinants of the seasonal variation in the occupancy rate focusing, in particular, on direct online organisation of the trip across 18 countries over the 1997-2007 period [6]. The goal of the research is to verify whether, and to what extent, differences in the use of internet by consumers for direct reservation with transport/accommodation operator explain differences in bed-places net occupancy rate in hotels and similar establishments. Our panel data regression takes the following form:

$$\Delta OCC_{it} = \beta_0 + \beta_1 eORG_{it} + \beta_2 ARR_{it} + \beta_3 BEDS_{it} + \beta_4 AIRP_{it} + \beta_5 LC_{it} + \beta_6 X_{it} + \gamma_t + u_i + \varepsilon_{it} \qquad (1)$$

t=1997, …, 2007 *i=1, …, 18 countries*

The dependent variable ΔOCC_i measures the seasonal variation in the occupancy rate (Lundtorp, 2001). Occupancy rates provide information on the number of occupied bed-places over the total bed-places availability in a given period. When measured on monthly or on seasonal basis, this variable indicates the seasonal patterns (Kandari and Ashish Chandra, 2004). Data on bed-places net utilization are derived from the Eurostat database [7].

$eORG_i$ indicates the rate of online direct reservation over the total number of travels in country *i*. As the Internet reduces search cost, this variable, which measures the amount of online booking, proxies a decline in the average search cost.

ARR_i measures total tourist arrivals for country *i*. It is computed as total arrivals of residents or non-residents checking in at a hotel or a similar establishment (Data source: Eurostat).

$BEDS_i$ is a proxy of the average size of the accommodation structures in country *i*. It is computed as the ratio of the total amount of bed-places to the total number of hotels and similar establishments in country *i* (Data source: Eurostat).

$AIRP_i$ measures the density of airports computed as the ratio between total number of airports [9] in each country (Data source: IATA) and total area (km^2) (Data source: Wikipedia).

LC_i indicates the presence of low cost airlines in country *i*, measured as the ratio between the total number of low cost airlines flying from/to country *i* (*Data source*: flylowcostairlines.org) and the total number of airports.
X is a matrix that includes other control variables such as GDP growth rate, inflation rate, population growth rate (Source of data: IMF).
γ_t indicates time effects;
u_i indicates countries' effects;
ε_{it} is the stochastic residuals.

Empirical Results

The results of equation (1) estimation over the 1997-2007 period are reported in table 1.
The F test null hypothesis that all the coefficients are jointly equal to zero is always rejected at 1 percent level.
The pooled cross-section specification might generate biased and inconsistent results, since it does not take into account unobserved heterogeneity among countries with respect to, for example, social conditions, cultural and institutional framework.
The Breusch-Pagan test, in fact, indicates that pooled cross-section is not the correct specification of the model. The null hypothesis [10] is rejected, indicating that individual shocks should be taken into account.
The Hausman specification test is then performed to investigate the correlation between the unobserved individual effect and the observed explanatory variables [11]. As reported in table 1, we do not reject the null hypothesis; therefore we can claim that the correct specification of the model is random effect (table 1, reg (2)).
The empirical evidence shows that direct online reservation increases significantly (at 5% level) the difference in net occupancy rate of bed-places between high and low season. Therefore, the use of internet for direct booking is positively associated with this measure of seasonality.
We outline two possible interpretations for this result. The first one postulates a smaller role for travel agency intermediation as a result of the ICT advances, which have expanded the scope for online direct booking. If this were the case, the result would follow by noting that one of the tour operators' main purposes is to reduce seasonality through specific contracts signed with the suppliers of tourist services (Succurro, 2006); according to this line of reasoning, the impact of the decline in search costs on occupancy rate fluctuations over the year would have been mediated by a change in the structure of tourism intermediaries.
An alternative explanation considers the direct effects of a decline in search costs in increasing the demand elasticity faced by each firm. This drives our results. In fact, the exploration of this channel will be the object of our analysis in the formal model.
The empirical result on the role of the internet on the seasonal variation in the occupancy rate needs additional considerations. Some researches provide strong support for the contention that web-presence represents an essential marketing tool for accommodation businesses. Koenig-Lewis and Bischoff (2004) find that both the low-occupancy and the poor performers cluster show statistically highly significant links with a lack of internet presence. Therefore, high occupancy and high performance would be associated to internet presence. Other studies have found that, despite the efforts to reduce peaks, monthly seasonality has, in fact, increased in some destinations with the rapid development of tourism (Butler 1994, Bar-On 1975). We can argue that, since the average occupancy rate has increased over time and, at the same time, the

seasonal variation in the occupancy rate has increased do to the direct online organization, the peak-season occupancy rate has grown at a higher rate than the off-peak season. In the extreme case that the number of tourists exceeds the capacities at hotels and facilities in peak season, this can explain the increasing concern for the social costs of seasonality that, however, is not the main goal of this paper.

The variable $BEDS_i$, indicating the average size of hotels and similar establishments, enters at 1 percent level with the expected negative sign. Firm's strategies aimed at decreasing the difference between high and low season tourist flows are widely adopted by larger hotels and accommodation structures since the higher the number of available bed-places, the higher the potential opportunity cost associated with empty rooms in low season [13].

The presence of low cost airlines in country *i* is significantly and positively associated with seasonal patterns. Indeed, while consumers can usually book scheduled flights over the whole year, the low cost airlines frequently offer their services to/from a specific tourist destination only for some periods of the year, which usually coincide with the peak periods. As a result, the higher the number of charter and low cost flights in the country, the higher the difference between high and low season number of passengers.

The density of airports enters negatively, suggesting that the higher the number of airports in the country, the lower the variation in net occupancy. The variable, however, is not significant.

The GDP growth rate is negatively and significantly associated with the dependent variable. Total investments in tourism promotion, public incentives to the private sector for improving the quality of the supplied services and for promoting specialized supply segments, off-season cultural events (festivals, typical products fairs, etc.) and strategies to capture the differentiation in tourism demand, are relatively higher in countries characterised by higher GDP growth, with the likely outcome of spreading tourism flows more evenly throughout the year.

The empirical evidence also shows that total arrivals, inflation rate and population are not significant in explaining differences in net bed-places occupancy rate among countries.

Moreover, the F test on the time dummy variables allows us to reject the hypothesis that all the coefficient are jointly equal to zero.

Finally, we consider the endogeneity problem potentially affecting our model. In fact, the dependent variable and some of the explanatory variables might be codetermined. The high presence of low cost airlines in the peak season, for example, could be explained by the strong seasonality characterizing some destinations, usually associated with natural causes such as climate change. In the same way, the seasonality can explain the GDP growth rate since intensive tourism flows throughout the year are considered the engine of the economic growth for several countries. The 'tourism-led growth hypothesis' has been strongly supported and an extended main season is generally regarded as a desirable goal. Other examples could be considered.

Several approaches can be used to tackle the endogeneity problem. The traditional approach consists in using an instrumental variables regression with external instruments [14]. An alternative approach uses internal instruments by exploiting the panel data structure. More specifically, we use a Generalized Method of Moment (GMM) estimator (Arellano and Bond 1991; Blundell and Bond 1998), treating all the explanatory variables as potentially endogenous. Thus, we rewrite eq.(1) in dynamic terms, as follows:

$$\Delta OCC_{it} = \beta_0 + \beta_1 \Delta OCC_{it-1} + \beta_2 eORG_{it} + \beta_3 ARR_{it} + \beta_4 BEDS_{it} + \beta_5 AIRP_{it} + \beta_6 LC_{it} + \beta_7 X_{it} + \gamma_t + u_i + \varepsilon_{it} \quad (2)$$

Eq.(2) can be properly estimated through the first differences GMM (GMM-DIFF) estimator proposed by Arellano and Bond (1991), which uses all the available lags of each independent variable in levels as instruments. However, the levels are poor instruments when variables exhibit strong persistence (weak instruments). For this reason, we employ the estimation of the system of equations (GMM-SYS) implemented by Blundell and Bond (1998). It combines the first differenced regression used in GMM-DIFF and the eq.(2) in levels, whose instruments are the lagged differences of the endogenous variables [15] [1].

The choice of the endogenous variables and the lags has been performed through the Difference-in-Sargan test. The endogenous variable is Low Cost Airlines for which the t-2 lag has been used, while t-3 lag has been used for the lagged variable. Table 1 shows the empirical results. The Null hypothesis of the Hansen test is not rejected, therefore the instruments satisfy the orthogonality condition required for their appropriateness. Moreover, we report the results of the tests proposed by Arellano and Bond (1991) to detect first and second-order serial correlation in the residuals. If ε_{it} are not serially correlated, the differenced residuals should show autocorrelation of first-order and absence of second-order serial correlation. As shown in table 1, the absence of second-order serial correlation, which is a necessary condition for the validity of the instruments, is satisfied in our analysis.

The coefficient of the lagged dependent variable is significant with a positive sign showing the opportunity of the dynamic specification of the model. With respect to the other explanatory variables, the GMM-System essentially confirms our previous estimation results.

Table 1 Occupancy rate variation and direct online booking

Dependent Variable:	**Pooled OLS**	**Random Effects**	**GMM System**
OCC_{it}	**(1)**	**(2)**	**(3)**
OCC_{it-1}			0.42* (0.032)
$e$$ORG_{it}$	15.12*** (1.85)	3.28** (1.50)	2.62* (2.32)
ARR_{it}		-0.001 (0.000)	-0.001 (0.001)
$BEDS_{it}$	0.003 (0.002)	-0.03* (0.001)	-0.009* (0.002)
LC_{it}	0.42*** (0.051)	0.507*** (0.134)	0.084** (0.272)
$AIRP_{it}$	0.001 (0.008)	-0.01 (0.018)	-0.057 (0.117)
GDP GROWTH $RATE_{it}$	0.116 (0.190)	-0.17* (0.099)	-0,485* (0.530)
INFLATION $RATE_{it}$	1.359*** (0.40)	-0.099 (0.14)	-0.068 (0.239)
POPULATION GROWTH $RATE_{it}$	-0.15** (0.07)	-0.036 (0.111)	0.024 (0.189)
Constant	-3.28* (1.81)	6.87*** (2.410)	

[1] For details, see Roodman (2006).

R-squared	0.66	0.40	
F test (a)	33.07***	25.95***	
Time Effects (F test)	0.25	3.57**	4.09**
Hausman Test		5.33	
Breusch-Pagan Test		257.48***	
Hansen Test (p value)			0.12
AR(1)			-2.32***
AR(2)			0.32
Observations	144	144	118

(a) It refers to Wald test when random effect model is considered
Robust standard errors in parenthesis
*, **, ***, for 10%, 5% and 1% significance level respectively

A formal model

The following model aims at illustrating a channel that explains the incentives at work in determining the positive relation between decline in search costs and variation in bed-places occupancy rates. The basic intuition follows the line of Bakos (1997), and highlights the increase in competitive pressure stemming from the lower search costs.
Our model adopts the product search theory framework, and builds on Spulber (1996), extending it to a two-period framework.
As it is standard in this framework, we assume that consumers visit a single hotel per period, and, after getting to know the price charged by that hotel, they have to decide whether to choose it, or to keep searching for a cheaper alternative, going through an additional round of search, where they will face exactly the same problem faced in the previous period. Consumers have perfect information on the hotel price distribution, although they do not know which hotel (and, as a consequence), which price, they will be matched with in each round. Search is time wasting, therefore costly. As a result, in each round consumers trade off future benefits, in terms of prospects of cheaper alternatives, to additional costs of search. Consumer's recursive strategy is therefore based on a reservation price – that is, a threshold price below which consumers accepts the offer and stop searching. Firms in turn know the distribution of consumers' valuation, but they do not know which consumer they are faced with at each round. An equilibrium of the game is constituted by a price charged by each firm and a reservation price chosen by each consumer such that no consumer and no firm has an incentive to deviate.
We now analyze the model in greater details.
Let us consider a tourism destination that consumers value in two seasons (denoted *s*: peak, or high season (denoted *h*), and offpeak, or low season (denoted *l*)) .
In the peak period, more consumers are interested in reaching the destination, and on average they attribute a higher value to it.
Assume that consumers' reservation value v is uniformly distributed in the $(\underline{v}, \bar{v})$ interval where $\underline{v}$ = 0 both in high and in low season, while $\bar{v} = 1$ offpeak, and $\bar{v} = 2$ in peak.
Consumers have the option of searching for hotels in the destination. Search is time-consuming, and consumers discount the future at a rate δ. Higher discount rates are associated to higher search costs, while lower discount rates are associated to lower search costs.
Hotels are assumed to be homogenous in quality, but they do differ in their cost structure. The heterogeneity could be attributed to differences in the owners' managerial skills. Their (constant across output levels) marginal cost k is uniformly distributed in the (0,1) interval.

We derive the equilibrium price distribution, and the equilibrium output in peak and offpeak. We then perform comparative statics to assess the impact of a decrease in the discount rate (corresponding to a decrease in search costs, associated to the Internet) on the difference in the number of tourists between the peak and the offpeak period.

Consumers know the price distribution of the hotels, but they do not know the specific price charged by single hotels. In their process of searching for the best deal, they adopt a standard stopping rule. They stop whenever they find an hotel with a price below their endogenously determined reservation price *r*.

The reservation price results from a standard recursive equation:

$$v - r = \frac{1}{1+\delta}\left[\int_0^r (v-p)dF(p) + \int_r^\infty (v-r)dF(p)\right] \qquad (1)$$

r is the price that equates the benefit from stopping (LHS of Equation 1, which identifies the difference between the value and the reservation price), and the expected benefit of continuing the search – that is, the discounted sum of the expected benefit net benefit of finding the hotel next period if search stops next period (first term of RHS in Equation (1)), and of the search value if the individual does not find the hotel next period.

Integrating by parts Equation (1) yields:

$$v = r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]$$

As $v \sim U(\underline{v}, \overline{v})$,it follows that $\left[r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]\right] \sim U(\underline{v}, \overline{v})$.

Hence,

$$v = L(r)(\bar{v} - \underline{v}) = r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]$$

And

$$v^h = 2L^h(r) = r + \frac{1}{\delta}\left[\int_0^r F^h(p)dp\right]$$

$$v^l = L^l(r) = r + \frac{1}{\delta}\left[\int_0^r F^l(p)dp\right]$$

And

$$L^h(r) = \frac{r + \frac{1}{\delta}\left[\int_0^r F^h(p)dp\right]}{2}$$

$$L^l(r) = r + \frac{1}{\delta}\left[\int_0^r F^l(p)dp\right]$$

Observe that, in any given period, consumers with a higher willingness to pay engage in less search, as

$$\frac{\partial r}{\partial v^h} = 2l^h(r) > 0$$

$$\frac{\partial r}{\partial v^l} = l^l(r) > 0$$

Also, consumers search less under a high discount rate (this allows us to regard a decrease in the discount rate as a decline in search cost), as $\frac{\delta v^h}{\delta r}$. A consumer with willingness to pay equal to 1 has the maximum reservation value in the offpeak low season, denoted $\bar{r}^l$, while a consumer with willingness to pay equal to 2 has the maximum willingness to pay in the peak high season, denoted $\bar{r}^h$.

The density of consumers with reservation value *r* can be represented by $h^s(r) = \frac{dL^s(r)}{dr}$, and is given by:

$$h^s(r) = \frac{dL^s(r)}{dr} = \begin{Bmatrix} 1 + \frac{F^l(r)}{\delta} & in\ l \\ \frac{1}{2} + \frac{F^h(r)}{2\delta} & in\ h \end{Bmatrix}$$

Each firm faces a demand function in each given round of searches. In each round of searches, the probability that a consumer with reservation value *r* finds the hotel and stops searching equals $F(r)$. It follows that, at each round *i*, with $i = 0, \dots, \infty$, $(1 - F(r))^i$ consumers with reservation value *r* remain to be served. As there are *N* firms, each of which receives, on average, the same amount of visits, it follows that, at each round, each firms receives $\frac{1}{N}$ of the consumers who are still searching. For each value of *r*, each firm receives an amount of consumer of density $(1 - F(r))^i \frac{h(r)}{N}$. The quantity produced by the firm is therefore obtained as by integration over the set of consumers with reservation values higher than the firm's price for all $p \leq r$:

$$D^i(p) = \int_p^{r} (1 - F(r))^i \frac{h^s(r)}{N} dr$$

The weighted demand is a function of the reservation prices distribution (in turn depending on the reservation values), along with the density $h^s(r) = \frac{dL^s(r)}{dr}$

It follows that the weighted demand $D(p)$ can be represented as follows:

$$D(p) = \sum_{i=0}^{\infty} \frac{D^i(p)}{(1+\delta)^i}$$

For any market-price distribution functions, the low season weighted demand for firm j has a linear form:

$$D_j^l(p) = \sum_{i=0}^{\infty} \int_p^{\bar{r}^l} \frac{\left(1 - F^l(r)\right)^i}{(1+\delta)^i} \frac{1 + \frac{F^l(r)}{\delta}}{N} dr = (\bar{r}^l - p)\frac{1+\delta}{\delta N}$$

For the high season, firm *j*'s weighted demand is:

$$D_j^{h^h}(p) = \sum_{i=0}^{\infty} \int_p^{\bar{r}} \frac{\left(1 - F^h(r)\right)^i}{(1+\delta)^i} \frac{\delta + F^h(r)}{2\delta N} dr = \left(\bar{r}^h - p\right)\frac{1+\delta}{2\delta N}$$

By inverting the demand functions, we get:

$$p^l = \bar{r}^l - q^l \frac{(\delta N)}{1+\delta}$$

$$p^h = \bar{r}^h - q^h \frac{(2\delta N)}{1+\delta}$$

Aggregate demand can therefore be written, for low and high periods respectively, as:

$$\int_{\hat{p}^l}^{\bar{p}^l} \left(\left(\bar{r}^l - p\right) \frac{1+\delta}{2\delta N} \right) dp$$

$$\int_{\hat{p}^h}^{\bar{p}^h} \left(\left(\bar{r}^h - p\right) \frac{1+\delta}{2\delta N} \right) dp$$

Observe that, as intuitively plausible, the demand function is positively correlated to the reservation price. The slope is larger in the peak period (as $\frac{(2\delta N)}{1+\delta} > \frac{(\delta N)}{1+\delta}$),

The firm chooses q as to maximize profits:

$$\Pi^s(q) = P^s(q) - qk$$

The optimization problem for the firm yields, for the off-peak period:

$$\Pi^l(q) = \left(\bar{r}^l - k - q^l \left(\frac{\delta N}{1+\delta} \right) \right) q^l$$

yielding:

$$q^l = \frac{(1+\delta)(\bar{r}^l - k)}{2\delta N}$$

This requires $\bar{r}^l \geq k$.

While for the peak period the optimization problem is the following:

$$\Pi^h(q) = \left(\bar{r}^h - k - q \left(\frac{2\delta N}{1+\delta} \right) \right) q$$

yielding:

$$q^h = \frac{(1+\delta)(\bar{r}^h - k)}{4\delta N}$$

q^s are positive only if: $(\bar{r}^s > k)$. This requires $\bar{r}^l \geq \ddot{k}^l$, and $\bar{r}^h \geq \ddot{k}^h$, where $\ddot{k}^s$ is the firm with the highest cost among those called to produce.

Prices are then:

$$p^l = \frac{(\bar{r}^l + k)}{2}$$

$$p^h = \frac{(\bar{r}^h + k)}{2}$$

Observe that the functional form of price, in high and low seasons, is the same except for $\bar{r}^s$, and $p^h > p^l$

The lowest prices, denoted $\hat{p}^s$, are those prevailing for the firm with the lowest cost, that is: *k=0*. They are:

$$\hat{p}^l = \frac{\bar{r}^l}{2}$$

$$\hat{p}^h = \frac{\bar{r}^h}{2}$$

It follows that the *F(p)* distribution satisfies:

$$F^l(p) = \frac{2p - \bar{r}^l}{\bar{r}^l}$$

$$F^h(p) = \frac{2p - \bar{r}^h}{\bar{r}^h}$$

We can now derive the reservation prices in low season:

$$1 = \bar{r}^l + \frac{1}{\delta}\left[\int_{\frac{\bar{r}^l}{2}}^{\bar{r}^l} \frac{2p - \bar{r}^l}{\bar{r}^l} dp\right]$$

It follows that:

$$\bar{r}^l = \frac{4\delta}{4\delta + 1}$$

Given the previous restrictions (that in equilibrium only firms with $k<\bar{r}^s$ operate), we have that in equilibrium only firms characterized by:

$$k \leq \frac{4\delta}{4\delta + 1}$$

operate.

And in the high season:

$$2 = \bar{r}^h + \frac{1}{\delta}\left[\int_0^{\bar{r}^h} \frac{2p - \bar{r}^h}{\bar{r}^h} dp\right]$$

It follows that:

$$\bar{r}^h = \frac{8\delta}{4\delta + 1}$$

Prices can therefore be rewritten as:

$$p^l = \frac{2\delta}{4\delta + 1} + \frac{k}{2}$$

$$p^h = \frac{4\delta}{4\delta + 1} + \frac{k}{2}$$

Each firm's profit may therefore be written as:

$$\pi^l = \left(\frac{2\delta}{4\delta + 1} + \frac{k}{2}\right)$$

$$p^h = \frac{4\delta}{4\delta + 1} + \frac{k}{2}$$

By substituting respectively for *k=0* and *k=1*, we obtain:

$$\hat{p}^l = \frac{2\delta}{4\delta + 1}$$

$$\hat{p}^h = \frac{4\delta}{4\delta + 1}$$

$$\bar{p}^l = \frac{4\delta}{4\delta + 1}$$

$$\bar{p}^h = \frac{8\delta}{4\delta+1}$$

Observe that

$$\hat{p}^l = \frac{2\delta}{4\delta+1} < \hat{p}^h = \frac{4\delta}{4\delta+1}$$

and

$$\bar{p}^l = \frac{4\delta}{4\delta+1} < \bar{p}^h = \frac{8\delta}{4\delta+1}$$

As intuitively plausible, prices in the high season exceed prices in the low season, due to the higher reservation prices in the high season, stemming from the (on average) higher values for tourism in that season.

The reservation price for the tourist with the lowest value, $\hat{r}^s$ is computed as follows:

$$v = L(r) = r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]$$

$$1 = r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]$$

$$1 = r + \frac{1}{\delta}\left[\int_0^r F(p)dp\right]$$

And the distribution function is:

$$F^l(p) = \frac{2p - \bar{r}^l}{\bar{r}^l} = \frac{2p - \frac{4\delta}{4\delta+1}}{\frac{4\delta}{4\delta+1}} = \frac{p(8\delta+2)}{4\delta} - 1$$

$$F^p(p) = \frac{2p - \bar{r}^h}{\bar{r}^p} = \frac{2p - \frac{8\delta}{4\delta+1}}{\frac{8\delta}{4\delta+1}} = \frac{p(8\delta+2)}{8\delta} - 1$$

The number of active consumers is:

$$Q^l = 1 - \hat{v}^l = 1 - \hat{p}^l = 1 - \frac{2\delta}{4\delta+1} = \frac{2\delta+1}{4\delta+1}$$

$$Q^h = 2 - \hat{v}^h = 2 - \hat{p}^h = 2 - \frac{4\delta}{4\delta+1} = \frac{4\delta+2}{4\delta+1}$$

Observe that $\frac{\partial Q^l}{\partial \delta} < 0$ and $\frac{\partial Q^h}{\partial \delta} < 0$.

The difference between peak and offpeak output is:

$$\Delta^{h,l} = \frac{4\delta+2}{4\delta+1} - \frac{2\delta+1}{4\delta+1} = \frac{2\delta+1}{4\delta+1}$$

The sensitivity of the difference between high and low season output is as follows:

$$\frac{\partial \Delta}{\partial \delta} = \frac{2(4\delta+1) - 4(2\delta+1)}{(4\delta+1)^2} = \frac{-2}{(4\delta+1)^2}$$

We have therefore established the following:

Proposition 1:
The difference between high season and low season output increases as the discount rate decreases.

The results apply straightforwardly to direct search. They show that, if the discount rate drops (for example, due to Internet and the availability of easy-to-use price comparison websites), the difference in capacity utilization in the peak period and in the base period increases. The result is based on the following mechanism. A low discount rate decreases the reservation value, and increases the expected length of the search process. This increases the price elasticity of each firm's individual demand (weighted demand, to use the previously adopted terminology). As a consequence, the total quantity increases in both periods. In other terms, a lower discount rate induces higher competition among tourism operators. Under our (commonly adopted) functional form assumptions, the difference between high and low season quantities increases with the level of competition, and this represents the driving force behind our result.
Our findings could extend to agency reservations. A decline in the search cost decreases the cost of visiting additional online agents; this increases competition among agents, and an analogous mechanism to that applicable for direct search emerges.

Conclusions

Internet is playing a key role in the development of the tourism industry since it encourages people to travel by improving access to the destinations and reducing search costs. Online booking also removes the need to book a package holiday through a travel agent, as travellers are able to search the internet and book themselves. This may also help to increase the variety of accommodation and resorts on offer.
Our research explores how direct online booking affects the variation in hotel bed-places occupancy rate between peak and off-peak periods, thereby contributing to three strands of literature, respectively the determinants of seasonality, the tourist information acquisition process and the impact of the internet on tourism. This paper also offers a contribute to the lack of theoretical framework on the possible causes of seasonality.
The empirical findings show that a reduction in search costs actually increases the difference between the peak and off-peak bed-places utilization rate in hotels and similar establishments. We advance two possible interpretations for this result. The first one postulates a smaller role for travel agency intermediation (known to reduce seasonality through specific contracts signed with the suppliers of tourist services) as a result of the ICT advances, which have expanded the scope for online direct booking. A second one considers the direct effects of a decline in search costs in increasing the demand elasticity faced by each firm. This channel is formally analyzed in a stylized search model. Our results show a channel that could help us provide a theoretical motivation to our result. A lower discount rate decreases the reservation value and increases the expected length of the search process. This increases the price elasticity of each firm's individual demand, with an effect similar to an increase in competition. As a result, the total quantity increases in both periods. However, under natural assumptions on the shape of the demand function, the difference between high and low season quantities increases with the level of competition, the discount rate and the difference between peak and off-peak demand.

In such cases, a reduction in search cost increases the variation in bed-places net occupancy rate. If interpreted in terms of seasonality, our results suggest that direct online booking has increased seasonality. This effect can be attributed to an increase in competitive pressure. A possible direction of future research may consist in analyzing the impact on firms' profit. Indeed, it is likely that, while competitive pressure tends to reduce firms' profit, the reduction in search cost also redistributes profits from the intermediation sector (hampered by the development of direct online booking) to the transport/accommodation providers. The direction of the net effect on the transportation/accommodation providers profit depends on the relative strength of the two forces, and is worth analyzing.

Notes

[1] The paper is the result of a joint work between the authors. However, Marianna Succurro is mainly responsible for literature review, methodology, data and empirical results, Federico Boffa for the theoretical model. Both the authors are responsible for the introduction and the conclusions.

[2] Some authors have proposed the *Travel Decision Net Model* which stipulates that a travel decision is composed of bundles of 'sub-decisions' that vary in decision timing and flexibility (Fesenmaier and Jeng, 2000; Jeng and Fesenmaier, 2002).

[3] Such as difficulty of the choice task, number of alternatives, complexity of the alternatives.

[4] Previous satisfaction, time constraints, perceived risk, composition of travelling party.

[5] Internal sources include personal experience, either with the specific destination or with similar destinations.

[6] The list of countries, chosen on the basis of data availability, is reported in table A1 in the Appendix.

[7] Eurostat database offers monthly data. In one month, net occupancy rate of bed-places is obtained by dividing total overnight stays by the product of bed-places on offer and the number of days when the bed-places are actually available for use (net of seasonal or other temporary closures for decoration, police order, ect) for the same group of establishments, multiplying the quotient by 100 to express the result as a percentage (Kandari and Ashish Chandra, 2004).

[8]Eurostat data on the type of organization of the trip, which are available both in terms of "number of tourism nights" and "number of trips", include: a) direct reservation with transport/accomodation operator; b) use of travel agent/tour operator; c) package travel; d) no type of organisation.

[9] The analysis includes only civil airports, open for public use (including joint use). Military and private airports are not considered.

[10] The null hypothesis of the Breush-Pagan test is that the groupwise variance is equal to zero. Under the null, there are not individual shocks and OLS estimation produce unbiased results. Otherwise, fixed or random effect models have to be used.

[11] The null hypothesis of the Hausman test is "Ho: difference in coefficients not systematic". Under the null, the correlation between the unobserved individual effects and the explanatory variables is zero. Hence, the correct specification of the model is Random Effect, which obtains efficient and consistent estimates. When the null is rejected, the correct specification of the model is Fixed Effects. Notice that, since the model fitted on these data fails to meet the asymptotic assumptions of the Hausman test, we used the "suest" command on Stata for a generalized Hausman test (see Stata for details). Fixed Effects estimation results are available on request.

[12] In fact, customers buying a service on a supplier's website choose from a much larger set of options than those that are available to a customer making a reservation on the telephone (Dana and Orlov, 2007) or on a catalogue

[13] The accommodation structures with a small number of bed places are usually family run businesses or agritourism. In some countries, agritourism can be even closed by law some months of the year, thereby lessening the costs of seasonality. See, for example, the Italian law on agritourism (*Legge 20 febbraio 2006, n.96 - Disciplina dell'agriturismo*).

[14] In an equation with an endogenous explanatory variable, an instrumental variable is a variable that does not appear in the equation, is uncorrelated with the error in the equation and is (partially) correlated with the endogenous explanatory variable (Wooldridge 2002).

[15] For details, see Roodman (2006).

References

Arellano, M., and Bond, S. (1991), 'Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations', *Review of Economic Studies*, Vol 58, pp277–297.

Ashworth, J., and B. Thomas (1999), 'Patterns of Seasonality in Employment in Tourism in the UK' *Applied Economics Letters* 6:735–739.

Avery, R. (1996), 'Determinants of Search for Nondurable Goods: An Empirical Assessment of the Economics of Information Theory', *Journal of Consumer Affairs*, Vol 30, pp 390–420.

Bakos, J. Y. (1997), 'Reducing Buyer Search Costs: Implication for Electronic Marketplaces', *Management Sciences*, vol. 43, n. 12, 1997.

Bar-On, R. (1975), Seasonality in Tourism: A Guide to the Analysis of Seasonality and Trends for Policy Making. Technical Series No. 2. London: The Economist Intelligence Unit, Series No. 2.

Bar-On, R. (1993), Seasonality. In VNR's Encyclopedia of Hospitality and Tourism, M. Khan, M. Olsen and T. Var, eds., pp. 705–734. New York: Van Nostrand Reinhold.

Bar-On, R. (1999), 'The Measurement of Seasonality and its Economic Impacts', *Tourism Economics* 5:437–458.

Baum, T., and L. Hagen (1999) Responses to Seasonality: The Experiences of Peripheral Destinations. International Journal of Tourism Research 1:299–312.

Blundell, R., and Bond, S. (1998) 'Initial conditions and moment restrictions in dynamic panel data models', *Journal of Econometrics*, Vol 87, pp 115–143.

Butler, R. (1994). Seasonality in tourism: Issues and problems. *In:* Seaton, A.V. (ed). *Tourism: The State of Art*, (pp. 332-339). Chichester, Wiley

Butler, R., and B. Mayo (1996), Seasonality in Tourism: Problems and Measurement. *In* Quality Management in Urban Tourism, P. Murphy, ed., pp. 9–23. Chichester: Wiley.

Cellini, R., Cuccia,T.(2007). Is cultural heritage really important for tourists? A contingent rating study. *Applied Economics*, 39, 261-271-

Calantone, R., and J. Johar (1984), 'Seasonal Segmentation of the Tourism Market using a Benefit Segmentation Framework', *Journal of Travel Research* 23(2):14–24.

Capò-Parrilla, J., Font, A.R., and Nadal, J.R.(2006), 'Accommodation determinants of seasonal patterns', *Annals of Tourism Research*, 34, 422-436.

Card, J., C. Chen, and S. Cole (2003), 'Online Travel Products Shopping: Differences between Shoppers and Nonshoppers', *Journal of Travel Research*, Vol. 42, N.2, pp. 133–139.

Choi, S, Lehto,X.Y., and Oleary, J. (2007), 'What Does the Consumer Want from a DMO Website? A Study of US and Canadian Tourists' Perspectives', *International Journal of Tourism Research*, Vol. 9, pp 59-72.

Coupey, E., Irwin, R., and Payne, J. (1998), ‘Product Category Familiarity and Preference Construction’, *Journal of Consumer Research*, Vol 24, pp 459–468.

Cuccia, T., Rizzo, I. (2010), ‘Tourism seasonality in cultural destinations: Empirical evidence from Sicily’, *Tourism Management*, doi:10.1016/j.tourman.2010.05.008

DiPietro R.B., Wang, Y., Rompf, P., and Severt D. (2007), ‘At destination Visitor Information Search and Venue Decision Strategies’, *International Journal of Tourism Research*, Vol 9, pp 175–188.

Drakatos, C. (1987), ‘Seasonal Concentration of Tourism in Greece’, *Annals of Tourism Research* 14:582–586.

Duncan, C., and Olshavsky, R. (1982), ‘External Search: The Role of Consumer Beliefs’, *Journal of Marketing Research*, Vol 19, pp 32–43.

Engel, J.F., Blackwell, R.D., and Miniard, P.W. (1995), *Consumer Behavior* (8th ed.), Fort Worth TX: The Dryden Press.

Engel J.F., Warshaw, M.R, and Kinnear, T.C.(1991), *Promotional Strategy* (7th ed.), Boston MA: Irwin.

Fernandez-Morales, A., and Mayorga-Toledano, M.C.(2008). Seasonal concentration of the hotel demand in Costa del Sol: a decomposition by nationalities. *Tourism Management*, 29, 940-949.

Fesenmaier, D.R., and Jeng, J. (2000), ‘Assessing structure in the pleasure trip planning process’, *Tourism Analysis*, Vol 5, pp 13–28.

Fodness, D., and Murray, B. (1999), ‘A Model of Tourist Information Search Behavior’, *Journal of Travel Research*, Vol 37, pp220–230.

Fodness, D., and Murray, B. (1998), ‘A Typology of Tourist Information Search Strategies’, *Journal of Travel Research*, Vol 37, pp 108–119.

Fodness, D., and Murray, B. (1997), ‘Tourist Information Search’, A*nnals of Tourism Research*, Vol 24, No. 3, pp 503-523.

Frechtling, D. (1996), Practical Tourism Forecasting. Oxford: Butterworth-Heinemann.

Getz, D. (1991) Festivals, Special Events and Tourism. New York: Van Nostrand Reinhold.

Getz, D. (1997) Event Management and Event Tourism. New York: Cognizant.

Gursoy, D., and McClearly, K.W. (2004), ‘An integrative model of tourists’ information search behavior’, *Annals of Tourism Research*, Vol 31, No 2, pp 353-373.

Gursoy, D., and Chen, J.S. (2000), ‘Competitive analysis of cross cultural information search behaviour’, *Tourism Management*,Vol 21, No 6, pp 583–590.

Higham, J., & Hinch, T.(2002), ‘Tourism, sport and seasons: the challenger and potential of overcoming seasonality in the sport and tourism sectors’, *Tourism Management*, 23, 175-185.

Hinch, T., and E. Jackson (2000), ‘Leisure Constraints Research: its Value as a Framework for Understanding Tourism Seasonability’, *Current Issues in Tourism* 3:87–106.

Hyde K.F. (2008), ‘Information processing and touring planning theory’, *Annals of Tourism Research*, Vol. 35, No3, pp 712-731.

Hwang, J.H., and Fesenmaier, D.R. (2004), ‘Coverage error embedded in self-selected internet based samples: A case study of Northern Indiana’, *Journal of Travel Research,* Vol 42, No 3, pp 297–304.

Jang, S.(2004), ‘Mitigatine tourism seasonality - a quantitative approach’, *Annals of Tourism Research*, 31, 819-836.

Jeffrey, D., and R. Barden (1999), ‘An Analysis of the Nature, Causes and Marketing Implications of Seasonality in the Occupancy Performance of English Hotels’, *Tourism Economics*, 5:69–91.

Jeng, J., and Fesenmaier, D.R. (2002),’Conceptualizing the travel decision-making hierarchy: a review of recent developments’, *Tourism Analysis*, Vol 7, pp 15-32.

Kandari O.P. and Ashish Chandra (2004), ‘*Tourism, Biodiversity and Sustainable Deelopment*’, Isha Books.

Kim S. (2010), ‘The diffusion of the Internet: Trend and causes’, *Social Science Research*, doi:10.1016/j.ssresearch.2010.07.005.

Koenig-Lewis, N., Bischoff E.E., (2005), ‘Seasonality Research: The State of the Art’, *International Journal of Tourism Research*, 7, 201–219, DOI: 10.1002/jtr.531

Koenig,N.,& Bischoff, E.E. (2004), ‘Analyzing seasonality in Welsh room occupancy data’, *Annals of Tourism Research*,31, 374-392

Koenig, N., and E. Bischoff (2003), ‘Seasonality of Tourism in Wales: A Comparative Analysis’, *Tourism Economics*, 9:229–254.

Krakover, S. (2000), ‘Partitioning Seasonal Employment in the Hospitality Industry’, *Tourism Management* 21:461–471.

Li, Xu and Wang, Y. (2010), ‘Evaluating the Effectiveness of Destination Marketing Organisations’ Websites: Evidence from China’, *International Journal of Tourism Research*, Vol. 12, pp 536-549.

Lundtorp, S. (2001) Measuring Tourism Seasonality. *In* Seasonality in Tourism, T. Baum and S. Lundtorp, eds., pp. 23–50. Oxford: Pergamon.

Manning, R., and L. Powers (1984), ‘Peak and Off-peak Use: Redistributing the Outdoor Recreation/Tourism Load’, *Journal of Travel Research* 23(2):25–31.

McEnnif, J. (1992) Seasonality of Tourism Demand in the European Community. EIU Travel and Tourism Analyst 3:67–88.

McIntosh, R.W., and Goeldner, C.R. (1990), *Tourism: Principles, Practices, Philosophies*, New York: Wiley.

Minghetti V. and Buhalis D. (2010), ‘Digital Divide in Tourism’, *Journal of Travel Research*, Vol. 49, No3, pp 267-281.

Morrison, A., S. Jing, J. O’Leary, and L. Cai (2001), ‘Predicting Usage of the Internet for Travel Bookings: An Exploratory Study’ *Information Technology & Tourism*, 4, pp. 15–30.

Moutinho, L.,(1987), ‘Consumer Behavior in Tourism’, *European Journal of Marketing*, Vol 21, pp 5-44.

Murphy, P. (1985), Tourism: A Community Approach. London: Methuen

O’Driscoll, T. (1985), Seasonality in the Trans-Atlantic Vacation Market. Annals of Tourism Research 12:109–110

Pan, B., and Fesenmaier, D.R. (2006), ‘Online Information Search. Vacation Planning Process’, *Annals of Tourism Research*, Vol. 33, No.3, pp 809-832.

Pearce, D.G., and Schott, C. (2005), ‘Tourism distribution channels: the visitors’ perspective’, *Journal of Travel Research*, Vol 44, pp 50–63.

Raitz, K., and Dakhil, M. (1989), ‘A Note about Information Sources for Preferred Recreational Environments’, *Journal of Travel Research*, Vol 27, No 1, pp 45-49.

Rossellò-Nadal, J., RieraFont, A., and Rossello, A. (2004), ‘The economic determinants of seasonal patterns’, *Annals ofTourismResearch*, 31, 697-711.

Schmidt, J., and Spreng, R. (1996), ‘A Proposed Model of External Consumer Information Search’, *Journal of the Academy of Marketing Science*, Vol 24, pp 246–256.

Sirakaya, E, and Woodside, A.G. (2005), ‘Building and testing theories of decision making by travellers’, *Tourism Management*, Vol 26, No 6, pp 815–832.

Snepenger, D.J., Meged, K., Snelling, M., and Worrall K. (1990), ‘Information Search Strategies by Destination-Naive Tourists’, *Journal of Travel Research*, Vol 29, No 2, pp 13-16.

Sørensen, N. (1999), ‘Modelling the Seasonality of Hotel Nights in Denmark by County and Nationality’, *Tourism Economics* 5:9–23.

Spencer,D.M., and Holecek,D.F.(2007), ‘Basic characteristics of the fall tourism market’, *Tourism Management*, 28, 491-504.

Spotts, D., and E. Mahoney (199), ‘Understanding the Fall Tourism Market’, *Journal of Travel Research*, 32(2):3–15

Spulber, D. (1996), ‘Market Making for Price-Setting Firms’, *The Review of Economic Studies*, Vol. 10, pp. 133-152

Srinivasan, N. (1990), ‘Pre-Purchase External Information Search for Information’, *Review of Marketing*, pp 153–189.

Stigler, G. (1961), ‘The Economics of Information’, *Journal of Political Economy*, Vol 19, pp 213-225.

Stiglitz, J., (1989). ‘Imperfect information in the product market’, in: R. Schmalensee & R. Willig (eds.), Handbook of Industrial Organization, edition 1, vol. 1, ch. 13, pp. 769-847, Elsevier

Succurro, M. (2006), ‘An economic analysis of contracts signed between tour operators and travel agents’, *European Journal of Law and Economics*, Vol 22, pp 199-218.

Sutcliffe, C., and M. Sinclair (1980), ‘The Measurement of Seasonality within the Tourist Industry: An Application to Tourist Arrivals in Spain’, *Applied Economics* 12(4):429–441.

Van Raaij, W. F. (1986), ‘Consumer Research on Tourism: Mental and Behavioral Constructs’, *Annals of Tourism Research*, Vol 13, pp1-9.

Vogt, C., and Fesenmaier, D. (1998), ‘Expanding the functional information search’, *Annals of Tourism Research*, Vol 25, pp 551-578.

Weaver, D., and M. Oppermann (2000) Tourism Management. Brisbane: Wiley.

Woo G.K., and Dong J.K. (2004), ‘Factors affecting online hotel reservation intention between online and non-online customers’, *Hospitality Management*, Vol. 23, pp 381-395.

APPENDIX

TABLE A1 Data and Sources

Net Occupancy rate of bed-places	Eurostat
Type of organisation of the trip	Eurostat
Total arrivals	Eurosta
Bed-places	Eurostat
Density of airports	IATA
Low Cost Airlines	www.flylowcostairlines.org
GDP growth rate	International Monetary Fund
Inflation rate	International Monetary Fund
Population growth rate	International Monetary Fund

TABLE A2 List of Countries

Belgium	Luxembourg
Czech Republic	Netherlands
Denmark	Poland
Germany	Portugal
Ireland	Slovenia
Greece	Slovakia
Spain	Finland
France	United Kingdom
Italy	Norway

TABLE A3 Summary Statistics

Variable	Mean	Standard Deviation	Min	Max
Variation in the occupancy rate	14.52	7.59	3.81	42.4
Direct booking	0.50	0.32	0.03	0.95
Total arrivals	198603.9	180740.4	2586	632760
Bed places	521.99	622.59	14	2143
Density of airports	84.11	105.61	2	388
Low Cost Airlines	20	12.07	1	41
GDP growth rate	3.36	2.05	-0.80	10.73
Inflation rate	2.90	2.18	0.001	13.2
Population growth rate	23.65	25.09	0.29	82.53