Tourism Management 42 (2014) 114–122

Contents lists available at ScienceDirect

Tourism Management

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

Package and no-frills air carriers as moderators of length of stay

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HIGHLIGHTS

- We analyze the determinants of the length of stay of air inbound tourists to Spain.
- We estimate an ordered logit model with moderating effects.
- We include activities at destination besides tourist, trip and stay characteristics.
- We find higher moderating effects of package booking than of low cost flight.

ARTICLE INFO

Article history:
Received 31 May 2012
Accepted 4 November 2013

Keywords:
Ordered logit
Low cost airline
Package
Moderating effect
Length of stay

ABSTRACT

This article analyses the determinants of length of stay among inbound tourists arriving by air in one of the world's most popular tourist countries, Spain. Special emphasis is placed on the effects of whether tourists booked the trip themselves or as part of a package and whether they travelled by low cost (LCA) or legacy airline. An ordered logit model is estimated. Relevant explanatory variables are related to tourist preferences and characteristics, trip characteristics, stay characteristics, and activities at destination. One of the main relevant results concerns the moderating effects. For instance, length of stay among package travellers is most affected by type of destination (city vs. coast), length of LCA trip by age, and length of legacy airline trip by accommodation type.

1. Introduction

The increasing expansion and consolidation of no-frills airlines, also referred to as low cost airlines (LCA), has resulted in some destinations receiving a large number of tourists arriving with LCA flights, in some cases even more than with legacy airlines or package trips. This is the case of Spain, one of the world's most important tourist destinations. According to the WTO, Spain is the 4th ranked tourism destination in the world, and according to the IET (*Instituto de Estudios Turísticos* – the Spanish Institute for Tourism Studies), Spain received 52.7 million tourists in 2010, 77% of whom travelled by air. Of the latter, 56% flew with an LCA and 84.3% lived in a European country, which means European countries are the main markets for Spanish destinations. On the other hand, it is worth mentioning for this study that the number of tourists travelling on package tours has decreased in recent years from around 43% in 2004 to around 28% in 2010 (Source: IET). According to the same source, the average length of stay in Spain also shortened for both kinds of tourist from 2004 to 2010: those who use package travel (from 9 nights in 2004 to 8.4 nights in 2010) and those who do not (from 11.8 nights to 10 nights).[1]

The relevance of low-cost tourism today is also reflected in the increasing number of academic studies emerging on the subject, although these are still in a minority (for the Spanish case see, for example, Castillo-Manzano & Marchena-Gómez, 2011; Martínez-Garcia, Ferrer-Rosell, & Coenders, 2012; Martínez-Garcia & Royo, 2010). Microeconomic research on determinants of trip duration has also increased in recent years (see Alegre, Mateo, & Pou, 2011; Alegre & Pou, 2006, 2007; Barros & Machado, 2010; Martínez-Garcia & Raya, 2008; Menezes, Moniz, & Vieira, 2008; Thrane, 2012; Yang, Wong, & Zhang, 2011; among others), probably due to destinations' growing interest in obtaining more information in this area and an observed reduction in trip length, which in many cases is associated with lower expenditure. However, to the best of

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[1] Data for all visitors, regardless of whether they arrived by air or not.

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http://dx.doi.org/10.1016/j.tourman.2013.11.002

our knowledge no study has yet analysed the moderating effect of booking the trip as a package and travelling by LCA or legacy airline on length of stay.

The main aim of this article is to study length of stay at destination for tourists travelling to Spain by air. Special emphasis is placed on the effects of whether tourists booked the trip themselves or as part of a package and whether they travelled by LCA or legacy airline. That is, we consider three different ways of booking: 1) booking a package, where the airline is already included and the tourist cannot choose airline type; 2) booking oneself and flying by LCA; and 3) booking oneself and flying by legacy airline. Besides the usual explanatory variables relating to individual, trip and stay characteristics, the moderating effects of how the trip is booked and the remaining explanatory variables are also of key interest.

This article has some other new elements with respect to the research published to date. Firstly, the inclusion of activities undertaken at destination. Secondly, the scope of the study, which is for a whole country (Spain) rather than just an airport or airline. Thirdly, the use of ordered logit models to account for the multimodality observed in the trip duration variable.

The article is structured as follows: first, we present the literature relevant to our study and then introduce the methodology used to estimate the model. This is followed by a description of the variables, the results, and finally the overall conclusions. An appendix is also included which contains a comparison between the statistical model used in this study and other statistical models.

2. Review of the literature

We begin this section with a general overview of the major research trends and most common methods and variables used in length of stay studies. We then specifically discuss two of the key variables in our article: how the trip is booked and activities undertaken at destination.

Length of stay has long attracted the interest of researchers (Archer & Shea, 1975; Fleischer & Pizam, 2002; Mak & Moncur, 1979; Mak, Moncur, & Yonamine, 1977; Silberman, 1985; Thumberg & Crotts, 1994; among others) with the number of studies published in this area rising since 2008. However, despite this increase, few studies have focused explicitly on the air traveller segment, and to the best of our knowledge only those by Martínez-Garcia and Raya (2008, 2009) and Raya-Vilchez and Martínez-Garcia (2011) have referred to LCA demand. Different studies have employed different methodologies, survival models being the most common (Barros, Butler, & Correia, 2010; Barros, Correia, & Crouch, 2008; Barros & Machado, 2010; Gokovali, Bahar, & Kozak, 2007; Hong & Jang, 2005; Machado, 2010; Martínez-Garcia & Raya, 2008, 2009; Menezes et al., 2008; Peypoch, Randriamboarison, Rasoamananjara, & Solonandrasana, 2012; Wang, Little, & Delhomme-Little, 2012). Most authors have analysed different specific regions (Barros et al., 2008; Menezes et al., 2008; Peypoch et al., 2012; Yang et al., 2011) and a few specific demand segments, such as golf tourists (Barros et al., 2010).

Most studies on length of stay include both trip and stay characteristics in the model, in addition to socio-demographic variables. In the case of the former, the most common variables are travel cost, destination attributes, organization, motivation, repeat visits to the same destination, accommodation, and travelling group. Some studies have also considered distance, destination, season, time of booking, number of trips per year/experience of travelling abroad, and satisfaction. Alegre and Pou (2006) and Martínez-Garcia and Raya (2008, 2009) conducted a review of the literature on this issue, including a justification of the variables used in explanatory models, and Yang et al. (2011) also discuss factors contributing to length of stay. In most studies using secondary data the variables to be included depend primarily on the information available. With regard to this, in the present article we propose a new factor affecting length of stay: activities undertaken at destination. To the best of our knowledge, this factor has not been systematically taken into account in any previous study.

Socio-demographic factors were used as determinants of length of stay as far back as Oppermann (1995, 1997), Seaton and Palmer (1997) and Sung, Morrison, Hong, and O'Leary (2001). More recently, in their analysis of determinants of length of stay in the Balearic Islands, Alegre and Pou (2006, 2007) and Alegre et al. (2011) found that socio-demographic variables played an important role in duration. The studies conducted on LCA travellers by Martínez-Garcia and Raya (2008) and Raya-Vilchez and Martínez-Garcia (2011) also focused on Spanish destinations, and both found sociodemographics – nationality and level of education, for example – to be relevant determinants of duration. Likewise, sociodemographics have also been found to be relevant in studies of other destinations, as in Barros et al. (2008 for Latin America), where younger Portuguese tourists with higher incomes were more likely to stay longer; Barros et al. (2010, Algarve), in which length of stay was related to nationality and age; Gokovali et al. (2007, Israel); Machado (2010, Madeira); Menezes et al. (2008, Azores), Wang et al. (2012, China) who found that tourists spending longer at the destination belonged to higher social classes and had a larger travel budget, whereas length of stay was negatively related to variables such as age and some destination attributes. The most important conclusion drawn by Peypoch et al. (2012, Madagascar) was that some of the most commonly used sociodemographic variables were more related to the dependent variable length of stay than destination attributes. Salmasi, Celidoni, and Procidano (2012, Italy) mainly concluded that income affected the decreasing trend in length of stay in recent years; and in Thrane and Farstad (2012) that nationality explained many of the differences in length of stay among international visitors to Norway. In general, age, income, education and nationality are the sociodemographic variables most frequently used in the literature. They are relatively easy to obtain and generally of interest to destination managers.

Other variables which seem to be relevant to duration and can generally be found in the literature are trip and destination characteristics, with effects and relevance depending on the individual study. For example, destination attributes were found to be significant in Barros et al. (2008), climate in Barros et al. (2010), and urban and coastal resorts in Martínez-Garcia and Raya (2008) and in Raya-Vilchez and Martínez-Garcia (2011), whereas Peypoch et al. (2012) concluded that sociodemographics were more relevant than destination attributes. Destination image was significant in Machado (2010) and Menezes et al.. (2008), prices in Alegre and Pou (2006) and Martínez-Garcia and Raya (2008), and familiarity and experience in Gokovali et al.. (2007). Other variables can be found in only one or a few studies, depending on data availability and the focus of each study.

The variable we use as a moderator in our study – how the trip is booked – has been employed in some studies as an explanatory variable with only main effects. Alegre and Pou (2006, 2007) and Martínez-Garcia and Raya (2008, 2009) found that booking a package holiday was not significant, whereas in Menezes et al. (2008) taking a charter flight increased expected length of stay. Yang et al. (2011) went one step further by analysing subsamples in a particular area in China and found that there were differences in factors affecting length of stay depending on how the trip was booked (package or individual tourists). Individual tourists stayed significantly longer when their reason for travel was visiting friends and relatives rather than sightseeing. However, package tourists on vacations stayed longer than sightseeing package tourists, while those travelling individually did not. These findings encourage the formal inclusion and testing of moderating effects.

Finally, most of the literature that includes activities done at destination does not directly address their effect on length of stay at said destination and activities are not included as an explanatory variable for trips which are not day visits. For example, Masiero and Nicolau (2012) studied price sensitivity to tourism activities, including duration as an explanatory variable, and Daniels and Norman (2003) and Raya (2012) studied determinants of trip duration for a specific sports tourism activity or event. In these two last cases however, the studies focused on said determinants for participants in the event, hence the effects of the activity on length of stay cannot be analysed. To our knowledge, only Barros and Machado (2010) included a limited number of activities at destination as determinants of duration (buying wine, attending casinos and visiting flora and fauna). Their main finding was that tourists doing these activities stayed longer at the destination.

3. Materials and methods

As a research topic, length of stay can be approached from general population surveys or from surveys of tourists carried out at destinations. The type of survey has an influence on the statistical approach, the set of available variables, and the type of tourist decisions that can be modelled. The survey we have used was carried out at destination and the methodology review below is based on this particular approach.

Estimating equations to predict tourists' length of stay poses considerable statistical challenges due to the limited dependent variable, which is integer and positive. Drawing on obvious analogies with duration or survival research, survival models have been used in a major stream of research (Barros et al., 2008, 2010; Barros & Machado, 2010; Gokovali et al., 2007; Hong & Jang, 2005; Machado, 2010; Martínez-Garcia & Raya, 2008; Menezes et al., 2008; Peypoch et al., 2012; Raya, 2012; Raya-Vilchez & Martínez-Garcia, 2011; Wang et al., 2012). Given the sheer distributional characteristics of the dependent variable, other authors use count-data models, such as Poisson regression (e.g. Rodriguez, Dávila, & Rodríguez, 2003) or negative binomial regression (e.g. Nicolau & Más, 2006). Each of these approaches assumes specific data generation processes, which may be considered unrealistic for a model predicting tourists' length of stay. Thrane (2012) has even suggested that, since the data generation process assumed by survival models is not tenable for length of stay, there is not much to be gained over simpler and more widely understood methods such as linear ordinary least squares (OLS) regression, which tends to produce similar results (Thrane & Farstad, 2012).

All of the aforementioned methods, including OLS, assume unimodal distributions for the dependent variable. Lengths of stay usually feature multiple modes around a few typical and conceptually meaningful durations (e.g. long weekend, one week, two weeks, and the like). Alegre and Pou (2006) encountered a bimodal distribution and grouped it into two categories to use a binary logit model. When we encounter three or more modes, we may group the length of stay variable into as many categories as modes by simply defining intervals around the modes. In the case of more than two modes, from more parsimonious to more general, the feasible approaches are ordered logit models, generalized ordered logit models, and multinomial logit models (for an overview, see Hosmer & Lemeshow, 2000; Fullerton, 2009; Appendix 1). In an alternative statistical tradition, Alegre et al. (2011) accommodated multiple modes by using mixture models and Salmasi et al. (2012) by using a quantile regression approach, modified to account for discreteness of duration.

In this research we have used the ordered logit model, which is more readily comparable to the traditional unimodal OLS, Poisson and negative binomial approaches, as it has a single parameter vector, which is easy to relate to the linear model family (see Appendix 1). To our knowledge, only Yang et al. (2011) have previously used the ordered logit model, albeit with the purpose of dealing with outliers by merging only the few longest stays into a single "long stay" category, and only Alegre and Pou (2007) and Nicolau and Más (2009) have used the multinomial logit model.

In the linear model we have:

$$y_i = \mathbf{x_i}\boldsymbol{\beta} + u_i \tag{1}$$

where y_i is the duration of the stay for the ith individual, u_i is a disturbance term with a given distribution (normal in the OLS case).

In the ordered logit model we have:

$$y_i^* = \mathbf{x_i}\boldsymbol{\beta} + u_i \tag{2}$$

with $y_i = 1$ if $y_i^* \le \tau_1$; $y_i = 2$ if $\tau_1 < y_i^* \le \tau_2$; $y_i = 3$ if $\tau_2 < y_i^* \le \tau_3$; ...; $y_i = K$ if $\tau_{K-1} < y_i$. Length of stay, now represented as y_i^*, is not observed and a categorized length y_i is observed instead, with K categories and K-1 τ thresholds, which are additional model parameters of the family of intercept parameters. u_i is a disturbance term with a logistic distribution with null location parameter and unit scale parameter. It can be shown that $E(u) = 0$ and $Var(u) = \pi^2/3 \approx 3.29$. The logistic distribution embedded in u_i and y_i^* is indeed unimodal, but y_i can take whichever form through the τ threshold parameters.

The ordered logit model is attractive in two situations. Firstly, for data that are naturally ordered (Hosmer & Lemeshow, 2000), for instance electoral participation (1: did not register; 2: registered but did not vote; 3: voted). Secondly, for the categorization of an underlying continuous y^* variable (e.g. Fullerton, 2009; Muthén, 1984), which is our case.

The β parameters in the $\boldsymbol{\beta}$ vector in an ordered logit model can be related to the K $prob(Y = k)$ probabilities through the τ thresholds and the cumulative logistic distribution function. However, this is extremely cumbersome and the results depend on the baseline value of the $\mathbf{x_i}$ vector. It is far more straightforward to interpret the ordered logit model as a linear model with limited measurement of the dependent variable. Even if the model is not linear in y, it is linear in y^*, and $\boldsymbol{\beta}$ can be interpreted in the usual manner with respect to y^* (Muthén, 1984). In the field of economics it is usual to interpret y^* as a propensity to a certain choice, in this case the propensity to choose ever longer stays. The units of the unobservable y^* variable are arbitrarily fixed in such a way that $Var(u) = \pi^2/3$. A natural way of interpreting the β coefficients is by standardizing y^* as:

$$\beta_s = \frac{\beta}{\sqrt{\mathrm{var}(y^*)}} = \frac{\beta}{\sqrt{\mathrm{var}(\mathbf{x}\boldsymbol{\beta}) + \pi^2/3}} \tag{3}$$

If x increases by one unit, y^* increases by β_s standard deviations, all other variables remaining constant. Thus, the usual interpretation in a linear standardized model fully applies to the ordered logit model.

Categorical predictors can be accommodated in the usual way as binary-coded variables. All variables in our article are, in fact, categorical. Moderating effects, also called interaction effects, can also be accommodated in the usual manner as products of these binary variables. In this article we consider interactions between how the trip is booked (as a package, without package by legacy airline, and without package by LCA) and all other variables in the model.

The ordered logit model makes the assumption that the same β coefficients hold for all categories, which is sometimes referred to as the parallel lines assumption or as the proportional odds assumption. Conceptually, this can be related to the linearity assumption made in OLS regression, Poisson regression, and negative binomial regression. The parallel lines assumption is relaxed in the multinomial logit model and in the generalized ordered logit model. In Appendix 1, we include a discussion of the assumptions deriving from these models and a comparison of their results with our data.

In this article we use secondary official statistics data. The data were provided by the *Instituto de Estudios Turísticos* (IET), an official agency within the Spanish Ministry of Industry, Energy and Tourism, producing most of the country's tourism data. The survey is known as the *Encuesta de Gasto Turístico (EGATUR)*, which studies tourist spending and other tourist information such as trip information and tourist sociodemographic characteristics. As regards air travellers, the EGATUR 2010 survey was conducted at 23 major Spanish airports by CAPI (Computer Assisted Personal Interview) when tourists were leaving the country.[2]

The main characteristics of the sampling process for the air-traveller subpopulation are presented in Table 1.

Our universe is a subset of EGATUR's universe, consisting of European leisure visitors arriving by air and staying overnight in Spain. Consistent with this, we did not consider business trips, study trips, and trips without an overnight stay. We also excluded flights from outside Europe because LCAs mostly operate short-haul flights and European countries are the main markets for inbound tourism in Spain. We also based our study only on trips with a single destination, thus excluding multi-stage trips, as the decision process regarding length of stay for these trips is expected to fundamentally differ from that for single-stage trips.

Stays of over 120 days (0.3% of cases) were excluded. The final sample size was $n = 61{,}334$. The large sample size makes it possible to use low p-values. All the variables included in the final model are significant at $\alpha = 0.01$. SPSS 19 software is used to estimate the ordered logit model (PLUM procedure) by maximum likelihood (ML).

4. Results

4.1. Data description

As observed in Fig. 1, the duration of stay is multimodal, with modes of 3–4 nights, 7 nights, 10, 14 and 21 nights. Thus, we have created the ordinal length of stay variable around these modes: 5 nights and fewer, from 6 to 8 nights, from 9 to 12 nights, from 13 to 15 nights and more than 16 nights. We performed a sensitivity analysis by randomly moving all category boundaries up or down by one day. We repeated the experiment twice without observing any sizeable changes in the ordered logit estimates or in the statistical significance of the variables.

Table 2 shows the bivariate relationship between length of stay and how trip is booked. We observe that only small differences seem to exist between those tourists arriving by legacy airline and those arriving by LCA. The main difference is found between booking the trip oneself (and using either type of airline) and travelling as part of a package. In other words, among both legacy and LCA users, about the same proportions are observed indistinctly in all categories of the length of stay variable (around 42% for 5 nights and fewer, around 28% for a week stay, 11% for stays of around 10 days, 9% for two-week stays and 8% for stays of over two weeks). By contrast, in the package column, more than half stay one week.

Table 1
Summary of the EGATUR sampling methodology.

Universe	Foreign visitors arriving by air to Spain (Isles included), through 23 majour airports
Regularity	Monthly
Sampling method	Random Stratified by airport (Aiports grouped in 9 strata) Quotas by country of residence and month
Sample size	73,000 air travellers per year
Data collection	Computer Assisted Personal Interviews conducted at the airport while waiting for the flight back home

Table 3 shows frequency distributions for all explanatory variables. Since all variables are categorical, numerical summaries cannot be computed. As far as activities at destination are concerned, eleven activities are included in the model. Regarding trip characteristics, six variables are included: previous stays in Spain; travel group; destination (the two major Spanish cities, Madrid and Barcelona, other unique capital cities and other locations); time of booking, which has two categories; season (coded as binary: summer season vs. otherwise) and type of accommodation. Sociodemographic variables are age, gender, country of residence, level of education and self-reported income category. At the bivariate level, all variables were significantly related to trip duration (p-value < 0.001 in Kruskal–Wallis non-parametric tests using the original numeric duration variable).

4.2. Model of trip duration

Table 4 presents the ordered logit results. The large sample size means it is unsurprising that the estimated model was globally significant (overall likelihood ratio test for all variables 27,102.3 with 99 d.f.). The goodness of fit measures are more informative, Nagelkerke's R-squared being 0.380, McFadden's 0.158 and McKelvey and Zavoina's 0.397.

All variables are individually significant (p-value < 0.01). We have computed the effects which are likely to be detected in the population (statistical test power) in order to show that our large sample results in a very high probability of detecting even very small effects. We have used the median and the first and third quartiles of all standard errors, and, taking into account $\alpha = 1\%$, the effects detected at 95% power are 0.060 for quartile 1, 0.082 for the median standard error, and 0.115 for quartile 3, which are all very small effects in a standardized scale. On the other hand, we also computed robust standard errors using the sandwich method (MLR option in MPLUS7.11, Muthén & Muthén, 1998–2012). The mean absolute relative difference between standard ML and sandwich standard errors was only 8.1% and even the largest differences would guarantee that any effect significant at 1% with the ML method would be significant at 5% with the sandwich method. Therefore, we report only the more usual ML standard errors in Table 4.

A joint likelihood ratio test of the null hypothesis of no moderating effects yields a χ^2 statistic of 1094.3 with 58 d.f. (p-value < 0.001). The goodness of fit measures of the main-effects-only model are Nagelkerke's $R^2 = 0.368$, McFadden's $R^2 = 0.152$ and McKelvey and Zavonia's $R^2 = 0.381$. The overall picture is that the model with moderating effects has a higher goodness of fit than the model without, although not dramatically so. That said, many of the moderating effects are meaningful from both the theoretical and management points of view, as shown below.

The fact that all variables are treated as categorical and coded as 0-1 dummy variables makes the size of estimates comparable

[2] See http://www.iet.tourspain.es/en-en/estadisticas/egatur/metodologia/paginas/referenciametodologica.aspx for details of EGATUR methodology and statistics.

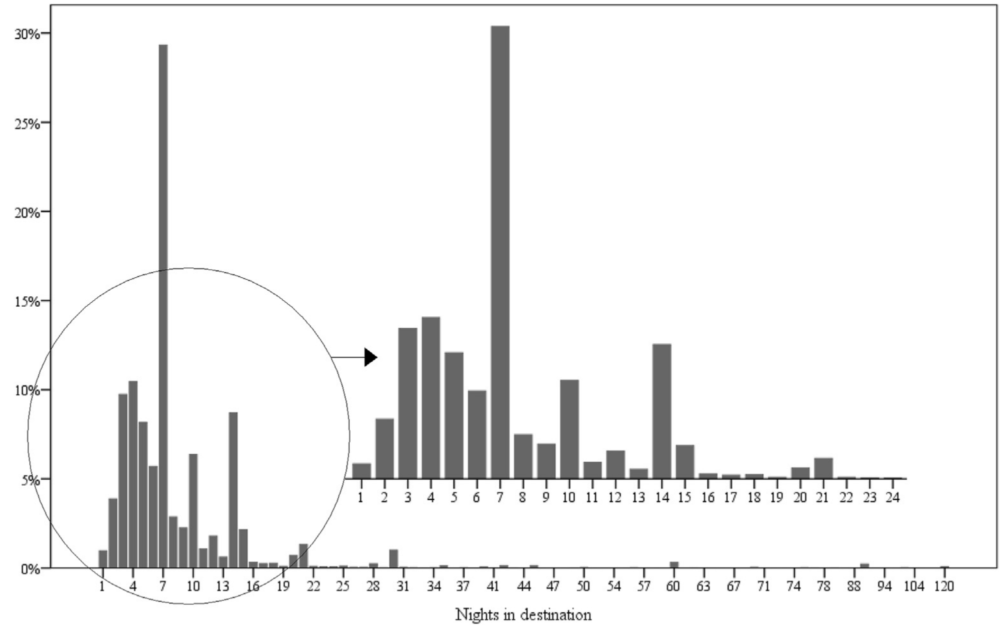

Fig. 1. Dependent variable length of stay. Mean=8.51; standard dev.=8.36.

across variables. Since all effects are significant, we have concentrated our interpretation on the largest. Effects are interpreted as the standard deviation increase in y^* when shifting from the reference category to a given category (Equation (3)). Reference categories are indicated for all predictors in Table 3. Main and moderating effects have been summed for an easier reading of Table 4, with each column representing the effect within a particular way of booking the trip. If the column values differ for a given row, there is a significant moderating effect (p-value < 0.01).

How the trip is booked has been used as the moderating variable. The intercept term shows the main effect, in other words, the effect of how the trip is booked within the reference category of all variables (no activities, first time in Spain, summer trip, 4-5 star hotel accommodation, travelling with partner, visiting locations other than main cities, booking months beforehand or longer, 25–44 years old, female, UK resident, university education, medium income). This main effect shows that booking the trip as part of a package makes the stay considerably longer than the reference means of booking (without package and by legacy airline). However, booking the trip oneself (without a package) and travelling by LCA leaves duration almost unchanged with respect to legacy airlines.[3] Contrary to our results, how the trip is booked was not significant in some previous studies which included only its main effect (Alegre & Pou, 2006, 2007; Martínez-Garcia & Raya, 2008, 2009), whereas it was found to be significant in others (Menezes et al., 2008 found longer lengths for charter flights in the Azores Islands and Yang et al., 2011 shorter lengths for package organization in domestic tourism in China).

As shown below, besides having a main effect, how the trip is booked moderates the effect of other variables. Only Yang et al. (2011) made an attempt to study moderating effects for package and non-package tourists (without considering airline type). They did so by means of a subsample analysis instead of formally modelling interaction effects. Among the variables included both in their study and ours, the only variable which substantially moderated the effect on length of stay was age.

The fact that our results differ from those obtained in some of the previous literature may be methodological. Unlike previous studies, we have subdivided this variable into three categories rather than two (package or not package) and formally tested moderating effects. The reasons for the variable's lack of significance in some previous studies may also be the smaller sample size, the small percentages of either package users or non-package users in studies of only one airport or only one destination, the dilution of moderating effects with opposite signs when only the main effects are considered, and the different destinations analysed.

The inclusion of activities undertaken by tourists at destinations is one of the new features included in this article, and overall it has been found to be relevant to trip duration. Specifically, coefficients are mostly positive, as found by Barros and Machado (2010), with respect to nature activities and visiting casinos. This means that duration is longer for almost all activities undertaken when compared with the reference of doing no activities. Those tourists who undertake activities may have them as their *primary* attraction or *E-attraction* for visiting the destination (which generates larger durations, see Botti, Peypoch, & Solonandrasana, 2008). Regarding our moderating effect estimates, no relevant interactions emerge in the case of nautical sports, hiking, cultural visits, going to a spa, going to a theme park, nightlife or visiting friends and relatives; that is, in general terms tourists doing these activities spend more days at destination and how the trip is booked is of no importance. Among those activities where moderating effects are not found, the highest increases in duration are found for spas and theme parks

Table 2
Categorized dependent variable by how trip is booked.

Length of stay	Legacy	Package	LCA
5 and fewer	44.7%	11.0%	40.9%
6–8	26.8%	57.9%	31.2%
9–12	11.1%	11.9%	11.4%
13–15	9.3%	17.5%	8.9%
16 and over	8.0%	1.6%	7.6%

[3] Castillo-Manzano and Marchena-Gómez (2011) found that a longer length of stay increases the probability of choosing an LCA over a legacy airline, although their study was not focused on length of stay but airline choice.

Table 3
Frequency distributions of explanatory variables.

	Count	Percent
Activities		
Nautical sports		
Yes	2412	3.9%
No[a]	58,922	96.1%
Hiking		
Yes	1375	2.2%
No[a]	59,959	97.8%
Other sports		
Yes	3851	6.3%
No[a]	57,483	93.7%
Attendance at sport events		
Yes	1644	2.7%
No[a]	59,690	97.3%
Cultural visits		
Yes	28,075	45.8%
No[a]	33,259	54.2%
Attendance at cultural events		
Yes	6692	10.9%
No[a]	54,642	89.1%
Other cultural activities		
Yes	10,368	16.9%
No[a]	50,966	83.1%
Spa		
Yes	3434	5.6%
No[a]	57,900	94.4%
Theme parks		
Yes	6040	9.8%
No[a]	55,294	90.2%
Nightlife		
Yes	15,069	24.6%
No[a]	46,265	75.4%
Visiting friends/relatives		
Yes	9673	15.8%
No[a]	51,661	84.2%
Trip Characteristics		
Has been to Spain before		
Yes	12,600	20.5%
No[a]	48,734	79.5%
Travel group		
With friends	8922	14.5%
In family	10,092	16.5%
Alone	15,712	25.6%
With partner[a]	26,608	43.4%
Destination		
Unique capitals[b]	5207	8.5%
Madrid	5511	9.0%
Barcelona	8715	14.2%
Other locations (mostly coastal)[a]	41,901	68.3%
Time of booking		
Weeks before or less	24,387	39.8%
Months before or longer[a]	36,947	60.2%
Season		
Not in summer	43,486	70.9%
Summer[a]	17,848	29.1%
Accommodation used		
Other accommodation	3861	6.3%
Home ownership	4489	7.3%
Hotel 3*	10,147	16.5%
Other kind of hotel	10,673	17.4%
Family/friends' housing	16,704	27.2%
Hotel 4–5*[a]	15,460	25.2%
How trip was booked		
Package	17,532	28.6%
No package with LCA	30,058	49.0%
No package with legacy[a]	13,744	22.4%
Socio-demographic profile		
Age		
65 and more	5308	8.7%
15–24	7822	12.8%
45–64	17,794	29.0%
25–44[a]	30,410	49.6%
Gender		
Male	31,043	50.6%
Female[a]	30,291	49.4%
Country of residence		
Austria, Switz. & Liechtenstein	3602	5.9%
France	4250	6.9%
Other European countries	5211	8.5%
Scandinavian countries	6266	10.2%
Italy	6609	10.8%
Benelux	6844	11.2%
Germany	9978	16.3%
United Kingdom[a]	18,574	30.3%
Level of education		
Up to high school	22,798	37.2%
University[a]	38,536	62.8%
Income category		
Low	3370	5.5%
High	16,818	27.4%
Medium[a]	41,146	67.1%

[a] Reference categories in the logit model: chosen either because they are the largest categories, or because they are the most standard, conceptually considered.
[b] The capital towns considered unique are: Bilbao, Córdoba, Girona, Granada, Salamanca, Santiago de Compostela, San Sebastián, Sevilla, Tarragona, Toledo and Valencia.

(duration increased by 0.20 and 0.15 standard deviations). For some other activities, effect changes (moderating effects) are found. The largest of these and also the largest differences are found for sports other than nautical sports or hiking. Those tourists who do other sports generally stay longer at destination, but those who book the trip as part of a package stay less time than those who book it themselves, regardless of the type of airline. For those who attended sporting and cultural events, only LCA users had substantially extended trip durations.

With regard to trip characteristics, length of stay varies substantially depending on the variables and their categories. Concerning the season of the trip, our results show, in line of those of Martínez-Garcia and Raya (2008; 2009), Rodríguez et al. (2003), and Thrane (2012), that tourists coming to Spain outside the summer season stay considerably fewer days than those coming in summer. Concerning who the tourist travelled with, our results show that those who travelled with friends stay shorter compared to those who travelled with a partner, a result consistent with Menezes et al. (2008). As regards moderating effects, using an LCA reduces the length of stay by more in both variables than when using a legacy airline or booking a package.

As far as accommodation is concerned, coefficients are mostly positive compared to the reference category (4–5* hotels), except those in the 3* hotel category, which are near 0, meaning that tourists staying in these hotels are indistinguishable from the reference. Tourists who own a second residence at the destination are those who stay longest; in fact, this is the most distinct category for the length of stay variable. This result has also been obtained previously by Barros et al. (2010), Martínez-Garcia and Raya (2008; 2009), Raya (2012) and Salmasi et al. (2012). As regards the moderating effect of accommodation, visitors using legacy airlines and LCAs show the main increases in duration for home ownership, family/friends' housing and other types of accommodation. Contrarily, package travellers have longer stays in other kinds of hotel.

As for the type of destination, going to any main city considerably reduces length of stay. Similar results were found by Martínez-Garcia and Raya (2008). Booking the trip as part of a package makes stays in these main cities even shorter. This reduction is largest in Madrid, closely followed by Barcelona.

No significant moderating effects emerge in the case of having previously been to Spain. We find a small negative main effect of

Table 4
Ordered Logit results. Standardized estimates and standard errors within how trip is booked.[a]

Variable categories	Legacy		Package		LCA	
	$\widehat{\beta}_s$	Se	$\widehat{\beta}_s$	Se	$\widehat{\beta}_s$	Se
Intercept	0.00	0.00	0.30	0.04	−0.05	0.04
Nautical sports	0.10	0.02	0.10	0.02	0.10	0.02
Hiking	0.08	0.02	0.08	0.02	0.08	0.02
Other sports	0.30	0.03	0.05	0.02	0.24	0.02
Attended sports events	−0.03	0.04	−0.20	0.06	0.11	0.03
Cultural visits	0.05	0.01	0.05	0.01	0.05	0.01
Attended cultural events	0.05	0.02	0.02	0.03	0.16	0.02
Other cultural activities	0.10	0.02	−0.06	0.02	−0.01	0.01
Spa visited	0.20	0.02	0.20	0.02	0.20	0.02
Visited theme parks	0.15	0.01	0.15	0.01	0.15	0.01
Nightlife	0.06	0.01	0.06	0.01	0.06	0.01
Visited friends/relatives	0.10	0.01	0.10	0.01	0.10	0.01
Has been to Spain before	−0.11	0.01	−0.11	0.01	−0.11	0.01
Not in summer	−0.25	0.02	−0.16	0.01	−0.30	0.01
Other accommodation	0.76	0.03	0.15	0.04	0.58	0.02
Home ownership	1.01	0.03	0.14	0.26	0.83	0.02
Hotel 3*	−0.07	0.03	−0.05	0.02	−0.04	0.02
Other kind of hotel	0.43	0.03	0.07	0.02	0.31	0.02
Family/friends' housing	0.54	0.02	0.12	0.15	0.45	0.02
Travelling with friends	−0.20	0.03	−0.15	0.02	−0.27	0.02
Travelling in family	0.13	0.02	0.05	0.02	0.14	0.02
Travelling alone	−0.04	0.02	−0.03	0.01	−0.04	0.01
Unique capitals	−0.60	0.02	−0.69	0.06	−0.53	0.02
Madrid	−0.85	0.03	−1.42	0.08	−0.90	0.02
Barcelona	−0.84	0.02	−1.15	0.03	−0.76	0.02
Booked weeks in advance or less	−0.16	0.01	−0.16	0.01	−0.16	0.01
65 and more	0.60	0.03	0.48	0.02	0.67	0.02
15–24	0.05	0.02	−0.03	0.02	0.06	0.02
45–64	0.12	0.02	0.13	0.01	0.17	0.01
Male	−0.03	0.01	−0.03	0.01	−0.03	0.01
Austria, Switz. and Liechtenstein	−0.09	0.03	0.08	0.03	0.10	0.03
France	−0.07	0.03	0.00	0.03	0.04	0.02
Other European countries	0.09	0.03	0.10	0.03	0.15	0.02
Scandinavian countries	0.15	0.03	0.05	0.02	0.18	0.02
Italy	−0.08	0.04	0.02	0.03	−0.11	0.02
Benelux	−0.04	0.03	0.13	0.02	0.00	0.02
Germany	0.06	0.03	0.21	0.02	0.21	0.02
Up to high school	−0.16	0.02	−0.01	0.01	−0.10	0.01
Low income	0.06	0.04	0.02	0.03	0.05	0.02
High income	0.11	0.02	0.04	0.01	0.05	0.01

[a] It must be noted that even if the table shows a set of estimates within each way of organizing the flight, the estimation was conducted in a single model with dummy variables and their products (interaction terms), as explained in the materials and methods section.

loyalty on length which contradicts most previous studies (Alegre & Pou, 2006; Alegre et al., 2011; Barros et al., 2008; Gokovali et al., 2007; Menezes et al., 2008; Thrane & Farstad, 2012; Wang et al., 2012; Yang et al., 2011). No significant moderating effects emerge either regarding booking shortly before travelling (small negative main effect of last-minute booking on length, as also obtained by Barros et al., 2008; by Thrane, 2012).

How the trip is booked moderates length of stay for all socio-demographic variables included in the model except gender. Older tourists stay longer than other age groups. The same result was found in the majority of previous studies, with a few exceptions such as Barros et al., 2008. When older travellers use LCAs or legacy airlines, their stay increases by 0.67 and 0.60 standard deviations, respectively, compared to the 25–44 age group. This increase is somewhat less when they travel as part of a package.

Concerning the country of residence, we have found that tourists from Germany travelling as part of a package or using an LCA stay longest (0.21 standard deviations of stay longer than UK residents), followed by tourists from Scandinavia using both LCA and legacy airlines (0.18 and 0.15 standard deviations longer than UK residents). On the other hand, results show that tourists from the Benelux stay longer when they travel on package trips and behave similarly to UK visitors when they book the trip themselves.

Tourists who have up to secondary school education stay less time than those with a university education. This result is also found in some previous studies (Barros et al., 2010; Barros & Machado, 2010; Machado, 2010), but differs from others (Gokovali et al., 2007; Martínez-Garcia & Raya, 2008, 2009; Menezes et al., 2008; Salmasi et al., 2012; Wang et al., 2012). Regarding the moderating effects, the main difference here is found between booking oneself and package trips, the latter group showing no effect in terms of education.

Finally, with regard to level of income, results show that high-income tourists who use a legacy airline have the longest increase in stay.

5. Conclusions

The purpose of this study was twofold. Firstly, to analyse the determinant factors of length of stay at destination for all European tourists arriving in Spain by air (most inbound tourism in Spain is European and travels by air). Secondly, to study the impact of tourists booking the trip themselves and flying by LCA or legacy airline or travelling as part of an organized package, both in terms of main and moderating effects. This article has some other new elements with respect to the research published to date. Firstly, the inclusion of activities undertaken at destination. Secondly, the scope of the study, which is for a whole country (Spain) rather than just an airport or airline.

Results show that both main and moderating effects of package travel are generally much more important than those of type of airline. This may be due to LCAs gradually capturing different market segments, which can lead to an increasing similarity between users of the two airline types. Moreover, services offered by the companies themselves (legacy and LCA) are in some cases becoming increasingly similar, which could also contribute to the fewer significant differences observed in our study, a trend we expect to continue in the future. Consequently, Destination Management Offices (DMOs) should not be less interested in LCA travellers than in legacy airline travellers. In line with this, our results show that for some predictor categories, LCA users have slightly longer stays than legacy airline users. Another important aspect to highlight, since it is one of the new features included in our research, is that tourists who report having done some activity at the destination generally stay longer.

As far as implications for management are concerned, assuming that DMOs have the objective of lengthening the stay of their tourists, some of the feasible undertakings would be: to increase marketing efforts directed at families and older people, especially when booking the trip themselves; to increase marketing efforts aimed at first-time visitors; to offer and market a large range of activities (in particular, those destinations that offer cultural events could seek to attract LCAs and their users); to foster hotel accommodation other than 3, 4 and 5-star hotels within the package travellers sector; to extend the origin markets beyond the still prevalent UK market (fruitful efforts can be made on residents in Scandinavian countries booking the trip themselves or on Benelux residents travelling as part of a package, or, generally speaking, among other European country residents); or, specifically for major cities, attracting more LCAs and fewer package tour operators to their airports.

As regards methodology, we have used an ordered logit model. To our knowledge, this is the first use of the model to deal with multimodality of the duration variable. This model has made it possible to estimate all moderating effects. Multinomial logit models could also have been used, as shown in Appendix 1, if the model had included fewer moderating effects. The ordered logit model can be accommodated to many related situations, for instance, attendance at sports events, cultural festivals, fairs, congresses, and the like (see, for instance, Raya, 2012; in the field of sports). In this case, an ordered categorization of the number of nights spent may be of special interest to destinations. For example, stays shorter than the length of the event, stays lasting the same as the event and stays longer than the event.

As regards limitations and further research, there are some advantages of using a database from an official statistics institution, as in this case. These are mainly related to the large sample size and scope (a whole country rather than just one destination or airport). The main disadvantage is that the set of available variables cannot be controlled by the researcher. Another issue is the time dimension. The EGATUR survey is conducted annually, so further research might be done to include a repeat cross-section analysis in order to capture trends in the effects of predictors.

Acknowledgements

We are grateful to the Spanish Institute of Tourism Studies (*Instituto de Estudios Turísticos*) for providing us with the raw data, and the University of Girona's Institute of Tourism Studies INSETUR for its financial support. The first author carried out this research with the support of a grant from the University of Girona (BR 18/2011). The authors want to thank Marc Saez at the University of Girona, Juan Luis Nicolau at the University of Alicante, and three anonymous reviewers for their helpful comments to previous versions of this article.

Appendix 1

Two anonymous reviewers suggested that some sort of comparison is valuable whenever more than one statistical model may be used. In this appendix, the ordered logit model is compared, on the one hand, with some of the stricter models assuming unimodality (OLS, Poisson regression, negative binomial regression) and, on the other, with the alternative logit models relaxing the parallel lines assumption.

Of the latter, the multinomial logit model includes a separate equation for each category, making it possible for each specific length of stay to have predictors operating in a specific way. It is equivalent to fitting *K*-1 binary logit models in which each length category is compared to a reference category (e.g. the first). If categories in fact behave ordinally, the multinomial and ordinal results basically provide the same information, but the multinomial solution includes far more parameters and is more cumbersome to interpret.

The multinomial model requires larger sample sizes than the ordered model. If moderating effects are to be included, the three-way contingency tables between each predictor, each duration and the moderator variable can contain no empty cells.

A related development is the generalized ordered logit model (Fu, 1998). It is equivalent to fitting *K*-1 binary logit models in which categories are merged into two adjacent sets: the first model compares the merged categories 2 to *K* with category 1; the second model compares the merged categories 3 to *K* with the merged categories 1 and 2; the last model compares the category *K* to the merged categories 1 to *K*-1. It is therefore as complex as the multinomial model, unless coefficients are constrained to be equal for those variables for which the parallel lines assumption is tenable (Williams, 2006). Admittedly, the generalized ordered logit model is ordinal only in the sense that it merges adjacent ordered categories. By contrast, the estimates of the coefficients across the *K*-1 equations are not constrained to be of the same sign, as should happen if ordering is to be preserved. Besides, the generalized ordered logit model may lead to negative probabilities. On these grounds, researchers may tend to favour the multinomial model when seeking a more flexible alternative to the standard ordered logit model.

A useful tool when choosing between logit models is a statistical test of the parallel lines assumption. When this assumption is rejected, either the multinomial or generalized models make statistical sense. Another issue is whether the results of the more complex model substantially differ, so as to make its interpretation richer than that of the more standard ordered logit model. The power of the parallel lines test is an issue. In a very large sample, as in our case, even trivial violations of the parallel lines assumption can be statistically significant (Williams, 2006). Finally, more heavily parametrized models require larger samples, unless the number of parameters is reduced somewhere else (e.g. by reducing the number of variables or moderating effects).

Besides the ordered logit, we also estimated an OLS regression, a Poisson regression, a negative binomial regression, a multinomial logit and a generalized ordered logit. Despite the large sample size used in our study, some empty cells were present and the moderating effect of accommodation could not be estimated in the multinomial and generalized ordered frameworks. Besides, the upper two length categories had to be merged.

We first compared the single equation models (ordered logit, OLS regression, Poisson regression, negative binomial regression) by treating the estimated coefficients as data, the models as variables, and correlating them for each pair of models (Table 5). This is done in this way because cardinal parameter values have different interpretations across models and cannot be compared. Regarding the comparison of statistical significance, while theoretically appealing, it is not very informative; given the huge sample size, nearly all effects had *p*-values lower than 0.0005, regardless of the model. Only two significant effects at 0.01 in the ordered logit model failed to be so in the negative binomial model, for instance.

Table 5
Correlations of model estimates between methods

	OLS	Poisson	Negative binomial
Poisson	0.971		
Negative binomial	0.983	0.994	
Ordered logit	0.986	0.950	0.963

Results show all correlations to be quite high, but it is worth noting that the strongest relationships are between Poisson and negative binomial regressions (0.994), and OLS and the ordered logit model (0.986). There seem, therefore, to be two clusters of methods, the first including both count-data models (Poisson and negative binomial regressions), and the second including the ordered logit and OLS.

We carried out the parallel lines test, whose null hypothesis implies that the classic ordered model is correct and thus the multinomial and generalized models are not needed. We rejected the hypothesis (p-value < 0.001).

When we examined the generalized ordered logit model results, we found a few small negative probabilities (-0.06 at the largest) and some coefficients with sign reversals across the cutting points (4.8% of all parameter estimates in the generalized model). These results show the generalized ordered logit model to be inappropriate for these data and favour either the multinomial model or the classic ordered model.

When we examined the multinomial logit results, only the variable indicating the tourists' country of residence showed a qualitatively different interpretation from the classic ordered logit model. On the other hand, with the multinomial model we are missing valuable information on the interaction between accommodation and method of booking. Given that our large sample size results in a high statistical power of the parallel lines test, and that our final multinomial model had 270 parameters, we chose to report only the estimates of the classic ordered model in this article. The full multinomial results are available from the corresponding author on request.

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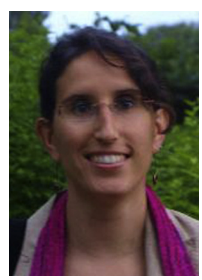

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