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The city-airport connection in the low-cost carrier era: Implications for urban transport planning

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ABSTRACT

This article, examines differences between the behavior of passengers of low-cost and network airlines when choosing their transport mode for travel to airports. It is found that a passenger flying with a low-cost carrier is 6% less likely to take a taxi to the airport, but more than 4% more likely to drive a rented car and 2% more likely to use public transport than a user of a network carrier.

1. Introduction

One of the features of air transport deregulation has been the development of low-cost carriers (LCCs) and their new management model, the main characteristics of which have undermined belief in the industry's previous structure, procedures, and business models and brought about major changes in the strategies and behavior of the different economic agents on both the supply and the demand sides of the air transport industry.

On the supply side, for example, there has been an upsurge in the use and importance of many secondary, often underused (Francis et al., 2004), regional airports compared to the hubs (Reynolds-Feighan, 2001). These airports have seen their bargaining power diminished by the aggressive bargaining methods of LCCs (Barrett, 2004) seeking to achieving minimum airport charges. Broadly speaking, competition between airports to attract LCCs can be said to be on the increase (Pels et al., 2009).

LCCs' use of secondary airports also means airline traffic is further scattered across multiple airports serving the same metropolitan area. This is a drawback for airport access planning, the main purpose of which is to reduce the market share of private vehicle use by both passengers and airport staff (Humphreys and Ison, 2005 on policies for changing airport employee travel behavior), as private vehicles are the modes of transportation that most contribute to noise, congestion levels, and air pollution (Graham, 2008) in airport hinterlands.

On the demand side, one of the most important changes brought about by the LCCs for our analysis is the increased demand for air transport services by younger and price-sensitive travelers (O'Connell and Williams, 2005). *A priori* this might be surmised to impact on the market shares of the various modes of transportation that passengers use to get to airports and benefit the less expensive. This would explain the interest that some LCCs in Europe have in either developing or working in cooperation with bus and coach companies (such as Terravision, tightly linked to the Ryanair group, or the Easybus connections to the airports around London where Easyjet operates).

This paper looks at differences in the behavior of LCC and network airline passengers when choosing of a mode of transportation to an airport? And if these differences do exist, what are they, and what effects do they have on airport ground access planning? Apart from some theoretical considerations, there have been fewer empirical studies looking at these questions.[1]

2. Data

The database comprised 20,383 passengers, 6247 of whom were LCC passengers. All of these were interviewed in departure lounges

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[1] Echevarne (2008) supposed that logic would dictate that low-cost passengers would generate a greater demand for car parking facilities at regional and secondary airports whilst traditional airline passengers would present a higher taxi usage. De Neufville (2006) similarly surmised that price-conscious travelers on low-cost carriers are the passengers most likely to use public transport, and that the market for airport access is now more closely aligned with the traditional market for urban public transport.

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Table 1
Technical data survey.

Airport		Alicante	Bilbao	Seville	Valencia	Santiago	Valladolid	Zaragoza
Airport traffic in 2008		9,578,308	4172,901	4,391,794	5779,336	1,917,434	479,716	594,952
Information gathering	Questionnaire	Available in 12 languages				Available in 6 languages	Available in 5 languages	Available in 4 languages
	General	Departing passengers > 15 years of age.						
Sampling (before weighting)	Sample size	2420	3182	4140	4965	3497	1042	1137
	Sampling method	Stratified by traffic segments with selections of flights for each route and groups of passenger participants done by systematic sampling.						
	Sampling error[a]	±2%	±1.7%	±1.5%	±1.4%	±1.5%	±2.7%	±2.5%
	Number of waves	1						
Field work	Time period	Sept. 22–28	May 4–10	June 6–12	July 12–18	June 28–July 4	June 15–21	June 15–21
	Location	Departure lounges.						
	Timetable	Mon–Sun. 6am–10pm shifts extended during peak traffic periods.						
	Year	2006	2007	2006	2006	2006	2005	2006

[a] $\pm$Error $= K\sqrt{(N-n)/(N-n)}\sqrt{pq/n}$, where: N = population size; n = sample size; $p = q = 0.5$ complementary probabilities of the answer to an event at the point of greatest indeterminacy; k = parameter for the level of answer to an event, where $k = 2$ for a 95.45% confidence level.

at seven different Spanish secondary airports, none of which had efficient rail-based public transportation to the city at the time the survey campaign was conducted (Table 1).[2] The size of the sample and the large number of passenger attributes and characteristics provide an effective database for an analysis of the air transport industry in Mediterranean countries (see Castillo-Manzano and López-Valpuesta (in press) for another application of this database).

The main features of AENA's (the Spanish Public Airport Authority) 2005–2007 survey that is used to construct the database are listed in Table 1. AENA has rotated annual surveys round some of its airports since 1996. The methodology used has, therefore, finely honed and there has been sufficient funding to obtain samples that closely approximate to a random process for a large population and with a low sampling error. As with similar databases, each observation was weighted according to the number of passengers on the flight so that the sample could be expanded to represent the population.

3. Methodology

Airport ground access systems play an important role in airport planning and management (Tsamboulas and Nikoleris, 2008) and are increasingly seen as a major problem worldwide. However, few studies have been done to date on the choice of means of airport access. Traditionally, travelers' choices of modes of transportation have been the object of microeconometric analyses using discrete choice models.

Since the focus of earlier studies has been on airport ground access and possible differences in the decisions and behavior of passengers according to whether they are business or tourism/leisure travelers it makes sense to complement this work with a study of differences in passengers' airport ground access mode choice behavior depending on whether they fly on low cost or network carriers. LCC growth is altering the classic distinction between business and tourist passengers. Firstly, there are generally no specific seats assigned to business passengers in these airplanes making it difficult to distinguish business travelers from other passengers on low-cost airline flights. Despite this, as the market share of LCCs rises, business passengers increasingly choose their services.

Without rejecting discrete demand models, the proposed methodology is framed by statistical causal inference and based on an estimation of the effect that a specific measure or fact can have on one or more relevant variables. In contrast with traditional analyses, this methodology allows consistent estimators of the effects of the evaluated measure to be obtained (Rotnitzky and Robins, 1995) by determining and isolating the possible impact of additional contaminating variables.

Starting with an N-size random sample (Table 2) we defined the binary variable D that indicates whether the observation corresponds to a passenger flying with an LCC ($D_i = 1$) or a traditional airline ($D_i = 0$). Thus, our N observations were divided into N_1 and N_0 observations (LCC vs. traditional airline). In our case, N_1 stands for the 6247 passengers who used an LCC, while N_0 represents the remaining 14,136 passengers. Thus, the condition that states that "N_0 is at least the same order of magnitude of N_1" is satisfied (Abadie and Imbens, 2006).

We defined the outcome variable Y_j as the decision to use a specific mode of transportation for a given city-airport transfer. In our case, we considered five possible modes of transportation: taxi, public bus, hotel bus, private car and rented car. Using the potential-outcome notation of the RCM (Rubin, 1974), the response variable was given as Y_{ij} (1) when i denoted a passenger using an LCC and as Y_{ij} (0) when i corresponded to a passenger flying on a traditional airline. Hence, Y_{ij} was equal to

$$Y_{ij} = D_{ij}Y_{ij}(1) + \left(1 - D_{ij}\right)Y_{ij}(0) \tag{1}$$

The Average Treatment Effect (ATE) of the LCC on the selected sample for each of the analyzed modes of transportation was (Imbens, 2004)

$$\alpha_j = E\left[Y_{ij}(1) - Y_{ij}(0)\right] = \frac{1}{N}\sum_{i=1}^{N}\left[Y_{ij}(1) - Y_{ij}(0)\right] \tag{2}$$

We also defined a K-dimensional vector of observed covariates as X. A triad was therefore observed for each individual (D_{ij}, Y_{ij}, X_{ij}).

The aim was to guarantee two conditions in the evaluation process. Firstly, the unconfoundedness condition (Rosenbaum and Rubin, 1983), also known as the conditional independence assumption, i.e. $D \perp (Y(1), Y(0))|X$. Secondly, we required compliance with the overlap condition, according to which every value of vector X is associated with a positive probability that allows (Hotz et al., 2005). The condition can be read as follows: $0 < P(D = 1|X) < 1$. To guarantee both conditions, the evaluation process conformed to the following phases (Heckman and Vytlacil, 2005).

3.1. Estimation of propensity score

Firstly, we noted whether the observations corresponded to a passenger using an LCC ($D_i = 1$) or a legacy airline ($D_i = 0$). We then estimated the propensity score, defined by Rosenbaum and

[2] A subway line connecting Valencia to its airport was opened a few months after the survey was conducted.

Table 2
Covariates and their descriptive statistics.

Variable	Description	Mean	Std. Dev.
a) Socio-demographic factors and employment status. Base category includes the unemployed.			
Sex	1 = male; 0 = female.	0.537	0.498
Age	1 = 30 and under; 2 = 31-49; 3 = 50–64; 4 = 65 and above.	1.985	0.825
Non-Spanish	1 = non-Spanish passenger; 0 otherwise.	0.300	0.458
Frequent flyer	Number of flights taken by passenger in previous twelve months: 1 = 0 flights; 2 = 1-3; 3 = 4-12; and 4 = over 12 flights.	2.433	1.003
Homemaker	1 = passenger is homemaker; 0 otherwise.	0.032	0.175
Self-employed	1 = passenger is non-salaried, generally self-employed; 0 otherwise.	0.168	0.374
Salaried worker	1 = passenger is salaried worker; 0 otherwise.	0.584	0.493
Student	1 = passenger is student; 0 otherwise.	0.108	0.311
Retired	1 = passenger is retired; 0 otherwise.	0.082	0.274
b) Trip category. Base category includes passengers visiting friends and relatives (VFR) on a network carrier.			
Low-cost carrier	1 = passenger is flying with a low-cost carrier (LCC); 0 otherwise.	0.306	0.461
Vacation	1 = vacation trip; 0 otherwise.	0.441	0.497
Business	1 = business trip; 0 otherwise.	0.310	0.462
Length of stay (LOS)	1 = passenger returns after one night or earlier; 2 = two nights to a week; 3 = seven to 14 days; 4 = more than two weeks but less than a month; 5 = more than a month.	2.408	0.955
c) Social interaction. Base category includes passengers traveling without children and not accompanied to/from the airport.			
Group size	1 = traveling alone; 2 = two people; 3 = three or more people.	1.684	0.741
Children	1 = traveling with children; 0 otherwise.	0.078	0.267
Seen off	1 = someone sees passenger off at airport; 0 otherwise.	0.279	0.448
d) Environment. Base category includes passengers traveling on workdays.			
Weekend	1 = survey taken on Saturday or Sunday, when taxi rate (flat or regular) is higher; 0 otherwise.	0.265	0.441
Hotel	1 = passenger departs from a hotel, boarding house, or other paid accommodation; 0 otherwise.	0.214	0.410
Home	1 = passenger departs from own primary or secondary home; 0 otherwise.	0.523	0.499
Friends or family	1 = passenger departs from home of friends or relatives; 0 otherwise.	0.142	0.349

Rubin (1983) as the conditional probability of "participating in the evaluated measure," given a vector X of observed covariates.

Different binary response models can be used to estimate the propensity score depending on the choice of hypothesis regarding the configuration of the F distribution function. In this case, we used the binary response model (e.g. logit or probit) that maximized the log pseudo-likelihood:

$$\varepsilon(X) = P(D = 1|X) = F(\beta X) \tag{3}$$

where β is the vector of parameters associated with X. Here, X comprised the 20 covariates presented in Table 2 along with their descriptive statistics.

Table 3
Probit estimation of the propensity score.

Covariate	Coefficient	Covariate	Coefficient
Sex	0.031	Business	−0.502***
Age	−0.039	Length of stay	0.077***
Non-Spanish	0.885***	Group Size	0.063***
Frequent flyer	0.029***	Children	−0.110
Homemaker	−0.089	Seen off	0.004
Self-employed	0.028	Weekend	−0.092**
Salaried worker	−0.027	Hotel	−0.183***
Student	0.205**	Home	−0.035
Retired	−0.018	Friends or family	0.155***
Vacation	−0.038	Constant	−0.907***
No. of observations (*before weighting*)		19930	
Log pseudo-likelihood		−14640197	
Pseudo R^2		0.137	
Wald Chi^2 without clusters (*p-value*)		4638753.72 (0.000)	

Note: *, **, or *** indicate coefficient significance at the 10%, 5%, and 1% levels calculated from standard errors robust to heteroskedasticity and clustered by airport of origin.

3.2. Estimation of average treatment effect

In a second phase, we calculated the average treatment effect of the measure being evaluated on the response variable, in our case, the probability of a passenger choosing a specific mode of transportation to get to the airport. The average effect on the selected sample was estimated using:

$$\alpha = E[\alpha(X)] \tag{4}$$

In our case, with Y being a discrete choice variable (using one of the five possible modes of transportation), we used a multinomial logit model to estimate the average treatment effect. Therefore, according to Hirano and Imbens (2001), the multinomial logit probability formula for a passenger i when a person chooses a mode of transportation j for five category outcomes and frequency weights is

$$p_{ij} = \Pr(y_i = j) = \begin{cases} 1/1 + \Sigma_{m=2}^{5} e^{(x_i^r \tau_m)}, & if \quad j = 1 \\ e^{(x_i' \tau_m)}/1 + \Sigma_{m=2}^{5} e^{(x_i^r \tau_m)}, & if \quad j \neq 1 \end{cases} \tag{5}$$

where:

$$x_i' \tau_m = \tau_{m0} + \alpha D_i + \tau_{m1} \widehat{\varepsilon}(x_i) + \tau_{m2} \left(\widehat{\varepsilon}(x_i) - E\left[\widehat{\varepsilon}(x) \right] \right) D_i + u_{ij} \tag{6}$$

Table 4
Multinomial estimation of relevant effects.

	LCC (D_i)	Constant	$\widehat{\varepsilon}(x_i)$	$(\widehat{\varepsilon}(x_i) - E[\widehat{\varepsilon}(x)])D_i$
Public Bus	0.227*	−1.825***	0.794	−1.154***
Hotel Bus	0.017	−3.290***	4.584***	−2.912***
Rent-a- car	0.169*	−1.251	1.966*	−0.178
Taxi	−0.218***	0.080	−0.795*	0.428

Note: *, **, or *** indicate coefficient significance at the 10%, 5%, and 1% levels, calculated from standard errors robust to heteroskedasticity and clustered by airport of origin.

Table 5
Marginal effect of $\widehat{\alpha}$.

Private Car	0.0003 → = 0.03%
Public Bus	0.0185 → Δ 1.85%
Hotel Bus	0.0010 → = 0.10%
Rent-a-Car	0.0385 → Δ 3.85%
Taxi	−0.0585 → ∇ 5.85%

3.3. *The marginal effect of* $\widehat{\alpha}$

As in binary outcome models, only the sign of the coefficient is directly interpreted in multinomial models. Thus, a positive coefficient in the multinomial logit means that, as the regressor increases, alternative *j* is more likely to be chosen than alternative *k*. In order to make the reading of the results easier, the odds ratios or relative-risk ratios for the binary variable D_i (using an LCC) are also considered. Following Cameron and Trivedi (2009), the relative probability or odds ratio of choosing alternative *j* rather than alternative *1*, also called the base outcome, is given by

$$\frac{\Pr(y_i = j)}{\Pr(y_i = 1)} = e^{x_i'\tau_j} \tag{7}$$

However, multinomial logit coefficients and odds ratios only allow the substitutability relationship between pairs of options to be studied, that is, the relationship between each option and the base category, which in our case is the private car. In order to overcome this focus on pairwise oppositions, we calculated the marginal effects of D_i across all considered options. This enabled the direct substitutability relationship, should one exist, to be obtained between the five modes of transportation for LCC passengers ($D_i = 1$), as opposed to the control group including all passengers flying with legacy airlines. According to Cameron and Trivedi (2009), the marginal effects at the mean (MEMs) for the multinomial logit model are:

$$\frac{\delta p_{ij}}{\delta D_i} = p_{ij}(\alpha_j - \overline{\alpha}_i) \tag{8}$$

$$\overline{\alpha}_i = \sum p_{il}\alpha_l,$$

where is a probability-weighted average of $\boldsymbol{\alpha}_l$.

4. Results

Table 3 summarizes the results of propensity score estimation (Model 3), in the context of the 20 covariates in Table 2. A probit specification was opted for as it maximized the log pseudo-likelihood.

A multinomial logit specification (Models 5 and 6) was then used to estimate the average treatment effects. The results are presented in Table 4.

Finally, the marginal effect at the mean of an LCC passenger is estimated by applying Model 8 (Table 5).

5. Conclusions

The results show that being a LLC passenger reduces the probability of choosing a taxi to go to the airport by 5.85%, but increases the likelihood of a LLC passenger and that of choosing a rented car or a public mode of transportation by about 4% and 2%, respectively. The outcome cannot be explained by factors such as LCC passengers having a lower income level than the network carrier passengers because the scores are corrected using income level proxy variables. It would therefore be more appropriate to speak of passengers who are increasingly price-conscious. There could, however, be a threshold type price effect on mode choice if there is a strong psychological shock in paying more for a 10 km taxi ride than for a 1000 km airplane flight. The average city-airport distance for the seven airports in our sample is 9.86 km, with a standard deviation of only 1.21. Generally-speaking, 10 km is a reasonable city-airport distance measure for Spanish secondary airports.

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