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Abstract

This paper analyses the duration of flight delays at Spanish airports. To do so, several hazard models are adopted to take into account the delays observed. The results show that the most important factors are certain airport characteristics and contextual characteristics. The policy implications are derived.

Keywords: hazard model, flights, Spanish airports, delays, duration.

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1. Introduction

This paper analyses the delays affecting flights at Spanish airports during the period 2004-2006, using several hazard models. Congestion in airports is a theme that has attracted researchers over a number of decades (Levine, 1969; Fisher, 1989; Forsyght, 1997; Odoni, 2001; Brueckner, 2002; De Neufville and Odoni, 2003; Hensher and Puckett, 2007; Madas and Zografos, 2008). The research referred to is, for the most part conceptual, aiming to design congestion pricing strategies. Capacity at congested airports is expressed in slots (i.e., an expression of capacity representing the permission given to a carrier to operate an air service at a slot-controlled airport on a specific date and time for the purpose of landing and take-off) and is allocated within the framework of voluntary guidelines developed and evolved over the years by IATA. Slot allocation in European Union airports falls within the scope of the European Union Single Market, thus being subject to a common regulatory framework under European Council Regulation. Under the congestion pricing strategy (Madas and Zografos, 2008), planned to come into force in 2010, historic slot rights will be abandoned and a congestion-based scheme, with fees varying according to the extent of congestion throughout the day, will be set by an administrative authority and each carrier could operate at any time or slot by paying the corresponding scarcity rent (i.e., congestion fee). In recent years, the European Commission (1993, 2001, 2004) has pursued a radical revision of the existing slot-allocation regime, aiming to alleviate the increasing scarcity of airport capacity. However, IATA regulation 95/93 denies the use of market-based mechanisms to allocate slots. The Union Commission proposes several market-based slot allocation mechanisms (Madas and Zagrafos, 2008). This paper contributes to filling the void, analysing congestion at Spanish airports from the perspective of flight delays.

The particular motivations for the present research are as follows. First, with the rapid, spectacular expansion of air travel, the public awareness and experience of congestion at airports concomitantly increases. Therefore, this phenomenon merits urgent investigation. Second, while research on airport congestion focuses on slot allocation, there are delays to flights which result from congestion that is not only determined by aircraft and passenger numbers, but by other airport characteristics.

Therefore, it is important to investigate the covariates that explain airport delays, such those analysed in the present study, Barros, Cavaignac and Peypoch (2008). Finally, unobserved heterogeneity has been a subject of concern and analysis in many recent works such as Chesher (1984) and Chesher and Santos Silva (2002), neglecting which is likely to lead to inconsistent parameter estimates or, more importantly, inconsistent fitted parameters. From an econometric perspective, there are two types of heterogeneity: that which is related to observed variables of airports, is described as observed heterogeneity, and that which cannot be related to the observed variables, which is known as unobserved heterogeneity. The former is captured by entering the relevant variable in the survival model, while the latter is captured by entering random parameters in that model. Thus, the aim of this research is twofold: first to analyse flight delays at Spanish airports and second, to take into account the nature of the heterogeneity in the delays analysed.

The remainder of the paper is organised as follows. Section 2 presents the contextual setting, followed by a brief literature review in Section 3. Section 4 describes the theoretical framework, while Section 5 explains the methodology and empirical specification. The data and estimation results are presented in Section 6. The results are discussed in Section 7. Finally, policy implications and our conclusions are presented in section 8.

2. Contextual setting

Spanish airports are currently managed by a public company (officially, a Public Business Entity), known as AENA (Aeropuertos y Navegación Aérea), which belongs to Spain's Ministry for Development. AENA is one of the largest and most advanced

ANSP (air navigation service providers) in the world. It is among the top five providers of air navigation in Europe. It is one of the top 50 Spanish companies and among the world's leading air transport companies. In addition to its management of all Spanish airports AENA is expanding into Europe and in the Americas. It has bought a 10% stake in TBI, a British airport management company (Barros, 2008b), which has enabled its entry into Sweden. In the Americas, AENA has a presence in the USA, Mexico, Colombia and Bolivia and Cuba. In 2006, AENA International directly operated 16 airports in Mexico, Colombia and Cuba, with traffic totalling around 26 million passengers and through its participation in TBI, also indirectly managed 11 airports in the United Kingdom, Sweden, the USA, Bolivia and Costa Rica, with 22 million passengers. AENA's seven control centres serviced 1,923,557 air movements in 2006 and its annual investments totalled €1,822 million in 2006.

Prior to the creation of AENA in 1990**,** data on Spanish airports was more easily available. Consequently, we find a number of papers analysing these airports in the two previous decades. For example, Murillo-Melchor (1999) analysed the productivity of 44 Spanish airports with a Malmquist DEA model (Malmquist, 1953), based on data from 1992-1994. Martin and Roman (2001) analysed 37 Spanish airports with a DEA-BCC model (Banker, Charnes and Cooper, 1984). Martin and Roman (2006, 2007) analysed 37 Spanish airports with alternative DEA models (Cross-efficiency, Sexton, Silkman and Hogan (1986), Doyle and Green (1994); Super-Efficiency, Andersen and Petersen (1993) and virtual efficiency). The present research adds to this research, adopting a survival model to analyse flight delays at Spanish airports, in a context in which data disclosure by AENA is scarce.

Table 1 presents some characteristics of the airports analysed, based in data obtained in several data sources (see data and results section).

Table 1. Characteristics of Spanish Airports, 2006

Id	Airport	Runway area (Meters ^{2})	Capacity (passengers/hour)	Check–in Counters (units)	Average conditional delay per-flight (minutes)	Average unconditional delay per-flight (minutes)
1	A Coruña	1940	1150	10	17.55	2.481
2	Albacete	2700	220	4	29.22	0.986
3	Alicante	3000	5400	42	19.98	2.995
4	Almeria	3200	2200	17	19.71	2.419
5	Asturias	2200	1950	11	18.77	2.520
6	Badajoz	2850	320	4	15.76	1.149
7	Barcelona	8552	8500	143	19.41	2.535
8	Bilbao	4600	3600	36	19.35	2.373
9	Cordoba	1380	140	1	49.15	1.430
10	El Hierro	1250	266	5	15.38	0.090
11	Fuerteventura	3400	3700	34	18.07	1.615
12	Girona-Costa Brava	2400	2450	18	20.75	1.585
13	Gran Canaria	3100	12560	86	17.38	0.926
14	Granada-Jaen	2990	1150	12	20.43	2.234
15	Ibiza	2800	4000	48	19.74	2.410
16	Jerez	2300	1650	13	18.05	1.919
17	La Gomera	1500	760	5	11.29	0.055
18	La Palma	2200	1400	13	18.05	0.640
19	Lanzarote	2400	5360	49	20.31	2.719
20	Leon	2100	250	3	15.53	1.963
21	Logroño	2000	611	5	19.43	3.479
22	Madrid Barajas	15450	18000	484	20.20	2.625
23	Malaga	3200	4500	85	17.28	0.573
24	Melilla	1428	960	4	20.49	2.720
25	Menorca	2350	2600	21	18.31	2.470
26	Murcia	2300	2600	18	18.28	2.254
27	Palma de Mallorca	6570	12200	204	20.51	2.155
28	Pamplona	2207	500	4	30.55	0.522
29	Reus	2455	1400	8	17.33	2.370
30	Salamanca	2500	400	4	17.61	2.260
31	San Sebastian	1754	500	6	18.76	1.745
32	Santander	2320	1025	8	21.72	1.310
33	Santiago	3200	2500	19	19.47	1.500
34	Zaragoza	6718	1050	6	17.80	0.819
35	Seville	3360	3250	42	19.32	1.755
36	Tenerife North	3400	4370	37	19.42	1.951
37	Tenerife South	3200	5700	87	17.53	1.935
38	Valencia	3200	3210	42	18.78	2.359
39	Valladolid	3000	800	8	21.80	1.262
40	Vigo	2400	1680	12	17.55	2.481
41	Vitoria	3500	1020	7	29.22	0.986

Mean	3253.02	3070.78	40.61	20.13	1.683
Median	2700.00	1680.00	13.00	19.32	1.951
Std. Dev.	2417.06	3750.55	81.82	5.80	1.018

From the table, it can observed that the average conditional delay per flight in the Spanish airports is 20.13 minutes, but this value varies from a minimum of 11.29 minutes at La Gomera Airport to a maximum of 49.5 minutes at Cordoba Airport. With such a wide range in the amounts of time lost, it is of interest to investigate the covariates that explain these delays. However, unconditional delays are, on average, 1.688 minutes, ranging from a minimum of 0.055 minutes at La Gomera airport and a maximum of 3.479 minutes at Logroño Airport.

3. Literature review

To the best of our knowledge, no previous paper has analysed flight delays at airports (Humphreys and Francis, 2002). There is some tradition of analysing empirically the technical efficiency and productivity at airports (Barros, 2008a; Barros and Dieke, 2008; Barros and Dieke, 2007; Gillen and Lall, 2001; Pels, Nijkamp and Rietveld, 2001; Pels, Nijkamp and Rietveld, 2003; Hooper and Hensher, 1997). In addition, there is the earlier-mentioned tradition of analysing airport congestion conceptually (Levine, 1969); Fisher, 1989; Forsyth, 1997); Odoni, 2001; Brueckner, 2002; De Neufville and Odoni, 2003; Hensher and Puckett, 2007; Madas and Zografos, 2008), but with no focus on flight delays. However, survival models in transportation abound. For example, Nam and Mannering (2000) apply a survival model to highway incidents; Chen and Niemeier (2005) propose a mass point survival model to analyse vehicle survival rates; Lee and Timmermans (2007) propose another latent class survival model. Other papers have examined individual behaviour in transportation. For example, Lin, Chen and Niemeier (2008) apply the Weibull survival model to analyse vehicle replacement.

The present paper contributes to this literature with alternative survival models to measure flight delays.

4. Theoretical Framework

The focus of this paper is on the delays of flights at Spanish airports. To this end, the hypotheses that will be tested in the empirical part of our paper are as follows:

H1: Certain structural characteristics of airports explain the flight delays, such as the number and length of runways and the approximation capacity. The more and the longer the runways, and the greater the approximation capacity, the shorter the delays. Runways have previously been used as a variable in airport studies by Sarkis (2000) and Sarkis and Talluri (2004).

H2: Internal characteristics of airports, such as the number of baggage belts, the number of check-in counters and the number of boarding gates, have an effect on the reduction of delays at the airport (Gillen and Lall, 1997, 2001).

H3: The traffic in the airport, measured by the number of passengers, the number of planes and the cargo traffic, contributes to the airport congestion and thus, to delays (Pels, Nijkamp and Rietveld, 2001).

H4: The airport's environmental context, including the population in the airport's vicinity and the GDP in that surrounding area, contributes to congestion and thus, to delays (Graham, 2005).

H5: A hub is the term applied to an airport that plays a centralising distribution role for international passenger and cargo traffic in transit to surrounding regions. Therefore, hubs may experience greater congestion levels, which may cause a ripple effect of delays across regions, countries and even continents (Barros and Dieke, 2007, 2008).

H6: Certain attributes of an airport, such as its customs and immigration procedures, the number of car-parking places and its infrastructural transport links to and from the urban centres served (e.g. railway or underground), may be a contributory factor in the delays (Gillen and Lall, 1997).

5. Research Design

In our study of flight delays at Spanish airports, the event we seek to explain is the delay duration, by means of a survival or hazard model (Cox and Oakes, 1984; Allison, 1984; Yamaguchi, 1991; Hosmer and Lemeshow, 1999; Kalbfleisch and Prentice, 2002; Cleeves, Gould and Gutierrez, 2002). Survival analysis, also known as duration models, is a branch of statistics which deals with death in biological organisms and failure in mechanical systems. This topic is called reliability theory or reliability analysis in engineering. The duration of an event is the time elapsed until a certain event occurs, or is completed. The length of a flight delay is an example of a duration event. The use of survival models to model duration is based on the fact that the error distribution in this context, by necessity, must be skewed to the right (Hosmer and Lemeshow, 1999). In particular, time, as a dependent variable, is strictly positive and therefore, the use of the traditional Gaussian distribution is not adequate to capture the characteristics of the time variable. Moreover, in trials, censoring occurs when an individual participant in the initial phase of the study subsequently disappears. Survival analysis can adequately accommodate the loss of observations when censoring occurs. Traditional regression models are inadequate for such an issue. Thus, survival models, such as the Cox model and the Weibull model, have emerged (Hosmer and Lemeshow, 1999). The dependent variable of interest is the average number of minutes of flight delays in each year, which is regressed against covariates.

Three issues must be addressed when analysing survival models: 1) identification of the data set (i.e., cross-section vs. panel data); 2) censoring of the data; and 3) heterogeneity of the population analysed. With regard to the first issue, the present study adopted a panel data approach. Therefore, time-variant modelling is adopted (Wooldridge, 2002).

In terms of censoring, the data used in the present study is uncensored because the delays were observed at the end of the year. A survival time is described as censored when there is a follow-up time but the event has not yet occurred or is not known to have occurred. For example, if the delay is being studied at the airport and the delayed flight has not yet departed by the time the observation is concluded, then the start of the delay is observed, but the end-time would be censored. If an airport for some reason is eliminated from a study before the end of the study period, then the follow-up time of the flight or flights concerned would also be considered to be censored, since the end-time is unobserved. In view of the fact that our data only comprises the total durations of flight delays, the length of all delays is fully determined. With regard to the third issue, ignoring heterogeneity results in asymptotic parameter underestimating (Cameron and Triverdi, 2005).

Normally, let T be a continuous non-negative, random variable that measures the passage of time, and let t denote a particular realisation (duration) of this variable (Allison, P.D., 1984). The distribution of the duration is $F(T)=Pr[T \leq t]$ and the corresponding density function is $f(t)=dF(t)/dt$. Duration analysis is particularly concerned with the "survival function": $S(t) =[1-F(t)]=Pr[T > t]$ and the "hazard function" $\lambda(t)=f(t)/S(t)$. The hazard function is the rate at which spells will be completed at duration t, conditional upon having lasted that long. The functions F, f, S and λ simply provide alternative means of characterising the distribution of T.

It can be shown that $\lambda(t)$=-$[dlog_e S(t)/dt]$, and one important role of the hazard function is that it provides a basis for defining ´duration dependence`. The underlying random variable is said to exhibit positive (negative) duration dependence at some time t^*, if $[d\lambda(t)/dt]>0$ (<0). Positive (negative) duration dependence implies that the probability that a spell is about to end increases (decreases) with an increase in the spell length. We begin by estimating a Cox survival model. Let $h[t|\mathbf{Z}(t)]$ be the hazard rate at time t for a failure with covariate vector $\mathbf{Z}(t)$; the basic Cox model is as follows (Klein and Moeschberger, 2003):

$$h[t/\mathbf{Z}(t)] = h_0(t) \cdot \exp[\beta^T \mathbf{Z}(t)] = h_0(t) \cdot \exp[\sum_{k=1}^{y} \beta_k Z_k(t)]$$

where $h_0(t)$ is the baseline hazard rate function. The use of a proportional hazard model means that the hazard rate of a subject is proportional to its baseline hazard rate $h_0(t)$, which is the basic assumption of Cox's model. In the model, $\boldsymbol{\beta}$ is the coefficient vector and $\mathbf{Z}(t) = [Z_1(t), Z_2(t), \ldots, Z_y(t)]^T$ is the covariate vector. $Z_i(t)$, $i = 1,2, \ldots, y$, is a time-dependent covariate if its value varies with time.

Assuming that there are no ties between the event times, the parameters are estimated by the partial likelihood function, given by:

$$L(\beta) = \prod_{i=1}^{n} \left\{ \frac{exp(\beta^T Z_i)}{\sum_{j \in R(t_i)} exp(\beta^T Z_j)} \right\}^{\delta_i}$$

where δ is a censoring indicator equal to one if observed and zero if censored and Y is a risk indicator which is equal to one if the individual is at risk in the current event and zero otherwise.

An assumption of the proportional hazard model is that the hazard function for an individual (i.e., observation in the analysis) depends on the values of the covariates and the value of the baseline hazard. Given two airports with particular values for the covariates, the ratio of the estimated hazards over time will be constant; hence the name of the method: the *proportional hazard* model. The validity of this assumption may be questionable, particularly when there is unobserved heterogeneity in the model. Therefore, the impact of the covariate may be dependent on time. There are tests to verify whether the proportional assumption is fulfilled. In this paper, the Schoenfeld test is adopted and the null hypothesis is that the proportional hazard is correct. The P-value of 0.0312 indicated that there was statistical evidence against the null hypothesis that the proportional hazards assumption was correct. Therefore, we adopted a parametric specification: the Weibull model (Box-Steffensmeier Reiter and Zorn, 2003). In the Weibull model, the baseline is defined by:

$$h_{0k}(t - t_{k-1}) = \alpha_k (t - t_{k-1})^{\alpha_k - 1}$$

where the time-dependent parameter, α_k is estimated separately for each event.

All models are estimated through maximum likelihood (Allison, 1984; Cox and Oakes, 1984; Yamaguchi, 1991).

6. Data and Findings

The data used to study the determinants of flight delays at Spanish airports covers the years 2005-2007. The data was obtained in several sources: First, from the AENA website (http://www.AENA.es). Second, airport characteristics from the airports web sites. Third, contextual airport characteristics obtained from Spanish regional statistics (AENA, 2007). Finally, data on the delays was obtained from the Central Office for Delay Analysis (CODA), a service of Eurocontrol (http://www.eurocontrol.int/eatm/public/standard_page/coda.html).

Table 2 presents the characteristics of the data used in the analysis.

Table 2. Characteristics of the Variables

Variable	Description	Type	Min.	Max.	Mean	Std. Dev.
Delay1	Average unconditional delay	Dependent variable	0.044	4.199	1.755	0.867
Delay2	Average conditional delay in minutes in airport in the year	Dependent variable	14.385	40.748	19.110	3.049
logRunarea	Log Runway area in metres (lenght×widt)	Variable testing hypothesis 1	10.532	13.739	11.791	0.553
Apron	Airport ramp number of stands	Variable testing hypothesis 1	1	263	25.846	42.578
Bag	Number of baggage belts	Variable testing hypothesis 2	0	53	6.273	8.441
Check	Number of check-in counters	Variable testing hypothesis 2	1	484	40.794	77.203
Gate	Number of boarding gates	Variable testing hypothesis 2	1	230	16.726	36.128
Log Pax	Log Number of passengers	Variable testing hypothesis 3	9.771	17.633	13.965	1.978

Planes	Number of planes	Variable testing hypothesis 3	1.185	483.284	55.302	87.883
Traffic	Cargo traffic in tons	Variable testing hypothesis 3	0	333137	15654	52913
logPopulation	Log Population in the airport vicinity	Variable testing hypothesis 4	0.188	15.620	12.542	3.007
logGDP	Log Gross Domestic Product in the airport vicinity	Variable testing hypothesis 4	12.124	18.890	16.123	1.325
Hub	Dummy variable which is 1 for airports functioning as hubs	Variable testing hypothesis 5	0	1	0.153	0.362
Customs	Dummy variable which is one for airports with customs	Variable testing hypothesis 6	0	1	0.846	0.362
Parking	Number of parking places in the airport	Variable testing hypothesis 6	60	17900	1791	3194
Train	Dummy variable which is one for airports with railway access	Variable testing hypothesis 6	0	1	0.051	0.221

The dependent variable is the average yearly delay of flights at Spanish airports, measured in minutes. There are two measures of delay: the unconditional average delay (Delay 1) takes into account all flights operating at the airport, while the average conditional delay (Delay 2) considers only the delayed flights. The estimated coefficients are always in the proportional-hazard metric. There are 39 airports in the data, which provide 120 observations. The frequency of events is shown in Table 3.

Table 3. Event Frequency

No. of events	25	44	43	4	4	—	—	—	—	—	—	—	—	—	—
Delay1 (minutes)	1	2	3	4	5	—	—	—	—	—	—	—	—	—	—
No. of Events	1	5	8	20	38	25	7	4	3	1	1	1	1	1	1
Delay2 (minutes)	14	15	16	17	18	19	20	21	22	23	25	26	27	30	40

The results of the model estimation for unconditional and conditional delays are presented in Tables 4 and 5, respectively. Model 1 (M1) is the Cox base model. However, this model is not supported by the Schoenfeld test (Schoenfeld, 1981). Model 2 is the Cox time-accelerated model. (M2) is the Weibull model accelerated model. Frailty and heterogeneity are synonymous in survival models. Unobserved heterogeneity may be group heterogeneity or shared heterogeneity. Group heterogeneity is specific to a “family” of airports or to a single airport observed in the three-year span. This is within heterogeneity. Shared heterogeneity is a latent common effect between all airports. Therefore, Model 3 (M3) is the Weibull accelerated model with gamma distributed frailty (group heterogeneity). Model 4 (M4) is the Weibull accelerated model with gamma frailty and shared frailty (shared heterogeneity). These two latter models allow for unobserved heterogeneity, (Cleves, Gould and Gutierrez, 2002).

Table 4. Estimation Results: dependent variable, Delay1 (unconditional delays)(1)

	M1		**M2**		**M3**		**M4**	
Variable	Coef.	s.e.	Coef	s.e.	Coef	s.e.(2)	Coef	s.e.(2)
logRunarea	**-0.215**	0.312	**-0.324**	0.236	**-0.412**	0.017	**-0.031**	0.026
Apron	**-0.037**	0.531	**-0.145**	0.328	**-0.084**	0.135	**-0.123**	0.036
Bag	**-0.024**	0.036	**-0.036**	0.034	**-0.121**	0.116	**-0.012**	0.195
Check	**-0.012**	0.047	**-0.025**	0.034	**-0.042**	0.217	**-0.025**	0.054
Gate	**-0.016**	0.321	**-0.037**	0.265	**-0.043**	0.218	**-0.024**	0.259
Log Pax	**0.015**	0.384	**0.048**	0.146	**0.075**	0.217	**0.048**	0.319
Planes	**0.136**	0.218	**0.014**	0.453	**0.016**	0.155	**0.026**	0.219
Traffic	**0.001**	0.126	**0.002**	0.125	**0.115**	0.126	**0.121**	0.518
logPopulation	0.113	0.375	0.045	0.372	0.043	0.038	**0.116**	0.383
logGDP	-0.126	0.127	-0.341	0.126	-0.218	0.219	-0.287	0.237
Hub	**0.217**	0.135	**0.529**	0.058	**0.419**	0.216	**0.507**	0.200
Customs	0.024	0.114	0.121	0.286	0.134	0.219	0.285	0.521
Parking	0.001	0.038	0.002	0.2136	0.027	0.514	0.021	0.584
Train	0.984	0.235	0.538	0.052	0.716	0.217	0.845	0.483
Constant	—		—		**0.176**	0.318	**0.321**	0.218
Ln P	—		**0.984**	0.034	**1.021**	0.034	**1.078**	0.067
Theta	—		—		**0.012**	0.006	**0.051**	0.032
LL	-86.32		-98.21		-120.52		-145.12	

(1) – *All models were estimated in Stata 9*
LL - Log Likelihood

Table 5: Estimation Results: dependent variable Delay2 (conditional delays)[1]

	M1		M2		M3		M4	
Variable	Coef.	s.e.	Coef	s.e.	Coef	s.e.(2)	Coef	s.e.(2)
logRunarea	**-1.728**	0.919	**-1.694**	0.835	**-1.009**	0.144	**-1.027**	0.038
Apron	**-0.163**	0.738	**-0.162**	0.554	**-0.131**	0.320	**-0.125**	0.062
Bag	-0.038	0.194	-0.062	0.159	-0.017	0.016	-0.023	0.219
Check	**-0.043**	0.052	**-0.062**	0.047	**-0.048**	0.154	**-0.038**	0.027
Gate	-0.019	0.121	-0.048	0.107	**-0.059**	0.109	**-0.027**	0.218
Log Pax	**0.099**	0.179	**0.059**	0.205	**0.080**	0.534	**0.073**	0.234
Planes	**0.015**	0.043	**0.023**	0.300	**0.023**	0.122	**0.031**	0.128
Traffic	**0.001**	0.002	**0.003**	0.007	**0.118**	0.139	**0.122**	0.217
logPopulation	0.181	0.126	0.190	0.076	0.075	0.195	**0.126**	0.245
logGDP	**-0.585**	0.036	**-0.673**	0.340	**-0.235**	0.409	**-0.328**	0.139
Hub	**0.890**	0.082	**0.770**	0.068	**0.723**	0.162	**0.612**	0.214
Customs	0.095	0.082	0.217	0.826	0.317	0.144	0.372	0.031
Parking	0.001	0.003	0.001	0.003	0.031	0.320	0.012	0.851
Train	1.738	0.045	0.983	0.037	0.817	0.016	0.917	0.734
Constant	—		—		**1.356**	0.176	**1.124**	0.132
Ln P	—		**1.741**	0.779	**1.741**	0.0006	**1.760**	0.092
Theta	—		**—**		**0.038**	0.00001	**0.042**	0.090
LL	-94.54		-95.32		-110.24		-121.32	

(1) – *All models were estimated in Stata 9*
LL - Log Likelihood

In all four of the models, the results are quite similar in their main effects. Given the model specification, a positive value for the parameters implies that the flight delay increases with increasing values in the respective variable. A negative value for the parameters implies a negative relationship. The results across the four models demonstrate that the parameters have the same signs.

The observed differences between unconditional delays and conditional delays is that the value of the parameters in the unconditional delay model is smaller than that observed in the conditional delay model, reflecting the smaller variablitity in the unconditional delays. Moreover, the variables have the same signs and are for the most part statistically significant in both models. A variable that is significant in unconditional delays, i.e., *bag,* becomes statistically insignificant in the conditional model. Furthermore, another statistically significant variable in the conditional delay model, *GDP*, becomes statistically insignificant in the unconditional model.

On the basis of the log likelihood statistic and the statistical significance of the theta variable, the Weibull model with heterogeneity provides the superior fit to the data in both specifications. The rationale for this result is that heterogeneity represents characteristics that influence the conditional probability of flight delays in different airports which are not measured or observed and therefore, not taken into account in the measurement errors of the variables (Chesher, 1984; Chesher and Santos-Silva, 2002). Heterogeneous behaviour is commonly observed in units. Therefore, not to take it into account is likely to lead to inconsistent parameter estimates or more importantly, inconsistent fitted-choice probabilities. In the present study, this implies that different airports can have different delay durations. The variance of unobserved individual specific parameters induces correlation across the alternatives in the airport characteristics and thus, survival models with heterogeneity are required. Based on the log likelihood of Model 4, it is concluded that shared frailty has a higher statistical representation than group frailty in both specifications. This may result from the fact that almost all the airports in the data are distinct, despite being managed by the same enterprise. This distinctiveness may reflect the various market conditions in Spain, with some regions specialising in tourism and attracting immense numbers of travellers in the summer; large urban connurbations, such as Madrid and Barcelona, with consistently high passenger turnovers throughout the year and other smaller, regional airports with a less intense traffic.

7. Discussion

Survival modelling has been shown to be a useful technique for the purpose of this research. Several duration or survival models were presented for comparative purposes. These consisted of the Cox model, the parametric Weibull model, a Weibull model that accounts for individual player heterogeneity and finally, a Weibull model that accounts for group heterogeneity and shared heterogeneity. Shared heterogeneity takes into account the different nature of Spanish airports. This last model was found to perform best in terms of its explanatory capability in both model specifications: unconditional delay and conditional delay. The models' results indicate that flight delays at Spanish airports are related positively and with statistical significance to the number of passengers, number of planes, the cargo traffic, population in the vicinity and being a hub airport. Delays are negatively related and with statistical significance to runways, capacity of approximation, number of gates, and GDP. This latter variable is statistically insignificant in the unconditional delay model. Moreover, *bags* is statistically significant and positive in unconditional delays. The results support the majority of the hypotheses and are broadly intuitive, signifying that flight delays at Spanish airports are explained by covariates such as airport infrastructures, the aiport's environmental context and the passenger and cargo traffic.

Relative to the hypotheses, as expected, the results for *Runway* and *apron* (approximation capacity*)* validate Hypothesis 1 in both unconditional and conditional delays. The greater the runway and the approximation capacity, the lower the delay times observed. This is an intuitive result. Moreover, the quality and quantity of airport passenger-processing equipment, such as baggage belts, check-in counters and boarding gates, can decrease the delays, validating Hypothesis 2 in both unconditional and conditional delays. However, *baggage belt* is not statistically significant in either specification, while *gates* is statistically significant in unconditional delays, but not statistically significant in conditional delays. This signifies that adequate airport passenger-processing equipment serves to facilitate the through-flow of traffic. Furthermore, the airport traffic measured by the number of passengers, number of planes and cargo explains the delays, validating Hypothesis 3, again in both specifications. This is also an intuitive finding. In addition, the environmental context of the airport's vicinity, measured by population and GDP, affects the delays. Population affects delays positively increasing them, while the effect of GDP is negative. Therefore, Hypothesis 4 is not validated.

Relative to Hypothesis 5, hubs are found to increase delays, which is also an intuitive result. Since hubs attract relatively large amounts of traffic, they operate under more pressuring conditions and therefore, tend to have delays, validating the fifth hypothesis. Finally, airport characteristics, such as customs, car parks and rail links, affect delays positively, but are statistically insignificant. Therefore, Hypothesis 6 is not validated.

8. Summary, Implications and Conclusions

In this paper, we have analysed airport congestion and resulting delays from a duration analysis perspective. This novel approach considers a number of potential explanatory variables. The covariates include data on the airport infrastructure (i.e. runway area, apron capacity) and facilities (baggage belts, check-in counters and boarding gates) as well as environmental variables (operations, passengers and cargo, population, GDP, etc).

The approach has been applied to data on Spanish airports. A number of hypotheses have been tested. In terms of policy implications, the results suggest that the solution to the problem of delays to flights at airports will require investment in infrastructure and support facilities.

The overall policy implication arsing from our research is that slot allocation alone will not eliminate congestion at airports. The management of the entire site (runways, number of stands, bagagge belts, check-in counters, boarding gates) and their integration with the traffic is needed in order to control and overcome congestion. In addition, increased and advanced computerisation of check-in procedures and baggage-handling would do much to alleviating this growing problem. Moreover, the environmental context is somewhat important and continuous investment is needed to maintain the competitiveness of airports, relative to their national and international rivals. The management of all airports by a sole company may actually be a contributory factor to congestion in the Spanish airport netweork. Conversely, competition could serve to attenuate the problem (Bel and Fageda, 2008).

However, there is no simple “more is better” approach that will ease airport congestion. It is vital, in addition to the above recommendations, to increase productivity in all sectors of the processing operation, by means of computerisation, in order to maximise the efficiency of through-flows of passenger and cargo traffic. To fail to do so will be to guarantee that the air-travel system will eventually grind to a halt, due to the ever-increasing weight of numbers of consumers, taking longer and longer to board their flights, disembark on landing and leave the destination airport.

With regard to comparison of our findings with previous research, as mentioned above, there is no similar published paper with which this paper can be compared.

This paper has two main limitations related to the data set. First, the data span is relatively short. Second, the sample procedure adopted was restricted to sole Spanish airports, thus the conclusions are limited. The limitations of the paper suggest directions for new research.

Hence, more investigation is needed to confirm the present results.

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