Revista de Economía Aplicada EA *Número 49 (XVII), 2009, págs. 135 a 156*

INFRASTRUCTURE DOMINANCE IN SHORT-HAUL AIR TRANSPORT MARKETS*

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In this paper, we analyze how an airline can take advantage of airport dominance of a whole network in a market characterized by short-haul routes and congestion. We estimate an equation system, which is based on theoretical grounds, for the Spanish market. We find that costs and demand benefits of airport dominance have to do with providing a high flight frequency. The high flight frequency that comes from the control of an airport network allows to be offered large discounts in fares to leisure travelers while charging higher fares for business travelers. Such benefits can seriously damage the competitive status of airlines that do not have a high airport presence. We conclude that a balanced allocation of airport slots is required to guarantee airline competition.

Key words: Competition, air transport, multiple equation models.

JEL classification: L13, L93, C30.

Air transport liberalization has produced positive effects on traveler welfare. Indeed, travelers enjoy a greater choice of alternatives, higher flight frequency and lower prices on the busiest routes. Nevertheless, there is a widespread agreement that the achievement, maintenance and increase of these benefits in the post-liberalization period depends fundamentally on effective competition on those routes. It follows that there is concern about the scale advantages airlines can hold in several markets as a consequence of their dominance of airport access.

In the European Union (EU), the allocation of slots is generally based on grandfather rights that give "ownership" to airlines on the basis of previous use. Hence, former flag carriers, which in the past enjoyed privileged monopolistic rights, can now claim large shares of slots in the main airports of their national network. This is particularly important in cases of airport congestion. Low cost

(*) The author would like to thank Germà Bel, Joan Ramon Borrell, Joan Calzada, Antón Costas, Ginés de Rus, Laura Fernàndez, Pedro Marín, Anna Matas, Gustavo Nombela and two anonymous referees for their useful suggestions. Earlier versions of this paper were presented at the 6th Encuentros de Economía Aplicada, 7th ATRS World Conference and the GARS workshop on EU Liberalization of Air Transport - Experience and the Next Steps Forward. The usual disclaimer applies.

airlines operating through regional airports have succeeded in competing with former flag carriers on an increasing number of routes but the "low cost effect" also relies on access to those regional airports.

There is extensive empirical literature on competition in the airline industry. The effect of airport dominance on airline prices is one of the main issues that emerge from this literature. Major contributions for the US case are, among others, Borenstein (1989, 1991), Hurdle *et al.* (1989), Morrison and Winston (1989), Dresner and Windle (1992), Evans and Kessides (1993) and Brueckner and Spiller (1994). Button *et al.* (1998) and Marín (1998), among others, discuss airline competition in the European context. It is generally found that airport dominance, along with route dominance, explains the ability of major airlines to charge higher prices than their competitors. In these studies, airport dominance usually implies higher prices due to the "premium" that major airlines can charge to passengers departing from their main hubs. Indeed, hub dominance can imply the exploitation of market power due to privileged access to airport facilities (slots, gates and so on) and to the use of marketing practices such as frequent flyer programs. These aspects are considered to be important entry barriers, particularly in cases of congestion.

However, product differentiation has not usually been treated as a primary assumption in previous studies. Important exceptions are the works of Marín (1995), Berry *et al.* (1996) and Schipper *et al.* (2002). Looking directly at differentiation in the airline industry is sensible if we are to explicitly test the cost and demand advantages of airport dominance. In addition, it is worth noting that the airport dominance of former European flag carriers can be even higher in small regional airports since low cost airlines only operate in some of them. Finally, in contrast to the United States, a common characteristic of EU domestic air markets is that they are basically made up of short-haul routes.

The objective of this paper is to examine how an airline can take advantage of airport dominance of a whole network in a European market characterized by short-haul routes and congestion. We estimate an empirical model using data from Spanish air routes for 2001 and 2002. As the Spanish domestic market is the largest in the European Union, results obtained in this paper are relevant for other European markets. Additionally, the analysis of the Spanish market allows us to capture the influence of airport congestion on airline competition. The airports of either Madrid or Barcelona are the endpoints of most Spanish routes and, during the period considered, both of them were highly congested.

The remainder of this paper fleshes out the effects of airport dominance on short-haul markets and tests them empirically. In Section 1, economic features that have the greatest influence on airline competition are analyzed. Section 2 presents the framework for the hypotheses that are to be tested in the empirical analysis. In Section 3, data used in the empirical analysis is specified. Section 4 describes the results obtained from the estimation. Finally, Section 5 discusses the implications of the results obtained.

1. The effects of airport dominance on airline competition

Competition in the provision of air transport services depends both on demand and supply characteristics. On the supply side, the seminal study of Caves *et al.* (1984) distinguishes between density and scale economies. Density economies refer to unit cost variations due to output increases on a route. Scale economies refer to unit cost variations due to proportional changes both in network size and in the output on each route conforming the network. The issue here is that, although the existence of density economies is generally accepted, there is no clear evidence of the existence of scale economies [Tretheway and Oum (1992)].

On the demand side, one must note the existence of two different types of travelers. On the one hand, business travelers are not as sensitive to prices but pay considerable attention to time[1]. Leisure travelers, on the other hand, are time insensitive but highly price sensitive. Furthermore, air transport is one clear example of an industry with consumer switching costs. This is due to the use of frequent flier programs (FFP) which create brand loyalty in travelers once they have bought services from a particular airline. Indeed, travelers who switch between airlines lose opportunities to earn points that yield benefits, such as free trips. Thus, switching costs are associated with the opportunity cost of these benefits[2].

Recognizing that density economies and demand heterogeneity are both prominent characteristics of the airline industry, it is clear that airport dominance may provide strong competitive advantages to airlines that take benefit of it. In fact, previous empirical studies about airline competition agree with this point. However, we can find different explanations of these competitive advantages in the literature. An airline can obtain advantages from airport dominance due to the exploitation of market power that comes from its privileged access to scarce resources [Borenstein (1989, 1991), Evans and Kessides (1993)]. Moreover, airlines with a high presence in an airport can make better use of marketing practices such as frequent flyer programs [Borenstein (1989, 1991, 1996), Mason and Baker (1996)]. Both explanations imply that airport dominance allows airlines to charge higher prices. Finally, an airline can reduce costs (and so prices) from a high utilization of an airport through the exploitation of density economies [Marin (1995), Berry *et al.* (1996)].

Our aim in this paper is to contribute to the literature by examining the different effects of airport dominance for the Spanish domestic market, which is a market based on short-haul routes. In this type of market, the benefits from airport dominance come from the role played by flight frequency. A higher flight frequency allows a better adjustment to traveler scheduling preferences and, in turn, reduces wait-

(1) It can be argued that business passengers are increasingly using the services of low cost airlines on inter-European routes. This is particularly true on routes where low cost airlines offer a high flight frequency due to the dominance of the corresponding regional airports.

(2) Klemperer (1987) analyses the role of switching costs in a two-stage model of oligopoly competition. In this model, price competition depends inversely on those costs. This relationship follows from the fact that a higher switching cost means that lower prices attract fewer consumers and, at the same time, lead to a greater sacrifice of profits from those consumers who are already members of a FFP.

ing time. Along with the business traveler's preference for airlines that offer flexibility in flight schedule, the demand side advantages that arise from high frequency are also related to FFP. A greater number of destinations make a free trip more valuable, and higher flight frequency at each airport speeds up the accumulation of points. Indeed, flight frequency can be understood as a quality variable because it determines waiting time and allows a more efficient exploitation of FFP.

In turn, these advantages on the demand side do not exclude the exploitation of density economies on the cost side. As long as a high flight frequency reduces the cost of a trip in terms of time, it could cause an additional increase in demand. A high flight frequency also leads to a high annual utilization of planes and crews [Doganis (1991)]. Furthermore, frequency allows a carrier to increase the proportion of business travelers per flight, which reduces the break-even load factor [OECD (2000)]. Finally, the cost diseconomies that arise from the use of smaller planes as frequency rises are especially important on long-haul routes [Wei and Hansen (2003)][3]. For short routes, a high flight frequency is not necessarily cost damaging, whereas the demand side advantages can be substantial. In fact, the increasing importance of regional operators that use smaller aircrafts with higher flight frequency in thin markets shows the important role that frequency plays on short-haul routes.

The main determinant of flight frequency in a given route network (and the size of this network) is the number of slots that an airline can use in the corresponding airports. Airlines could benefit from airport dominance by providing a high flight frequency. Indeed, they can capture business travelers through the exploitation of demand side economies and, at the same time, they can take advantage of cost economies to capture leisure travelers. Hence, we want to test whether airport dominance allows high prices in the fares addressed to business travelers and large discounts in the fares addressed to leisure travelers. In the following section, we develop a methodology to test the effects of airport dominance in short-haul airline markets.

2. The empirical model

2.1. Demand

Given that service frequency is the main determinant of quality in short-haul air transport markets, demand conditions in a vertical product differentiation model must be stated. In a typical product differentiation model [Anderson *et al.* (1992)], the demand for a product with a specific quality depends on the potential number of consumers, the prices and quality of that product and on other varieties of that product. In our model, we denote demand of airline in market (route) "k" by Q_{jk}. Services of airline "j" are associated with a set of prices and a specific flight frequency (which determines quality).

(3) Aircraft costs correspond to three stages: takeoff, in-flight time and landing. With regard to the size of the aircraft, scale diseconomies arise in takeoff and landing, while scale economies arise at the cruise speed. This explains why aircrafts that minimize costs are smaller on short-haul than on long-haul routes.

The price of each transport service is not unique because airlines can discriminate across passengers (i.e; business or leisure travelers), using different fares with different restrictions. The available data does not allow the estimation of a demand equation that includes the prices effectively charged to each passenger. On the contrary, we must rely on aggregate demand data to account for the different competition conditions associated with the different types of passengers. However, it can be argued that quality effects will be mostly related to business passengers and price effects will be mostly related to leisure passengers.

For the empirical specification, the demand for the transport services of airline "j" (j = 1, …, n) that competes on route "k", (Q_{jk}), can be expressed as the product of a market demand function (Q_k) and an airline market share function (MS_{jk}), where $MS_{jk} = Q_{jk}/Q_k$.

Thus, and taking into account that the equilibrium condition in a vertical product differentiation model excludes cross price elasticities among firms, an airline's demand function can be expressed as:

$$Q_{jk} = Q_k\,(P_k, S_k, N_k)\; MS_{jk}\,(P_{jk}/P_k,\, S_{jk}/S_k), \qquad [1]$$

where market demand (Q_k) depends on average quality (S_k), average price (P_k) and the potential number of travelers (N_k). The market share of each airline (MS_{jk}) depends on its own quality (S_{jk}) and price (P_{jk}), compared to market average values (S_k, P_k).

Imposing the logarithmic form, the empirical specification for the demand equation on route k can be expressed as follows:

$$\log(Q_k) = \alpha_1 + \beta_{11}\log(P_k) + \beta_{12}\log(S_k) + \beta_{13}\log(N_k) + \beta_{14}D^{island} + \\ + \beta_{15}win01 + \beta_{16}sum02 + \varepsilon_{1k,} \qquad [2]$$

where the dependent variable is the total number of passengers carried on each route (Q_k). We include the following explanatory variables in the demand equation:

1) Average price on route k (P_k).

In order to account for the different fares, we approximate average prices through the average prices in the full economy fare ($P^{eco}{}_k$) and a dummy variable ($D^{discount}{}_k$) that takes value 1 where airlines set relevant discounts on the full economy fare and zero otherwise.

The full economy fare is defined as the economy fare without discounts, without restrictions on changes and refunds and without minimum stay requirements. Full economy fares can be considered to be a reference for all other fares. Business and lowest fares are calculated by airlines by applying a mark-up and a discount, respectively, on full economy fares.

The variable for price discounts is constructed as the ratio between average prices in the lowest fares and full economy fares. We evaluate the existence of relevant discounts, using statistical. Discounts are considered to be relevant when the price ratio considered takes a value lower than the standard deviation with respect to the mean. This dummy variable interacts with the average price in the full economy fares. Thus, the final expression of the average prices on route "k" is as follows: $\beta_{11}\log(P_k) = \beta'_{11}\log(P^{eco}{}_k) - \beta''_{11}[\log(P^{eco}{}_k)\, D^{discount}{}_k]$.

2) Average quality on route *k* (S_k).

The discussion about switching costs and frequent flier variables in Section 1 refers to the demand effects, especially for business trips, of flight frequency as a quality variable. Hence, the variable for quality in the empirical specification of the demand equation refers to flight frequency.

One must take into account the possible endogeneity of frequency since variations in demand can be adjusted to through variations in service frequency. This frequency depends on the quantity and spread of an airline's slots in the corresponding airports. The availability of new slots in the period considered, 2001 and 2002, was very low in the main Spanish airports and the allocation rules for the existing slots are tight, which supports the exogeneity of this variable. However, we estimate two alternative versions of the demand equation according to the treatment of this variable.

3) Potential number of consumers on route "k" (N_k) is approximated through the average population of the origin and destination regions of the route.

4) We include a dummy variable that takes value 1 for routes that have an island as an endpoint ($D^{island}{}_k$) as route fixed effects. This variable can capture traffic generation due to the lack of competition from other transport modes and due to the tourism effect.

5) We include dummy variables for winter 2001 (win01) and summer 2002 (sum02) as seasonal effects. According to the period of our data set, this means that summer 2001 is considered to be the baseline period.

6) ε_{1k} is a random error term.

Imposing the logarithmic form, the empirical specification for the market share equation of airline "j" on route "k" can be expressed as follows:

$$\log(MS_{jk}) = \alpha_2 + \beta_{21}(P_{jk}/P_k) + \beta_{22}\log(S_{jk}/S_k) + \beta_{23}D^{island} + \\ + \beta_{24}win01 + \beta_{25}sum02 + \varepsilon_{2jk} \quad [3]$$

where the dependent variable is the market share of each airline on the route in terms of passengers carried (MS_{jk}). We include the following explanatory variables in the market share equation:

1) The relative prices of each airline with respect to the market average (P_{jk}/P_k).

Airline price differences in full economy fares are small[4]. In addition, we expect that these differences are fundamentally related to the different levels of quality, which are captured through the relative flight frequency.

Thus, we approximate the price effect in the market share equation through the dummy variable for relevant discounts on the full economy fares, which is constructed in the same way as the analogous variable for the demand equation. Discounts are considered to be relevant (and the dummy variable takes value 1) when the ratio between the prices charged by each airline in the lowest fare and average market prices in the full economy fare takes a value lower than the stan-

(4) Our data show a much more homogeneous distribution of the base fare than of the discounts across airlines. Indeed, the variation coefficient of the variable for the relative prices in the full economy fare is 0.07 while the variation coefficient of the variable for the discounts is 0.24.

dard deviation with respect to the mean. Thus, the variable for relative prices in the empirical specification of the market share equation refers to the dummy variable for price discounts ($P_{jk}/P_k = D^{discount}{}_{jk}$).

2) The relative quality of the product of each airline with respect to the market average (S_{jk}/S_k).

As we mention above, the quality effect on the demand side is approximated through flight frequency. Hence the variable for relative quality in the empirical specification of the market share equation is measured through the relative flight frequency of each airline with respect to the route average.

It may be necessary to account for the possible endogeneity of the relative frequency if we find such endogeneity for the analogous variable in the demand equation.

3) As in the demand equation, we add a set of control variables for the empirical specification, which refer to route and seasonal fixed effects. We include a dummy variable for routes that have an island as an endpoint ($D^{island}{}_k$) as route fixed effects and dummy variables for winter 2001 (win01) and summer 2002 (sum02) as seasonal effects. In the analysis of short-haul airline markets, a relevant feature of routes where islands are one of the endpoints is the lack of competition from other transport modes. This could distort airline competition for this type of routes because collusion behavior is easier to implement here. In addition to this, concerning the market examined in the empirical analysis, rivals of the former Spanish flag carrier have a long tradition as providers of charter flights. Thus, systematic differences across carriers in terms of market share can be expected according to the type of endpoints where they address their services.

4) ε_{2jk} is a random error term.

The sign of the variables for relative prices and relative flight frequency can be seen as evidence of the way in which airlines compete to attract the different types of travelers. Since, a positive sign can be expected in the coefficient of the variable for price discounts, given that competition to attract leisure passengers should focus fundamentally on prices. So, higher discounts should be associated with a higher market share of leisure passengers. Additionally, a positive sign is expected in the variable for relative frequency. This effect should be associated primarily with business passengers.

2.2. Supply

Having determined the demand conditions, we need to characterize airline competition in a non-cooperative oligopoly framework. We assume a two-stage decision by airlines. In the first stage, airlines choose capacity, which depends on the aircraft fleet and flight frequency. Thus, perceived quality is determined in this first stage. In the second stage, given the capacities and quality offered by all airlines, they choose prices. Kreps and Scheinkman (1983) show that a two-stage game, in which two firms make simultaneous determinations of first capacity and then price, is equivalent to the traditional one-stage Cournot model. Moreover, several empirical studies find that airlines' market behavior is similar to the Cournot solution [Brander and Zhang (1990), Oum *et al.* (1993)]. Thus, the assumption of competition à la Cournot is reasonable.

Given the demand conditions previously formulated, the inverse market demand function takes the following form:

$$P_k = F(Q_k, S_k, N_k), \quad [4]$$

where quality (S_k) refers to flight frequency. The cost function can be expressed as follows:

$$C_{jk} = C_{jk} (Dist_{k,}, Q_{jk}, \omega_j) \quad [5]$$

where C_{jk} is the total costs of airline "j" from operating on route "k". Total airline costs depend on route distance ($Dist_k$), output (Q_{jk}) and input prices (ω_j). It must be said that the empirical model exploits differences across routes, so that the exclusion of input prices (mainly wages and salaries) should not affect the results given that they can be considered airline specific fixed costs[5].

The reduced form of the Cournot profit function for each airline j = 1, ..., n in market "k" can be expressed as follows:

$$\pi_{jk}(Q_k) = Q_{jk}P_k(.) - C_{jk}(.). \quad [6]$$

Profit maximization by each airline "j" leads to the following set of first order conditions:

$$\frac{P_{jk}(.) - C'_{jk}(.)}{P_{jk}} = \frac{1}{E_{jk}(S_k/S_{jk})(n_k - 1)}, \quad [7]$$

where E_{jk} is the specific price-demand elasticity of each airline, C'_{jk} is the marginal cost ($C'_{jk} = \partial C_{jk}/\partial Q_{jk}$) and n_k is the number of competitors. From [7], it is possible to identify the pricing equation as a mark-up on marginal costs:

$$P_{jk} = \phi_{jk}(S_{jk}/S_k, n_k)\, C'_{jk} (Dist_k, Q_{jk}), \quad [8]$$

where the mark-up (ϕ_{jk}) is a function of the airlines' relative quality (S_{jk}/S_k) and the number of competitors (n_k), while marginal costs (C'_{jk}) are a function of route distance ($Dist_k$) and the number of passengers carried on it (Q_{jk}).

In airline markets one must account for the price that is charged to each passenger. However, the available data does not allow the estimation of a pricing equation at that level of detail. Under the Cournot assumption, prices are understood as a mark-up on marginal costs. As we mention above, full economy fares can be considered to be a price reference for all other fares so that prices of the lowest fare can be understood as a discount on prices of the full economy fare.

(5) It is also worth noting that an airline's output is determined by the product of service frequency, aircraft size and load factor. We argue that the main effect on costs of all these aspects refer to the exploitation of density economies so that their impact should be mostly captured by the variable for demand. Data availability do not allow us to consider other additional aspects, such as the type of engine used by the plane. The possible bias of not considering these other additional aspects in the interpretation of the results of the empirical analysis must be taken into account.

Thus, our approach relies on estimating a pricing equation for the full economy fare and identifying the determinants of discounts on the lowest fare through a binary choice model. In this way, the discount policy can be stated as a discrete choice ($D^{discount}{}_{jk}$) of making or not making discounts of a significant amount, which can be expressed as follows:

$$U_{jk} = F(C'_{jk}/C'_{k}, n_k)$$

$$D^{discount}{}_{jk} = \begin{cases} 1 \text{ if } U_{jk} > 0 \\ 0 \text{ if } U_{jk} \leq 0 \end{cases} \quad [9]$$

where U_{jk} is the utility that airlines obtain from discounts. This utility depends on the airlines' relative marginal costs with regard to the market average (C'_{jk}/C'_{k}), which is mostly determined by cost economies related to traffic density. Airlines with lower relative costs should be more willing to cut prices because the profitability of this strategy should be higher for them. In addition, the utility that airlines obtain from discounts also depends on the intensity of competition (n_k), which approximates the benefits of discounts in terms of attracting passengers.

Imposing the logarithmic form, the empirical specification for the airlines' pricing equation in the full economy fare can be expressed as follows:

$$\log(P_{jk}) = \alpha_3 + \beta_{31}\log(Dist_k) + \beta_{32}\log(Q_{jk}) + \beta_{33}\log(S_{jk}) + \\ + \beta_{34}\log(HHI_k) + \beta_{35}win01 + \beta_{36}sum02 + \varepsilon_{3jk}, \quad [10]$$

where the dependent variable is prices of the full economy fare (P_{jk}). The explanatory variables included in this pricing equation are the following:

1) The number of kilometers that separate the origin and destination airports of the route ($Dist_k$).

This variable allows us to estimate the cost economies related to actual routing distance. Although the analysis focuses on short-haul routes, there is still some variation in the kilometers flown across the routes of our sample. There are several reasons for costs increasing less than proportionally to kilometers flown. Longer routes involve higher average speeds, less intensive consumption of fuel and a lower frequency of some fixed costs (such as airport fees).

2) The number of passengers carried for each airline on the route (Q_{jk}), which allows an estimate of cost economies related to route traffic density. Recall that the existence of density economies in the provision of air transport services is generally accepted.

3) The quality of the product offered by each airline (S_{jk}).

This quality is measured through a variable for airport presence, which is built through the average share of each airline, in terms of annual national departures, in the origin and destination airports of the route. Hence, the variable for quality in the empirical specification of the pricing equation refers to airport presence.

As we mention above, the discussion about switching costs and frequent flier variables in Section 1 refers to the demand effects, especially for business trips, of flight frequency as a quality variable. Given that airport presence and flight frequency are correlated, the use of the former variable seems to be appropriate in the analysis of the prices charged by airlines since one of our main goals is to test the effects of airport dominance on the supply side.

This variable can have a cost effect in terms of the exploitation of density economies but this effect should be captured by the variable for demand.

4) The Herfindahl-Hirschman Index (HHI_k) to accurately assess the effect of the intensity of competition on prices. It must be taken into account that our sample is based on non monopoly routes.

5) We add a set of control variables for the empirical specification, which refer to seasonal fixed effects. These variables are constructed in the same way as the analogous variables in the demand and market share equations.

6) ε_{3jk} is a random error term.

The empirical specification for the discount policy equation takes the following form:

$$D^{discount}{}_{jk} = \delta + \gamma_1 \log(equip_{jk}/equip_k)_{jk} + \gamma_2 \log(AP_{jk}/AP_k)_{jk} + \\ + \gamma_3 HHI_k + \gamma_4 D^{island}{}_k + \gamma_5 win01 + \gamma_6 sum02 + \eta_{jk}, \quad [11]$$

where the dependent variable ($D^{discount}{}_{jk}$) is a dummy variable that takes value 1 when the ratio between average and the full economy fare takes a value lower than the standard deviation with respect to the mean.

The explanatory variables included in this equation are the following:

1) The relative size of the aircraft used by airlines with respect to the market average ($equip_{jk}/equip_k$).

2) The share of each airline, in terms of departures, in the corresponding airports of the route with respect to the market average (AP_{jk}/ AP_k).

3) The Herfindahl-Hirschman Index (HHI_k) to accurately assess the effect of the intensity of competition on discounts.

4) We include a dummy variable for routes with an island as an endpoint ($D^{island}{}_k$) as route fixed effects. The dummy variable for routes where islands are one of the endpoints can affect discounts in two opposite ways. First, discounts could be higher since more leisure travelers are expected at islands destinations. Secondly, discounts could be lower since competition coming from other transport modes does not take place here. Thus, the sign of the coefficient for this variable is ambiguous.

5) We include dummy variables for winter 2001 (win01) and summer 2002 (sum02) as seasonal fixed effects.

6) η_{jk} is a random error term.

The variables for the size of the aircraft and airport presence can have both costs (related to density economies) and quality effects. Nevertheless, we do not expect a significant quality effect in the fares addressed to leisure passengers.

The cost effect related to density economies could be captured by a demand variable but our policy discount equation allows us to take the role of airport presence into account when calculating the probability of making discounts. Indeed, the main interest of this equation is to explicitly capture the influence of airport dominance on the probability that airlines will make discounts to attract price-sensitive consumers.

The fact that a major airport presence allows airlines to charge higher prices in the fares addressed to business travelers and, additionally, allows more frequent discounts in the fares addressed to leisure travelers, would be consistent with the argument that airlines derive competitive advantages from airport dominance through product differentiation.

3. Data

The sample used in the empirical analysis is composed of 35 Spanish domestic routes in which more than one airline is operating with regular flights, and we differentiate between the summer and winter seasons. In general terms, the structure of prices (in the full fares) and flight schedules of airlines vary between, but not within, seasons. This inter-season variation is especially important in the Spanish case because it is a strongly tourist-oriented market. We include dummy variables for season (win01, sum02) to capture seasonal fixed-effects. It is worth noting that the period considered encompasses the period in which the terrorists attacks of September 11th took place, which led to a worldwide downturn of demand for air transport services[6]. The choice of this period for the empirical analysis is related to the availability of traffic data at the airline and route level.

The data set considers round trips for 35 routes with non-stop services. It is important to point out that the demand data does not distinguish between connecting and final traffic. In this way, there is always an interaction with the passengers connecting to other destinations that influences the final price of the ticket. The potential bias of this data limitation should be taken into account when interpreting the results of the empirical analysis.

Demand data has been obtained from Spanish Civil Aviation. Data on frequency, aircraft size and prices have been obtained for a sample week for each season. Information regarding flight frequency and aircraft size has been obtained from the Official Airlines Guide (OAG). The round trip prices, differentiating between the lowest fares, the full economy fares and the business fares charged by each airline, have been obtained from their respective websites.

Variables of prices for the different fares are used in order to capture demand heterogeneity. Unfortunately, a weighted distribution of passengers in the different fares is not available. This could affect our results if the distribution varies substantially across routes and airlines. The use of variables that refer to route characteristics can help in controlling for these differences.

There is a high variability in the prices charged by airlines in the lowest fare. In order to account for this variability, we have obtained this data under homogeneous conditions for each airline. That is, data have been collected one month before travel-

(6) According to the Airports Council International (ACI), the worldwide reduction in the number of passengers moved was 2.5 per cent in 2001 and 0.2 per cent in 2002. Data of the Spanish airport agency (AENA) indicate that the total number of passengers moved by Spanish airports decreased by 1.1 per cent in 2002 (while traffic increased in 2001). The decrease in domestic passenger traffic was 2.3 per cent in 2002. According to the Ministry of Transport, the traffic reduction was lower for Iberia than for its competitors.

ing, the price is for the first trip of the week and the return is on Sunday. However, this homogeneous procedure for obtaining our data does not avoid a possible bias when using the variable for discounts in a continuous form because airlines can easily and rapidly adjust discount prices. This explains our preference for using the variable for discounts in a discrete form. Furthermore, it must be said that our variable for price discounts refers to the maximum discount that can be obtained in a specific time period but not to the number of travelers that can make use of this maximum discount. In this way, it can be expected that travelers with a flexible schedule (usually leisure travelers) benefit to a greater extent from these discounts.

The population variable is the total average population in the regions of origin and destination of a route, obtained from the Statistics National Institute.

Data on the percentage of national departures of airlines from origins and destinations for each season have been obtained from the Spanish Airports and Air Navigation (AENA) agency. As we mentioned above, the variable for airport presence is built through the average share of each airline, in terms of annual national departures, at the origin and destination airports of the route. An alternative measure of airport presence could be the share of each airline in terms of annual domestic departures at the origin airport. However, as Tables A1 and A2 in the appendix show, the former seems to be a better measure in our context because the sample is based on three origin airports and the share of the former Spanish flag carrier is high in the majority of origin and destination airports for the period considered.

Finally, a few facts about the Spanish air transport market must be considered. The main competitor of the former Spanish flag carrier, Iberia, is Spanair, mainly owned by the Scandinavian airline, SAS. In third place is Air Europa, owned by a firm devoted to tourist activities. Iberia was privatized in a gradual process that finished in 2001. British Airways is currently one of Iberia's major shareholders. According to the Spanish Civil Aviation (Ministry of Transport), the Spanish air market is made up of about 100 routes, and Iberia had a monopoly on half of them in the period considered. On routes where Spanair and/or Air Europa offer services, Iberia's market share ranged from 50 to 90 per cent. Table 1 shows the descriptive statistics of the main variables used in the empirical analysis.

4. Estimation and results

The demand, market share and pricing equations are estimated as an equation system, with the policy discount equation estimated separately from the other equations. It can be easily shown that our system of equations is over-identified. It is common to estimate over-identified systems through some methods based on instrumental variables. In this way, all the equations of the system are estimated through the Two Stage Least Squares estimator (TSLS). Estimates have been made equation by equation, providing the other equations of the system with the instruments for the endogenous explanatory variables of each equation. A simultaneous estimation of the system is considered to be more efficient, but any possible misspecification of an equation is transferred to the rest of the system.

Table 2 shows the results for the demand equation where prices are treated as endogenous variables. All explanatory variables have the expected signs, al-

Table 1: DESCRIPTIVE STATISTICS

Variables (route level)	Mean	Standard deviation	Minimum value	Maximum value
Traffic density (number of passengers per season)	376.242	417.447	17.525	2.413.967
Round trip prices (full economy class; euros)	264.45	108.42	99.78	535.28
Price discounts (percentage)	0.68	0.16	0.33	1
Weekly flight frequency	79	76.28	11	445
Population of the city-pairs	2.887	893.713	841.668	5.114.656
Distance	746	647	131	2.190
Airline´s market share (percentage)	0.39	0.22	0.01	0.92
Herfindahl-Hirschman Index	0.51	0.12	0.33	0.85

Source: Own elaboration.

Table 2: DEMAND EQUATION RESULTS – TSLS – (N = 85)

Instruments for $\log(P_k)$ and $\log(S_k)$: $\log(Dist_k)$, $\log(equip_k)$, $\log(AP_k)$, $\log(Dn_k)$
Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory variables	Dependent variable: $\log(Q_k)$	
	(1) S_k (exogenous)	(2) S_k (endogenous)
Intercept	0.75 (1.63)	0.73 (2.32)
$\log(P_k)$	-0.54 (0.11)***	-0.56 (0.19)***
$\log(P_k)D^{discount}_k$	0.03 (0.09)	0.04 (0.10)
$\log(S_k)$	1.06 (0.05)***	1.10 (0.09)***
$\log(N_k)$	0.47 (0.11)***	0.45 (0.17)***
D^{island}_k	0.15 (0.10)	0.14 (0.11)
$win01_k$	-0.36 (0.08)***	-0.35 (0.08)***
$sum02_k$	0.21 (0.07)***	0.21 (0.07)***
R^2adj.	0.91	0.90
F-Statistic	129.04***	86.84***

1. Significance at the 1% (***), 5% (**), 10%(*).

2. The variable for quality (S_k) is measured through flight frequency (FQ_k).

Source: Own elaboration.

though the dummy variable for islands is not significant. We found that the possible bias of considering frequency as an exogenous variable is modest, as could be expected from restrictions regarding the use of slots. Given the potential number of travelers and the fixed effects, it is found that prices and flight frequency are the main determinants of demand. The overall significance of the demand equation is very high.

In addition, our results show a relatively high elasticity of demand to flight frequency since the corresponding parameter takes a value greater than one. This result is consistent with the S-curve effect of service frequency on airline demand [Wei and Hansen (2005)]. Indeed, demand increases can be even more than proportional to frequency increases because of the quality effect.

On the contrary, we find a relatively low price elasticity of demand. Aggregate demand increases by about 6 per cent for every 10 per cent decrease in average prices. The high proportion of routes with islands as endpoints (19 of 35) in our sample could explain the low price elasticity of demand. Although routes where islands are one of the endpoints should have a high number of leisure passengers, the lack of intermodal competition can make passengers less sensitive to prices. For this reason, we have estimated the demand equation for sub-samples of routes differentiated by having or not islands as endpoints. The coefficient of prices for routes that have an island as an endpoint takes a value of about -0.40, while that value is -1.07 for routes that do not have an island as an endpoint.

Table 3: MARKET SHARE EQUATION RESULTS – TSLS – (N = 215)

Instruments for $\log(P_{jk}/P_k)$: $\log(equip_{jk}/equip_k)$, $\log(AP_{jk}/AP_k)$
Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory variables	Dependent variable: $\log(MS_{JK})$
Intercept	-1.37 (0.08)***
$\log(P_{jk}/P_k)$	1.36 (0.31)***
$\log(S_{jk}/S_k)$	0.88 (0.05)***
D^{island}_{jk}	0.21 (0.1)***
$win01_k$	-0.44 (0.17)***
$sum02_k$	0.008 (0.05)
R^2adj.	0.72
F-Statistic	135.25***

1. Significance at the 1% (***), 5% (**), 10%(*).

2. The variable for relative prices (P_{jk}/P_k) is measured through the dummy variable for price discounts ($D^{discount}_{jk}$).

3. The variable for relative quality (S_{jk}/S_k) is measured through relative flight frequency (FQ_{jk}/FQ_k).

Source: Own elaboration.

Table 3 shows the results for the market share equation, where the variable for relative prices is treated as endogenous. As in the demand equation, the variable for relative service frequency could be endogenous. However, the same argument and test for including this variable as exogenous in the demand equation applies in the market share equation.

All explanatory variables have the expected signs. Coefficients for the variables for price discounts and relative quality are positive. Hence, airlines obtain larger market shares when setting higher discounts and when offering higher flight frequencies. Thus, the evidence is that airlines compete both in price and quality to attract passengers. It can be expected that price competition is more important for the leisure segment of the market, whereas quality competition dominates in the business segment of the market. We also find systematic differences in routes with islands as endpoints.

Table 4: PRICING EQUATION RESULTS – TSLS – (N = 215)

Instruments for $\log(Q_{jk})$: $\log(N_k)$, D^{island}_k
Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory variables	Dependent variable: $Log(P_{JK})$
Intercept	3.60 (0.19)***
$\log(Dist_k)$	0.43 (0.007)***
$\log(Q_{jk})$	-0.06 (0.01)***
$\log(S_{jk})$	0.08 (0.01)***
$\log(HHI_k)$	0.03 (0.06)
$win01_k$	-0.02 (0.01)*
$sum02_k$	0.12 (0.01)***
R^2adj.	0.95
F-Statistic	792.21***

1. Significance at the 1% (***), 5% (**), 10%(*).

2. The variable for quality (S_{jk}) is measured through flight frequency (AP_{jk}).

Source: Own elaboration.

Table 4 shows the results for the pricing equation of the full economy fare, where the variable for demand is treated as endogenous. All the variables have the expected signs.

We find some evidence of cost economies related to distance and traffic density. Full economy fares decrease by 4 per cent for every 10 per cent increase in distance. The size of density economies is smaller (a 10 per cent increase in route traffic density induces a 0.6 per cent price reduction), but the negative sign of the variable for demand is consistent with the existence of decreasing marginal costs.

Marginal costs can be understood as the sum of the costs of carrying an additional passenger for a given capacity (which is expected to be constant) and the costs of providing additional capacity [Brander and Zhang (1990)]. Additional capacity can be provided by using bigger planes and/or by increasing service frequency. Bigger planes are generally more efficient, while higher service frequency increases the annual utilization of planes and crews. Both ways of increasing capacity would imply decreasing marginal costs [Doganis (1991)]. However, it is worth noting here that those effects should be exhausted at some traffic levels. In this way, marginal costs should be constant if route traffic density is high.

In addition, a positive sign in the coefficient of the variable for airport presence is found. Full economy fares increase by about 1 per cent for every 10 per cent increase in airport presence. Although the size of the airport presence effect seems to be modest, it must be recognized that this effect refers exclusively to the mark-up that airlines charge on marginal costs.

The variable for the Herfindahl-Hirschman Index is not significant. Taking into account that our sample is based on non monopoly routes, previous studies have shown that the effect of this variable should not be too important. Graham *et al.* (1983) find that prices are positively correlated with route concentration, although this relationship decreases with the level of concentration. Borenstein (1989) finds that airport dominance matters more than route dominance in explaining airline prices. Finally, Evans and Kessides (1993) find an important price differential in comparisons between monopoly and duopoly routes, but the difference is quite small when a third or fourth competitor is added.

Table 5: POLICY DISCOUNT EQUATION – LOGIT – (N = 215)

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory variables	Dependent variable: $Ddiscount_{jk}$
Intercept	-2.48 (0.78)***
$\log(equip_{jk}/equip_k)$	2.71 (0.88)***
$\log(AP_{jk}/AP_k)$	1.24 (0.33)***
$\log(HHI_k)$	-0.75 (1.10)
D^{island}_k	-0.97 (0.54)*
$win01_k$	2.53 (0.51)***
$sum02_k$	0.79 (0.54)
Pseudo R^2	0.28
Wald test (χ^2)	48.08***

1. Significance at the 1% (***), 5% (**), 10%(*).

Source: Own elaboration.

Table 5 shows the results of the estimation for the policy discount equation. All variables have the expected signs, although the variable for the Herfindahl-Hirschman Index is not significant. We take into account a possible endogeneity bias of the variable for aircraft size using data from the previous year[7]. In this equation, the positive sign of the variable for airport presence is especially important, which means that an airline's share of an airport's slots positively influences the probability of discounts. The fact that a higher airport presence allows higher prices in the full fares along with more frequent discounts on the lowest fares is consistent with the product differentiation explanation of the airport dominance advantages. Finally, the negative sign of the dummy variable for islands shows that the negative effect of the lack of intermodal competition outweighs the positive effect of more leisure travelers.

To sum up, the main result that can be inferred from the pricing and policy discount equations is that higher scales of operations in an airport allow airlines both to increase demand and reduce costs. An airline that takes benefit from airport dominance can increase demand since it offers a higher quality product. In turn, the airline can also reduce costs by its better exploitation of density economies. From our estimation, it can be inferred that a 1 per cent increase in frequencies implies a 0.08 per cent increase in prices in the full fares, while a 1 per cent increase in the relative frequencies offered by an airline implies a 1.24 per cent increase in the discounts available. Overall, in our context, the cost effect seems to be more important than the quality effect.

The evidence for the U.S. case [Borenstein (1989, 1991), Evans and Kessides (1993), Berry *et al.* (1996)] shows that the quality (and market power) effects of airport control on an airline's prices is higher than the cost effect. However, the cost effect was more important than the quality effect in the study by Marín (1995) for the case of the European market. Our analysis seems to find a possible explanation for that contradiction, since it demonstrates that the effects of airport dominance vary for different types of fares. As airlines use different fares to discriminate prices among different types of travelers (business and leisure travelers), it is sensible to argue that it is necessary to differentiate the type of consumers to which airlines address their services to achieve a comprehensive knowledge of the effects of airport dominance.

We have estimated alternative specifications of the demand equation, the market share equation and the policy discount equation to examine the sensitivity of the results to the way in which variables for prices are constructed. The variable for prices in the alternative specification of the demand equation is an average between prices in the lowest fare and full economy fare, while the variable for price discounts in the alternative specifications of the market share equation and the policy discount equation is measured as a ratio between prices in the lowest

(7) Discounts are strongly associated with the evolution of load factor figures since airlines try to maximize the average yield per passenger. Other factors being constant, a bigger aircraft makes it more difficult to increase the proportion of seats sold. Thus, it could be argued that the amount of discounts and the size of the aircraft are simultaneously determined. However, the possible endogeneity bias should be modest given that airline choices on aircraft size can not be rapidly altered and depend on route characteristics (distance, demand forecasts, etc) and on the real fleet at their disposal.

fare and full fare. The results for such alternative specifications are essentially identical to those in our previous estimation[8].

In the period considered, Iberia's dominance of the national airport network had two effects. First, Iberia was able to offer products of higher quality than its rivals on most routes. This allowed them to attract business travelers through the exploitation of demand side economies. Second, Iberia took advantage of cost economies to capture leisure travelers by applying more frequent price discounts. Both effects had an impact on competition in the Spanish domestic market. Iberia carried a higher proportion of business passengers per flight and achieved higher load factors per flight than its rivals[9]. As we mentioned above, the large size of the Spanish market indicates that our results may be extrapolated to other EU countries.

5. Concluding remarks

The objective of this paper is to test the cost and demand advantages that an airline can obtain from airport dominance in a market of short-haul routes and characterized by congestion in its main airports. Our empirical model shows that these advantages were related to flight frequency in the case of the Spanish market during the period 2001-02.

Competition in the leisure segment of the market is mainly focused on price. Taking into account that a high service frequency allows a high utilization of crews and planes along with a cumulative exploitation of density economies, it can be argued that airport dominance allows airlines to take advantage of cost economies when competing for leisure travelers. As a result, airlines that benefit from airport dominance are able to offer larger and/or more discounts in a market segment where prices must adjust to costs.

In the business segment of the market, on the other hand, competition is mainly focused on quality. In this case, airport dominance provides airlines with demand side economies. A high service frequency is especially attractive for business travelers who are concerned more with reducing trip times than with saving money on a ticket for which they do not usually pay. Moreover, a high service frequency allows an airline to exploit marketing devices such as FFPs more efficiently. As a result, airlines that benefit from airport dominance can charge high prices in the full fares without losing market share.

The fact that an airline that controls an airport network can offer large discounts in the leisure segment of the market and, at the same time, can offer a convenient

(8) Results of this estimation are available upon request from the author.

(9) Even though the flight frequency offered by Iberia (44.15) was well above those of Spanair (17.67) and Air Europa (19.29), the average load factor of Iberia was 0.70, while the load factors of Spanair and Air Europa were 0.57 and 0.64, respectively. Additionally, according to data from the Association of European Airlines (AEA) for the period considered, the percentage of business travelers flying with Iberia was more than 9 per cent, while this figure was less than 6 per cent in the case of Spanair.

flight schedule in the business segment of the market threatens the competitive position of its rivals, and can seriously damage the effectiveness of competition.

In the Spanish market, Iberia has held advantages from airport control in the period considered. Contrary to other network carriers, the former Spanish flag carrier has shown a strong record of profits during the last years. The dominance of a relatively large domestic market, within a context of airport congestion, arises as one possible explanation.

We feel that the implementation of new rules for airport space allocation, especially regarding slots, could improve the scope of airline competition. In the Spanish case, forecasts for the main airports predict a large traffic increase for the period 2000-2015. Plans call for a doubling of the capacity of the largest airports in the national network. A more balanced distribution of new slots in these airports is required to guarantee airline competition. The use of market mechanisms, such as slot auctions, higher posted prices or the development of a secondary trading market are policy measures which may overcome inefficiencies in the current airport space allocation procedures.

Appendix

Table A1: Routes of the spanish domestic market included in the sample

Routes with origin in Madrid	Routes with origin in Barcelona	Routes with origin in Palma Mallorca
Madrid-Barcelona	Barcelona-Málaga	Palma de Mallorca-Valencia
Madrid-Málaga	Barcelona-Sevilla	Palma de Mallorca-Málaga
Madrid-Valencia	Barcelona-Bilbao	Palma de Mallorca-Alicante
Madrid-Santiago	Barcelona-Santiago	Palma de Mallorca-Bilbao
Madrid-Bilbao	Barcelona-Vitoria	Palma de Mallorca-Menorca
Madrid-Vigo	Barcelona-Palma Mallorca	Palma de Mallorca-Ibiza
Madrid-Alicante	Barcelona-Ibiza	
Madrid-Sevilla	Barcelona-Menorca	
Madrid-La Coruña	Barcelona-Tenerife	
Madrid-Jerez	Barcelona-Las Palmas	
Madrid-Santander	Barcelona-Lanzarote	
Madrid-Palma Mallorca		
Madrid-Las Palmas		
Madrid-Tenerife		
Madrid-Ibiza		
Madrid-Lanzarote		
Madrid-Fuerteventura		
Madrid-La Palma		

Source: Own elaboration.

Table A2: IBERIA'S MARKET SHARE IN THE MAIN SPANISH AIRPORTS. 2002

Airport	percentage of national departures	percentage of total departures
A Coruña	100%	90%
Santander	100%	93%
Jerez	91%	63%
Sevilla	87%	74%
Valencia	84%	70%
Vigo	79%	81%
Bilbao	71%	46%
Menorca	69%	61%
Alicante	67%	30%
Barcelona	66%	49%
Ibiza	65%	51%
Asturias	65%	71%
Madrid	64%	55%
Santiago	60%	66%
Málaga	60%	27%
Gran Canaria	53%	24%
Fuerteventura	47%	8%
Palma de Mallorca	43%	25%
Tenerife	36%	21%
Lanzarote	27%	11%

Note: Data for Gran Canaria, Fuerteventura, Tenerife and Lanzarote airports do not include traffic moved by Binter Canarias. This regional airline was segregated from the Iberia group in July 2002.

Source: AENA.

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Fecha de recepción del original: mayo, 2006
Versión final: septiembre, 2007

RESUMEN

En este trabajo, se analiza cómo una compañía aérea puede beneficiarse del dominio de una red de aeropuertos en un mercado caracterizado por rutas de corto radio y congestión. Se estima un sistema de ecuaciones para el mercado español de transporte aéreo. Los resultados muestran que los beneficios del dominio aeroportuario, tanto en términos de demanda como de coste, son consecuencia de ofrecer una frecuencia de servicio elevada. Una frecuencia elevada permite ofrecer mayores descuentos en las clases de tarifas para viajeros por motivos personales y, a su vez, establecer precios más elevados en las clases de tarifas para viajeros por negocios. Tales beneficios pueden perjudicar la posición competitiva de aquellas aerolíneas con presencia limitada en los aeropuertos. De ahí que una asignación equilibrada del espacio en los aeropuertos sea crucial para garantizar la competencia.

Palabras clave: Competencia, transporte aéreo, modelos de ecuaciones simultáneas.

Clasificación JEL: L13, L93, C30.