

DOES AIRLINE COMPETITION WORK IN SHORT-HAUL MARKETS?

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ABSTRACT: 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. In order to tackle this issue, we estimate an equation system, which is based on theoretical grounds, for the Spanish domestic market. We find that costs and demand benefits of airport dominance have to do with providing a high flight frequency. Such benefits can damage seriously the effectiveness of competition as long as the competitive status of major airline's rivals is threatened.

I. Introduction

Air transport liberalization in the European Union (EU) has produced positive effects on traveler welfare. In domestic markets, travelers enjoy a greater choice among a number of alternatives, higher flight frequency and lower prices in the busiest routes. Nevertheless, there is a consensus that the achievement, maintenance and increase of these benefits in the post-liberalization period depends fundamentally on effective competition on those routes.¹ It follows that there is concern about the scale advantages major airlines hold in their domestic markets as a consequence of their dominance of airport access.

Indeed, the allocation of slots in European airports is based on grandfather rights that give "ownership" to airlines on the basis of previous use. Hence flag carriers, which had a monopoly or duopoly in the provision of domestic or international services in the regulation period, can claim the majority of slots in most airports within their national network. This is particularly relevant in case of airport congestion. In addition to this, a common characteristic of EU domestic markets is that most of routes are 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 market characterized by short-haul routes and congestion. In order to meet this objective, we estimate an empirical model, which is based on theoretical grounds, for the Spanish domestic market during 2001 and 2002

At this point, it must be pointed out that the results of this study can be applied to the rest of the EU with some confidence because the Spain domestic market is the largest in the European Union, as is shown in table 1. The size of Spanish domestic aviation results from three factors. First, major cities in Spain are far from each other. Second, many high-density connections serve the country's islands. Finally, the quality of service on alternative transport modes is relatively low. Therefore, the large size of the Spanish market, along with a strong tradition of charter airlines, allows us to claim that the Spanish market is an upper bound in terms of competition opportunities in the European context. Additionally, the analysis of the Spanish market allows capturing the influence of airport congestion on airline competition. Indeed, the airports of Madrid or Barcelona are one of the endpoints of the majority of Spanish routes. In the period considered both airports were highly congested.²

(Insert table 1 about here)

There is an extensive empirical literature on competition in the airline industry.³ The effect of airport dominance on airline prices is one of the main issues that emerges from this literature. 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, the price effects of airport dominance follow exclusively from the “premium” that major airlines can charge to passengers departing from their main hubs. However, the airport dominance of European flag carriers can be even higher in small airports. While low cost airlines operating from secondary airports near major cities have succeeded in competing with flag carriers on many inter-European routes, the “low cost effect” is much more modest in domestic markets.

In addition, product differentiation has not usually been treated as a primary assumption in previous studies.⁴ However, looking directly at differentiation in the airline industry is sensible if we are to test explicitly the cost and demand advantages of airport dominance. Indeed, we argue that product differentiation explains the advantages that follow from slot control.

It must be understood that this study is focused on markets based fundamentally on short-haul routes. In this way, the average distance of our route sample is 746 kilometers. In short-haul routes, flight frequency is the major determinant of quality and it has effects on airlines costs (Doganis 2001). Indeed, such frequency influences costs and demand on a route as long as it determines capacity and waiting time for airlines services. In turn, the flight frequency that airlines can offer depends on airport access. Thus the main competitive advantage that an airline can achieve from airport dominance in a short-haul market comes from offering a high frequency of flights.

Wei and Hansen (2005) show that airlines can obtain higher returns in market shares from increasing service frequency than from increasing aircraft size in non-stop duopoly markets. Their empirical model is focused on the demand side due to the unavailability of good instruments on the supply side. In this paper, we jointly estimate demand and supply functions.

The remainder of this paper fleshes out the effects of airport dominance on short-haul markets and tests them empirically. In the next section, we analyze economic features that have the greatest influence on airline competition. In the third section, we provide the framework for the hypotheses that are to be tested in the empirical analysis. In the fourth, we specify the data used in the empirical analysis, the results of which we describe in the fifth. Finally, the last section focuses on the implications of the results.

II. Airline Competition

Competition in the provision of air transport services depends both on demand and supply side 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 increases of output on a route. Scale economies refer to unit cost variations due to proportional changes both in the size of the route network and in the output on each route of the network. The issue here is that although the existence of density economies is generally accepted in the sector, there is no clear evidence addressing the existence of scale economies (Tretheway and Oum 1992). In fact, density economies along with constant scale economies imply that it is not necessarily cost efficient to have just one airline dominate all the main airports of a national network.

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.⁵ Leisure travelers, on the other hand, are time insensitive but price sensitive. Furthermore, air transport is one of the main examples of industries with consumer switching costs (SC). This is due to the use of frequent flier programs (FFP) to create brand loyalty in travelers once they have bought an airline's services (Suzuki and Walter 2001). Indeed, travelers who switch airlines lose opportunities to obtain points toward various benefits, such as free trips. Thus SC are associated to the opportunity cost of these benefits.

Klemperer (1987) analyses the role of SC in a two-stage model of oligopoly competition. In the second period, SC and the market shares of each firm are determined by sales in the first period. Price competition depends inversely on the SC in that second period. This relationship follows from the fact that a higher SC means that lower prices attract fewer consumers and, at the same time, lead to a greater sacrifice of profits from those consumers already captured by an FFP. Thus, in case of high SC, there will be few incentives to reduce prices and equilibrium is going to be found near monopoly prices.

Klemperer's analysis implies the hypothesis that different competition conditions arise depending on the market segment to which airlines address their services. Indeed, passengers can be differentiated by the amount of SC they bear. FFPs play a limited role (and SCs are not relevant) in the market segment focused on leisure travelers. As a result, price competition can be tough. However, FFPs can play an important role (SCs should be relevant) in the market segment focused on business travelers and may soften price competition. Other features, such as quality, can become the main competition variable.

Recognizing that density economies and demand heterogeneity are both prominent characteristics of the airline industry, it is clear that the benefits of airport dominance in a market based on short-haul routes come from the role played by flight frequency. A higher flight frequency allows a better adjustment to traveler scheduling preferences, and in turn, reduces waiting 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 makes a free trip more valuable, and higher flight frequency at each airport speeds 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 2001). Furthermore, frequency allows a carrier to increase the proportion of business travelers per flight, which reduces the break-even load factor (OCDE 2000). Finally, the cost diseconomies that arise from the use of smaller planes as frequency rises are especially relevant in long-haul routes (Wei and Hansen 2003).⁶ Over shorter routes, we want to stress, a high flight frequency is not necessarily cost damaging, whereas the demand side advantages can be substantial.

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, particularly in case of airport congestion. Given that the allocation of slots in Europe is based on grandfather rights, we argue that European flag carriers could benefit from airport dominance in their domestic markets by providing a high flight frequency in the majority of routes. Indeed, they can capture business travelers through flight schedule flexibility and leisure travelers through price discounts. In the following section, we develop a methodology to test the effects of airport dominance in airline markets.

III. The empirical model

III.1. Demand

Given that service frequency is the main determinant of quality in short-haul air transport markets, the demand conditions in a vertical product differentiation model can be stated. Products are defined by the pair (S,P) where P is price and S is the quality of the product. It is assumed that each airline offers a product of a specific quality in each market where it operates, so that it is possible to distinguish products according to an increasing ordering of quality: $S_1 < S_2 < \dots < S_n$. Prices for each variant of quality do not have a predetermined ranking: P_1, P_2, \dots, P_n . However, higher levels of quality are generally associated with higher prices.

It is also assumed that each consumer buys one unit of the product that maximizes her utility; given the prices and quality of available products, or alternatively, she does not buy any product. Hence the utility of consumer i from consuming the product of quality S_τ at price P_τ can be expressed as follows:

$$U_{i\tau}(\theta, \tau) \begin{cases} = \theta S_\tau - P_\tau & \text{if the consumer buys one unit of the product} \\ 0 & \text{if the consumer does not buy any unit of the product} \end{cases} \quad (1)$$

Consumer preferences for quality, θ , are distributed in the interval $[0, +\infty]$ according to a cumulative distribution function $F(\theta)$, where $F(0) = 0$ and $F(+\infty) = 1$.⁷ In the choice between adjacent quality varieties, a consumer with a preference for quality $\tilde{\theta}$ will be indifferent to varieties τ and $\tau-1$ if $U(\tilde{\theta}, \tau) = U(\tilde{\theta}, \tau-1)$, that is, $\tilde{\theta} S_\tau - P_\tau = \tilde{\theta} S_{\tau-1} - P_{\tau-1}$. Rearranging, the equilibrium condition is obtained:

$$\tilde{\theta} = \frac{P_\tau - P_{\tau-1}}{S_\tau - S_{\tau-1}}. \quad (2)$$

Thus, the demand of the product with quality S_τ will be equal to the proportion of the potential number of consumers, N , with a preference for quality, θ , such that $\theta > \tilde{\theta}$. That is;

$$Q_\tau = N[1 - F((P_\tau - P_{\tau-1}) / (S_\tau - S_{\tau-1}))]. \quad (3)$$

The equation (3) shows the demand for a product with a specific quality, which depends on the potential number of consumers and the prices and quality of the products associated with different quality varieties. Thus, this equation can be also expressed as follows:

$$Q_\tau = f(N, P_\tau, P_{\tau-1}, S_\tau, S_{\tau-1}). \quad (3')$$

In air transport markets, the equations (3) and (3') show the demand of transport services of the airline j in the market (route) k , Q_{jk} . The services of the airline j are associated with a set of prices and a specific flight frequency (which determines quality). The price of each transport service is not unique because airlines can discriminate across the different types of passengers (i.e; business or leisure passengers), using different fare classes with different restrictions.

The available data does not allow estimating 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 is sensible to argue 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 the airline j ($j=1, \dots, n$) that competes in the 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:

$$Q_{jk} = Q_k(P_k, S_k, N_k) MS_{jk}(P_{jk}/P_k, S_{jk}/S_k, 1) \quad (4)$$

Where market demand (Q_k) depends on the average quality (S_k), the average prices (P_k) and variables for the potential number of travelers (N_k). The market share of each airline (MS_{jk}) depends on the relative quality (S_{jk}) and the relative prices (P_{jk}) of each airline with regard to the market average (S_k, P_k).

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

$$\log(Q_k) = \alpha_1 + \beta_{11} \log(P_k) + \beta_{12} \log(S_k) + \beta_{13} \log(N_k) + \beta_{14} D^{island} + \beta_{15} win01 + \beta_{16} sum02 + \varepsilon_{1k} \quad (5)$$

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

- 1) The average prices in route k (P_k).

In order to account for the different fare classes, we approximate average prices through the average prices in the unrestricted economy class (P_k^{eco}) and a dummy variable ($D_{jk}^{discount}$) that takes value 1 where airlines set relevant discounts on the economy (unrestricted) class and zero in other case.⁸ We evaluate the existence of relevant discounts, using a strict statistic criterion. Discounts are considered to be relevant when the variable for price discounts (the rate between the lowest fare class and the unrestricted economy fare class) takes a value lower than the standard deviation with

respect to the mean. This dummy variable interacts with the average price in the unrestricted fare class. Thus, the final expression of the average prices in route k is as follows: $\beta_{11} \log(P_k) = \beta'_{11} \log(P^{\text{eco}}_k) - \beta''_{11} [\log(P^{\text{eco}}_k) D^{\text{discount}}_{jk}]$.

2) The average quality in route k (S_k).

The discussion about switching costs and frequent flier variables in section II refers to the demand effects, especially for business trips, of flight frequency as a quality variable. Hence we approximate the average quality through the average 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. Such 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 was very low in the main Spanish airports and the allocation rules for the existing slots are very 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) The potential number of consumers in route k (N_k) is approximated through the average population of the origin and destination regions of the route.

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

5) We include as seasonal effects dummy variables for winter at 2001 (win01) and summer at 2002 (sum02). According to the period of our data set, this means that summer at 2001 is considered to be the baseline period. We do not have data available for winter at 2002.

6) ε_{jk} is a random error term.

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

$$\log(MS_{jk}) = \alpha_2 + \beta_{21} (P_{jk}/P_k) + \beta_{22} \log(S_{jk}/S_k) + \beta_{23} D^{\text{island}}_k + \beta_{24} \text{win01} + \beta_{25} \text{sum02} + \varepsilon_{2jk} \quad (6)$$

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

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

Airlines price differences in the unrestricted fare classes are small.⁹ In addition, we expect that such 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 economy (unrestricted) class, which is constructed in the same way as in the analogous variable for the demand equation. Alternatively, we could use the relative prices in the lowest fare class in a continuous form. However, due to the high variability of such prices, we do not have good instruments for producing such a variable.

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 is approximated through flight frequency. Hence the variable for relative quality 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. Such variables are constructed in the same way as the analogous variables in the demand equation.

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 coming from other transport modes. This fact could distort airline competition for this type of routes as long as collusion behavior is easier to implement here. Furthermore, the two rivals of the Spanish flag carrier, Spanair and Air Europa, have a long tradition as providers of charter flights and their operating base is established in the major tourist destination, Palma de Mallorca. 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 variables for prices and flight frequency can be seen as evidence of the way in which airlines compete to attract the different types of travelers. Indeed, 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. That

is, 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.

III.2. Supply

Having determined demand conditions, we need to characterize airlines competition in a non-cooperative oligopoly framework. We begin with the assumption that the decision process of airlines has two stages. In the first stage, such 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 in the framework, they choose prices. Kreps and Scheinkman (1983) show that a two-stage game in which two firms make simultaneous determinations of 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.¹⁰ Thus, the assumption of competition *à la Cournot* seems to be sensible.

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

$$P_k = F(Q_k, S_k, N_k), \quad (7)$$

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

$$C_{jk} = C_{jk}(Dist_k, Q_{jk}, FQ_{jk}, equip_{jk}, lf_{jk}, \omega_j) \quad (8)$$

where C_{jk} is the total costs of airline j from operating on the 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 as long as they can be considered airline specific fixed costs. In turn, an airline's output is determined by the product of service frequency (FQ_{jk}) and aircraft size ($equip_{jk}$). In order to obtain the quantity finally sold, such product must be multiplied by load factor (lf_{jk}).

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

$$\pi_{jk}(Q_k) = Q_{jk}P_k(\cdot) - C_{jk}(\cdot). \quad (9)$$

Profit maximization by each airline leads to the following first order conditions:

$$\frac{\partial \pi_{jk}}{\partial Q_{jk}} = 0 = P_k(\cdot) - \frac{\partial C_{jk}(\cdot)}{\partial Q_{jk}} + \lambda \frac{\partial P_k}{\partial Q_{jk}} Q_{jk}, \quad (10)$$

where $\lambda = \partial Q_k / \partial Q_{jk}$ is the conduct parameter, which takes value 1 under the *Cournot* assumption. Solving equations (7) and (10) simultaneously for each airline and assuming symmetry across airlines, first order conditions can be expressed as follows:

$$\frac{P_{jk}(\cdot) - C'_{jk}(\cdot)}{P_{jk}} = \frac{1}{E_{jk}(S_k/S_{jk})(n_k - 1)}, \quad (11)$$

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 (n_k). From (11), it is possible to identify the pricing equation as a mark-up on marginal costs:

$$P_{jk} = \phi_{jk}(S_{jk}/S_k, n_k) C'_{jk}(Dist_k, Q_{jk}), \quad (12)$$

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}).

Note that a high flight frequency could have a cost reducing effect in short-haul routes. In addition flight frequency is considered to be the main determinant of quality in short-haul air transport markets. Thus, the effect of a frequency increase on the prices charged by airlines could be ambiguous, given that this variable influences both price determinants in an opposite direction:¹¹

$$\frac{\partial P_{jk}}{\partial FQ_{jk}} = \frac{\partial \phi_{jk}}{\partial FQ_{jk}} [\cdot] + \frac{\partial C'_{jk}}{\partial Q_{jk}} \frac{\partial Q_{jk}}{\partial FQ_{jk}} [\cdot], \quad \text{where } \partial \phi / \partial FQ_{jk} [\cdot] > 0 \text{ and } \frac{\partial C'_{jk}}{\partial Q_{jk}} \frac{\partial Q_{jk}}{\partial FQ_{jk}} [\cdot] < 0.$$

In airline markets one must account for the price that is charged to each passenger. However, the available data does not allow estimating a pricing equation at that level of detail. Under the *Cournot* assumption, prices are understood as mark-up on marginal costs. This must be the case for prices in the economy unrestricted fare class, which is considered to be a price reference for all fare classes. Indeed, prices in the business and

lowest fare classes can be understood as a mark-up and a discount respectively on prices in the economy unrestricted fare class.

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

$$U_{jk} = F(C_{jk}/C_k, n_k)$$

$$D_{jk}^{discount} = \begin{cases} 1 & \text{if } U_{jk} > 0 \\ 0 & \text{if } U_{jk} \leq 0 \end{cases} \quad (13)$$

where U_{jk} is the utility that airlines obtain from discounts. This utility depends on the airlines' relative costs with regard to the market average (C_{jk}/C_k), which is mostly determined by cost economies related to traffic density. In addition, it depends on the intensity of competition (n_k), which approximates benefits of discounts in terms of attracting passengers.

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

$$\log(P_{jk}) = \alpha_3 + \beta_{31} \log(Dist_k) + \beta_{32} \log(Q_{jk}) + \beta_{33} \log(S_{jk}) + \beta_{34} \log(HHI_k) + \beta_{35} win01 + \beta_{36} sum02 + \varepsilon_{3jk}, \quad (14)$$

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

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

This variable allows estimating cost economies related to actual routing distance. There are several reasons that explain that costs increase less than proportionally to kilometers flown. Long-haul 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 in the route (Q_{jk}), which allows an estimate of cost economies related to route traffic density. As we mentioned above, 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}).

Such 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. An alternative measure could be the share of each airline in terms of annual domestic departures on 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 Spanish flag carrier is high in the majority of origin and destination airports.

As we mention above, the discussion about switching costs and frequent flier variables in section II 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 as long as 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) in order to assess accurately the effect on prices of the intensity of competition. 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. Such variables are constructed in the same way as the analogous variables in the demand and market share equation.

The variable dummy for routes with an island as an endpoint is excluded from the equation to be estimated because its effects should be captured by the variable for route traffic density.

6) ε_{3jk} is a random error term.

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

$$D_{jk}^{discount} = \delta + \gamma_1 \log(equip_{jk} / equip_k) + \gamma_2 \log(AP_{jk} / AP_k) + \gamma_3 HHI_k + \gamma_4 D_k^{island} + \gamma_5 win01 + \gamma_6 sum02 + \eta_{jk} \quad (15)$$

where the dependent variable is a dummy variable that takes value 1 when airlines apply a relevant discount to the prices of the economy unrestricted class ($D^{discount}$), and

zero otherwise. This dummy variable is built in the same way as the analogous variable for the demand and market share equations.

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) in order to assess accurately the effect on discounts of the intensity of competition.

4) We include as route fixed effects a dummy variable for routes with an island as an endpoint (D^{island}_k).

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 to 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 a priori ambiguous

5) We include as seasonal fixed effects variables dummy for winter at 2001 ($wim01$) and summer at 2002 ($sum02$).

6) η_{jk} is a random error term.

The variables for the size of the aircraft and airport presence can have cost and quality effects. Nevertheless, we do not expect a significant quality effect in the fare classes 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 capture explicitly 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 fare classes addressed to business travelers, and additionally allows more frequent discounts in the fare classes addressed to leisure travelers, would be consistent with the argument that airlines derive competitive advantages from airport dominance through product differentiation.

IV. Data

The sample used in the empirical analysis is composed of 35 Spanish domestic non-stop routes in which more than one airline is operating with regular flights, and we differentiate between the summer and winter. In general terms, the structure of prices (in the full-fare classes) and flight schedules of airlines vary between, but not within, seasons. Such 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*) in all the equations to be estimated as seasonal fixed effects. All data refers to 2001 and 2002.

Information about the total number of passengers carried by each airline on each route has been obtained from the “Boletín de la Oferta por Tramos y Mercados del Programa de Vuelos Regulares” that publishes the General Directorate of Civil Aviation (Ministry of Transport).

Demand data refers to non-stop service, without distinguishing between connecting and final traffic. We exclude from the analysis routes with intermediate points, which show a much higher demand inconvenience and higher costs than non-stops routes in short-haul markets. Indeed, Lijensen et al. (2002) show that direct and non direct flights are imperfect substitutes. However, the indirect flight is not a substitute when it lasts about twice as long as the direct flight. This must be the case in the majority of short-haul routes. Additionally, the Spanish flag carrier is the one airline that can effectively exploit a network effect (in terms of additional demand) that might arise from connections to international destinations. Indeed, the fact that our data does not allow distinguishing between connecting and final traffic should not bias our results as long as connecting passengers refers mostly to services of the network carrier. The possible network effect, which is omitted due to data restrictions, should reinforce results related to airport dominance advantages such that it even damages the smaller airlines.

Data on frequency, aircraft size and prices have been obtained for a sample week. Information regarding flight frequency and aircraft size has been obtained from the Official Airlines Guide (OAG). The round trip prices, differentiating between the lowest fare class, the economy (unrestricted) fare class and the business class, charged by each airline have been obtained from their respective websites.

Variables of prices for the different fare classes are used in order to capture demand heterogeneity. Unfortunately, a weighted distribution of passengers in the different fare classes is not available. This fact could affect our results if the distribution varies substantially across routes and airlines. The use of variables that make reference to route characteristics can help in controlling for these differences. In any case, the interpretation of the results should take this possible bias into account.

There is a high variability in the prices charged by airlines in the lowest fare class. 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 traveling, 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 the exact amount of the discount can change in very short time. This explains our preference for using the variable for discounts in a discrete form. However, in the appendix we present the results of alternative specifications of some of the equations of the system developed in section III. In particular, the variable for prices in the alternative specification of the demand equation is an average between prices in the lowest fare class and prices in the economy unrestricted fare class, while the variable for discounts in the alternative specifications of the market share equation and the policy discount equation is measured in a continuous form.

The population variable is the total average population in the regions of origin and destination of a route, according to the population on the first of January according to the Statistics National Institute (INE). Data on the percentage of national departures of airlines from origins and destinations have been obtained from the “Anuario Estadístico de Tráfico” published by the Spanish Airports and Air Navigation (AENA) agency.

Finally, a few facts about the Spanish air transport market will be helpful. The main competitor of the 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 the Iberia’s major shareholders. According to the General Directorate of Civil Aviation (Ministry of Transports), the Spanish market is composed of about 100 routes, and Iberia maintains a monopoly on half of them. In routes where

Spanair and/or Air Europa offer services, Iberia's market share lies between 50 and 90 per cent. Table 2 shows the descriptive statistics of the main variables used in the empirical analysis.

(Insert table 2 about here)

V. 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 rest of the equations. It can be easily shown that our system of equations is over identified. It is common to estimate over identified systems through some method based on the Instrumental Variables Technique. 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 moves to the rest of the system.

(Insert table 3 about here)

Table 3 shows the results for the demand equation where prices are treated as endogenous variables. All the explanatory variables have the expected signs, although the dummy variable for islands is not significant. We found that the possible bias of considering frequency an exogenous variable is modest, as it 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. Indeed, 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's 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 (16 of 35) in our sample could explain the low price elasticity of demand. Indeed, 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.

(Insert table 4 about here)

Table 4 shows the results for the market share equation, where the variable for relative prices is treated as endogenous. As in the demand equation, there is an endogeneity issue regarding the variable referencing relative service frequency. However, the same argument and test for including this variable as exogenous in the demand equation applies in the market share equation.

All the explanatory variables have the expected signs. Indeed, coefficients for the variables for price discounts and relative quality are positive. Thus, the evidence is that airlines compete both in price and quality to attract passengers. It can be expected that price competition is more relevant 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.

(Insert table 5 about here)

Table 5 shows the results for the pricing equation in the economy unrestricted fare class, where the variable for demand is treated as endogenous. All the variables have the expected signs.

Evidence is found that cost economies related to distance and traffic density are substantial. Indeed, average prices in the unrestricted economy fare class decreases by about 4 and 1 per cent for every 10 per cent decrease in distance and increase in route traffic density. Although the size of the density economies obtained seems to be modest, it must be said that the negative sign of the variable for demand is consistent with the existence of decreasing marginal costs. Indeed, 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). The additional capacity can be provided using bigger planes and/or increasing service frequency. Bigger planes are generally more efficient and higher service frequency increases the annual utilization of the planes and crew. Thus, the costs of providing additional capacity decrease so that, under our interpretation, it is sensible to find that marginal costs decrease with the level of demand.

In addition, a positive sign in the coefficient of the variable for airport presence is found. In this way, average prices in the economy unrestricted fare class 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 such 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 relevant. In this way, Graham et al. (1983) find that prices are positively correlated with route concentration, although this relationship decreases with the level of concentration. Additionally, 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.

(Insert table 6 about here)

Table 6 shows the results of the estimation for the policy discount equation. All the variables have the expected sign, although the variable for the Herfindahl-Hirschman Index is not significant. We account for a possible endogeneity bias of the variable for aircraft size using data from the previous year.¹² In this equation, the positive sign of the variable for airport presence is especially relevant, 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 fare classes along with more frequent discounts in the lowest fare classes 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 to both increase demand and reduce costs. Indeed, the evidence for the U.S. case (Borenstein 1990, Evans and Kessides 1993, Berry et al. 1996) shows that the quality effect 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) of the inter-

European market. Our analysis seems to find a possible explanation for that contradiction, since it demonstrates that it is necessary to differentiate across the type of consumers to which airlines address their services.

Tables A3, A4 and A5 in the appendix show the results of the estimation of the alternative specifications of the demand equation, the market share equation and the policy discount equation. The results are essentially identical to our previous estimation.

In the Spanish case, Iberia's dominance of the national airport network has the two following implications. First, Iberia is able to offer products of higher quality than its rivals for most of the routes where it operates. This allows the flag carrier to capture a high proportion of business travelers. And second, Iberia can take advantage of the cost economies derived from airport dominance to capture leisure travelers through more frequent price discounts. Both effects can damage future competition in the Spanish domestic market because the flag carrier can have a higher proportion of business passengers per flight and higher load factors per flight than its rivals. As we mentioned above, the large size of the Spanish market allows us to conclude that our results are representative for the other EU domestic markets.

VI. Concluding remarks

The contribution of this paper to the literature is to test the cost and demand advantages that an airline can obtain from airport dominance of a whole network in a market characterized by short-haul routes and congestion. Our empirical model shows that such advantages are related to provide a high flight frequency.

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 major carriers can take advantage of the cost economies derived from airport dominance when they compete for leisure travelers. As a result, they are able to offer major 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 can allow major carriers to take advantage of demand side economies. Indeed, a high service frequency is especially attractive for business travelers who are concerned more with reducing the trip time than

with saving money on a ticket, for which they usually do not pay. Moreover, high service frequency allows an airline to exploit marketing devices such as FFPs more efficiently. As a result, major carriers can charge high prices in the full fare classes without losing market share. The trend to convergence on prices in these fare classes can be explained by the modest effect that smaller airlines obtain from charging lower prices than their rivals (in terms of attracting business passengers).

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 flight schedule in the business segment of the market threatens the competitive position of its rivals, so that the effectiveness of competition can be seriously damaged.

In European domestic markets, flag carriers can hold the advantages from airport control. Contrary to other network carriers, the Spanish flag carrier has shown a strong record of profits in last years. The dominance of a relatively large domestic market, within a context of airport congestion, arises as one of the possible explanations.

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, recent forecasts for the main airports predict a large traffic increase for the period 2000-2015. Thus, plans call for a doubling of the capacity of the main airports in the national network. A more balanced distribution of new slots in such airports is required to guarantee airline competition.

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Notes

1. The empirical literature on air transport generally rejects the hypothesis that potential competition has an important disciplining effect. See for example Morrison and Winston (1987) or Hurdle et al. (1989).
2. Madrid and Barcelona airports are among the worst European airports in terms of average delays per movement (Reynolds-Feighan and Button 1999). In addition to this, the maximum

number of movements operated per hour was expected by 2004 at Madrid airport (Ministry of Transports, Order of October 19th) and by 2003 at Barcelona airport (Ministry of Transports, Order of October 22nd).

3. Major contributions for the US case refer, among others, to Morrison and Winston (1989), Borenstein (1989), Dresner and Windle (1992), Evans and Kessides (1993) and Brueckner and Spiller (1994). Button et al. (1998) and Marín (1998), among others, discuss airlines competition in the European context.

4. Relevant exceptions are the works of Marín(1995), Berry et al.(1996) and Schipper et al.(2002).

5. It can be argued that business passengers are increasingly using services of low cost airlines in inter-European routes. However, this is particularly true in routes where low cost airlines offer a high flight frequency.

6. Indeed, aircraft costs take place in three stages: during takeoff, during in-flight time at the cruise speed and during 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 fact explains that aircrafts that minimize costs have a lower size in short-haul than in long-haul routes.

7. $F(\theta)$ must be interpreted as the proportion of consumers with a preference for quality less than θ .

8. The unrestricted economy fare class is defined as the full economy fare class without restrictions on changes and refunds and without minimum stay requirements

9. Indeed, our data shows 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 class is equal to 0.07 while the variation coefficient of the variable for the discounts is 0.24.

10. See for example Brander and Zhang (1990) and Oum et al. (1993).

11. Alternatively, we could make explicit a model for the optimum amount of flight frequency. In the context of airport congestion and tight rules for slot allocation, we claim that flight frequency is exogenous. However, we test for a possible endogeneity bias in the empirical analysis.

12. The amount of discounts made is strongly associated to the evolution of load factor figures as long as airlines pursue to maximize the average yield per passenger. Other factors being constant, a higher size of the aircraft makes 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 to the extent that airline choices on aircraft size can not be rapidly altered and depend on route characteristics (distance, demand forecasts, etc) and on the actual fleet at their disposal

References

- Berry, S., Carnall, M. and Spiller, P. (1996) "Airline hubs: costs, markups and the implications of customer heterogeneity". *NBER Working Paper* 5561, 1-38.
- Borenstein, S. (1989) "Hubs and high fares: dominance and market power in the U.S airline". *Rand Journal of Economics* 20(3), 344-365.
- Brander, J.A and Zhang, A. (1990) "A market conduct in the airline industry: An empirical investigation". *Rand Journal of Economics* 21(4), 567-583.
- Brueckner, J.K and Spiller, P. (1994), "Economies of traffic density in the deregulated airline industry". *Journal of Law and Economics* 37(2), 379-415.
- Button, K.J, Haynes, K. and Stough, R. (1998) *Flying into the future: Air transport policy in the European Union*. Edward Elgar, Cheltenham.
- Caves, D.W, Christensen, L.R. and Tretheway, M.W. (1984) "Economies of density versus Economies of Scale: Why trunk and locals service airline costs differ". *Rand Journal of Economics* 15(4), 471-489.
- Dresner, M. and Windle, R. (1992) "Airport dominance and yields in the US airline industry". *Logistics and Transportation Review* 28 (4), 319-339.
- Doganis, R. (2001) *Flying off course: The economics of international airlines*. Routledge, London.
- Evans, W.N. and Kessides, I. (1993) "Localized market power in the U.S. airline industry". *The Review of Economics and Statistics* 75(1), 66-75.
- Hurdle, G., Johnson, R.L., Joskow, A.S., Werden, G.J. and Williams, M.A. (1989) "Concentration, potential entry, and performance in the airline industry". *Journal of Industrial Economics* 38(2), 119-139.
- Klemperer, P. (1987) "Markets with consumer switching costs". *Quarterly Journal of Economics* 102(2), 375-394.
- Kreps, D. and Scheinkman, J. (1983) "Quantity precommitment and Bertrand Competition yield Cournot outcomes". *Bell journal of Economics* 14(2), 326-337.
- Lijesen, M., Rietveld, P. and Nijkamp, P. (2002) "How do carriers price connecting flights? Evidence from intercontinental flights from Europe". *Transportation Research-E* 38 (3-4), 239-252.
- Marín, P.L. (1998) Productivity Differences in the Airline Industry: Partial Deregulation versus Short Run Protection. *International Journal of Industrial Organization* 16, 395-414.
- Marín, P.L. (1995) "Competition in European Aviation: Pricing policy and market structure". *Journal of Industrial Economics* 43(2), 141-159.
- Morrison, S and Winston, C. (1989) "Enhancing the performance of the deregulated air transportation system". *Brooking Papers: Microeconomics* 1, 61-112.

- Morrison, S. and Winston C. (1987) “Empirical implications and tests of the contestability hypothesis”. *Journal of Law and Economics* 30, 53-66.
- OCDE (2000) *Airline mergers and alliances*. Series Roundtables on Competition Policy, DAFPE/CLP, Paris.
- Oum, T.H, Zhang, A. and Zhang, Y. (1993) “Interfirm rivalry and firm-specific price elasticities in deregulated airline markets”. *Journal of Transport Economics and Policy* 27 (2), 171-192.
- Reynolds-Feighan, A. and Button, K.J. (1999), “An assessment of the capacity and congestion levels at European airports”. *Journal of Air Transport Management* 5(3), 113-134.
- Schipper, Y., Rietveld, P. and Nijkamp, P. (2002) “European Airline Reform: An Empirical Welfare Analysis”. *Journal of Transport Economics and Policy* 36(2), 189-209.
- Suzuki, Y. and Walter, C.K. (2001) “Potential cost savings of frequent flyer miles for business travel”. *Transportation Research-E* 37 (6), 1-14
- Tretheway, M. and Oum, T. H. (1992) *Airline economics: Foundations for Strategy and Policy*. The Centre for Transportation Studies (University of British Columbia), Vancouver.
- Wei, W. and Hansen, M. (2005) “Impact of aircraft size and seat availability on airline’s demand and market share in duopoly markets”. *Transportation Research-E* 41(4), 315-327.
- Wei, W. and Hansen, M. (2003) “Cost economics of aircraft size”. *Journal of Transport Economics and Policy* 37(2), 279-96.

Tables

Table 1. Number of annual passengers carried in EU air markets. 2002

<u>Market</u>	<u>Passengers (10³)</u>
Spain	29,022
France	27,021
United Kingdom	22,617
Italy	22,527
Germany	20,402
Sweden	7,445
Portugal	2,930
Finland	2,766

Source: Eurostat

Table 2. Descriptive statistics

Variables (route level)	Mean	Standard Deviation	Minimum Value	Maximum value
Traffic density (number of passengers)	376,242	417,447	17,525	2,413,967
Prices (unrestricted economy class; euros)	264.45	108.42	99.78	535.28
Price discounts (euros)	0.68	0.16	0.33	1
Weekly flight frequency	79	76.28	11	445
Population of the city-pairs	2,887,733	893,713	841,668	5,114,656
Distance	746	647	131	2190
Airline's market share	0.39	0.22	0.01	0.92
Herfindahl-Hirschman Index	0.51	0.12	0.33	0.85

Table 3. Demand equation (TSLS). Num. observations = 85

Instruments for $\log(P_k)$ and $\log(S_k)$: $\log(\text{Dist}_k)$, $\log(\text{equip}_k)$, $\log(\text{AP}_k)$, Competitors
 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)**
$\log(P_k)D^{\text{discount}}$	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)**
R²adj.	0.91	0.90
F-Statistic	129.04**	86.84**

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

Table 4. Market share equation (TSLS). Num. observations = 215

Instruments for $\log(P_{jk}/P_k)$: $\log(\text{equip}_{jk}/\text{equip}_k)$, $\log(\text{AP}_{jk}/\text{AP}_k)$

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory Variables	Dependent Variable: $\log(\text{MS}_{jk})$
Intercept	-1.37 (0.08)**
$\log(P_{jk}/P_k)$	1.36 (0.31)**
$\log(S_{jk}/S_k)$	0.88 (0.05)**
Disland_{jk}	0.21 (0.1)**
win01_k	-0.44 (0.17)**
sum02_k	0.008 (0.05)
R²adj.	0.72
F-Statistic	135.25**

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

Table 5. Pricing Equation (TSLS). Num. observations = 215

Instruments for $\log(Q_{jk})$: $\log(N_k)$, Disland_k

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory Variables	Dependent Variable: $\log(P_{jk})$
Intercept	3.60 (0.19)**
$\log(\text{Dist}_k)$	0.43 (0.007)**
$\log(Q_{jk})$	-0.06 (0.01)**
$\log(S_{jk})$	0.08 (0.01)**
$\log(\text{HHI}_k)$	0.03 (0.06)
win01_k	-0.02 (0.01)+
sum02_k	0.12 (0.01)**
R²adj.	0.95
F-Statistic	792.21**

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

Table 6. Policy discount equation (logit). Num. observations = 215

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory Variables	Dependent variable: D^{discount}_{jk}
Intercept	-2.48 (0.78)**
$\log(\text{equip}_{jk}/\text{equip}_k)$	2.71 (0.88)**
$\log(\text{AP}_{jk}/\text{AP}_k)$	1.24 (0.33)**
$\log(\text{HHI}_k)$	-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%(⁺)

Appendix

Table A1. Routes of the Spanish domestic market included in the sample

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

Table A2. Iberia's market share in the main Spanish airports. 2002

<u>Airport</u>	<u>Percentage of national departures</u>	<u>Percentage of total departures</u>
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%	67%
Fuerteventura	47%	55%
Palma de Mallorca	43%	25%
Tenerife	36%	61%
Lanzarote	27%	58%

Table A3. Alternative specification of demand equation (TSLS).**Num. observations = 85**Instruments for $\log(P_k)$ and $\log(S_k)$: $\log(\text{Dist}_{tk})$, $\log(\text{equip}_k)$, $\log(\text{AP}_k)$, Competitors

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory variables	Dependent Variable: $\log(Q_k)$	
	(1) S_k (exogenous)	(2) S_k (endogenous)
Intercept	0.42 (1.54)	0.53 (2.21)
$\log(P_k)$	-0.51 (0.10)**	-0.54 (0.17)**
$\log(S_k)$	1.06 (0.06)**	1.10 (0.09)**
$\log(N_k)$	0.49 (0.10)**	0.47 (0.16)**
Disland_k	0.18 (0.10) ⁺	0.18 (0.10) ⁺
win01_k	-0.42 (0.08)**	-0.42 (0.08)**
sum02_k	0.17 (0.07)*	0.18 (0.07)*
R²adj.	0.90	0.90
F-Statistic	135.99**	93.21**

1. Significance at the 1% (**), 5% (*), 10%(⁺)**Table A4. Alternative specification of market share equation (TSLS).****Num. observations = 215**Instruments for $\log(P_{jk}/P_k)$: $\log(\text{equip}_{jk}/\text{equip}_k)$, $\log(\text{AP}_{jk}/\text{AP}_k)$

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory Variables	Dependent Variable: $\log(\text{MS}_{jk})$
Intercept	-3.34 (0.78)**
$\log(P_{jk}/P_k)$	-6.00 (2.16)**
$\log(S_{jk}/S_k)$	0.88 (0.17)**
Disland_{jk}	0.79 (0.32)*
win01_k	-1.51 (0.63)*
sum02_k	-0.67 (0.35) ⁺
R²adj.	-
F-Statistic	20.87**

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

Table A5. Alternative specification of policy discount equation (OLS).

Num. observations = 215

Coefficients (White standard errors; Robust to heterocedasticity)

Explanatory Variables	Dependent variable: Discount_{jk}
Intercept	-0.42 (0.06)**
$\log(\text{equip}_{jk}/\text{equip}_k)$	-0.11 (0.05)*
$\log(\text{AP}_{jk}/\text{AP}_k)$	-0.04 (0.02)*
$\log(\text{HHI}_k)$	-0.08 (0.08)
Disland_k	-0.10 (0.03)**
win01_k	-0.26 (0.03)**
sum02_k	-0.13 (0.03)**
Pseudo R²	0.32
Wald test (χ^2)	20.87**

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