A Dynamic Oligopoly Game of the US Airline Industry: Estimation and Policy Experiments

Victor Aguirregabiria*
University of Toronto

Chun-Yu Ho*
Boston University

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Abstract

This paper studies the contribution of demand, costs, and strategic factors to the adoption of hub-and-spoke networks by companies in the US airline industry. Our results are based on the estimation of a dynamic oligopoly game of network competition that incorporates three factors which may explain the adoption of hub-and-spoke networks: (1) travelers value the services associated with the scale of operation of an airline in the hub airport (e.g., more convenient check-in and landing facilities); (2) an airline's operating costs and entry costs in a route may decline with the airline's scale operation in the origin and destination airports of the route (e.g., economies of scale and scope); and (3) a hub-and-spoke network may be an effective strategy to deter the entry of other carriers. We estimate the model using data from the Airline Origin and Destination Survey with information on quantities, prices, and entry and exit decisions for every airline company in 2,970 routes. We propose and implement a relatively simple method for counterfactual experiments in estimated models with multiple equilibria. We find that the most important factor to explain the adoption of hub-and-spoke networks is that the cost of entry in a route declines very importantly with the scale of operation of the airline in the airports of the route. Strategic entry deterrence has also a significant contribution.

Keywords: Airline industry; Hub-and-spoke networks; Entry costs; Industry dynamics; Estimation of dynamic games; Counterfactual experiments in models with multiple equilibria.

JEL codes: C10, C35, C63, C73, L10, L13, L93.

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1 Introduction

The market structure of the US airline industry has undergone important changes since the deregulation in 1978 that removed restrictions on the routes that airlines could operate and on the fares they charged.[1] Soon after deregulation, most airline companies adopted a *hub-and-spoke* system for the structure of their routes. In a hub-and-spoke network an airline concentrates most of its operations in one airport, that is called the "hub". All other cities in the network (the "spokes") are connected to the hub by non-stop flights. Those travelers who want to travel between two cities on the spokes should take a connecting flight at the hub. Several explanations have been proposed to explain the adoption of hub-and-spoke networks. These explanations can be classified in three groups: demand factors, cost factors and strategic factors. Travelers value the services associated with the scale of operation of an airline in the hub airport, e.g., more convenient check-in and landing facilities, higher flight frequency.[2] A second group of factors has to do with how an airline costs (either variable, fixed or entry costs) depend on its scale of operation in an airport. It is well-known that larger planes are cheaper to fly on a per-seat basis. Hub-and-spoke airlines can exploit these economies of scale by seating in a single large plane (flying to the hub city) passengers who have different final destinations. These economies of scale may be sufficiently large to compensate for larger distance travelled with the hub-and-spoke system.[3] Also, there may be economies of scope for an airline in an airport: an airline's fixed operating costs and/or entry costs in a route may decline with the airline's scale operation in the origin and destination airports of the route. These cost savings may be partly due to technological reasons but also to contractual arrangements between airports and airlines. Finally, a third factor is that a hub-and-spoke network can be an effective strategy to deter the entry of competitors.

[1] Borenstein (1992) and Morrison and Winston (1995) provide excellent overviews on the airline industry. Early policy discussions are in Bailey et al (1985) and Morrison and Winston (1986). Recent discussion of evaluating the deregulation can be found in Transportation Research Board (1999), Kahn (2001) and Morrison and Winston (2000).

[2] Of course, this demand factor may be offset, at least partly, by the fact that flights between spoke cities are stop-flights and therefore longer than non-stop flights.

[3] See Hendricks, Piccione and Tan (1995) for a monopoly model that formalizes this argument.

Hendricks, Piccione and Tan (1997) formalize this argument in a three-stage game of entry similar to the one in Judd (1985). To illustrate this argument, consider a hub airline who is an incumbent in the market-route between its hub-city and a spoke-city. A non-hub carrier is considering to enter in this market. Suppose that this market is such a monopolist can get positive profits but under duopoly both firms suffer losses. If the hub carrier concedes the market to the new entrant, its profits in connecting markets will fall. When this network effect is large enough, the hub operator's optimal response to the opponent's entry is to stay in the spoke market. This is known by potential entrants and therefore entry can be deterred.[4]

The main goals of this paper are, first, to develop an estimable dynamic structural model of airlines network competition that incorporates the demand, cost and strategic factors described above, and second, to use that model to measure the contribution of each of these factors to explain hub-and-spoke networks. To our knowledge, this is the first study that estimates a dynamic game of network competition. In our model, airline companies decide, every quarter, which routes to operate (directional city-pairs), the origin and destination airports to use (in cities with more than one airport), the type of product to provide (i.e., direct flight, stop-flight, or both), and the fares for each route-product they serve. The model is estimated using data from the Airline Origin and Destination Survey with information on quantities, prices, and entry and exit decisions for every airline company in 2,970 city-pair markets.

This paper builds on an extends a significant literature on structural models of competition in the airline industry. The studies more closely related are Berry (1990 and 1992), Berry, Carnall, and Spiller (2006) and Ciliberto and Tamer (2006). **** MORE COMMENTS ON THE EMPIRICAL RESULTS OF THESE PAPERS **** Berry (1990) and Berry, Carnall, and Spiller (2006) estimate structural models of demand and price competition with differ-

[4]Hendricks, Piccione and Tan (1999) extend this model to endogenize the choice of being a hub or a non–hub carrier. See also Oum, Zhang, and Zhang (1995) for other game that can explain the choice of a hub-spoke network for strategic reasons.

entiated product and obtain estimates of effects of hubs on costs and consumers' willingness to pay. Berry (1992) and Ciliberto and Tamer (2006) estimate static models of entry in route markets and obtain estimates of the effects of hubs on fixed operating costs. A limitation of these entry models is that the specification of variable profits assumes that airlines have homogeneous products and variable costs. In our model, products are differentiated and airlines have different variable costs. Our specification of demand and variable costs is similar to the one in Berry, Carnall, and Spiller (2006) but in our model product characteristics such as direct flight, stop-flight, hub size, and origin and destination airports, are endogenous. This extension is important to study the factors that explain hub-and-spoke networks. Most importantly, our model of network competition is dynamic. A dynamic model is necessary to distinguish between fixed costs and sunk entry costs, which have different implications on market structure. Bresnahan and Reiss (1993) showed that the difference between entry and exit thresholds provide information on sunk cost which is important to determine the market structure and industry dynamics. Also importantly, a dynamic game is needed to study the hypothesis that a hub-and-spoke network is an effective strategy to deter the entry of non-hub competitors.

The paper also makes two methodological contributions to the recent literature on the econometrics of dynamic discrete games.[5] In a dynamic game, the dimension of the state space, and the cost of estimating the parameters of the model with a given precision, increases exponentially with the number of heterogeneous players. Given the relatively large number of (heterogeneous) airlines in our application (i.e., twenty-seven), the state space of our dynamic game is extremely large. Furthermore, our model of network competition implies that the optimal response of an airline in a route depends not only on payoff-relevant state variables in that route but also in other connected routes. This network aspect of our model also increases very importantly the dimension of the state space. To deal with this

[5] See Aguirregabiria and Mira (2007), Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007), and Pesendorfer and Schmidt-Dengler (2008) for recent methodological contributions in this literature.

high dimensionality problem we combine the nested pseudo likelihood (NPL) proposed by Aguirregabiria and Mira (2007) with interpolation techniques. A second methodological contribution of this paper is that we propose and implement an approach to deal with multiple equilibria when making counterfactual experiments with the estimated model. Under the assumption that the equilibrium selection mechanism (which is unknown to the researcher) is a smooth function of the structural parameters, we can use a Taylor expansion to obtain an approximation to the counterfactual choice probabilities. The main advantage of this approach is that it is completely agnostic on the form of the equilibrium selection mechanism and therefore the predictions are more robust that other approaches which require stronger assumptions on equilibrium selection. An intuitive interpretation of our approach is that we select the counterfactual equilibrium which is "closer" (in a Taylor-approximation sense) to the equilibrium estimated from the data. The data is used not only to identify the equilibrium in the population but also to identify the equilibrium in the counterfactual experiments.

Our empirical results can be summarized as follows. We find that the scale of operation (i.e., *hub-size*) of an airline in an airport has a (statistically) significant effect on travelers' willingness to pay (positive effect) and on variable, fixed and entry costs (negative effect). However, the most sizeable effect is on the cost of entry. Descriptive evidence shows that the difference between the probability that an incumbent stays in a route and the probability that a non-incumbent decides to enter in that route declines importantly with the airline's hub-size in the airports of that route. In the structural model, this descriptive evidence translates into a sizeable negative effect of hub-size on sunk entry costs. Given the estimated model, we implement counterfactual experiments which provide measures of airlines propensities to use hub-and-spoke networks when eliminate each of the demand, cost and strategic factors in our model. These experiments show that, for most of the large carriers, the hub-size effect on entry costs is the most important factor to explain hub-and-spoke networks. Strategic entry deterrence is the second most important factor to explain hub-and-spoke networks.

The rest of the paper is organized as follows. Sections 2 presents the model and our basic assumptions. The data set and the construction of our working sample are described in section 3. Section 4 discusses the estimation procedure and presents the estimation results. Section 5 describes our procedure to implement counterfactual experiments and our results from these experiments. We summarize and conclude in section 6.

2 Model

The industry is configured by N airline companies, A airports and C cities or metropolitan areas. Some cities have more than one airport. Airlines and airports are exogenously given in our model.[6] Following Berry (1990, 1992) and Berry, Carnall and Spiller (2006), among others, we define a market in this industry as a directional round-trip between an origin city and a (final) destination city, what we denote as a *route* or *city-pair*. There are $M \equiv C(C-1)$ routes or markets. We index time (a quarter) by t, markets by m, and airlines by i. Within a market, an airline may provide several products. It can offer direct-flights, stop-flights, or both. For cities with more than one airport, the airline can choose the origin and destination airport of the route. Therefore, two routes between the same cities but with different airports are considered differentiated products within the same market. A product, in given market, can be described as a triple (NS, OA, DA), where $NS \in \{0,1\}$ is the indicator variable for "non-stop flight", and $OA \in \{1,2,3\}$ and $DA \in \{1,2,3\}$ are the indexes for the origin and destination airports, respectively.[7] The set of possible products in a market m is D_m. For instance, in a route with two airports in the origin city and one airport in the destination city, we have that $D_m \equiv \{0,1\} \times \{1,2\} \times \{1\}$. We index products by d.

Our model provides a Markov perfect equilibrium for the whole industry. In this equilibrium, the M local markets are interconnected through the existence of network effects. The industry equilibrium can be seen as the combination of M local equilibria, one for each

[6] However, the estimated model can used to study the effects of introducing new hypothetical airports or airlines.

[7] In our data, every city or metropolitan area has at most three airports.

market/route. We can define an equilibrium in a single local market conditional on airlines beliefs about their behavior in the rest of local markets. In the equilibrium of the industry, these beliefs are self-fulfilling. This interconnection provides a joint dynamics for the whole airline industry. There are two sources of network effects: (1) consumers value the network of an airline; and (2) entry costs and operating costs depend on an airline's network.

2.1 Consumer demand and variable profits

In this subsection we present a model of demand and price competition in the spirit of the one in Berry, Carnall and Spiller (2006, BCS hereinafter). For notational simplicity, we omit the time subindex t for most of this subsection, but all the variables may vary over time. Let H_m be the number of potential travelers in the market (city-pair) m, which is an exogenous variable. Every quarter, travelers decide whether to purchase a ticket for this route, which airline to patronize, and the product to buy. The indirect utility function of a consumer who purchases product (i, d, m) is:

$$U_{idm} = \beta_{idm} - p_{idm} + v_{idm} \tag{1}$$

where p_{idm} is the price and β_{idm} is the "quality" or willingness to pay for this product of the average consumer in the market. The variable v_{idm} is consumer specific and it captures consumer heterogeneity in preferences for difference products. A traveler decision of not purchasing any air ticket for this route is called the *outside alternative*. The index of the outside alternative is $i = 0$. Quality and price of the outside alternative are normalized to zero. Therefore, β_{idm} should be interpreted as relative to the value of the outside alternative. Product quality β_{idm} depends on exogenous characteristics of the airline and the route, and more importantly for this paper, it also depends on the scale of operation of the airline in the origin and destination airports.

We consider the following specification of product quality:

$$\begin{aligned} \beta_{idmt} &= \beta_1 \, NS + \beta_2 \, HUB^O_{imt} + \beta_3 \, HUB^D_{imt} + \beta_4 \, (1 - NS) HUB^C_{imt} + \beta_5 \, DIST_m \\ &+ \xi^{(1)}_i + \xi^{(2)}_{Omt} + \xi^{(3)}_{Dmt} + \xi^{(4)}_{idmt} \end{aligned} \tag{2}$$

$\beta's$ are parameters. NS is a dummy variable for "non-stop flight". $DIST_m$ is the non-stop distance between the origin and destination cities. We include this variable as a proxy of the value of air transportation relative to the outside alternative (i.e., relative to other transportation modes). Air transportation is a more attractive transportation mode when distance is relatively large. $\xi_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in quality which are constant over time and across markets. $\xi_{Omt}^{(2)}$ (and $\xi_{Dmt}^{(3)}$) represents the interaction of origin-airport dummies (destination airport dummies) and time dummies. These terms account for shocks, such as seasonal effects, which can vary across cities and over time. $\xi_{idmt}^{(4)}$ is an airline-market-time specific demand shock. The variables HUB_{imt}^{O}, HUB_{imt}^{D} and HUB_{imt}^{C} are indexes that represent the scale of operation or "hub size" of airline i in the origin, destination and connecting (if any) airports of route m, respectively. Therefore, the terms associated with these variables capture consumer willingness to pay for the services associated with the scale of operation of airline i in origin, destination and connecting airports. Following previous studies, we measure the hub-size of an airline in an airport as the sum of the population in the cities that the airline serves from this airport (see Section 3 for more details). Note that these product characteristics are endogenous because they depend on the entry decisions of airline i in routes-markets which are connected (i.e., share an airport) with market m.

A consumer purchases product (i, d, m) if and only if the associated utility U_{idm} is greater than the utilities of the rest of alternatives available in market m. These conditions describe the unit demands of individual consumers. To obtain aggregate demands we have to integrate individual demands over the idiosyncratic v variables. The form of the aggregate demands depends on our assumption on the probability distribution of consumer heterogeneity. We consider a nested logit model. This specification of consumer heterogeneity is simpler than in BCS paper. The main reason for our simplifying assumptions is that we have to compute the Nash-Bertrand equilibrium prices and variable profits for many different configurations of the market structure, and this is computationally demanding when consumer heterogeneity has the form in BCS. Our nested logit model has two nests. The first nest represents the decision of which airline (or outside alternative) to patronize. The second nest consists of the choice of type of product $d \in D_m$. We have that $v_{idm} = \sigma_1\ v_{im}^{(1)} + \sigma_2\ v_{idm}^{(2)}$, where $v_{im}^{(1)}$ and $v_{idm}^{(2)}$ are independent Type I extreme value random variables and σ_1 and σ_2 are parameters which measure the dispersion of these variables, with $\sigma_1 \geq \sigma_2$. Let s_{idm} be the market share of product (i,d) in market m, i.e., $s_{idm} \equiv q_{idm}/H_m$. And let $s_{d|im}$ be the market share of product (i,d,m) within the products of airline i in market m, i.e., $s_{d|im} \equiv s_{idm}/\left(\sum_{d'} s_{id'm}\right)$. In the nested logit model: $s_{idm} = s_{d|im}\ \bar{s}_{im}$, where $s_{idm} = s_{d|im}\ \bar{s}_{im}$, where $s_{d|im} = e_{idm}[\sum_{d' \in D_m} e_{id'm}]^{-1}$, $\bar{s}_{im} = (\sum_{d \in D_m} e_{idm})^{\sigma_2/\sigma_1}[1 + \sum_{j=1}^{N}(\sum_{d \in D_m} e_{jdm})^{\sigma_2/\sigma_1}]^{-1}$, $e_{idm} \equiv a_{idmt} \exp\{(\beta_{idm} - p_{idm})/\sigma_2\}$, and a_{idm} is the indicator of the event "airline i provides product d in market m at current period". A property of the nested logit model is that the demand system can be represented using the following closed-form demand equations: for $a_{idm} = 1$,

$$\ln\left(s_{idm}\right) - \ln\left(s_{0m}\right) = \frac{\beta_{idm} - p_{idm}}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s_{i|dm}\right) \tag{3}$$

where s_{0m} is the share of the outside alternative, i.e., $s_{0m} \equiv 1 - \sum_{i=1}^{N}\sum_{d \in D_m} s_{idm}$.

Travelers demand and airlines price competition in this model are static and at the local market level. The variable profit of airline i in market m is:

$$R_{im} = \sum_{d \in D_m} \left(p_{idm} - c_{idm}\right)\ q_{idm} \tag{4}$$

where c_{idm} is the marginal cost of product (i,d) in market m, that it is assumed to be constant with respect to quantity sold. Our specification of the marginal cost is similar to the one of product quality:

$$\begin{aligned} c_{idmt} &= \delta_1\ NS + \delta_2\ HUB_{imt}^{O} + \delta_3\ HUB_{imt}^{D} + \delta_4\ (1 - NS)HUB_{imt}^{C} + \delta_5\ DIST_m \\ &+\ \omega_i^{(1)} + \omega_{Omt}^{(2)} + \omega_{Dmt}^{(3)} + \omega_{idmt}^{(4)} \end{aligned} \tag{5}$$

$\delta's$ are parameters. $\omega_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in marginal costs which are constant over time and across markets. $\omega_{Omt}^{(2)}$ and $\omega_{Dmt}^{(3)}$ captures time-variant, airport-specific shocks in costs which are common to all the airlines. $\omega_{idmt}^{(4)}$ is an airline-market-time specific shock.

Given quality indexes $\{\beta_{idm}\}$ and marginal costs $\{c_{idm}\}$, airlines which are active in market m compete in prices ala Nash-Bertrand. The Nash-Bertrand equilibrium is characterized by the system of first order conditions or price equations:[8]

$$p_{idm} - c_{idm} = \sigma_2 + \left[1 - \frac{\sigma_2}{\sigma_1}\left(1 - \bar{s}_{im}\right)\right] \left[\sum_{d' \in D_m} \left(p_{id'm} - c_{id'm}\right) \; s_{d'|im}\right] \tag{6}$$

Equilibrium prices depend on the qualities and marginal costs of the active firms/products. It is simple to verify that equilibrium price-cost margins, $p_{idm} - c_{idm}$, and equilibrium quantities, q_{idm}, depend on qualities and marginal costs only through the vector of cost-adjusted qualities $\tilde{\beta}_m \equiv \{\tilde{\beta}_{idm}\}$ with $\tilde{\beta}_{idm} \equiv \beta_{idm} - c_{idm}$. Equilibrium variables profits are:

$$R_{im} = \sum_{d \in D_m} r_{id}^*(\tilde{\beta}_m, a_m) \; q_{id}^*(\tilde{\beta}_m, a_m) \tag{7}$$

where a_m is the vector of activity indicators $\{a_{idm}\}$ at market m, and $r_{id}^*()$ and $q_{id}^*()$ represent equilibrium price-cost margins and quantities, respectively.

2.2 Fixed costs and sunk entry costs

The total profit of airline i in market m at quarter t has three components:

$$\Pi_{imt} = R_{imt} - FC_{imt} - EC_{imt} \tag{8}$$

R_{imt} is the equilibrium variable profit that we have defined above, and FC_{imt} and EC_{imt} represent fixed operating costs and entry costs, respectively. Both fixed costs and entry costs are paid at quarter t but they refer to the airline's operations at quarter $t + 1$.[9] Let a_{idmt} be the indicator of the event "airline i will provide product d in market m at period $t + 1$". According to this definition, $a_{idm,t-1}$ represents the incumbent status of airline i in market

[8] See section 7.7 in Anderson, De Palma and Thisse (1992).

[9] We adopt this timing for notational convenience, and it does not have implications on the predictions of the model.

m, product d and period t. At period t, $a_{idm,t-1}$ is a predetermined state variable and a_{idmt} is a current decision variable. Our specification of fixed costs and entry costs is:

$$\begin{aligned} FC_{imt} &= \sum_{d \in D_m} a_{idmt} \ (FC_{idmt} + \varepsilon_{idmt}) \\ EC_{imt} &= \sum_{d \in D_m} (1 - a_{idm,t-1}) \ a_{idmt} \ EC_{idmt} \end{aligned} \tag{9}$$

The product-specific fixed cost $FC_{idmt} + \varepsilon_{idmt}$ is paid only if the airline decides to provide product d in route m next period, i.e., if $a_{idmt} = 1$. The product-specific entry cost EC_{idmt} is paid only when the airline does not provide this product in the market at period t but it decides to start providing the product next period, i.e., if $a_{idm,t-1} = 0$ and $a_{idmt} = 1$. The terms $\{FC_{idmt}\}$ and $\{EC_{idmt}\}$ are common knowledge for all the airlines. However, the ε components of fixed costs are private information of the airline. There are two main reasons why we incorporate these private information shocks. First, while the existence of an equilibrium is not guaranteed in dynamic games of complete information, dynamic games of incomplete information have at least one equilibrium under mild regularity conditions (see Doraszelski and Satterthwaite, 2007). And second, private information state variables are a convenient way of introducing unobservables in empirical dynamic games. Unobservables which are private information and independently distributed across players can explain part of the heterogeneity in players' actions without generating a endogeneity problem. The private information shocks $\{\varepsilon_{idmt}\}$ are assumed to be independently and identically distributed over firms and over time.

Our specification of the common knowledge component of fixed costs and entry costs is similar to the one of marginal costs and consumers' willingness to pay:

$$\begin{aligned} FC_{idmt} &= \gamma_1^{FC} \ NS + \gamma_2^{FC} \ HUB_{imt}^O + \gamma_3^{FC} \ HUB_{imt}^D + \gamma_4^{FC}(1 - NS)HUB_{imt}^C + \gamma_5^{FC} DIST_m \\ &+ \gamma_i^{FC(1)} + \gamma_{Omt}^{FC(2)} + \gamma_{Dmt}^{FC(3)} \\ EC_{idmt} &= \gamma_1^{EC} \ NS + \gamma_2^{EC} \ HUB_{imt}^O + \gamma_3^{EC} \ HUB_{imt}^D + \gamma_4^{EC}(1 - NS)HUB_{imt}^C + \gamma_5^{EC} DIST_m \\ &+ \eta_i^{EC(1)} + \eta_{Omt}^{EC(2)} + \eta_{Dmt}^{EC(3)} \end{aligned} \tag{10}$$

where $\gamma's$ and $\eta's$ are parameters. Note that fixed costs and entry costs depend on the hub-size or scale of operation of the airline in each of the airports of the route.

2.3 Dynamic game of network competition

At the end of every quarter, once variable profits and fixed costs have been realized, airlines decide the routes that they will operate and the products they will provide next quarter. The decision is dynamic because part of the cost of entry in a route is sunk and it will not be recovered after exit. Airlines are forward-looking and take into account the implications of the entry-exit decision on future profits and on the expected future reaction of competitors. Entry-exit decisions in a route have implications on the airline's profits at other route-markets which are interconnected due to the existence of hub-size effects. In our model, airlines also take into account that profits at different route-markets are interconnected.

The estimation and solution of a dynamic game where the airline's headquarters centralizes entry-exit and product decisions at all local markets would be very challenging. Given the large number of local markets (i.e., $M = C(C-1) = 55 * 54 = 2970$), the dimension of the state space in that centralized game would be extremely large. Instead, we consider that an airline's entry-exit and product decisions are decentralized at the route-market level. More importantly, we incorporate two simplifying assumptions that reduce very significantly the complexity of this dynamic game.

ASSUMPTION NET-1: The shocks $\{\varepsilon_{idmt}^{FC}, \varepsilon_{idmt}^{EC}\}$ are private information of the local manager of airline i at route-market m. These shocks are unknown to the managers of airline i at markets other than m.

ASSUMPTION NET-2: The local manager at market m maximizes the value of the airline at the set of routes/markets which share a common airport with route m. We represent this set of local markets as Λ_m. Therefore, the local manager maximizes

$$E_t \left(\sum_{s=0}^{\infty} \delta^s \left[\sum_{m' \in \Lambda_m} \Pi_{im',t+s} \right] \right) \tag{11}$$

where $\delta \in (0, 1)$ is the time discount factor.

The number of routes in the set Λ_m is $2C$ (i.e., 110, in our application), which is much smaller than M (i.e., 2970). This reduces the dimension of the state space in several orders of magnitude. At the same time, the assumption maintains the network structure of the model and, very importantly, the feature that every local manager takes into account that entry/exit decisions in his market has implications on the airline's profits at connected markets.

An airline decision in market m at period t is a vector $a_{imt} \equiv \{a_{idmt} : d \in D_m\}$. Let x_{mt} be the vector with all the payoff-relevant, common knowledge state variables for the entry-exit decisions in market m at period t. This vector includes, for every airline and every route-market n connected with market m: airlines' incumbent status, $\{a_{in,t-1}\}$; hub-sizes, $\{HUB_{int}\}$; airport shocks in cost-adjusted quality, $\{\xi^{(2)}_{Ont} - \omega^{(2)}_{Ont}\}$ and $\{\xi^{(3)}_{Dnt} - \omega^{(3)}_{Dnt}\}$; airline's shocks in cost-adjusted quality, $\{\xi^{(4)}_{idnt} - \omega^{(4)}_{idnt}\}$; airport shocks in fixed cots, $\{\eta^{FC(2)}_{Ont}\}$ and $\{\eta^{FC(3)}_{Dnt}\}$; and airport shocks in entry costs, $\{\eta^{EC(2)}_{Ont}\}$ and $\{\eta^{EC(3)}_{Dnt}\}$. We use the vector $\varepsilon_{imt} \equiv \{\varepsilon_{idmt} : d \in D_m\}$ to represent the private information shocks of the local manager of airline i in route m. An airline's payoff-relevant information in market m at quarter t is $\{x_{mt}, \varepsilon_{imt}\}$. We assume that an airline's strategy in market m depends only on these payoff relevant state variables, i.e., Markov equilibrium assumption.

Let $\boldsymbol{\sigma} \equiv \{\sigma_i(x_{mt}, \varepsilon_{imt}) : i = 1, 2, ..., N\}$ be a set of strategy functions, one for each airline (local manager), such that σ_i is a function from X into $\{0,1\}^{|D|}$, where X is the support of x_{mt} and $|D|$ is the number of elements in the set of product types D. A Markov Perfect Equilibrium (MPE) in this game is a set of strategy functions such that each local manager's strategy maximizes the value of the airline (in the subset of market Λ_m) for each possible state $(x_{mt}, \varepsilon_{imt})$ and as given other airlines' strategies, More formally, $\boldsymbol{\sigma}$ is a MPE if for every airline i and every state $(x_{mt}, \varepsilon_{imt})$ we have that:

$$\sigma_i(x_{mt}, \varepsilon_{imt}) = \arg \max_{a_i \in \{0,1\}^{|D|}} \left\{ \, v_i^{\boldsymbol{\sigma}}(a_i | x_m) + \varepsilon_{imt}(a_i) \, \right\} \tag{12}$$

where $v_i^{\boldsymbol{\sigma}}(a_i | x_{mt}) + \varepsilon_{imt}(a_i)$ is the value of airline i if it chooses alternative a_i given that the current state is $(x_{mt}, \varepsilon_{imt})$ and that all firms will behave in the future according to their strategies in $\boldsymbol{\sigma}$. This value has two components: $\varepsilon_{imt}(a_i)$, which is the contribution of private information shocks; and $v_i^{\boldsymbol{\sigma}}(a_i|x_{mt})$, which is common knowledge and contains both current and future expected profits. We call $v_i^{\boldsymbol{\sigma}}$ the choice-specific value function. By definition:

$$v_i^{\boldsymbol{\sigma}}(a_i|x_{mt}) \equiv E\left(\sum_{s=0}^{\infty} \delta^s \left[\sum_{m' \in \Lambda_m} \Pi_i\left(\boldsymbol{\sigma}_{m't+s}, x_{m't+s}, \varepsilon_{im't+s}\right)\right] \mid x_{mt},\ a_{imt} = a_i\right) \tag{13}$$

where $\boldsymbol{\sigma}_{mt+s} \equiv \boldsymbol{\sigma}\left(x_{mt+s}, \boldsymbol{\varepsilon}_{mt+s}\right)$. Equations (12) and (13) describe a MPE as a fixed point in the space of strategy functions. In this definition of MPE, the functions $v_i^{\boldsymbol{\sigma}}$ depend also on airline i's strategy. Therefore, in equilibrium σ_i is a best response to the other players' strategies and also to the own behavior of player i's in the future.[10] The rest of this subsection describes how we can characterize a MPE in this model as a fixed point of a mapping in the space of conditional choice probabilities.

Given a set of strategy functions $\boldsymbol{\sigma}$ we can define a set of *Conditional Choice Probability (CCP)* functions $\mathbf{P} = \{P_i(a_i|x) : (a_i, x) \in \{0,1\}^{|D|} \times X\}$ such that $P_i(a_i|x)$ is the probability that firm i provides the combination of products a_i given that the common knowledge state is x. That is,

$$P_i(a_i|x) \equiv \int I\left\{\sigma_i(x, \varepsilon_i) = a_i\right\}\ dG_\varepsilon(\varepsilon_i) \tag{14}$$

These probabilities represent the expected behavior of airline i from the point of view of the rest of the airlines. It is possible to show (see Aguirregabiria and Mira, 2007) that the value functions $v_i^{\boldsymbol{\sigma}}$ depend on players' strategy functions only through players' choice probabilities. To emphasize this point we will use the notation $v_i^{\mathbf{P}}$ instead $v_i^{\boldsymbol{\sigma}}$ to represent these value functions. Then, we can use the definition of MPE in expression (12) to represent a MPE in terms of CCPs. A set of CCP functions $\mathbf{P}$ is a MPE if for every airline i and every state x we have that:

$$P_i(a_i|x) = \int I\left\{a_i = \arg\max_{a_i^* \in \{0,1\}^{|D|}} \left\{\ v_i^{\mathbf{P}}(a_i^*|x) + \varepsilon_i(a_i^*)\ \right\}\right\} dG_\varepsilon(\varepsilon_i) \tag{15}$$

[10] That is, this best response function incorporates a *'policy iteration'* in the firm's dynamic programming problem. The *Representation Lemma* in Aguirregabiria and Mira (2007) shows that we can use this type of best response functions to characterize every MPE in the model. A set of strategy functions is a MPE in this model if and only if these strategies are a fixed point of this best response function. This is an example of the *one-stage-deviation principle* (see Fudenberg and Tirole, 1991, chapter 4, pp. 108-110).

An equilibrium exits (see Doraszelski and Satterthwaite, 2007, and Aguirregabiria and Mira, 2007) but it is not necessarily unique. An equilibrium in this dynamic game provides a description of the joint dynamics of prices, quantities, products and incumbent status for all the possible routes in the US airline industry.

3 Data

We use data from the Airline Origin and Destination Survey (DB1B) collected by the Office of Airline Information of the Bureau of Transportation Statistics. The DB1B survey is a 10% sample of airline tickets from the large certified carriers in US and it is divided into 3 parts, namely DB1B-Coupon, DB1B-Market and DB1B-Ticket. The frequency is quarterly and it covers every quarter since 1993-Q1. A record in this survey represents a ticket. For each record or ticket the available variables include the operating carrier, the ticketing carrier, the reporting carrier, the origin and destination airports, miles flown, the type of ticket (i.e., round-trip or one-way), the total itinerary fare, and the number of coupons.[11] The raw data set contains millions of tickets for each quarter. For instance, the DB1B 2004-Q4 contains 8,458,753 records. To construct our working sample we have used the DB1B dataset over the year 2004. We describe here the criteria that we have used to construct our working sample, as well as similarities and differences with related studies which have used the DB1B database.

(a) Definition of a market and a product. We define a market as a round-trip travel between two cities, an origin city and a destination city. This market definition is the same as in Berry (1992) and Berry, Carnall and Spiller (2006), among others. Our definition of market is also similar to the one used by Borenstein (1989) or Ciliberto and Tamer (2006) with the only difference that they consider airport-pairs instead of city-pairs. The main reason why we consider city-pairs instead of airport-pairs is to allow for substitution in the demand (and in

[11] This data set does no contain any information on ticket restrictions such as 7 or 14 days purchase in advance. Other information that is not available is the day or week of the flight or the flight number.

the supply) of routes that involve airports located in the same city. We distinguish different types of products within a market. The type of product depends on whether the flight is non-stop or stop, and on the origin and destination airports. Thus, the itineraries New York (La Guardia)-Los Angeles, New York (JFK)-Los Angeles, and New York (JFK)-Las Vegas-Los Angeles are three different products in the New York-Los Angeles route-market.

(b) Selection of markets. We started selecting the 75 largest US cities in terms of population in 2004. We use city population estimates from the Population Estimates Program in the Bureau of Statistics to find out the 75 largest US cities in 2004.[12] For each city, we use all the airports (classified as primary airports by the Federal Aviation Administration) in the city. Some of the 75 cities belong to the same metropolitan area and share the same airports. We group these cities. Finally, we have 55 cities or metropolitan areas and 63 airports. Table 1 presents the list of "cities" with their airports and population.[13] To measure market size we use the total population in the cities of the origin and destination airports. The number of possible markets (routes) is therefore $M = 55 * 54 = 2,970$. Table 2 presents the top 25 routes in 2004 with their annual number of passengers according to DB1B.

(c) Definition of carrier. There may be more than one airline or carrier involved in a ticket. The DB1B distinguishes three types of carriers: operating carrier, ticketing carrier, and reporting carrier. The operating carrier is an airline whose aircraft and flight crew are used in air transportation. The ticketing carrier is the airline that issued the air ticket. And the reporting carrier is the one that submits the ticket information to the Office of Airline Information. According to the directives of the Bureau of Transportation Statistics (Number 224 of the Accounting and Reporting Directives), the first operating carrier is responsible for submitting the applicable survey data as reporting carrier. For more than 70% of the

[12] The Population Estimates Program produces annually population estimates based upon the last decennial census and up-to-date demographic information. We use the data from the category “Cities and towns”.

[13] Our selection criterion is similar to Berry (1992) who selects the 50 largest cities, and uses city-pair as definition of market. Ciliberto and Tamer (2006) select airport-pairs within the 150 largest Metropolitan Statistical Areas. Borenstein (1989) considers airport-pairs within the 200 largest airports.

tickets in this database the three variables are the same. For the construction of our working sample we use the *reporting carrier* to identify the airline and assume that this carrier pays the cost of operating the flight and receives the revenue for providing this service.

(e) Selection of tickets. We apply several selection filters on tickets in the DB1B database. We eliminate all those tickets with some of the following characteristics: (1) one-way tickets, and tickets which are neither one-way nor round-trip; (2) more than 6 coupons (a coupon is equivalent to a segment or a boarding pass); (3) foreign carriers;[14] and (4) tickets with fare credibility question by the *Department of Transportation*.

(f) Airlines. According to DB1B, there are 31 airlines operating in our selected markets in 2004. However, not all these airlines can be considered as independent because some of them belong to the same corporation or have very exclusive code-sharing agreements.[15] We take this into account in our analysis. Table 3 presents our list of 23 airlines. The notes in the table explains how some of these "airlines" combine several carriers. The table also reports the number of passengers in our selected markets and the number of markets that each airline operates. While *Southwest* is the company that flies more passengers in the selected markets (more than 25 million passengers), it is only the fourth airline in terms of number of markets in which it is active. American, Delta, and United, in this order, are the leaders in number of operated routes.

(g) Definition of active carrier in a route-product. We consider that airline i provides product d in route-market m at quarter t if during that quarter the airline had at least 20 passengers per week (260 per quarter) in that route and for that product.

(h) Construction of quantity and price data. A ticket/record in the DB1B database may correspond to more than one passenger. The DB1B-Ticket dataset reports the number of passengers in a ticket. Our quantity measure q_{idmt} is the number of passengers in the DB1B

[14] For example, there may be a ticket sold and operated by Bristish Airway and reported by American Airline. This situation represents less than 1% of our raw data.

[15] Code sharing is a practice where a flight operated by an airline is jointly marketed as a flight for one or more other airlines.

survey at quarter t that corresponds to airline i, market m and product d. The DB1B-Ticket dataset reports the total itinerary fare. We construct the price variable p_{idmt} (measured in dollars-per-passenger) as the ratio between the sum of fares of tickets in group (i, d, m, t) and the sum of passengers of tickets in the same group.

(i) Measure of hub size. *** OTHER MEASURES OF HUB-SIZE. NUMBER OF PASSENGERS ACTUALLY FLOWN. NUMBER OF ROUTES. ****For each airport and airline we construct a measure of the scale of operation, or *hub-size*, of the airline at the airport. Following Berry (1990) and Berry, Carnall and Spiller (2006), we measure the hub-size of an airline-airport as the sum of the population in other markets that the airline serves from this airport. The reason to weight routes by the number of passengers travelling in the route is that more popular routes are more valued by consumers and therefore this hub measure takes into account this service to consumers. Table 4 presents, for each airline, the two airports with highest hub sizes. According to our measure, the largest hub sizes are: Delta Airlines at Atlanta (48.5 million people) and Tampa (46.9); Northwest at Detroit (47.6) and Minneapolis. Paul (47.1); Continental at Washington International (46.9) and at Cleveland (45.6); American at Dallas-Fort Worth (46.7) and Chicago-O'Hare (44.4); and United at Denver (45.9) and San Francisco (45.8). Note that Southwest, though flying more passengers than any other airline, has hub-sizes which are not even within the top 50.

(j) Descriptive statistics. Our working dataset is an unbalanced panel with six dimensions: route (2970 values), airline (23 values), origin-destination airports (a maximum of 9 values), direct flight indicator (2 values), and time period (4 quarters). The number of observations is 249,530. Tables 5 and 6 present statistics that describe market structure and its dynamics. **** MORE ON DESCRIPTIVE STATISTICS *****

4 Estimation of the structural model

Our approach to estimate the structural model proceeds in three stages. First, we estimate the parameters in the demand system using information on prices, quantities and characteristics of each observed airline-route-product. Given the estimated demand parameters, the Nash-Bertrand equilibrium conditions provide the value of marginal costs for every airline-route-product *observed* in the data. In a second step, we estimate the marginal cost function in equation (5) using the sample of estimated marginal costs for the observed products. Steps 1 and 2 provide estimates of the effects of hub-size on demand and variable costs. Furthermore, we obtain estimates of variable profits for every possible, observed or not, airline-route-product. Finally, given these estimates of variable profits, we obtain fixed costs and entry costs from the dynamic game of market entry-exit. For this third step we use a recursive pseudo maximum likelihood (PML) estimator as proposed in Aguirregabiria and Mira (2007). To deal with the very large dimension of the state-space in our dynamic game, we combine the recursive PML procedure with an interpolation method.

4.1 Estimation of the demand system

The demand model can be represented using the regression equation:

$$\ln\left(s_{idmt}\right) - \ln\left(s_{0mt}\right) \;=\; Z_{idmt}\,\beta + \left(\frac{-1}{\sigma_1}\right) p_{idmt} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s_{i|dmt}\right) + \xi_{idmt}^{(4)} \qquad (16)$$

The vector of regressors Z_{idmt} is the one in equation (2): i.e., dummy for direct-flight, hub-size variables, distance, airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies. It is well-known that an important econometric issue in the estimation of this demand system is the endogeneity of prices and conditional market shares $\ln\left(s_{i|dmt}\right)$. Equilibrium prices depend on the characteristics (observable and unobservable) of all products, and therefore the regressor p_{idmt} is correlated with the unobservable $\xi_{idmt}^{(4)}$. Similarly, the regressor $\ln\left(s_{i|dmt}\right)$ depends on unobserved characteristics and it is endogenous. In our model, we have other potential endogeneity problem. The hub-size variables, included in the vector Z_{idmt}, depend on the entry decisions of airline i in routes connected with route m. Therefore, these variables may be correlated with the demand shock $\xi_{idmt}^{(4)}$. We consider the following identifying assumptions.

**** WHICH ARE THE IDENTIFICATION ASSUMPTIONS IN BERRY (1990) AND IN BCS (2006)? ****

ASSUMPTION D1: Idiosyncratic demand shocks $\{\xi_{idmt}^{(4)}\}$ *are private information of the manager of airline* i *at route* m*. Furthermore, for any two markets* $m \neq m'$*, the demand shocks* $\xi_{idmt}^{(4)}$ *and* $\xi_{idm't}^{(4)}$ *are independently distributed.*

After controlling for airline fixed effects, $\xi_i^{(1)}$, and for airport-time effects, $\xi_{Omt}^{(2)}$ and $\xi_{Dmt}^{(3)}$, the local demand shocks of an airline-route are not correlated across routes. Under Assumption D1 the hub variables HUB_{im}^{O} and HUB_{im}^{D} are independent of $\xi_{idmt}^{(4)}$ and therefore are exogenous variables: $E\left(\xi_{idmt}^{(4)} \mid HUB_{im}^{O},\, HUB_{im}^{D}\right) = 0$.

ASSUMPTION D2: For any two airlines $i \neq j$ *and any two different markets* $m \neq m'$*, the demand shocks* $\xi_{idmt}^{(4)}$ *and* $\xi_{jdm't}^{(4)}$ *are independently distributed.*

Under this assumption the hub variables of other airlines in the same market are such that $E\left(\xi_{idmt}^{(4)} \mid HUB_{jm}^{O},\, HUB_{jm}^{D}\right) = 0$. Furthermore, by the equilibrium condition, prices depend on the hub size of every active firm in the market. Therefore, we can use HUB_{jm}^{O} and HUB_{jm}^{D} as instruments for the price p_{idmt} and the market share $\ln\left(s_{i|dmt}\right)$. Note that Assumptions D1 and D2 are testable. Using the residuals from the estimation we can test for spatial (cross market) correlation in idiosyncratic demand shocks $\xi_{idmt}^{(4)}$. To avoid the small sample bias of IV estimation, we want to use the smallest number of instruments with the largest explanatory power. We use as instruments the average value of the hub sizes (in origin and in destination airports) of the competitors.

Note that in our estimation of demand (and marginal costs) there is a potential self-selection bias due to fact that we observe prices and quantities only for those products which are active in the market. If idiosyncratic demand shocks $\{\xi_{idmt}^{(4)}\}$ affect entry-exit decisions, then that self-selection bias will exist. The following assumption implies that current demand shocks do not contain any information on future profits and therefore they are not part of the vector of state variables in the entry-exit dynamic game.

ASSUMPTION D3: The demand shocks $\xi_{idmt}^{(4)}$ are independently distributed over time.

Tables 8 presents estimates of the demand system. To illustrate the endogeneity problem, we report both OLS and IV estimation results. The magnitude of the price coefficient in the IV estimates is much smaller than that in the OLS. The willingness to pay for a direct flight can be obtained as the ratio between the DIRECT coefficient and the FARE and it is equal to $152 (in the IV estimates) which is similar to the estimates in previous papers. The estimated effects of the hub indexes are also plausible. Expanding the scale of hub operation in origin and destination airports increase the demand. The hub effect from origin airport is stronger than that from the destination airport. The result is also consistent with hub effect obtained in the literature such as Berry (1990). Finally, longer nonstop distance makes consumer more inclined to use airplane transportation than other transportation modes.

*** Tests of Assumptions D1, D2 and D3. ***

*** COMPARE THE ESTIMATES WITH BCS, LEDERMAN, ETC ****

4.2 Estimation of variable costs

Given the Nash-Bertrand price equations and our estimates of demand parameters, we can obtain estimates of marginal costs as $\hat{c}_{idmt} = p_{idmt} - \hat{r}_{idmt}$, where $\{\hat{r}_{idmt}\}$ are the estimated margins which are obtained by solving the system of equations:

$$\hat{r}_{idmt} = \hat{\sigma}_2 + \left[1 - \frac{\hat{\sigma}_2}{\hat{\sigma}_1}\left(1 - \bar{s}_{imt}\right)\right] \left[\sum\nolimits_{d' \in D} \hat{r}_{id'mt} \; s_{d'|imt}\right] \tag{17}$$

Note that these estimates of marginal costs are obtained only for route-airline-product-quarter combinations which are observed in the data. That is, these estimates are available only if product (i, d, m) exits at quarter t. The marginal cost function can be represented using the regression $\hat{c}_{idmt} = Z_{idmt} \; \delta + \omega_{idmt}^{(4)}$. The vector of regressors Z_{idmt} has the same interpretation as in the demand equation: dummy for direct-flight, hub-size variables, distance, airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies.

As in the estimation of demand, the hub-size variables are potentially endogenous regressors in the estimation of the marginal cost function. These variables may be correlated with the cost shock $\omega^{(4)}_{idmt}$. We consider the following identifying assumptions.

ASSUMPTION MC1: Idiosyncratic cost shocks $\{\omega^{(4)}_{idmt}\}$ are private information of the manager of airline i at route m. Furthermore, for any two markets $m \neq m'$, the shocks $\omega^{(4)}_{idmt}$ and $\omega^{(4)}_{idm't}$ are independently distributed.

ASSUMPTION MC2: The marginal cost shocks $\omega^{(4)}_{idmt}$ are independently distributed over time.

Assumption MC1 implies that the hub size variables are exogenous regressors in the marginal cost function. Assumption MC2 implies that $\omega^{(4)}_{idmt}$ is not a state variable in the entry-exit game and therefore there is not self-selection bias in the estimation of the marginal cost function. Under these assumptions, the vector of parameters δ can be estimated consistently by OLS.

Table 9 presents OLS estimates of the marginal cost function. The marginal cost of a direct flight is $12 larger than the marginal cost of an stop-flight, but this difference is not statistically significant. Distance has a significantly positive effect on marginal cost. The airline scale of operation (hub size) at the origin and destination airports reduce marginal costs.

*** Tests of Assumptions MC1 and MC2. ***

*** COMPARE THE ESTIMATES WITH BCS, LEDERMAN, ETC ****

4.3 Estimation of the dynamic game

Assumption NET1-NET2 establish that the manager of an airline at a local market/route maximizes the value of the airline at the set of routes which share a common airport with his route. According to these assumptions, the relevant one-period profit for the local manager of route m if he chooses the combination of products a_{im} is $E\left(\sum_{m' \in \Lambda_m} \Pi_{im't} \mid a_{imt} = a_{im}, x_{mt}, \varepsilon_{imt}\right)$.

We can write this profit function as:

$$E\left(\sum\nolimits_{m'\in\Lambda_m} \Pi_{im't}(a_{im}) \mid a_{imt}=a_{im}, x_{mt}, \varepsilon_{imt}\right) = w_{imt}^{\mathbf{P}}(a_{im})'\boldsymbol{\theta} + \varepsilon_{imt}(a_{im})$$

where $\boldsymbol{\theta}$ is a vector of structural parameters and $w_{imt}^{\mathbf{P}}(a_i)$ is a vector of observable variables. Let $\boldsymbol{\eta}^{FC(1)}$ and $\boldsymbol{\eta}^{EC(1)}$ be the vectors with the airline fixed-effect parameters; and let $\boldsymbol{\eta}_O^{FC(2)}$, $\boldsymbol{\eta}_D^{FC(3)}$, $\boldsymbol{\eta}_O^{EC(2)}$ and $\boldsymbol{\eta}_D^{EC(3)}$ be the vectors with airport-origin and airport-destination fixed-effect parameters. Then, the vectors $\boldsymbol{\theta}$ and $w_{imt}(a_i)$ have the following definitions:

$$\boldsymbol{\theta} = \begin{pmatrix} 1 \\ \gamma_{00}^{FC} \\ \gamma_{01}^{FC} \\ \gamma_{1}^{FC} \\ \gamma_{2}^{FC} \\ \gamma_{00}^{EC} \\ \gamma_{01}^{EC} \\ \gamma_{1}^{EC} \\ \gamma_{2}^{EC} \\ \boldsymbol{\eta}^{FC(1)} \\ \boldsymbol{\eta}_O^{FC(2)} \\ \boldsymbol{\eta}_D^{FC(3)} \\ \boldsymbol{\eta}^{EC(1)} \\ \boldsymbol{\eta}_O^{EC(2)} \\ \boldsymbol{\eta}_D^{EC(3)} \end{pmatrix} \quad \text{and} \quad w_{imt}(a_i) = \begin{pmatrix} R_{imt} \\ a_{i0m,t-1} \\ a_{i1m,t-1} \\ (a_{i0m,t-1}+a_{i1m,t-1})\, HUB_{imt}^{O} \\ (a_{i0m,t-1}+a_{i1m,t-1})\, HUB_{imt}^{D} \\ (1-a_{i0m,t-1})a_{i0} \\ (1-a_{i1m,t-1})a_{i1} \\ [(1-a_{i0m,t-1})a_{i0}+(1-a_{i1m,t-1})a_{i1}]\, HUB_{imt}^{O} \\ [(1-a_{i0m,t-1})a_{i0}+(1-a_{i1m,t-1})a_{i1}]\, HUB_{imt}^{D} \\ (a_{i0m,t-1}+a_{i1m,t-1})\ \mathbf{1}_i \\ (a_{i0m,t-1}+a_{i1m,t-1})\ \mathbf{1}_{Omt} \\ (a_{i0m,t-1}+a_{i1m,t-1})\ \mathbf{1}_{Dmt} \\ [(1-a_{i0m,t-1})a_{i0}+(1-a_{i1m,t-1})a_{i1}]\ \mathbf{1}_{Om} \\ [(1-a_{i0m,t-1})a_{i0}+(1-a_{i1m,t-1})a_{i1}]\ \mathbf{1}_{Dm} \\ [(1-a_{i0m,t-1})a_{i0}+(1-a_{i1m,t-1})a_{i1}]\ \mathbf{1}_{i} \end{pmatrix}$$

where $\mathbf{1}_i$ is a $N\times 1$ vector with a 1 at the $i-th$ position and zeroes otherwise; $\mathbf{1}_{Om}$ is a $C\times 1$ vector with a 1 at the position of the origin airport in market m and zeroes otherwise; and $\mathbf{1}_{Dm}$ has the same definition but for the destination airport.

We assume that private information shocks $\{\varepsilon_{imt}(a_i)\}$ are iid Type 1 extreme value random variables with dispersion parameter σ_ε. Under these assumptions, the equilibrium mapping in CCPs has the following form:

$$\begin{aligned} \Psi_{imt}(a_i|\mathbf{P}) &= \frac{\exp\left\{v_{imt}^{\mathbf{P}}(a_i)/\sigma_\varepsilon\right\}}{\sum_{a_i^*\in\{0,1\}^2}\exp\left\{v_{imt}^{\mathbf{P}}(a_i^*)/\sigma_\varepsilon\right\}} \\ &= \frac{\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_i)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon}+\tilde{e}_{imt}^{\mathbf{P}}(a_i)\right\}}{\sum_{a_i^*\in\{0,1\}^2}\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_i^*)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon}+\tilde{e}_{imt}^{\mathbf{P}}(a_i^*)\right\}} \end{aligned} \tag{18}$$

$\tilde{w}^{\mathbf{P}}_{imt}(a_i)$ is the expected and discounted value of current and future vectors w_i given that the current state is (x_{mt}, z_m), that airline i choose alternative i and that all the firms behave in the future according to their probabilities in $\mathbf{P}$. Similarly, $\tilde{e}^{\mathbf{P}}_{imt}(a_i)$ is the expected and discounted value of $e_{imt+s} \equiv -\ln P_i(a_{imt+s}|x_{mt+s}, z_m)$ given given that the current state is (x_{mt}, z_m), that airline i choose alternative i and that all the firms behave in the future according to their probabilities in $\mathbf{P}$.

Nested Pseudo Likelihood (NPL) Estimator. For the sake of notational simplicity, let's use $\boldsymbol{\theta}$ to represent $\boldsymbol{\theta}/\sigma_\varepsilon$. For arbitrary values of $\boldsymbol{\theta}$ and $\mathbf{P}$, define the likelihood function:

$$\begin{aligned} Q(\boldsymbol{\theta}, \mathbf{P}) &\equiv \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{N} \ln \Psi_{imt}(a_{imt}|\boldsymbol{\theta}, \mathbf{P}) \\ &= \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{N} \ln \frac{\exp\left\{\tilde{w}^{\mathbf{P}}_{imt}(a_{imt})'\boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}_{imt}(a_{imt})\right\}}{\sum_{a_i \in \{0,1\}^2} \exp\left\{\tilde{w}^{\mathbf{P}}_{imt}(a_i)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon} + \tilde{e}^{\mathbf{P}}_{imt}(a_i)\right\}} \end{aligned} \tag{19}$$

Let $\boldsymbol{\theta}_0$ be the true value of the $\boldsymbol{\theta}$ in the population, and let $\mathbf{P}_0$ be the true equilibrium CCPs in the population. If the model is correct, then $\mathbf{P}_0$ is an equilibrium associated with $\boldsymbol{\theta}_0$: i.e., $\mathbf{P}_0 = \Psi(\boldsymbol{\theta}_0, \mathbf{P}_0)$. A two-step estimator of $\boldsymbol{\theta}$ is defined as a pair $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ such that $\hat{\mathbf{P}}$ is a nonparametric consistent estimator of $\mathbf{P}_0$ and $\hat{\boldsymbol{\theta}}$ maximizes the pseudo likelihood $Q(\boldsymbol{\theta}, \hat{\mathbf{P}})$. The main advantage of this estimator is its simplicity. However, it has several important limitations (see Aguirregabiria and Mira, 2007). In particular, it can be seriously biased due to the imprecise nonparametric estimates of $\hat{\mathbf{P}}$. The NPL estimator is defined as a pair $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ that satisfies the following two conditions (Aguirregabiria and Mira, 2007):

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg\max_{\boldsymbol{\theta} \in \Theta} \; Q(\boldsymbol{\theta}, \hat{\mathbf{P}}) \\ \hat{\mathbf{P}} &= \Psi(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}}) \end{aligned} \tag{20}$$

That is, $\hat{\boldsymbol{\theta}}$ maximizes the pseudo likelihood given $\hat{\mathbf{P}}$ (as in the two-step estimator), and $\hat{\mathbf{P}}$ is an equilibrium associated with $\hat{\boldsymbol{\theta}}$. This estimator has lower asymptotic variance and finite sample bias than the two step estimator. A simple (though not necessarily efficient) algorithm to obtain the NPL estimator is just a recursive extension of the two-step method.

We can start with an initial estimator of CCPs, say $\hat{\mathbf{P}}_0$, not necessarily a consistent estimator of $\mathbf{P}_0$, and then apply the following recursive procedure. At iteration $K \geq 1$, we update our estimates of $(\boldsymbol{\theta}_0, \mathbf{P}_0)$ by using the pseudo maximum likelihood estimator $\hat{\boldsymbol{\theta}}_K = \arg\max_{\boldsymbol{\theta}\in\Theta}$ $Q(\boldsymbol{\theta}, \hat{\mathbf{P}}_{K-1})$ and then the policy iteration $\hat{\mathbf{P}}_K = \Psi(\hat{\boldsymbol{\theta}}_K, \hat{\mathbf{P}}_{K-1})$, that is:

$$\hat{\mathbf{P}}_{K,imt}(a_i) = \frac{\exp\left\{\tilde{w}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i)'\hat{\boldsymbol{\theta}}_K + \tilde{e}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i)\right\}}{\sum_{a_i^*\in\{0,1\}^2}\exp\left\{\tilde{w}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i^*)'\hat{\boldsymbol{\theta}}_K + \tilde{e}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i^*)\right\}} \tag{21}$$

Upon convergence this algorithm provides the NPL estimator. Maximization of the pseudo likelihood function with respect to $\boldsymbol{\theta}$ is extremely simple because $Q(\boldsymbol{\theta}, \mathbf{P})$ is globally concave in $\boldsymbol{\theta}$ for any possible value of $\mathbf{P}$. The main computational burden in the implementation of the NPL estimator comes from the calculation of the present values $\tilde{w}_{imt}^{\mathbf{P}}$ *and* $\tilde{e}_{imt}^{\mathbf{P}}$. We now describe in detail on the computation of these values.

Computing the present values $\tilde{w}_{imt}^{\mathbf{P}}$ *and* $\tilde{e}_{imt}^{\mathbf{P}}$. Let $f_{xi}^{\mathbf{P}}(x_{mt+1}|x_{mt}, z_m, a_{imt})$ be the transition probability of the vector of incumbent status $\{x_{mt}\}$ conditional on the current choice of airline i. This transition probability is a known function of the vector of CCPs $\mathbf{P}$. It is possible to show that (for notational simplicity I omit z_m as an argument in CCPs, transitions and values):

$$\begin{aligned}
\tilde{w}_{imt}^{\mathbf{P}}(a_i) &= w_{imt}(a_i) + \delta \sum_{x_{mt+1}\in\{0,1\}^{2N}} f_{xi}^{\mathbf{P}}(x_{mt+1}|x_{mt}, a_i)\ W_{iw}^{\mathbf{P}}(x_{mt+1}) \\
\tilde{e}_{imt}^{\mathbf{P}}(a_i) &= \delta \sum_{x_{mt+1}\in\{0,1\}^{2N}} f_{xi}^{\mathbf{P}}(x_{mt+1}|x_{mt}, a_i)\ W_{ie}^{\mathbf{P}}(x_{mt+1})
\end{aligned} \tag{22}$$

where $W_{iw}^{\mathbf{P}}(.)$ is a $1 \times \dim(\boldsymbol{\theta})$ vector and $W_{ie}^{\mathbf{P}}(.)$ is a scalar and both are (basis functions for) valuation operators. Define the matrix $\mathbf{W}_i^{\mathbf{P}} \equiv \{[W_{iw}^{\mathbf{P}}(x), W_{ie}^{\mathbf{P}}(x)] : x \in \{0,1\}^{2N}\}$. Then, the valuation basis $\mathbf{W}_i^{\mathbf{P}}$ is defined as the unique solution in $\mathbf{W}$ to the following contraction mapping:

$$\mathbf{W} = \sum_{a_i\in\{0,1\}^2} \mathbf{P}_i(a_i) * \left\{[\mathbf{w}_i(a_i), -\ln \mathbf{P}_i(a_i)] + \delta\ \mathbf{F}_{xi}^{\mathbf{P}}(a_i)\ \mathbf{W}\right\} \tag{23}$$

where $\mathbf{P}_i(a)$ is the column vector of CCPs $\{P_i(a_i|x) : a_i \in \{0,1\}^2; x \in \{0,1\}^{2N}\}$. The computational cost to obtain these values is equivalent to solving once the dynamic programming

(DP) of an airline. However, due to the relatively large number of heterogeneous players, this DP problem has high dimensionality. The number of states x is $2^{2*27} \simeq 10^{16}$. It is clear that solving this problem exactly would be extremely demanding.

We use interpolation-randomization in a very similar way as in Rust (1997) to approximate $\mathbf{W}_i^{\mathbf{P}}$, $\tilde{w}_{imt}^{\mathbf{P}}(a_i)$ and $\tilde{e}_{imt}^{\mathbf{P}}(a_i)$. Let $X^* = \{x_1, x_2, ..., x_{|X^*|}\}$ be a subset of the actual state space $\{0,1\}^{2N}$. The number of elements in this subset, $|X^*|$, is given by the amount of high-speed memory in our computer. The grid points in X^* can be selected by making $|X^*|$ random draws from a uniform distribution over the set $\{0,1\}^{2N}$. Define the following transition probabilities:

$$f_{xi}^{\mathbf{P}*}(x'|x, a_i) = \frac{f_{xi}^{\mathbf{P}}(x'|x, a_i)}{\sum_{x'' \in X^*} f_{xi}^{\mathbf{P}}(x''|x, a_i)} \tag{24}$$

And let $\mathbf{F}_{xi}^{\mathbf{P}*}(a_i)$ be the matrices of transition probabilities associated with $f_{xi}^{\mathbf{P}*}$. Similarly, we define $\mathbf{P}_i^*(a_i)$ and $\mathbf{w}_i^*(a_i)$ as $\mathbf{P}_i(a_i)$ and $\mathbf{w}_i(a_i)$, respectively, but restricted to the set X^*. Then, we can define $\mathbf{W}_i^{\mathbf{P}*}$ as the unique solution in $\mathbf{W}$ to the following contraction mapping:

$$\mathbf{W} \quad = \quad \sum_{a_i \in \{0,1\}^2} \mathbf{P}_i^*(a_i) * \left\{ [\mathbf{w}_i^*(a_i), -\ln \mathbf{P}_i^*(a_i)] + \delta \ \mathbf{F}_{xi}^{\mathbf{P}*}(a_i) \ \mathbf{W} \right\} \tag{25}$$

Given $\mathbf{W}_i^{\mathbf{P}*}$, our approximation to the values $\tilde{w}_{imt}^{\mathbf{P}}(a_i)$ and $\tilde{e}_{imt}^{\mathbf{P}}(a_i)$ is:

$$\begin{aligned} \tilde{w}_{imt}^{\mathbf{P}*}(a_i) &= w_{imt}(a_i) + \delta \sum_{x_{mt+1} \in X^*} f_{xi}^{\mathbf{P}*}(x_{mt+1}|x_{mt}, a_i) \ W_{iw}^{\mathbf{P}*}(x_{mt+1}) \\ \tilde{e}_{imt}^{\mathbf{P}*}(a_i) &= \delta \sum_{x_{mt+1} \in X^*} f_{xi}^{\mathbf{P}*}(x_{mt+1}|x_{mt}, a_i) \ W_{ie}^{\mathbf{P}*}(x_{mt+1}) \end{aligned} \tag{26}$$

As discussed in Rust (1997), this approximation has several interesting properties. In general, these approximations are much more precise than the ones based on simple forward simulations. For our estimates we have considered a set X^* with $10,000$ cells which are random draws from a uniform distribution.

Estimation results. Table 11 presents our estimation results for the entry-exit game. We find very significant (both statistically and economically) hub-size effects in fixed operating costs and in entry costs. The effects are particularly important for the case of entry costs.

Sunk entry costs are approximately twice the fixed operating costs of a quarter. *** More discussion. Specification tests.

5 Disentangling demand, cost and strategic factors

We now use our estimate model to measure the contribution of demand, cost and strategic factors to explain why most companies in the US airline industry operate using a hub-and-spoke network. Define the $hub - ratio$ of an airline as the fraction of passengers flying with that airline who have to take a connecting flight in the hub airport of that airline.[16] We analyze how different hub-size effects contribute to the observe hub-ratio of different airlines. The parameters that measure hub-size effects are: cots-adjusted qualities, $\left(\hat{\beta}_2 - \hat{\delta}_2\right)$ and $\left(\hat{\beta}_3 - \hat{\delta}_3\right)$; fixed costs, γ_1^{FC} and γ_2^{FC}; and entry-costs, γ_1^{EC} and γ_2^{EC}. For each of these groups of parameters we perform the following experiments. We make the parameters (for a single airline) equal to zero. Then, we calculate the new equilibrium, and obtain the value of the hub-ratio for that airline.

Let $\boldsymbol{\theta}$ be the vector of structural parameters in the model. An equilibrium associated with $\boldsymbol{\theta}$ is a vector of choice probabilities $\mathbf{P}$ that solves the fixed point problem $\mathbf{P} = \boldsymbol{\Psi}(\boldsymbol{\theta}, \mathbf{P})$. For a given value $\boldsymbol{\theta}$, the model can have multiple equilibria. The model can be completed with an equilibrium selection mechanism. This mechanism can be represented as a function that, for given $\boldsymbol{\theta}$, selects one equilibrium within the set of multiple equilibria associated with $\boldsymbol{\theta}$. We use $\boldsymbol{\pi}(\boldsymbol{\theta})$ to represent this (unique) selected equilibrium. Our approach here (both for the estimation and for counterfactual experiments) is completely agnostic with respect to the equilibrium selection mechanism. We assume that there is such a mechanism, and that it is a smooth function of $\boldsymbol{\theta}$. But we do not specify any specific equilibrium selection mechanism $\boldsymbol{\pi}(.)$. Let $\boldsymbol{\theta}_0$ be the true value of $\boldsymbol{\theta}$ in the population under study. Suppose that the data (and the population) come from a unique equilibrium associated with $\boldsymbol{\theta}_0$. Let $\mathbf{P}_0$ be the equilibrium in the population. By definition, $\mathbf{P}_0$ is such that $\mathbf{P}_0 = \boldsymbol{\Psi}(\boldsymbol{\theta}_0, \mathbf{P}_0)$ and

[16] In the calculation of this ratio we do not consider passengers whose flights have origin or destination in the hub airport of the airline.

$\mathbf{P}_0 = \boldsymbol{\pi}(\boldsymbol{\theta_0})$. Suppose that given these data and assumptions we have a defined above a consistent estimator of $(\boldsymbol{\theta}_0, \mathbf{P}_0)$. Let $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$ be this consistent estimator. Note that, even after the estimation of the model, we do not know the function $\boldsymbol{\pi}(\boldsymbol{\theta})$. All what we know is that the point $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$ belongs to the graph of this function $\boldsymbol{\pi}$. We want to use the estimated model to study airlines' behavior and equilibrium outcomes under counterfactual scenarios which can be represented in terms of different values $\boldsymbol{\theta}$. Let $\boldsymbol{\theta}^*$ be the vector of parameters under a counterfactual scenario. We want to know the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. The key issue to implement this experiment is that given $\boldsymbol{\theta}^*$ the model has multiple equilibria, and we do not know the function $\boldsymbol{\pi}$. We propose here a method to deal with this problem. The method is based on the following assumptions for the equilibrium mapping and the equilibrium selection mechanism.

Assumption: The mapping $\boldsymbol{\Psi}$ is continuously differentiable in $(\boldsymbol{\theta}, \mathbf{P})$, and the equilibrium selection mechanism $\boldsymbol{\pi}(\boldsymbol{\theta})$ is a continuously differentiable function of $\boldsymbol{\theta}$ around $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$.

Under this assumption we can use a first order Taylor expansion to obtain an approximation to the counterfactual choice probabilities $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$ around our estimator $\hat{\boldsymbol{\theta}}_0$. An intuitive interpretation of our approach is that we select the counterfactual equilibrium which is "closer" (in a Taylor-approximation sense) to the equilibrium estimated from the data. The data is not only used to identify the equilibrium in the population but also to identify the equilibrium in the counterfactual experiments. Given the differentiability of the function $\boldsymbol{\pi}(.)$ and of the equilibrium mapping, a Taylor approximation to $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$ around our estimator $\hat{\boldsymbol{\theta}}_0$ implies that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right) + \frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'}\left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) + O\left(\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2\right) \tag{27}$$

Note that $\boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right) = \hat{\mathbf{P}}_0$ and that $\boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right) = \boldsymbol{\Psi}\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)\right)$. Differentiating this last expression with respect to $\boldsymbol{\theta}$ we have that

$$\frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} = \frac{\partial \boldsymbol{\Psi}\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)\right)}{\partial \boldsymbol{\theta}'} + \frac{\partial \boldsymbol{\Psi}\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)\right)}{\partial \mathbf{P}'}\ \frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} \tag{28}$$

And solving for $\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)/\partial \boldsymbol{\theta}'$ we can represent this Jacobian matrix in terms of Jacobians of $\boldsymbol{\Psi}$ evaluated at the estimated values $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$. That is,

$$\frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} = \left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'} \tag{29}$$

Solving expression (29) into (27) we have that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \hat{\mathbf{P}}_0 + \left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'} \left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) + O\left(\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2\right) \tag{30}$$

Therefore, under the condition that $\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2$ is small, the term $\left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'}$ $\left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right)$ provides a good approximation to the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. Note that all the elements in $\left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'} \left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right)$ are known to the researcher. The most attractive features of this approach are its simplicity and that it is quite agnostic about the equilibrium selection.

Table 12 presents our estimates of the effects on the hub-ratio of eliminating hub-size effects in cost-adjusted qualities, fixed costs and entry costs. For the moment we report estimates only for two airlines: American and United. The most important effects come from eliminating hub-size effects in entry costs. Furthermore, we find that strategic effects are important.

6 Conclusions

To be written

BERRY (1990): Incumbent airlines are the major source of financing for many airports and therefore gain a large degree of bureaucratic control over airport operations. This control may enable them to block the entry or expansion of rivals. *** THIS IS AN ALTERNATIVE (NO TECHNOLOGICAL) INTERPRETATION OF HUB-SIZE EFFECTS ON ENTRY COSTS ***

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Table 1. Cities, Airports and Population

City, State	Airports	City Pop.	City, State	Airports	City Pop.
New York-Newark-Jersey	LGA, JFK, EWR	8,623,609	Las Vegas, NV	LAS	534,847
Los Angeles, CA	LAX, BUR	3,845,541	Portland, OR	PDX	533,492
Chicago, IL	ORD, MDW	2,862,244	Oklahoma City, OK	OKC	528,042
Dallas, TX[(1)]	DAL, DFW	2,418,608	Tucson, AZ	TUS	512,023
Phoenix-Tempe-Mesa, AZ	PHX	2,091,086	Albuquerque, NM	ABQ	484,246
Houston, TX	HOU, IAH, EFD	2,012,626	Long Beach, CA	LGB	475,782
Philadelphia, PA	PHL	1,470,151	New Orleans, LA	MSY	462,269
San Diego, CA	SAN	1,263,756	Cleveland, OH	CLE	458,684
San Antonio,TX	SAT	1,236,249	Sacramento, CA	SMF	454,330
San Jose, CA	SJC	904,522	Kansas City, MO	MCI	444,387
Detroit, MI	DTW	900,198	Atlanta, GA	ATL	419,122
Denver-Aurora, CO	DEN	848,678	Omaha, NE	OMA	409,416
Indianapolis, IN	IND	784,242	Oakland, CA	OAK	397,976
Jacksonville, FL	JAX	777,704	Tulsa, OK	TUL	383,764
San Francisco, CA	SFO	744,230	Miami, FL	MIA	379,724
Columbus, OH	CMH	730,008	Colorado Spr, CO	COS	369,363
Austin, TX	AUS	681,804	Wichita, KS	ICT	353,823
Memphis, TN	MEM	671,929	St Louis, MO	STL	343,279
Minneapolis-St. Paul, MN	MSP	650,906	Santa Ana, CA	SNA	342,715
Baltimore, MD	BWI	636,251	Raleigh-Durham, NC	RDU	326,653
Charlotte, NC	CLT	594,359	Pittsburg, PA	PIT	322,450
El Paso, TX	ELP	592,099	Tampa, FL	TPA	321,772
Milwaukee, WI	MKE	583,624	Cincinnati, OH	CVG	314,154
Seattle, WA	SEA	571,480	Ontario, CA	ONT	288,384
Boston, MA	BOS	569,165	Buffalo, NY	BUF	282,864
Louisville, KY	SDF	556,332	Lexington, KY	LEX	266,358
Washington, DC	DCA, IAD	553,523	Norfolk, VA	ORF	236,587
Nashville, TN	BNA	546,719			

Note (1): Dallas-Arlington-Fort Worth-Plano, TX

Table 2. Top Routes/Markets in 2004

	ORIGIN CITY	DESTINATION CITY	# Passengers (Annual)
1.	New York	Chicago	782,420
2.	Chicago	New York	759,950
3.	Chicago	Las Vegas	748,310
4.	New York	Las Vegas	740,440
5.	Los Angeles	Las Vegas	739,810
6.	Los Angeles	New York	735,180
7.	New York	Los Angeles	685,190
8.	Atlanta	New York	645,680
9.	New York	Atlanta	595,630
10.	Oakland	Los Angeles	556,010
11.	Los Angeles	Oakland	540,000
12.	New York	San Francisco	509,240
13.	Chicago	Los Angeles	479,060
14.	New York	Miami	478,940
15.	San Francisco	New York	464,510
16.	Los Angeles	Chicago	464,300
17.	New York	Tampa	448,770
18.	Chicago	Phoenix	438,880
19.	Dallas	Houston	419,360
20.	Dallas	New York	391,220
21.	Houston	Dallas	380,470
22.	Boston	New York	369,250
23.	Phoenix	Las Vegas	363,300
24.	New York	Boston	360,240
25.	New York	Washington	360,110

Source: DB1B Database

Table 3
Airlines

	Airline (Code)	# Passengers(1) (in thousands)	# Markets(2) in 2004-Q4
1.	Southwest (WN)	25,026	975
2.	American (AA)(3)	20,064	1,464
3.	United (UA)(4)	15,851	1,142
4.	Delta (DL)(5)	14,402	1,280
5.	Continental (CO)(6)	10,084	689
6.	Northwest (NW)(7)	9,517	822
7.	US Airways (US)	7,515	555
8.	America West (HP)(8)	6,745	585
9.	Alaska (AS)	3,886	73
10.	ATA (TZ)	2,608	152
11.	JetBlue (B6)	2,458	45
12.	Frontier (F9)	2,220	176
13.	AirTran (FL)	2,090	199
14.	Mesa (YV)(9)	1,554	260
15.	Midwest (YX)	1,081	76
16.	Trans States (AX)	541	63
17.	Reno Air (QX)	528	59
18.	Spirit (NK)	498	16
19.	Sun Country (SY)	366	21
20.	PSA (16)	84	48
21.	Ryan International (RD)	78	3
22.	Allegiant (G4)	67	5
23.	Aloha (AQ)	44	8

Note (1): Annual number of passengers in 2004 for our selected markets
Note (2): An airline is active in a route if it has at least 20 passengers/week
Note (3): American (AA) + American Eagle (MQ) + Executive (OW)
Note (4): United (UA) + Air Wisconsin (ZW)
Note (5): Delta (DL) + Comair (OH) +Atlantic Southwest (EV)
Note (6): Continental (CO) + Expressjet (RU)
Note (7): Northwest (NW) + Mesaba (XJ)
Note (8): On 2005, America West merged with US Airways.
Note (9): Mesa (YV) + Freedom (F8)

Table 4
Airlines and Hub Size (2004-Q4)

	Airline (Code)	Largest Hub-Size (people in millions)	Second largest Hub-Size (people in millions)
1.	Southwest (WN)	MCI (31.5)	BWI (30.5)
2.	American (AA)	DFW (46.7)	ORD (44.4)
3.	United (UA)	DEN (45.9)	SFO (45.8)
4.	Delta (DL)	ATL (48.5)	TPA (46.8)
5.	Continental (CO)	IAH (46.9)	CLE (45.6)
6.	Northwest (NW)	DTW (47.6)	MSP (47.1)
7.	US Airways (US)	CLT (39.2)	BOS (38.6)
8.	America West (HP)	PHX (39.6)	LAS (36.1)
9.	Alaska (AS)	SEA (29.0)	PDX (26.0)
10.	ATA (TZ)	IND (26.2)	MDW (25.0)
11.	JetBlue (B6)	LGB (10.7)	OAK (10.2)
12.	Frontier (F9)	DEN (35.1)	PDX (14.2)
13.	AirTran (FL)	ATL (30.7)	MEM (25.4)
14.	Mesa (YV)	AUS (23.1)	BNA (22.2)
15.	Midwest (YX)	MKE (29.9)	MCI (14.6)
16.	Trans States (AX)	STL (25.4)	PIT (12.6)
17.	Reno Air (QX)	PDX (25.9)	OMA (10.7)
18.	Spirit (NK)	DTW (13.9)	LAX (12.4)
19.	Sun Country (SY)	MSP (21.6)	JFK (0.6)
20.	PSA (16)	ATL (10.0)	IND (8.9)
21.	Ryan International (RD)	ATL (4.4)	LAX (0.4)
22.	Allegiant (G4)	LAS (0.7)	OKC (0.5)
23.	Aloha (AQ)	LAS (4.2)	

Table 5
Descriptive Statistics of Market Structure
2,970 markets. Period 2004-Q1 to 2004-Q4

	2004-Q1	2004-Q2	2004-Q3	2004-Q4	All Quarters
Markets with 0 airlines	7.27%	11.48 %	11.68%	11.75%	10.55 %
Markets with 1 airline	13.06%	17.17%	17.21%	17.34%	16.20%
Markets with 2 airlines	14.71%	18.89%	18.38%	19.33%	17.83%
Markets with 3 airlines	15.93%	17.10 %	16.40%	16.33%	16.44%
Markets with 4 airlines	15.82%	12.86%	14.14%	13.57%	14.10%
Markets with more than 4 airlines	33.20 %	22.49%	22.19%	21.68%	24.89%
Herfindahl Index (median)	4650	4957	4859	5000	4832
Distribution of Monopoly Markets:					
Delta	15.13%	17.65%	15.26%	15.61%	15.96%
American	14.87%	14.12%	15.07%	12.33%	14.04%
Northwest	13.85%	13.33%	12.72%	14.45%	13.58%
United	11.28%	12.35%	14.68%	15.22%	13.52%
Continental	9.23%	10.78%	13.31%	11.56 %	11.35%
US Airways	8.72%	6.47%	4.89%	5.39%	6.22%
Southwest	3.33%	7.84%	6.46%	4.62%	5.70%
Distribution of # Entrants:					
Markets with 0	-	86.23%	73.91%	74.98%	78.37%
Markets with 1	-	12.26%	21.48%	20.30%	18.01%
Markets with 2	-	1.38%	4.14%	4.41%	3.31%
Markets with >2	-	0.13%	0.47%	0.30%	0.30%
Distribution of # Exits:					
Markets with 0	-	49.29%	75.62%	71.72%	65.54%
Markets with 1	-	31.58%	20.24%	22.26%	24.69%
Markets with 2	-	12.05%	3.54%	5.08%	6.89%
Markets with >2	-	7.07%	0.61%	0.94%	2.87%

Table 6
Transition Probability of Market Structure (Quarter 2 to 3)

	# Firms in Q3						
# Firms in Q2	**0**	**1**	**2**	**3**	**4**	**>4**	**Total**
0	**86.26%**	**11.40%**	**2.34%**	0.00%	0.00%	0.00%	100.00%
1	**8.27%**	**73.62%**	**15.55%**	**2.56%**	0.00%	0.00%	100.00%
2	**1.42%**	**13.48%**	**59.93%**	**20.04%**	**4.26%**	**0.89%**	100.00%
3	**0.20%**	**3.76%**	**20.20%**	**52.28%**	**19.21%**	**4.36%**	100.00%
4	0.00%	**0.79%**	**4.19%**	**21.20%**	**54.19%**	**19.63%**	100.00%
>4	0.00%	0.00%	**0.30%**	**2.69%**	**13.90%**	**83.11%**	100.00%

Table 8
Demand Estimation[1]
Data: 85,497 observations. 2004-Q1 to 2004-Q4

	OLS		IV	
FARE ($100)	-0.329	(0.005)	-1.366	(0.110)
$\ln(\mathbf{s}_{i\|d})$	0.500	(0.003)	0.113	(0.051)
DIRECT	1.217	(0.051)	2.080	(0.184)
HUBSIZE-ORIGIN	0.032	(0.001)	0.027	(0.002)
HUBSIZE-DESTINATION	0.041	(0.001)	0.036	(0.002)
DISTANCE	0.098	(0.002)	0.329	(0.013)

(1) All the estimations include airline dummies, origin-airport dummies × time dummies, and destination-airport dummies × time dummies. Stadard errors in parentheses.

Table 9
Marginal Cost Estimation[1]
Data: 85,497 observations. 2004-Q1 to 2004-Q4
Dep. Variable: Marginal Cost in $100

	Estimate (Std. Error)	
DIRECT	0.012	(0.011)
HUBSIZE-ORIGIN	-0.073	(0.012)
HUBSIZE-DESTINATION	-0.036	(0.013)
DISTANCE	5.355	(0.012)

(1) All the estimations include airline dummies, origin-airport dummies × time dummies, and destination-airport dummies × time dummies.

Table 11
Estimation of Dynamic Game of Entry-Exit[1]

Data: 4,970 markets × 27 airlines × 3 quarters = 402,570 observations

	Estimate (in million $)	**(Std. Error)**
Fixed Costs:		
γ_{00}^{FC} (stop-flight)	0.571	(0.006)
γ_{01}^{FC} (direct-flight)	0.620	(0.006)
γ_{1}^{FC} (hubsize origin)	-0.036	(0.005)
γ_{1}^{FC} (hubsize destination)	-0.022	(0.005)
Entry Costs:		
γ_{00}^{EC} (stop-flight)	0.977	(0.015)
γ_{01}^{EC} (direct-flight)	1.004	(0.016)
γ_{1}^{EC} (hubsize origin)	-0.306	(0.018)
γ_{1}^{EC} (hubsize destination)	-0.272	(0.020)
σ_{ε}	0.316	(0.015)

(1) All the estimations include airline dummies, origin-airport dummies, and destination-airport dummies. Stadard errors in parentheses.

Table 12
Effects of Different Parameters on an Airline Hub-Ratio

	Hub-Ratios						
		No hub-size effects in variable profits		**No hub-size effects in fixed costs**		**No hub-size effects in entry costs**	
Carrier	**Observed**	*No Strat.*	*Strategic*	*No Strat.*	*Strategic*	*No Strat.*	*Strategic*
American	78.9	75.2	73.1	71.9	68.6	47.2	35.5
United	81.2	78.8	74.9	70.4	66.0	42.1	30.7