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

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**Abstract**

This paper estimates the contribution of demand, cost and strategic factors to explain why most companies in the US airline industry operate using a hub-spoke network. We postulate and estimate a dynamic oligopoly model where airline companies decide, every quarter, which routes (directional city-pairs) to operate, the type of product (direct flight vs. stop-flight), and the fare of each route-product. The model incorporates three factors which may contribute to the profitability of hub-spoke networks. First, consumers may value the scale of operation of an airline in the origin and destination airports (e.g., more convenient checking-in and landing facilities). Second, operating costs and entry costs may depend on the airline's network because economies of density and scale. And third, a hub-spoke network may be an strategy to deter the entry of non hub-spoke carriers in some routes. We estimate our dynamic oligopoly model using panel data from the Airline Origin and Destination Survey with information on quantities, prices, and entry and exit decisions for every airline company over more than two thousand city-pair markets and several years. Demand and variable cost parameters are estimated using demand equations and Nash-Bertrand equilibrium conditions for prices. In a second step, we estimate fixed operating costs and sunk costs from the dynamic entry-exit game. Counterfactual experiments show that hub-size effects on entry costs is, by far, the most important factor to explain hub-spoke networks. Strategic entry deterrence is also significant and more important to explain hub-spoke networks than hub-size effects on demand, variable costs or fixed costs.

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

**JEL codes:** L11, L13.

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# 1 Introduction

The market structure of the US airline industry has undergone important changes since the deregulation in 1978 which removed entry and exit restrictions and allowed carriers to set airfares.[1] Soon after deregulation, most airline companies adopted a 'hub-spoke' system for the structure of their routes. In a 'hub-spoke' network an airline concentrates most of its operations in one airport, that is called the 'hub'. All other cities in the network are connected to the hub by non-stop flights. Those travellers who want to travel between two cities on the spokes should take a connecting flight at the hub. Several studies have documented a so-called "hub-premium": after controlling for airline fixed effects, the fares of hub carriers are higher than those of non-hub carriers on the same route.[2] Several (non-exclusive) explanations have been proposed to explain both the adoption of hub-spoke networks and the hub premium. These explanations can be classified in three groups: demand factors, cost factors and strategic factors. Compared to a 'point-to-point network' in which all cities are connected by non-stop flights, the hub-spoke system can have both positive and negative effects on consumers demand. On the one hand, consumers may value the scale of operation of an airline in the origin and destination airports, e.g., more convenient checking-in and landing facilities. On the other hand, for those travelling between spoke cities, stop-flights are longer and therefore less preferred than direct flights. A second group of factors that might explain the adoption of hub-spoke networks is the existence of economies of density and scale (see Caves, Christensen and Tretheway, 1984). The cost per passenger on a route may decline with the number of passengers travelling on that route, and these economies of density may be sufficiently large to compensate for larger distance travelled with the hub-spoke system.[3] Berry (1990) estimates a structural model of demand and price competition

[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] See Borenstein (1989), Evans and Kessides (1993) and Berry, Carnall, and Spiller (2006), among others.

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

with differentiated product in US airline industry and finds that an airline's hub both increases its demand and reduces its variable cost. Also, there may be economies of scope in the fixed operating costs of routes of an airline at the same airport. Other cost factor that might be important but that has received less attention is that economies of scope in the cost of entry in a route, either because technological reasons or contractual reasons between airports and airlines. Finally, a third factor is that a hub-spoke network can be an effective strategy to deter the entry of competitors. Hendricks, Piccione and Tan (1997) formalize this argument in a three-stage game of entry similar to the one in Judd (1985). Consider a hub airline who is an incumbent in the market-route between two spoke cities. Suppose that a non-hub carrier decides to enter in this spoke market. If the hub carrier concedes the spoke market to the new entrant, this will have a negative effect on its profits in the associated connecting markets. When this network effect is large enough, the hub operator's optimal response to entry on a spoke market is to stay in the spoke market. This is known by potential entrants and therefore entry can be deterred.[4]

The main goal of this paper is to estimate the contribution of demand, cost and strategic factors to explain the propensity of US airlines to operate using hub-spoke networks. With this purpose, we postulate and estimate a dynamic oligopoly model where airline companies decide, every quarter: which routes (directional city-pairs) to operate; the type of product, i.e., direct flight vs. stop-flight, and, in the case of cities with more than one airport, the origin and destination airports; and the fares for each route-product they serve. The model incorporates the demand, cost and strategic factors that we have described above. 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 over more than two thousand city-pair markets and several years. In a first step, demand and variable cost parameters are estimated using demand equations and Nash-Bertrand equilibrium conditions in prices. The spatial structure of the model provides instruments for the identification of

[4] See also Oum, Zhang, and Zhang (1995) for other game that can explain the choice of a hub-spoke network for strategic reasons.

demand parameters. In a second step, we estimate fixed operating costs and sunk entry costs in the dynamic game of entry and exit. We use the nested pseudo likelihood (NPL) method proposed by Aguirregabiria and Mira (2007).

Previous studies related to this paper are Berry (1990 and 1992), Berry, Carnall, and Spiller (2006) and Ciliberto and Tamer (2006). 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 they consider very restrictive specifications of variable profits that assume that airlines have homogeneous products and variable costs. Berry (1990) and Berry, Carnall, and Spiller (2006) estimate differentiated product supply-demand models to disentangle the effects of hubs on costs and consumers' willingness to pay. However, the studies in this second group do not estimate entry models and cannot obtain the effects of hubs on fixed costs or entry costs. This paper presents several contributions with respect to these previous studies. First, our model of market entry-exit is one where products are differentiated and airlines have different variable costs. Second, 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-spoke networks. And third, but perhaps most importantly, the model of market entry-exit is dynamic. Considering 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. More importantly, a dynamic game is needed to study the hypothesis that a hub-spoke network is an effective strategy to deter the entry of non-hub competitors. We find that hub-size effects on entry costs is, by far, the most important factor to explain hub-spoke networks. Strategic entry deterrence is also significant and more important to explain hub-spoke networks than hub-size effects on demand, variable costs or fixed costs.

The paper also contributes to the recent literature on estimation of dynamic discrete games. Competition in oligopoly industries involves important investment decisions which are partly irreversible. Dynamic games are powerful tools for the analysis of these dynamic strategic interactions. Until very recently, econometric models of discrete games had been limited to relatively simple static games. Two main econometric issues explain this limited range of applications: the computational burden in the solution of dynamic discrete games, and the indeterminacy problem associated with the existence of multiple equilibria. The existence of multiple equilibria is a prevalent feature in most empirical games where best response functions are non-linear in other players' actions. Models with multiple equilibria do not have a unique reduced form and this incompleteness may pose practical and theoretical problems in the estimation of structural parameters. The computational burden in the structural estimation of games is specially severe. The dimension of the state space, and the cost of computing an equilibrium, increases exponentially with the number of heterogeneous players. An equilibrium is a fixed point of a system of best response operators and each player's best response is itself the solution to a dynamic programming problem. Recent papers (Aguirregabiria and Mira, 2007, Bajari, Benkard and Levin, 2007, Pakes, Ostrovsky and Berry, 2007, and Pesendorfer and Schmidt-Dengler, 2007) have proposed different methods for the estimation of dynamic games. These methods deal with the problem of multiple equilibria in the model. Under the assumption that the data come from only one equilibrium, players' choice probabilities can be interpreted as players' beliefs about the behavior of their opponents. Given these beliefs, one can interpret each player's problem as a game against nature with a unique optimal decision rule in probability space, which is the player's best response. While equilibrium probabilities are not unique functions of structural parameters, the best response mapping is a unique function of structural parameters and players' beliefs about the behavior of other players. These methods use best response functions evaluated at consistent nonparametric estimates of players' beliefs.

This paper contains two methodological contributions to the econometrics of dynamic discrete games. Given the relatively large number of heterogeneous agents (i.e., twenty-seven airlines), the state space of our dynamic game includes many continuous state variables. To deal with this large dimensionality problem we combine the nested pseudo likelihood (NPL) method with interpolation techniques. And second, 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. 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.

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 presents the counterfactual experiments, based on the estimated model, that we implement to measure the effects of demand, costs and strategic factors in the adoption of hub-spoke networks. Section 6 concludes.

# 2 Model

The industry is configured by $N$ airline companies, $A$ airports and $C$ cities or metropolitan areas. Both airlines and airports are exogenously given in our model.[5] 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 $M \equiv C(C-1)$ potential routes

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

or markets. Within a market, an airline may provide several products. We consider two forms of product differentiation, other than airline: direct-flights versus stop-flights; and, for those cities with more than one airport, the origin and destination airport. Therefore, two routes between the same cities but with different airports are considered differentiated products within the same market. We index markets by $m$, airlines by $i$, and type of product by $d$. Time is discrete (a quarter) and indexed by $t$. The type of product, $d$, consists of three elements: $d = (NSD, OA, DA)$ where $NSD \in \{0, 1\}$ is the indicator variable for a "non-stop flight", and $OA \in \{1, 2, 3\}$ and $DA \in \{1, 2, 3\}$ are the indexes for the airport in the origin and in the destination cities, respectively.[6] In principle, the set of product types is $D \equiv \{0, 1\} \times \{1, 2, 3\} \times \{1, 2, 3\}$. Of course, not all product types are available in every market. Most markets have only one airport pair, i.e., $(OA, DA) = (1, 1)$. Our model provides a separate (Markov perfect) equilibrium for each of the $M$ markets. However, these local market equilibria are interconnected through the existence of network effects. This interconnection provides a joint dynamics for the whole US airline industry. There are two exogenous 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 (i.e., economies of density and scope).

## 2.1 Consumer demand and price competition

In this subsection we present a model of demand and price competition in the spirit of the one in Berry, Carnall and Spiller (2007, BCS hereinafter). For notational simplicity, we omit the time subindex $t$ for most of this subsection. It should be understood that all the variables here may vary over time. Let $H_m$ be the number of potential travellers in the market (city-pair) $m$, which is an exogenous variable. Every quarter consumers decide whether to purchase a ticket for this route, which airline to patronize, and the type of product. The

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

indirect utility function of a consumer who purchases product $(i, d, m)$ is:

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

where $p_{idm}$ is the price and $\beta_{idm}$ is the *quality* of the product. The variable $v_{idm}$ is consumer specific and it captures consumer heterogeneity in preferences for difference products. Quality $\beta_{idm}$ depends on exogenous characteristics of the airline and the route. More importantly, it depends on the scale of operation of the airline in the origin and destination airports. In section 4, equation (15), we provide an specification of $\beta_{idm}$ in terms of measures of the airline's operation in the origin and destination airports. A traveller 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, qualities $\beta_{idm}$ should be interpreted as relative to the value of the outside alternative.

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 the consumer heterogeneity has the form in BCS. However, as we show in section 4, our estimates of the hub effects on demand and variable costs are very similar to the ones 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 $d \in D$. 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 $\sigma_1$ and $\sigma_2$ are parameters which measure the dispersion of these variables, with

$\sigma_1 \geq \sigma_2$. Let $x_{idm} \in \{0,1\}$ be the indicator of the event "airline $i$ provides product $d$ in market $m$ (at period $t$)". 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., $s_{d|im} \equiv s_{idm}/\left(\sum_{d'} s_{id'm}\right)$. Then, the demand equation for product $(i,d,m)$ is $s_{idm} = s_{d|im}\ \bar{s}_{im}$, where

$$s_{d|im} = \frac{x_{idm}\ \exp\left\{\dfrac{\beta_{idm} - p_{idm}}{\sigma_2}\right\}}{\sum\limits_{d' \in D} x_{id'm}\ \exp\left\{\dfrac{\beta_{id'm} - p_{id'm}}{\sigma_2}\right\}} \tag{2}$$

and

$$\bar{s}_{im} = \frac{\left(\sum\limits_{d \in D} x_{idm}\ \exp\left\{\dfrac{\beta_{idm} - p_{idm}}{\sigma_2}\right\}\right)^{\sigma_2/\sigma_1}}{1 + \sum\limits_{j=1}^{N}\left(\sum\limits_{d \in D} x_{jdm}\ \exp\left\{\dfrac{\beta_{jdm} - p_{jdm}}{\sigma_2}\right\}\right)^{\sigma_2/\sigma_1}} \tag{3}$$

A property of the nested logit model is that the demand system can be represented using the following closed-form demand equations: if $x_{idm} = 1$,

$$\ln(s_{idm}) - \ln(s_{0m}) \quad = \quad \frac{\beta_{idm} - p_{idm}}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s_{i|dm}\right) \tag{4}$$

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

Consumers demand and price competition in this model are static. The variable profit of airline $i$ in market $m$ is:

$$R_{im} = \sum_{d \in D} (p_{idm} - c_{idm})\ q_{idm} \tag{5}$$

where $c_{idm}$ is the marginal cost of product $(i,d)$ in market $m$, that it is assumed to be constant. 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:[7]

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

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

Equilibrium prices depend on the qualities and marginal costs of the active firms. It is simple to verify that equilibrium price-cost margins, $r_{idm} \equiv p_{idm} - c_{idm}$, and equilibrium quantities, $q_{idm}$, depend on qualities and marginal costs only through the cost-adjusted qualities $\tilde{\beta}_{idm} \equiv \beta_{idm} - c_{idm}$. We use the function $R_i(\tilde{\beta}_m, x_m)$ to represent equilibrium variables profits:

$$R_i(\tilde{\beta}_m, x_m) = \sum_{d \in \{S,NS\}} r^*_{id}(\tilde{\beta}_m, x_m)\ q^*_{id}(\tilde{\beta}_m, x_m) \tag{7}$$

where $\tilde{\beta}_m$ and $x_m$ are the vectors of cost-adjusted qualities and activity indicators for the $N$ airlines, and $r^*_{id}()$ and $q^*_{id}()$ represent equilibrium price-cost margins and quantities, respectively.

## 2.2 Dynamic entry-exit game

At the end of a every quarter $t$, airlines decide which routes to operate and which products to provide next period. We use the following notation: $x_{idmt}$ is the indicator of the event "airline $i$ provides product $d$ in market $m$ at period $t$", and it is a state variable at period $t$; $a_{idmt}$ is the indicator of the event "airline $i$ will provide product $d$ in market $m$ at period $t+1$", and it is a decision variable at period $t$. Of course, $a_{idmt} \equiv x_{idm,t+1}$, but it will be convenient to use different letters to distinguish the state variable and the decision variable. An airline decision in market $m$ at period $t$ is a vector $a_{imt} \equiv \{a_{idmt} : d \in D\}$. An airline chooses $a_{imt}$ to maximize its expected current and future discounted profits $E_t\left(\sum_{s=0}^{\infty} \delta^s \left[\sum_{m=1}^{M} \Pi_{im,t+s}\right]\right)$, where $\delta \in (0,1)$ is the time discount factor, and $\Pi_{imt}$ is the (total) profit of airline $i$ in market $m$ at quarter $t$. The decision is dynamic because part of the cost of entry in a route is sunk and it will not be recovered after exit. Current profits have three components:

$$\Pi_{imt} = R_i(\tilde{\beta}_m, x_{mt}) - FC_{imt} - EC_{imt} \tag{8}$$

$R_i(\tilde{\beta}_m, x_{mt})$ 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 have two components: one component that is common knowledge to all the airlines and other that is private information. Private information state variables are a convenient way of introducing unobservables in the econometric model. Furthermore, under certain regularity conditions dynamic games of incomplete information have at least one equilibrium while that is not the case in dynamic games of complete information (see Doraszelski and Satterthwaite, 2003).[8] Our specification of these costs is:

$$\begin{aligned} FC_{imt} &= \sum_{d \in D} x_{idmt} \ \left( \gamma_{idm}^{FC} + \varepsilon_{idmt}^{FC} \right) \\ EC_{imt} &= \sum_{d \in D} (1 - x_{idmt}) \ a_{idmt} \ \left( \gamma_{idm}^{EC} + \varepsilon_{idmt}^{EC} \right) \end{aligned} \tag{9}$$

The $\gamma$ components are common knowledge for all the airlines, while the $\varepsilon$ components are private information shocks. Fixed costs are paid only if the airline operates in the route, i.e., if $x_{idmt} = 1$. The fixed cost $\gamma_{idm}^{FC}$ depends on the scale of operation of the airline in the origin and destination airports. That is the hub-size effect in fixed costs. Entry costs are paid only when the airline decides to start providing a product in a market, i.e., if $x_{idmt} = 0$ and $a_{idmt} = 1$. Note that entry costs are paid at period $t$, but the airline starts operating at period $t + 1$. Though there is a fixed cost and an entry cost for each product $d$, our specification of $\gamma_{idm}^{FC}$ and $\gamma_{idm}^{EC}$ can allow for economies of scope. The private information shocks $\varepsilon_{idmt}^{FC}$ and $\varepsilon_{idmt}^{EC}$ are assumed to be independently and identically distributed over firms and over time.

Let $z_m$ be the vector with all the exogenous, payoff-relevant, common knowledge variables in market $m$. This vector includes market size, airlines' qualities, marginal costs, fixed costs, and entry costs. That is:

$$z_m \equiv \{H_m, \ \tilde{\beta}_{idm}, \ \gamma_{idm}^{FC}, \ \gamma_{idm}^{EC} : d = 0, 1 \ ; \ i = 1, 2, ..., N\} \tag{10}$$

We use the vector $\varepsilon_{imt} \equiv \left\{ \varepsilon_{idmt}^{FC}, \varepsilon_{idmt}^{EC} : d \in D \right\}$ to represent an airline's private information shocks. An airline's payoff-relevant information in market $m$ at quarter $t$ is $\{x_{mt}, z_m, \varepsilon_{imt}\}$. We assume that an airline's strategy in market $m$ depends only on these payoff relevant state variables, i.e., Markov equilibrium assumption.

[8] 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 endogeneity problem.

Let $\boldsymbol{\sigma} \equiv \{\sigma_i(x_{mt}, z_m, \varepsilon_{imt}) : i = 1, 2, ..., N\}$ be a set of strategy functions, one for each airline, such that $\sigma_i$ is a function from $\{0,1\}^{N|D|} \times Z \times \mathbb{R}^{2|D|}$ into $\{0,1\}^{|D|}$, where $Z$ is the support of $z_m$ 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 airline's strategy maximizes the value of the airline (in the local market) for each possible state $(x_{mt}, z_m, \varepsilon_{imt})$ and taking other firms' strategies as given. More formally, $\boldsymbol{\sigma}$ is a MPE if for every airline $i$ and every state $(x_{mt}, z_m, \varepsilon_{imt})$ we have that:

$$\sigma_i(x_{mt}, z_m, \varepsilon_{imt}) = \arg \max_{a_i \in \{0,1\}^{|D|}} \left\{ \ v_i^{\boldsymbol{\sigma}}(a_i | x_m, z_{mt}) + \varepsilon_{imt}(a_i) \ \right\} \tag{11}$$

where $v_i^{\boldsymbol{\sigma}}(a_i | x_{mt}, z_m) + \varepsilon_{imt}(a_i)$ is the value of airline $i$ if it chooses alternative $a_i$ given that the current state is $(x_{mt}, z_m, \varepsilon_{imt})$ 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 $v_i^{\boldsymbol{\sigma}}(a_i | x_{mt}, z_m)$, 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:

$$v_i^{\boldsymbol{\sigma}}(a_i | x_{mt}, z_m) \ \ \equiv \ \ E\left( \sum_{s=0}^{\infty} \delta^s \ \Pi_i \left( \boldsymbol{\sigma}_{mt+s}, x_{mt+s}, z_m, \varepsilon_{imt+s} \right) \ | \ x_{mt}, \ z_m, \ a_{imt} = a_i \right) \tag{12}$$

where $\boldsymbol{\sigma}_{mt+s} \equiv \boldsymbol{\sigma} \left( x_{mt+s}, z_m, \boldsymbol{\varepsilon}_{mt+s} \right)$. Equation (11) describes a MPE as a fixed point in the space of strategy functions. Note that, in this definition of MPE, the functions $v_i^{\boldsymbol{\sigma}}$ depend also on airline $i$'s strategy. Therefore, in equilibrium $\sigma_i$ is a best response to the other players' strategies and also to the own behavior of player $i$'s in the future.[9] 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 $\mathbf{P} = \{P_i(a_i | x, z) : (a_i, x, z) \in \{0,1\}^{|D|} \times \{0,1\}^N \times Z\}$ such that $P_i(a_i | x, z)$

[9] 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).

is the probability that firm $i$ provides the combination of products $a_i$ given that the common knowledge state is $(x, z)$. That is,

$$P_i(a_i|x,z) \equiv \int I\left\{\sigma_i(x,z,\varepsilon_i) = a_i\right\}\ dG_\varepsilon(\varepsilon_i) \tag{13}$$

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 (11) 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 $(x, z)$ we have that:

$$P_i(a_i|x,z) = \int I\left\{a_i = \arg \max_{a_i^* \in \{0,1\}^{|D|}} \left\{\ v_i^{\mathbf{P}}(a_i^*|x,z) + \varepsilon_i(a_i^*)\ \right\}\right\} dG_\varepsilon(\varepsilon_i) \tag{14}$$

An equilibrium exits (see Doraszelski and Satterthwaite, 2003, and Aguirregabiria and Mira, 2007) but it is not necessarily unique.

An equilibrium in this dynamic game applies to a single market or route. The equilibria at different markets are linked by the existence of network (hub) effects. An airline's quality ($\beta$), marginal cost ($c$), fixed cost ($\gamma^{FC}$) and entry cost ($\gamma^{EC}$) in a particular route depend on the number of other routes the airline has at the origin and destination airports. Therefore, quality and costs in a market depend on the equilibrium in other markets. Our model incorporates an important simplifying assumption: when an airline decides its entry or exit in a route, it ignores its effect in the profits at other routes. Despite this simplifying assumption, our model provides predictions on the effect of the own hub-size and the hub-size of competitors on airlines entry-exit decisions. Therefore, we can use our model to study the entry deterrence effect of hub-spoke networks.[10]

[10] In fact, our model can be interpreted as generalization of the three-stage game in Hendricks, Piccione and Tan (1997). In that game, the hub is exogenously given or predetermined (as in our model).

# 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 records/tickets for a 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 previous 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.[12] To measure market size, we use the total population in the cities of the origin and destination airports. 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 market.

[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.

[12] 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 of routes that involve airports located in the same city.

*(b) Selection of markets.* We start selecting the 75 largest US cities in terms of population in 2004.[13] For each city, we use all the airports in the city. Some of the 75 cities belong to the same metropolitan area and share the same airports. We group these cities. We have 55 cities or metropolitan areas and 63 airports. Table 1 presents the list of cities with their population and number of airports.[14] 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. We can distinguish three types of carriers in DB1B: 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 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 ticket records 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;[15] and (4) tickets

[13] 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. 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".

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

[15] 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.

with fare credibility question by DOT.

*(e) 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. 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.

*(f) Definition of active carrier.* Let $x_{idmt}$ be the indicator of the event "airline $i$ provides product $d$ in market $m$ at period $t$". We make this indicator equal to one if during quarter $t$ airline $i$ has at least 20 passengers per week (260 per quarter) in market $m$ and product $d$.

*(g) 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 survey at quarter $t$ that correspond to airline $i$, market $m$ and product $d$. The DB1B-Ticket dataset reports the total itinerary fare. We use a weighted average of ticket fares to obtain price variables as "dollars per passenger".

*(h) Measure of hub size.* For each market and airline we construct two variables that measure the scale of operation (or hub size) of the airline at the origin-airport ($HUB_{im}^{O}$) and at the destination-airport ($HUB_{im}^{D}$). 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.

Table 5 presents different statistics describing market structure and its dynamics.

# 4 Estimation of the structural model

In this section, we describe our approach to estimate the structural model. Our approach proceeds in three stages. First, we estimate the parameters in the demand system using information on prices and quantities. Given the estimated demand parameters, Nash-Bertrand equilibrium conditions provide estimates of marginal costs for each airline-market-product-quarter that we observe in the data. However, for the estimation of the entry-exit model we need to know variable profits for every possible combination of airline-product-market, observed or not. Therefore, in a second step, we use the estimated marginal costs (from the actually observed products) to estimate a marginal cost function that depends on hub-size variables and airline and airport dummies. This estimated function provides marginal costs for counterfactual combinations of airline-market-product. We discuss endogeneity and selection issues and provide specification tests. Third, given estimated variable costs in steps 1 and 2, we estimate fixed costs and entry costs from the dynamic game of market entry-exit.

## 4.1 Estimation of the demand system

We consider the following specification of product quality $\beta_{idmt}$ in terms of observable and unobservable variables for the econometrician.

$$\beta_{idmt} = \beta_1 \; d^{NS} + \beta_2 \; HUB_{im}^{O} + \beta_3 \; HUB_{im}^{D} + \beta_4 \; DIST_m + \xi_i^{(1)} + \xi_{Omt}^{(2)} + \xi_{Dmt}^{(3)} + \xi_{idmt}^{(4)} \quad (15)$$

$\beta_1$, $\beta_2$, $\beta_3$ and $\beta_4$ are parameters. $d^{NS}$ is a dummy variable for "non-stop flight". $HUB_{im}^{O}$ and $HUB_{im}^{D}$ are indexes that represent the scale of operation of airline $i$ in the origin and destination airports of route $m$, respectively. $DIST_m$ is the nonstop 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 differences between airlines' qualities which are constant over time and across markets. $\xi_{Omt}^{(2)}$ represents the interaction of origin-airport dummies and time dummies, and $\xi_{Dmt}^{(3)}$ captures the interaction of destination-airport dummies and time dummies. These two 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 $HUB_{im}^{O}$ and $HUB_{im}^{D}$ measure hub size and they have been defined in section 3.

The demand model can be represented using the regression equation:

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

where the vector of regressors $X_{idmt}$ includes hub size variables, dummy for direct-flight, distance, airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies. The main econometric issue in the estimation of the demand system in equation (**??**) is the endogeneity of prices and 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 $\xi_{idmt}^{(4)}$. We expect this correlation to be positive and therefore the OLS estimator of the price coefficient to be upward biased, i.e., it underestimates the own-price demand elasticities. Similarly, the regressor $\ln\left(s_{i|dmt}\right)$ depends on unobserved characteristics and it is endogenous. Our approach to deal with this endogeneity problem combines the *control function* and the *instrumental variables* approaches. First, airline dummies, and the interaction of city dummies and time dummies capture part of the unobserved heterogeneity (i.e., control function approach). And second, to control for the endogeneity associated with the unobservable $\xi_{idmt}^{(4)}$ we use instruments.

Note that the hub variables $HUB_{im}^{O}$ and $HUB_{im}^{D}$ depend on the entry decisions of airline $i$ in markets different than $m$. Therefore, these variables depend on the demand shock

$\xi^{(4)}_{idm't}$ in markets $m'$ different than $m$. The specification of the stochastic process of $\xi^{(4)}_{idmt}$ is particularly important to determine which instruments are valid in the estimation of demand parameters. We consider the following assumption:

*ASSUMPTION D1: For any airline $i$ and any two markets $m \neq m'$, the demand shocks $\xi^{(4)}_{idmt}$ and $\xi^{(4)}_{idm't}$ are independently distributed.*

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

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

Under this assumption the hub variables of other airlines in the same market are such that $E\left(\xi^{(4)}_{idmt} \mid HUB^{O}_{jm}, HUB^{D}_{jm}\right) = 0$. Furthermore, by the equilibrium condition, prices depend on the hub size of every active firm in the market. Therefore, we can use $HUB^{O}_{jm}$ and $HUB^{D}_{jm}$ as instruments for the price $p_{idmt}$ and the market share $\ln\left(s_{i|dmt}\right)$. Note that Assumptions 1 and 2 are testable. Using the estimation residuals we can test for spatial (cross market) correlation in idiosyncratic demand shocks $\xi^{(4)}_{idmt}$. 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 the idiosyncratic demand shocks $\{\xi^{(4)}_{idmt}\}$ 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* $\xi^{(4)}_{idmt}$ 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.

## 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 $t$. However, for the estimation of the entry-exit model we need to know marginal costs for every possible airline-product-market. To obtain these estimates we specify marginal costs as a function of airline, product and market characteristics, estimate the parameters in this function, and then use the estimated function to predict marginal costs for products which are not observed in the sample. Other reason why we estimate this marginal cost equation is because we want to measure hub effects on marginal costs. Our specification of the marginal cost function is very similar to the one of the product qualities:

$$c_{idmt} = \delta_1 \ d^{NS} + \delta_2 HUB_{im}^{O} + \delta_3 HUB_{im}^{D} + \delta_4 DIST_m + \omega_i^{(1)} + \omega_{Omt}^{(2)} + \omega_{Dmt}^{(3)} + \omega_{idmt}^{(4)} \tag{18}$$

We make the following assumptions on the idiosyncratic shocks in marginal costs.

*ASSUMPTION MC1: For any airline $i$ and any two markets $m \neq m'$, the marginal cost shocks $\omega_{idmt}^{(4)}$ and $\omega_{idm't}^{(4)}$ are independently distributed.*

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

Assumption MC1 implies that the hub size variables are exogenous regressors. Assumption MC2 implies that $\omega_{idmt}^{(4)}$ 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.

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.

Given our estimates of demand and marginal cost parameters we construct the following estimates of cost-adjustment qualities for every possible tuple $(i, d, m, t)$:

$$\begin{aligned}\hat{\beta}_{idm} &= \left(\hat{\beta}_1 - \hat{\delta}_1\right) d + \left(\hat{\beta}_2 - \hat{\delta}_2\right) HUB_{im}^{O} + \left(\hat{\beta}_3 - \hat{\delta}_3\right) HUB_{im}^{D} + \left(\hat{\beta}_4 - \hat{\delta}_4\right) DIST_m \\ &+ \left(\hat{\xi}_i^{(1)} - \hat{\omega}_i^{(1)}\right) + \left(\hat{\xi}_{Om}^{(2)} - \hat{\omega}_{Om}^{(2)}\right) + \left(\hat{\xi}_{Dm}^{(3)} - \hat{\omega}_{Dm}^{(3)}\right)\end{aligned} \tag{19}$$

## 4.3 Estimation of the dynamic entry-exit game

*Specification of fixed costs and entry costs.* The common knowledge component of fixed costs and entry costs depend on hub sizes at the origin and destination airports.

$$\begin{aligned} \gamma_{idm}^{FC} &= \gamma_1^{FC} d + \gamma_2^{FC}\ HUB_{im}^{O} + \gamma_3^{FC} HUB_{im}^{D} + \eta_i^{FC(1)} + \eta_{Om}^{FC(2)} + \eta_{Dm}^{FC(3)} \\ \gamma_{idm}^{EC} &= \gamma_1^{EC} d + \gamma_2^{EC}\ HUB_{im}^{O} + \gamma_3^{EC} HUB_{im}^{D} + \eta_i^{EC(1)} + \eta_{Om}^{EC(2)} + \eta_{Dm}^{EC(3)} \end{aligned} \tag{20}$$

where $\gamma's$ and $\eta's$ are parameters. Given this specification of fixed and entry costs, the one-period profit function has the following linear-in-parameters form:

$$\Pi_{imt}(a_i) = w_{imt}(a_i)'\boldsymbol{\theta} + \varepsilon_{imt}(a_i)$$

where: $\Pi_{imt}(a_i)$ is the profit of airline $i$ in market $m$ at quarter $t$ if it chooses alternative $a_i \in \{0,1\}^2$; $\boldsymbol{\theta}$ is a vector of structural parameters and $w_{imt}(a_i)$ 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 $\theta$ and $w_{imt}(a_i)$ have the following definitions:

$$\boldsymbol{\theta} = \begin{pmatrix} 1 \\ \gamma_{00}^{FC} \\ \gamma_{01}^{FC} \\ \gamma_1^{FC} \\ \gamma_2^{FC} \\ \gamma_{00}^{EC} \\ \gamma_{01}^{EC} \\ \gamma_1^{EC} \\ \gamma_2^{EC} \\ \boldsymbol{\eta}^{FC(1)} \\ \boldsymbol{\eta}_O^{FC(2)} \\ \boldsymbol{\eta}_D^{FC(3)} \\ \boldsymbol{\eta}^{EC(1)} \\ \boldsymbol{\eta}_O^{EC(2)} \\ \boldsymbol{\eta}_D^{EC(3)} \end{pmatrix} \quad \text{and} \quad w_{imt}(a_i) = \begin{pmatrix} R_i(\tilde{\beta}_m, x_{mt}) \\ x_{i0mt} \\ x_{i1mt} \\ (x_{i0mt} + x_{i1mt})\ HUB_{im}^O \\ (x_{i0mt} + x_{i1mt})\ HUB_{im}^D \\ (1 - x_{i0mt})a_{i0} \\ (1 - x_{i1mt})a_{i1} \\ [(1 - x_{i0mt})a_{i0} + (1 - x_{i1mt})a_{i1}]\ HUB_{im}^O \\ [(1 - x_{i0mt})a_{i0} + (1 - x_{i1mt})a_{i1}]\ HUB_{im}^D \\ (x_{i0mt} + x_{i1mt})\ \mathbf{1}_i \\ (x_{i0mt} + x_{i1mt})\ \mathbf{1}_{Om} \\ (x_{i0mt} + x_{i1mt})\ \mathbf{1}_{Dm} \\ [(1 - x_{i0mt})a_{i0} + (1 - x_{i1mt})a_{i1}]\ \mathbf{1}_{Om} \\ [(1 - x_{i0mt})a_{i0} + (1 - x_{i1mt})a_{i1}]\ \mathbf{1}_{Dm} \\ [(1 - x_{i0mt})a_{i0} + (1 - x_{i1mt})a_{i1}]\ \mathbf{1}_i \end{pmatrix}$$

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 $\sigma_\varepsilon$. Under these assumptions, the equilibrium mapping in CCPs has the following form:

$$
\begin{aligned}
\Psi_{imt}(a_i|\mathbf{P}) &= \frac{\exp\left\{v_{imt}^{\mathbf{P}}(a_i)/\sigma_\varepsilon\right\}}{\sum_{a_i^*\in\{0,1\}^2}\exp\left\{v_{imt}^{\mathbf{P}}(a_i^*)/\sigma_\varepsilon\right\}} \\
&= \frac{\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_i)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon}+\tilde{e}_{imt}^{\mathbf{P}}(a_i)\right\}}{\sum_{a_i^*\in\{0,1\}^2}\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_i^*)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon}+\tilde{e}_{imt}^{\mathbf{P}}(a_i^*)\right\}}
\end{aligned}
\tag{21}
$$

$\tilde{w}_{imt}^{\mathbf{P}}(a_i)$ is the expected and discounted value of current 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, $\tilde{e}_{imt}^{\mathbf{P}}(a_i)$ 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:

$$
\begin{aligned}
Q(\boldsymbol{\theta},\mathbf{P}) &\equiv \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{N}\ln\Psi_{imt}(a_{imt}|\boldsymbol{\theta},\mathbf{P}) \\
&= \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{N}\ln\frac{\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_{imt})'\boldsymbol{\theta}+\tilde{e}_{imt}^{\mathbf{P}}(a_{imt})\right\}}{\sum_{a_i\in\{0,1\}^2}\exp\left\{\tilde{w}_{imt}^{\mathbf{P}}(a_i)'\dfrac{\boldsymbol{\theta}}{\sigma_\varepsilon}+\tilde{e}_{imt}^{\mathbf{P}}(a_i)\right\}}
\end{aligned}
\tag{22}
$$

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):

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg\max_{\boldsymbol{\theta}\in\Theta} \; Q(\boldsymbol{\theta}, \hat{\mathbf{P}}) \\ \hat{\mathbf{P}} &= \Psi(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}}) \end{aligned} \tag{23}$$

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:

$$\hat{\mathbf{P}}_{K,imt}(a_i) = \frac{\exp\left\{\tilde{w}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i)'\hat{\boldsymbol{\theta}}_K + \tilde{e}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i)\right\}}{\sum_{a_i^*\in\{0,1\}^2} \exp\left\{\tilde{w}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i^*)'\hat{\boldsymbol{\theta}}_K + \tilde{e}_{imt}^{\hat{\mathbf{P}}_{K-1}}(a_i^*)\right\}} \tag{24}$$

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):

$$
\begin{aligned}
\tilde{w}_{imt}^{\mathbf{P}}(a_i) &= w_{imt}(a_i) + \delta \sum_{x_{mt+1} \in \{0,1\}^{2N}} f_{xi}^{\mathbf{P}}(x_{mt+1}|x_{mt}, a_i)\ W_{iw}^{\mathbf{P}}(x_{mt+1}) \\
\tilde{e}_{imt}^{\mathbf{P}}(a_i) &= \delta \sum_{x_{mt+1} \in \{0,1\}^{2N}} f_{xi}^{\mathbf{P}}(x_{mt+1}|x_{mt}, a_i)\ W_{ie}^{\mathbf{P}}(x_{mt+1})
\end{aligned}
\tag{25}
$$

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:

$$
\mathbf{W} = \sum_{a_i \in \{0,1\}^2} \mathbf{P}_i(a_i) * \left\{ [\mathbf{w}_i(a_i), -\ln \mathbf{P}_i(a_i)] + \delta\ \mathbf{F}_{xi}^{\mathbf{P}}(a_i)\ \mathbf{W} \right\}
\tag{26}
$$

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:

$$
f_{xi}^{\mathbf{P}*}(x'|x, a_i) = \frac{f_{xi}^{\mathbf{P}}(x'|x, a_i)}{\sum_{x'' \in X^*} f_{xi}^{\mathbf{P}}(x''|x, a_i)}
\tag{27}
$$

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:

$$
\mathbf{W} = \sum_{a_i \in \{0,1\}^2} \mathbf{P}_i^*(a_i) * \left\{ [\mathbf{w}_i^*(a_i), -\ln \mathbf{P}_i^*(a_i)] + \delta\ \mathbf{F}_{xi}^{\mathbf{P}*}(a_i)\ \mathbf{W} \right\}
\tag{28}
$$

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:

$$
\begin{aligned}
\tilde{w}_{imt}^{\mathbf{P}*}(a_i) &= w_{imt}(a_i) + \delta \sum_{x_{mt+1} \in X^*} f_{xi}^{\mathbf{P}*}(x_{mt+1}|x_{mt}, a_i)\ W_{iw}^{\mathbf{P}*}(x_{mt+1}) \\
\tilde{e}_{imt}^{\mathbf{P}*}(a_i) &= \delta \sum_{x_{mt+1} \in X^*} f_{xi}^{\mathbf{P}*}(x_{mt+1}|x_{mt}, a_i)\ W_{ie}^{\mathbf{P}*}(x_{mt+1})
\end{aligned}
\tag{29}
$$

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-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, $\gamma_1^{FC}$ and $\gamma_2^{FC}$; and entry-costs, $\gamma_1^{EC}$ and $\gamma_2^{EC}$. 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.

[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.

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 $\mathbf{P}_0 = \boldsymbol{\pi}(\boldsymbol{\theta}_{\mathbf{0}})$. 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:

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

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

$$\frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} = \frac{\partial \boldsymbol{\Psi}\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)\right)}{\partial \boldsymbol{\theta}'} + \frac{\partial \boldsymbol{\Psi}\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)\right)}{\partial \mathbf{P}'} \frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} \tag{31}$$

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,

$$\frac{\partial \boldsymbol{\pi}\left(\hat{\boldsymbol{\theta}}_0\right)}{\partial \boldsymbol{\theta}'} = \left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'} \tag{32}$$

Solving expression (32) into (30) we have that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \hat{\mathbf{P}}_0 + \left(I - \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \boldsymbol{\Psi}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)}{\partial \boldsymbol{\theta}'}\left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) + O\left(\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2\right) \tag{33}$$

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

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**Table 1**
**Cities (or Metropolitan Areas), 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 (Rountrip) in 2004**

| | ORIGIN CITY | DESTINATION CITY | # Passengers (Annual, Rountrip) |
|---|---|---|---|
| 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] 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): We consider that airline is active in a market if it has at last 20 passengers per 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 (people in millions) | Second largest Hub (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\mid 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:* | | |
| $\gamma_{00}^{FC}$ (stop-flight) | 0.571 | (0.006) |
| $\gamma_{01}^{FC}$ (direct-flight) | 0.620 | (0.006) |
| $\gamma_{1}^{FC}$ (hubsize origin) | -0.036 | (0.005) |
| $\gamma_{1}^{FC}$ (hubsize destination) | -0.022 | (0.005) |
| *Entry Costs:* | | |
| $\gamma_{00}^{EC}$ (stop-flight) | 0.977 | (0.015) |
| $\gamma_{01}^{EC}$ (direct-flight) | 1.004 | (0.016) |
| $\gamma_{1}^{EC}$ (hubsize origin) | -0.306 | (0.018) |
| $\gamma_{1}^{EC}$ (hubsize destination) | -0.272 | (0.020) |
| $\sigma_{\varepsilon}$ | 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 |