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

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Abstract

This paper studies the contribution of demand, costs, and strategic factors to the adoption of hub-and-spoke networks in the US airline industry. Our results are based on the estimation of a dynamic oligopoly game of network competition that incorporates three groups of factors that may explain hub-and-spoke networks: (1) travelers may value the services associated with the scale of operation of an airline in the hub airport; (2) operating costs and entry costs in a route may decline with the airline's scale of operation in the origin and destination airports (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 the routes between the 55 largest US cities. As methodological contributions, we propose and apply a method to reduce the dimension of the state space in dynamic games, and a procedure to deal with the problem of multiple equilibria when using a estimated model to make counterfactual experiments. 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 importantly with the scale of operation of the airline in the airports of the route. For some of the larger carriers, strategic entry deterrence is the second most important factor to explain hub-and-spoke networks.

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 transformations since the 1978 deregulation that removed restrictions on the routes that airlines could operate and on the fares they could charge.[1] Soon after deregulation, most airline companies decided to organize their route maps using the structure of hub-and-spoke networks. In a hub-and-spoke route network an airline concentrates most of its operations in one airport, called the "hub". All other cities in the network (the "spokes") are connected to the hub by non-stop flights. Those customers who travel between two spoke-cities should take a connecting flight at the hub. An important feature of the hub-and-spoke system is that it fully connects n cities using the minimum number of direct connections, $n-1$. Furthermore, within the class of connected networks with minimum number of direct connections, it is the system that minimizes the number of stops.[2] These features imply that a connected hub-and-spoke system is the optimal network of a monopolist when there are significant fixed costs associated with establishing direct connections, travellers dislike stops, and cities are homogenous in demand and costs (i.e., Theorem 2 in Hendricks, Piccione and Tan, 1995). However, hub-and-spoke networks are not necessarily optimal in richer environments with heterogeneous cities and oligopolistic competition. Other arguments have been proposed to explain the adoption of hub-and-spoke networks. They can be classified in demand factors, cost factors and strategic factors. According to demand-side explanations, some travelers value different 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.[3] Cost-side explanations claim that some costs depend on the airline's scale of operation in an airport. For instance, larger planes are typically cheaper to fly on a per-seat basis: airlines can exploit these economies

[1] Borenstein (1992), Morrison and Winston (1995), and Borenstein and Rose (2007) provide excellent overviews of the US airline industry. For recent analyses of the effect of the deregulation, see Alam and Sickles (2000), Morrison and Winston (2000), Kahn (2001), and Färe, Grosskopf, and Sickles (2007).

[2] In a hub-and-spoke network, a traveller between city A and B should make no stops if either A or B is the hub, and should make only one stop if both A and B are spoke cities. A "snake" or linear network can also (fully) connect n cities using only $n-1$ direct connections. However, in the snake network travellers should make more than one stop when travelling between some cities.

[3] The willingness to pay for these services is partly offset by the fact that consumers prefer non-stop flights to stop-flights.

of scale by seating in a single 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. An airline's fixed cost of operating in a route, as well the fixed cost to start operating in a route by first time, may also decline with the airline's scale of operation in the airports of the route. For instance, some of these costs, such as maintenance and labor costs, may be common across different routes in the same airport (i.e., economies of scope). Furthermore, some of these cost savings may not be only technological but they may be linked to contractual arrangements between airports and airlines.[4] A third hypothesis that has been suggested to explain hub-and-spoke networks is that it 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 model in Judd (1985). The key argument is that, for a hub-and-spoke airline, there is complementarity between profits at different routes. If an airline exits from a city-pair between a hub-city and a spoke-city, then it also stops operating any other route that involves that spoke-city. Therefore, hub-and-spoke airlines are willing to operate some routes even when profits in that single route are negative. This is known by potential entrants, and therefore entry may be deterred.[5]

This paper develops an estimable dynamic game of airlines network competition that incorporates the demand, cost and strategic factors described above. We estimate this model and use it 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, in which markets (city-pairs) to operate, and the fares for each route-product, they serve. The model is estimated using data from the

[4] Airports' fees may include discounts to those airlines that operate many routes in the airport.

[5] Consider a hub airline who is a monopolist in the market-route between its hub-city and a spoke-city. A non-hub carrier is considering to enter in this route. Suppose that this market-route is such that a monopolist gets positive profits but under duopoly both firms suffer losses. For the hub carrier, conceding this market to the new entrant implies that it will also stop operating in other connecting markets and, as a consequence of that, its profits will fall. The hub operator's optimal response to the opponent's entry is to stay in the spoke market. Therefore, the equilibrium strategy of the potential entrant is not to enter. Hendricks, Piccione and Tan (1999) extend this model to endogenize the choice of hub versus non-hub carrier. See also Oum, Zhang, and Zhang (1995) for a similar type of argument that can explain the choice of a hub-spoke network for strategic reasons.

Airline Origin and Destination Survey with information on quantities, prices, and route entry and exit decisions for every airline company in the routes between the 55 largest US cities (1,485 city-pairs). To test our hypotheses on the sources of hub-and-spoke networks, airline costs should be measured at the route level. Though there is plenty of public information available on the balance sheets and costs of airline companies, this is information is not at the airline-route level or even at the airline-airport. Therefore, our approach to estimate the demand and cost parameters of the model is based on the *principle of revealed preference*. Under the assumption that airlines maximize expected profits, an airline's decision to operate or not in a route *reveals* information on costs at the airline-route level. We exploit information on airlines entry-exit decisions in city-pairs to estimate these costs.

This paper builds on and extends two important literatures in the Industrial Organization of the airlines industry: the theoretical literature on airline network competition, especially the work of Hendricks, Piccione, and Tan (1995, 1997, and 1999); and the empirical literature on structural models of competition in the airline industry, in particular the work of Berry (1990 and 1992), Berry, Carnall, and Spiller (2006), and Ciliberto and Tamer (2009). We extend the static duopoly game of network competition in Hendricks, Piccione, and Tan (1999) to a dynamic framework with incomplete information, and N firms. Berry (1990) and Berry, Carnall, and Spiller (2006) estimate structural models of demand and price competition with a differentiated product and obtain estimates of the effects of hubs on marginal costs and consumers' demand. Berry (1992) and Ciliberto and Tamer (2006) estimate static models of entry that provide measures of the effects of hubs on fixed operating costs. Our paper extends this previous literature in two important aspects. First, our model is dynamic. A dynamic model is necessary to distinguish between fixed costs and sunk entry costs, which have different implications on market structure. A dynamic game is also needed to study the hypothesis that a hub-and-spoke network is an effective strategy to deter the entry of non-hub competitors. Second, our model endogenizes airline networks in the sense that airlines take into account how operating or not in a city-pair has implications on its profits (current and future) at other related routes.

The paper presents also two methodological contributions to the recent literature on the econometrics of dynamic discrete games.[6] First, we propose an method to reduce the dimension of the state space in dynamic games. Our method extends to the context of dynamic games previous approaches in Hendel and Nevo (2006) and Nevo and Rossi (2008). 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 show how to obtain an approximation to the counterfactual equilibrium. This method is agnostic on the form of the equilibrium selection mechanism, and therefore it is more robust than approaches which require stronger assumptions on equilibrium selection. An intuitive interpretation of our method is that we select the counterfactual equilibrium which is "closer" (in a Taylor-approximation sense) to the equilibrium estimated in the data. The data are used not only to identify the equilibrium in the population but also to identify the equilibrium in the counterfactual experiments.

Our empirical results show that the scale of operation of an airline in an airport (i.e., its hub-size) has statistically significant effects on travelers' willingness to pay, and on marginal (per-passenger) costs, fixed operating costs, and costs of starting a new route (i.e., route entry costs). Nevertheless, the most substantial impact is on the cost of entry in a route. Descriptive evidence shows that the difference between the probability that 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 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 to measure airlines' propensities to use hub-and-spoke networks when we eliminate each of the demand, cost and strategic factors in our model. These experiments show that the hub-size effect on entry costs is the most important factor to explain hub-and-spoke networks. For some of the larger carriers, strategic entry deterrence is the second most

[6] See Aguirregabiria and Mira (2007), Bajari, Benkard and Levin (2007), and Pakes, Ostrovsky and Berry (2007) for recent contributions to this literature.

important factor to explain hub-and-spoke networks.

The rest of the paper is organized as follows. Sections 2 presents our model and assumptions, and our approach to reduce the state space of the dynamic game. 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

2.1 Framework

The industry is configured by N airline companies and C cities or metropolitan areas. For the moment, we consider that each city has only one airport, though we will relax this assumption. Airlines and airports are exogenously given in our model.[7] A market in this industry is a *city-pair*. There are $M \equiv C(C-1)/2$ markets or *city-pairs*. We index time by t, markets by m, and airlines by i. The *network* of an airline consists of the set of city-pairs in which the airline operates non-stop flights or direct connections. Our market definition is not *directional*, i.e., if an airline operates flights from A to B, then it should operate flights from B to A. Let $x_{imt} \in \{0,1\}$ be a binary indicator of the event "airline i operates non-stop flights in city-pair m at period t", and let $\mathbf{x}_{it} \equiv \{x_{imt} : m = 1, 2, ..., M\}$ be the network of airline i at period t. The whole industry network is represented by the vector $\mathbf{x}_t \equiv \{\mathbf{x}_{it} : i = 1, 2, ..., N\} \in X$, with $X \equiv \{0,1\}^{NM}$. We define a *route* as a directional round-trip between two cities, e.g., a round-trip from Chicago to Los Angeles. The number of all possible routes is $C(C-1) = 2M$, and we index routes by r. A network describes implicitly all the routes for which an airline provides flights, either stop or non-stop. $L(\mathbf{x}_{it})$ is the set with all routes associated with network $\mathbf{x}_{it}$.[8]

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

[8] For instance, consider an industry with $C = 4$ cities, say A, B, C, and D. The industry has 6 markets or city-pairs that we represent as AB, AC, AD, BC, BD, and CD. The number of possible routes is 12. If airline i's network is $\mathbf{x}_{it} \equiv \{x_{iABt}, x_{iACt}, x_{iADt}, x_{iBCt}, x_{iBDt}, x_{iCDt}\} = \{1,1,0,0,0,0\}$, then this airline is active in two

Every period (quarter) t, airlines compete in prices taking as given the current industry network $\mathbf{x}_t$, and exogenous shocks in demand and variable costs, that we represent using the vector $\mathbf{z}_t \in Z$. An airline chooses the prices for all the routes in its route-set $L(\mathbf{x}_{it})$. Price competition determines current profits for each airline and route. Section 2.2 presents the details of our model of consumer demand, Nash-Bertrand price competition, and variable profits. Every quarter, airlines also decide their networks for next period. There is *time-to-build* such that fixed costs and the entry costs are paid at quarter t but entry-exit decisions are not effective until quarter $t+1$. We represent this decision using the vector $\boldsymbol{a}_{it} \equiv \{a_{imt} : m = 1, 2, ..., M\}$, where a_{imt} is a binary indicator for the decision "airline i will operate non-stop flights in city-pair m at period $t+1$". It is clear that $\mathbf{x}_{i,t+1} = \boldsymbol{a}_{it}$, but it is convenient to use different letters to distinguish state and decision variables. The airline's total profit function is:

$$\Pi_i \left(\boldsymbol{a}_{it}, \mathbf{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it} \right) = \sum_{r \in L(\mathbf{x}_{it})} R_{ir}(\mathbf{x}_t, \mathbf{z}_t) - \sum_{m=1}^{M} a_{imt} \; F_{imt} \tag{1}$$

where $R_{ir}(\mathbf{x}_t, \mathbf{z}_t)$ is the Nash-Bertrand equilibrium variable profit of airline i in route r, and F_{imt} represents the sum of fixed costs and entry costs for airline i in market m and quarter t. Section 2.3 describes our assumptions on fixed costs and entry costs. We anticipate here two important features. First, the term $\boldsymbol{\varepsilon}_{it} \equiv \{\boldsymbol{\varepsilon}_{imt} : m = 1, 2, ..., M\}$ represents a vector of idiosyncratic shocks in the fixed costs of airline i. These shocks are private information of this airline and are independently and identically distributed over airlines and over time with CDF G_ε. [9] Second, fixed and entry costs depend on the airline's scale of operation in the airports of the city-pair. More specifically, we consider that fixed and entry costs may decline with an airline's hub-size in the city-pair, defined as the number of direct connections that the airline has in the two cities that define the market. This cost structure implies that markets are interconnected through

markets, AB and AC, and it serves six routes, the non-stop routes AB, BA, AC, and CA, and the stop routes BC and CB.

[9] There are two main reasons why we incorporate these private information shocks. As shown by Doraszelski and Satterthwaite (2007), without private information shocks, this type of dynamic game may not have an equilibrium. Doraszelski and Satterthwaite show that, under mild regularity conditions, the incorporation of private information shocks implies that the game has at least one equilibrium. A second reason is that private information state variables independently distributed across players are convenient econometric errors that can explain part of the heterogeneity in players' actions without generating endogeneity problems.

hub-size effects. Therefore, an airline's entry-exit decision in a city-pair has implications on its own profits and on other airlines' profits at other city-pairs.

Airlines maximize intertemporal profits. They are forward-looking and take into account the implications of their entry-exit decisions on future profits and on the expected future reaction of competitors. Airlines also take into account network effects (i.e., hub-size effects) when making their entry-exit decisions. We assume that airlines' strategies depend only on payoff-relevant state variables, i.e., Markov perfect equilibrium assumption. An airline's payoff-relevant information at quarter t is $\{\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}\}$. Let $\boldsymbol{\sigma} \equiv \{\sigma_i(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}) : i = 1, 2, ..., N\}$ be a set of strategy functions, one for each airline. 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 for each possible state $(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it})$ and taking as given other airlines' strategies.

Let $V_i^{\boldsymbol{\sigma}}(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it})$ represent the value function for airline i given that the other companies behave according to their respective strategies in $\boldsymbol{\sigma}$, and given that airline i uses his best response/strategy. By the principle of optimality, this value function is implicitly defined as the unique solution to the following Bellman equation:

$$V_i^{\boldsymbol{\sigma}}(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}) = \max_{\boldsymbol{a}_{it}} \left\{ \Pi_i\left(\boldsymbol{a}_{it}, \mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}\right) + \beta\ E\left[V_i^{\boldsymbol{\sigma}}(\mathbf{x}_{t+1}, \mathbf{z}_{t+1}, \varepsilon_{it+1}) \mid \mathbf{x}_t, \mathbf{z}_t, \boldsymbol{a}_{it}\right] \right\} \tag{2}$$

where $\beta \in (0, 1)$ is the discount factor. The set of strategies $\boldsymbol{\sigma}$ is a MPE if, for every airline i and every state $(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it})$, we have that:

$$\sigma_i(\mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}) = \arg\max_{\boldsymbol{a}_{it}} \left\{ \Pi_i\left(\boldsymbol{a}_{it}, \mathbf{x}_t, \mathbf{z}_t, \varepsilon_{it}\right) + \beta\ E\left[V_i^{\boldsymbol{\sigma}}(\mathbf{x}_{t+1}, \mathbf{z}_{t+1}, \varepsilon_{it+1}) \mid \mathbf{x}_t, \mathbf{z}_t, \boldsymbol{a}_{it}\right] \right\} \tag{3}$$

That is, every airline strategy is its best response to the other airlines' strategies. An equilibrium in this dynamic game provides a description of the dynamics of prices, quantities, and airlines' incumbent status for every route between the C cities of the industry.

2.2 Consumer demand and price competition

A product is a *route*, i.e., a directional round-trip between two cities. For each product/route (r), there are two forms of product differentiation: the airline (i), and the indicator of non-stop flight

(NS).[10] For notational simplicity, we use k instead of the triple (i, r, NS) to index differentiated products. Also, we omit the time subindex t for most of this subsection. Let H_r be the number of potential travelers in route r. Every quarter, travelers decide which product to purchase, if any. The indirect utility of a consumer who purchases product k is $U_k = b_k - p_k + v_k$, where p_k is the price of product k, b_k is the "quality" or willingness to pay for product k of the average consumer in the market, and v_k is a consumer-specific component that captures consumer heterogeneity in preferences. We use the index $k = 0$ to represent a traveler's decision of not travelling by air, i.e. the *outside alternative*. Quality and price of the outside alternative are normalized to zero.[11]

Product quality b_k depends on exogenous characteristics of the airline and the route, and on the endogenous scale of operation of the airline in the origin and destination airports. We consider the following specification of product quality:

$$b_k \;=\; \alpha_1\; NS_k + \alpha_2\; HUB_k^O + \alpha_3\; HUB_k^D + \alpha_4\; DIST_k + \xi_i^{(1)} + \xi_r^{(2)} + \xi_k^{(3)} \tag{4}$$

α_1 to α_4 are parameters. NS_k is a dummy variable for "non-stop flight". $DIST_k$ is the distance between the origin and destination cities, and it is a proxy of the value of air transportation relative to the outside alternative, i.e., air travelling may be a more attractive transportation mode for longer distances. $\xi_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in quality which are constant over time and across markets. $\xi_r^{(2)}$ represents the interaction of (origin and destination) city dummies and time dummies. These terms account for demand shocks, such as seasonal effects, which can vary across cities and over time. $\xi_k^{(3)}$ is a demand shock that is airline and route specific. The variables HUB_k^O and HUB_k^D are indexes that represent the scale of operation or "hub size" of airline i in the origin and destination airports of route r, respectively. These variables capture consumer willingness to pay for the services associated with the scale of operation of an airline in the origin, destination and connecting airports. Following previous studies, we measure hub-size of an airline in an airport as the sum

[10] We do not model explicitly other forms of product differentiation, such as flights frequency or service quality. Consumers' valuation of these other forms of product differentiation will be embedded in the airline fixed-effects and the airport fixed-effects that we include in the demand estimation.

[11] Therefore, b_k should be interpreted as willingness to pay relative to the value of the outside alternative.

of the population in the cities that the airline serves from this airport (see Section 3 for more details).

A consumer purchases product k if and only if the utility U_k is greater than the utilities of any other choice alternative available for route r. This condition describes the unit demand of an individual consumer. To obtain aggregate demand, q_k, we have to integrate individual demands over the idiosyncratic variables v_k. The form of the aggregate demand depends on the probability distribution of consumer heterogeneity. We consider a nested logit model with two nests. The first nest represents the decision of which airline (or outside alternative) to patronize. The second nest consists of the choice of stop versus non-stop flight. We have that $v_k = \sigma_1 \; v_{ir}^{(1)} + \sigma_2 \; v_k^{(2)}$, where $v_{ir}^{(1)}$ and $v_k^{(2)}$ are independent Type I extreme value random variables, and σ_1 and σ_2 are parameters that measure the dispersion of these variables, with $\sigma_1 \geq \sigma_2$. Let s_k be the market share of product k in route r, i.e., $s_k \equiv q_k / H_r$. And let s_k^* be the market share of product k within the products of airline i in route r, i.e., $s_k^* \equiv s_k / \left(s_{ir0} + s_{ir1}\right)$. A property of the nested logit model is that the demand system can be represented using the following closed-form demand equations:[12]

$$\ln\left(s_k\right) - \ln\left(s_0\right) \;=\; \frac{b_k - p_k}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right) \; \ln\left(s_k^*\right) \tag{5}$$

where s_0 is the share of the outside alternative, i.e., $s_0 \equiv 1 - \sum_{i=1}^{N}(s_{ir0} + s_{ir1})$.

Travelers' demand and airlines' price competition in this model are static. The variable profit of airline i in route r is $R_{ir} = (p_{ir0} - c_{ir0})q_{ir0} + (p_{ir1} - c_{ir1})q_{ir1}$, where c_k is the marginal cost of product k, that is constant with respect to the quantity sold. Our specification of the constant marginal cost is similar to the one of product quality:

$$c_k \;=\; \delta_1 \; NS_k + \delta_2 \; HUB_k^O + \delta_3 \; HUB_k^D + \delta_4 \; DIST_k + \omega_i^{(1)} + \omega_r^{(2)} + \omega_k^{(3)} \tag{6}$$

δ_1 to δ_4 are parameters. $\omega_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in marginal costs. $\omega_r^{(2)}$ captures time-variant, city-specific shocks in costs which are common

[12]The nested logit model implies the following relationships. Define $e_k \equiv I_k \exp\{(b_k - p_k)/\sigma_1\}$, and I_k is the indicator of the event "product k is available in route r". Then, $s_k = s_k^* \; \bar{s}_{ir}$; $s_k^* = e_k/(e_{ir0} + e_{ir1})$; and $\bar{s}_{ir} = (e_{ir0} + e_{ir1})^{\sigma_2/\sigma_1}[1 + \sum_{j=1}^{N}(e_{jr0} + e_{jr1})^{\sigma_2/\sigma_1}]^{-1}$.

for all the airlines. $\omega_k^{(3)}$ is a shock in the marginal cost that is airline, route and time specific. Given quality indexes $\{b_k\}$ and marginal costs $\{c_k\}$, airlines active in route r compete in prices ala Nash-Bertrand. The Nash-Bertrand equilibrium is characterized by the system of price equations:[13] $p_k - c_k = \sigma_1(1-\bar{s}_k)^{-1}$, where $\bar{s}_k = (e_{ir0}+e_{ir1})^{\sigma_2/\sigma_1}[1+\sum_{j=1}^{N}(e_{jr0}+e_{jr1})^{\sigma_2/\sigma_1}]^{-1}$, $e_k \equiv I_k \exp\{(b_k - p_k)/\sigma_2\}$, and I_k is the indicator of the event "product k is available in route r", that depends on airlines' current networks in $\mathbf{x}_t$. Equilibrium prices depend on the qualities and marginal costs of all the airlines and products that are active in the same route.

2.3 Fixed costs and route entry costs

The sum of fixed costs and entry costs of airline i in market m at quarter t is:

$$F_{imt} = FC_{imt} + \varepsilon_{imt} + (1 - x_{imt})\ EC_{imt} \tag{7}$$

where $FC_{imt} + \varepsilon_{imt}$ and EC_{imt} represent fixed costs and entry costs, respectively, of operating non-stop flights in city-pair m. The fixed cost $FC_{imt} + \varepsilon_{imt}$ is paid only if the airline decides to operate in city-pair m, i.e., if $a_{imt} = 1$. The entry cost EC_{imt} is paid only when the airline is not active in market m at period t but it decides to operate in the market next period, i.e., if $x_{imt} = 0$ and $a_{imt} = 1$. The terms $\{FC_{imt}\}$ and $\{EC_{imt}\}$ are common knowledge for all the airlines. However, the component ε_{imt} is private information of the airline. This private information shock is assumed to be independently and identically distributed over firms and over time. Our specification of the common knowledge components of fixed costs and entry costs is similar to the one of marginal costs and consumers' willingness to pay:

$$\begin{aligned} FC_{imt} &= \gamma_1^{FC} + \gamma_2^{FC}\ \overline{HUB}_{imt} + \gamma_3^{FC} DIST_m + \gamma_{4i}^{FC} + \gamma_{5c}^{FC} \\ EC_{imt} &= \eta_1^{EC} + \eta_2^{EC}\ \overline{HUB}_{imt} + \eta_3^{EC} DIST_m + \eta_{4i}^{EC} + \eta_{5c}^{EC} \end{aligned} \tag{8}$$

$\gamma's$ and $\eta's$ are parameters. $\overline{HUB}_{imt}$ represents the average hub-size of airline i in the airports of city-pair m. γ_{4i}^{FC} and η_{4i}^{EC} are airline fixed-effects. γ_{5c}^{FC} and η_{5c}^{EC} are city fixed-effects.

[13] See page 251 in Anderson, De Palma and Thisse (1992).

2.4 Reducing the dimensionality of the dynamic game

From a computational point of view, the solution and the estimation of the dynamic game of network competition in sections 2.1 to 2.3 is extremely challenging. Solving the dynamic game requires one to 'integrate' value functions over the space of the state variables $\{\mathbf{x}_t, \mathbf{z}_t\}$. This space has a huge number of possible states. Given the number of cities and airlines in our empirical analysis,[14] the number of possible values of the industry network $\mathbf{x}_t$ is $|X| = 2^{NM} \simeq 10^{10,000}$, that is intractable. To deal with this computational complexity, we introduce several simplifying assumptions that reduce very significantly the dimension of the dynamic game and make its solution and estimation manageable.

Suppose that every airline has M local managers, one for each market or city-pair. A local manager decides whether to operate non-stop flights in his local-market, i.e., he chooses a_{imt}. Let R_{imt} be the *variable profit that local manager* (i, m) *is concerned with*, that is defined as the sum of airline i's variable profits over all the non-stop and one-stop routes that include city-pair m as a segment.[15] To illustrate this concept, consider as an example the variable profit of the local manager of American Airlines in the city-pair Boston-Chicago. Remember that we have defined a route as a directional round-trip between two cities. The set of routes that contain Boston-Chicago as a segment are the following: non-stop Boston-Chicago (1 route); non-stop Chicago-Boston (1 route); one-stop routes with origin at Boston, stop at Chicago, and destination to any other city ($C - 2$ routes); one-stop routes with origin at Chicago, stop at Boston, and destination to any other city ($C - 2$ routes); one-stop routes with origin at any other city, stop at Chicago, and destination Boston ($C - 2$ routes); and one-stop routes with origin at any other city, stop at Boston, and destination Chicago ($C - 2$ routes). Therefore, the number of routes included in the variable profit of a local manager are $2 + 4(C - 2)$. Given that the number of cities in our application is $C = 55$, the number of routes included in the variable profit of a local-manager is 214. It is important to emphasize that an airline's variable

[14] We consider $N = 22$ airlines, $C = 55$ cities, and $M = 1,485$ city-pairs.

[15] For simplicity in our computation of R_{imt}, we consider only non-stop and one-stop routes. Routes with more than one stop represent a very small fraction of tickets and total revenue in the dataset.

profit in a route is the result of the Nash-Bertrand equilibrium described in section 2.2, and it depends on the incumbent status of all the airlines for that route. Therefore, the variable profit of a local-manager depends on the incumbent status, x, of every airline at many different city-pairs. For instance, if Southwest decides to enter in the local-market Madison-Chicago, this decision has a negative effect on the profit of the local manager of American Airlines at city-pair Boston-Chicago. This is because AA will see reduced its profit from the routes Madison-Boston and Boston-Madison with stop at Chicago.

ASSUMPTION NET-1: The local manager at market m chooses $a_{imt} \in \{0, 1\}$ to maximize the expected and discounted value of the stream of local-market profits, $E_t(\sum_{s=1}^{\infty} \beta^s \Pi_{im,t+s})$, where $\Pi_{imt} \equiv R_{imt} - a_{imt} \left(FC_{imt} + \varepsilon_{imt} + (1 - x_{imt}) EC_{imt} \right)$.

ASSUMPTION NET-2: The shocks $\{\varepsilon_{imt}\}$ are private information of local manager (i, m). These shocks are unknown to the managers of airline i at markets other than m.

Assumptions NET-1 and NET-2 establish that an airline's network decision is decentralized at the city-pair level. It is important to note that, given our definition of the variable profits R_{imt}, this decentralized decision-making can generate equilibria with the entry deterrence studied by Hendricks, Piccione and Tan (1997). In particular, every local manager takes into account that exit from his city-pair market eliminates profits from every route that includes this city-pair as a segment. This complementarity between profits of different routes may imply that a hub-spoke network is an effective strategy to deter the entry of competitors.

Assumptions NET-1 and NET-2 simplify the computation of players' best responses. However, the state space of the decision problem of a local manager is still $X \times Z$, and the dimension of this state space is computationally intractable. To deal with this issue, we consider a Markov Perfect Equilibrium where players' strategy functions do not depend on the whole vector of variables $\{\mathbf{x}_t, \mathbf{z}_t\}$, but only on a subset of this vector. This approach is in a similar spirit as Hendel and Nevo (2006) and Nevo and Rossi (2008). However, these previous papers consider single-agent dynamic decision problems, and here we extend the approach to the context of dynamic games. We assume that local managers, when calculating their best responses, do not use all the information in $\{\mathbf{x}_t, \mathbf{z}_t\}$. Instead, the strategy of a local-manager, say (i, m), depends on ε_{imt} and on the vector of payoff-relevant variables

$$\mathbf{w}_{imt} \equiv \left\{x_{imt},\, R_{imt},\, \overline{HUB}_{imt},\, n_{mt},\, \overline{HUB}_{mt}\right\} \tag{9}$$

where n_{mt} is the number of incumbent airlines in market m at period t; $\overline{HUB}_{mt}$ is the average hub-size in market m at period t considering all the active airlines; and x_{imt}, R_{imt}, and $\overline{HUB}_{imt}$ have been defined above. This assumption can be interpreted either in terms of players' incomplete information, or bounded rationality, or limited computational resources.

ASSUMPTION NET-3: For every local-manager (i, m), his strategy function is $\sigma_{im}(\mathbf{w}_{imt}, \varepsilon_{imt})$, that is a function from $W \times \mathbb{R}$ into $\{0, 1\}$.

Let $\boldsymbol{\sigma} \equiv \{\sigma_{im}(\mathbf{w}_{imt}, \varepsilon_{imt}) : i = 1, 2, ..., N;\ m = 1, 2, ..., M\}$ be a set of strategy functions, one for each local-manager. And let $\mathbf{P} = \{P_{im}(\mathbf{w}_{imt}) : i = 1, 2, ..., N;\ m = 1, 2, ..., M;\ \mathbf{w}_{imt} \in W\}$ be the vector of *conditional choice probabilities* (CCPs) associated with $\boldsymbol{\sigma}$, such that $P_{im}(\mathbf{w}_{imt})$ is defined as:

$$P_{im}(\mathbf{w}_{imt}) \equiv \int 1\{\sigma_{im}(\mathbf{w}_{imt}, \varepsilon_{imt}) = 1\} dG_{\varepsilon}(\varepsilon_{imt}) \tag{10}$$

where $1\{.\}$ is the indicator function. $P_{im}(\mathbf{w}_{imt})$ is the probability that local-manager (i, m) operates in the market. Given $\mathbf{P}$, let $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1} | a_{imt}, \mathbf{w}_{imt})$ be the Markov transition probability of the vector $\{\mathbf{w}_{imt}\}$ induced by the vector of strategy functions $\mathbf{P}$. This transition probability depends on players' strategies in $\mathbf{P}$ and therefore it is not a primitive of the model but an equilibrium outcome. We describe the structure of this transition probability function at the end of this subsection. For the moment, it is important to emphasize that this transition probability is fully consistent with the equilibrium of the model. The best response of a local-manager is the solution of a dynamic programming problem. Let $V_{im}^{\mathbf{P}}(\mathbf{w}_{imt})$ be the (integrated) value function of the DP problem in the best response of player (i, m). This value function is the unique solution to the Bellman equation $V = \Gamma_{im}^{\mathbf{P}}(V)$, where $\Gamma_{im}^{\mathbf{P}}(.)$ is the following Bellman operator:

$$\Gamma_{im}^{\mathbf{P}}(V)(\mathbf{w}_{imt}) \equiv \int \max_{a \in \{0,1\}} \left\{ \Pi_{imt}(a) - a\ \varepsilon_{imt} + \beta \sum_{\mathbf{w}'} V(\mathbf{w}')\ f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}' | a, \mathbf{w}_{imt}) \right\} dG_{\varepsilon}(\varepsilon_{imt}), \tag{11}$$

with $\Pi_{imt}(a) \equiv R_{imt} - a\,(FC_{imt} + (1 - x_{imt})EC_{imt})$. Then, given $V_{im}^{\mathbf{P}}$, the best response of a local manager can be described as: $\{a_{imt} = 1\}$ if and only if:

$$\Pi_{imt}(1) - \Pi_{imt}(0) - \varepsilon_{imt} + \beta \sum_{\mathbf{w}'} V_{im}^{\mathbf{P}}(\mathbf{w}') \left[f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}'|1, \mathbf{w}_{imt}) - f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}'|0, \mathbf{w}_{imt}) \right] > 0 \tag{12}$$

The best response probability mapping, that we denote by $\Psi_{im}(\mathbf{w}_{imt}; \mathbf{P})$, is just the best response function integrated over the distribution of the private information shock ε_{imt}:

$$\Psi_{im}(\mathbf{w}_{imt}; \mathbf{P}) \equiv G_{\varepsilon}\left(\Pi_{imt}(1) - \Pi_{imt}(0) + \beta \sum_{\mathbf{w}'} V_{im}^{\mathbf{P}}(\mathbf{w}') \left[f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}'|1, \mathbf{w}_{imt}) - f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}'|0, \mathbf{w}_{imt}) \right] \right) \tag{13}$$

We can define a Markov Perfect Equilibrium (MPE) in our dynamic game of network competition as a vector $\mathbf{P} \in [0,1]^{NM|W|}$ that is a solution to the fixed point problem $\mathbf{P} = \Psi(\mathbf{P})$, where $\Psi(\mathbf{P})$ is the vector of best-response (probability) functions $\{\Psi_{im}(\mathbf{w}; \mathbf{P})\}$ for every player (i, m) and any $\mathbf{w} \in W$.

Now, we describe the structure of the transition probability functions $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt}, \mathbf{w}_{imt})$. The vector of variables $\mathbf{w}_{imt}$ is a deterministic function of the state variables in the original problem, $\{\mathbf{x}_t, \mathbf{z}_t\}$. More specifically: $n_{mt} \equiv \sum_{j=1}^{N} x_{jmt}$; $\overline{HUB}_{imt} = \sum_{m' \in C_m} x_{imt}$, where C_m is the set of markets with a common city with market m; $\overline{HUB}_{mt} = N^{-1} \sum_{j=1}^{N} \overline{HUB}_{jmt}$; and R_{imt} is the sum of the Bertrand equilibrium variable profits from different routes. We use the vector function $w_{im}()$ to represent in a compact form this deterministic relationship between $\mathbf{w}_{imt}$ and $(\mathbf{x}_t, \mathbf{z}_t)$, i.e., $\mathbf{w}_{imt} = w_{im}(\mathbf{x}_t, \mathbf{z}_t)$. Given the structure of the model,[16] we have that the transition probability $\Pr(\mathbf{w}_{imt+1}|\boldsymbol{a}_t, \mathbf{x}_t, \mathbf{z}_t)$ is equal to $\sum_{\mathbf{z}_{t+1} \in Z} 1\{\mathbf{w}_{imt+1} = w_{im}(\boldsymbol{a}_t, \mathbf{z}_{t+1})\}\; p_{\mathbf{z}}(\mathbf{z}_{t+1})$, where $p_{\mathbf{z}}$ is the PDF of $\mathbf{z}_t$. We denote this transition probability as $g_{im}^{\mathbf{w}}(\mathbf{w}_{imt+1}|\boldsymbol{a}_t)$. Note that the functions $g_{im}^{\mathbf{w}}$ are primitives of the model, i.e., they do not depend on players' behavior. Also, note that these probability functions are conditional on the vector $\boldsymbol{a}_t$ that includes all the players' actions at period t. When calculating future expected profits of alternative actions, a player cannot integrate next period profits using the transition probability $g_{im}^{\mathbf{w}}(\mathbf{w}_{imt+1}|\boldsymbol{a}_t)$ because he does not know other players' current actions at period t. Instead, he uses the transition probability

[16] In particular, given the deterministic transition $x_{imt+1} = a_{imt}$, and the iid assumption on the demand and cost shocks in $\mathbf{z}_t$.

$f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt}, \mathbf{w}_{imt})$. By definition, the relationship between $f_{im}^{\mathbf{w},\mathbf{P}}$ and $g_{im}^{\mathbf{w}}$ is the following:

$$f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{im}, \mathbf{w}_{imt}) \equiv \sum_{\boldsymbol{a}_{-(im)}} g_{im}^{\mathbf{w}}(\mathbf{w}_{imt+1}|a_{im}, \boldsymbol{a}_{-(im)})\ Q_{im}^{\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{imt}) \tag{14}$$

where $Q_{im}^{\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{imt})$ is the probability distribution of the actions of players other than (i,m) from the point of view of player (i,m), who observes only $\mathbf{w}_{imt}$, and given players' strategies in $\mathbf{P}$. Other players' actions depend on other players' $\mathbf{w}'s$ which are unknown for a local manager. Therefore, the probability function $Q_{im}^{\mathbf{P}}$ depends on the probability distribution $\Pr(\mathbf{w}_{-(im)t}|\mathbf{w}_{imt}, \mathbf{P})$. That is,

$$Q_{im}^{\mathbf{P}}(\boldsymbol{a}_{-(im)t}|\mathbf{w}_{imt}) \equiv \sum_{\mathbf{w}_{-(im)t}} \left[\prod_{(j,n)\neq(i,m)} P_{jn}(a_{jnt}|\mathbf{w}_{jnt}) \right] \Pr(\mathbf{w}_{-(im)t}|\mathbf{w}_{imt}, \mathbf{P}) \tag{15}$$

By Bayes rule, we have that $\Pr(\mathbf{w}_{-imt}|\mathbf{w}_{imt}, \mathbf{P}) = p^*(\mathbf{w}_{imt}, \mathbf{w}_{-imt}|\mathbf{P})/p_{im}^*(\mathbf{w}_{imt}|\mathbf{P})$, where $p^*(\mathbf{w}_t|\mathbf{P})$ and $p_{im}^*(\mathbf{w}_{imt}|\mathbf{P})$ are the ergodic probability distributions of $\{\mathbf{w}_t\}$ and $\{\mathbf{w}_{imt}\}$, respectively, induced by the CCPs in $\mathbf{P}$.

For given transition probabilities $\{f_{im}^{\mathbf{w},\mathbf{P}}\}$, the solution of the DP problems that define players' best response probabilities is a relatively simple computational task. Each of these DP problems has a state space with dimension $|W|$ that in our application is equal to 3960 points. However, computing exactly the transition probabilities $\{f_{im}^{\mathbf{w},\mathbf{P}}\}$ is not trivial, and in fact it suffers of a curse of dimensionality. In particular, the exact computation of the ergodic probability distribution $p^*(\mathbf{w}_t|\mathbf{P})$ requires one calculate the Markov transition probability of $\mathbf{w}_t$ that lives in the space $W_{all} \times W_{all}$, where the dimension of W_{all} is $|W|^{NM}$. To deal with this computational problem, we use Monte Carlo simulation to approximate the transition probability functions $\{f_{im}^{\mathbf{w},\mathbf{P}}\}$. Our simulator is in the spirit of the random-grid approximation method proposed by Rust (1997). We describe in detail this approximation method in the Appendix.

Since we use Monte Carlo simulation to approximate the transition probability functions $f_{im}^{\mathbf{w},\mathbf{P}}$, one might argue that we could also use simulation methods to approximate value functions and choice probabilities that depend on the whole vector of state variables $\{\mathbf{x}_t, \mathbf{z}_t\}$, without the need to impose assumption NET-3. However, given the huge space of $\{\mathbf{x}_t, \mathbf{z}_t\}$, Monte Carlo simulation alone, without the additional structure imposed by Assumption NET-3, provides very imprecise approximations to the equilibrium of the dynamic game.

3 Data and descriptive statistics

3.1 Construction of the working sample

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. The frequency is quarterly. A record in this survey represents a ticket. Each record or ticket contains information on the 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.[17] The raw data set contains millions of tickets for each quarter. For instance, the number of records in the fourth quarter of 2004 is 8,458,753. To construct our working sample, we have used the DB1B dataset over the four quarters of 2004. We describe here the criteria 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. From the point of view of entry-exit decisions, a market is a non-directional city-pair. For the model of demand and price competition, a product or route is a round-trip between two cities, an origin city and a destination city. These market definitions are 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 (2009) 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 the supply) of routes that involve airports located in the same city. In the demand, we distinguish differentiated products within a product-route. In particular, we distinguish non-stop and stop flights, and the different airlines.

[17] This dataset does no contain information on ticket restrictions such as 7 or 14 days purchase in advance. Another information that is not available is the day or week of the flight or the flight number.

(b) Selection of markets. We start selecting the 75 largest US cities in 2004 based on population estimates from the Bureau of Statistics.[18] For each city, we consider all the airports which are classified as primary airports by the Federal Aviation Administration. Some of the 75 cities belong to the same metropolitan area and share the same airports. We group these cities. Finally, we have 55 metropolitan areas ('cities') and 63 airports. Table 1 presents the list of 'cities' with their airports and population.[19] To measure market size, we use the total population in the cities of the origin and destination airports. The number of possible city-pairs is $M = (55 * 54)/2 = 1,485$. Table 2 presents the top 20 city-pairs by annual number of round-trip non-stop passengers in 2004 according to DB1B.

(c) Airlines. 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.[20] For more than 70% of the tickets in this database the three types of carriers 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.

According to DB1B, there are 31 carriers or 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.[21] We take this into account in our analysis. Table 3 presents our list of 22 airlines. The notes in the table explains

[18] The Population Estimates Program of the US Bureau of Statistics 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".

[19] 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.

[20] 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.

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

how some of these airlines are a combination of the original carriers. The table also reports the number of passengers and of city-pairs in which each airline operates for our selected 55 cities. *Southwest* is the company that flies more passengers (more than 25 million passengers) and that serves more city-pairs with non-stop flights (373 out of a maximum of 1,485). American, United and Delta follow in the ranking, in this order, but they serve significantly fewer city-pairs than Southwest.

(d) 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; and (4) tickets with fare credibility question by the *Department of Transportation*.

(e) Definition of active carrier in a route-product. We consider that an airline is active in a city-pair if during the quarter the airline has at least 20 passengers per week (260 per quarter) in non-stop flights for that city-pair.

(f) 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_{kt}, with $k \equiv (i, r, NS)$, is the number of passengers in the DB1B survey at quarter t that corresponds to airline i, route r and non-stop flight indicator NS. The DB1B-Ticket dataset reports the total itinerary fare. We construct the price variable p_k (measured in dollars-per-passenger) as the ratio between the sum of fares for those tickets that belong to product k and the sum of passengers in the same group of tickets.

(g) Measure of hub size. For each airport and airline, we construct two measures of the scale of operation, or *hub-size*, of the airline at the airport. The first measure of hub size is the number of direct connections of the airline in the airport. This hub size measured is the one included in the cost functions. The second measure of hub size follows Berry (1990) and Berry, Carnall and Spiller (2006), and it is the sum of the population in the cities that the airline serves with

nonstop flights from this airport. The reason to weigh routes by the population in the destination city is that more populated cities are typically more valued by consumers and therefore this hub measure takes into account this higher willingness to pay.

Our working dataset for the estimation of the entry-exit game is a balanced panel of 1,485 city-pairs, 22 airlines, and 3 quarters, which make $98,010$ observations. The dataset on prices and quantities for the estimation of demand and variable costs is an unbalanced panel of 2,970 routes, 22 airlines, and 4 quarters, and the number of observations is $85,497$.

3.2 Descriptive statistics

A network $\mathbf{x}_{it}$ is a *pure* hub-and-spoke system if there is a city, the hub city, that appears in all the direct connections in $\mathbf{x}_{it}$. Though there are some airlines with pure hub-and-spoke networks in out dataset, they are not so common. However, *quasi* hub-and-spoke networks are the most common networks in the US airline industry. In order to study an airlines' propensity to use hub-and-spoke networks (both in the actual data and in our model), we use the following ratio. Given an airline's network, $\mathbf{x}_{it}$, we define the airline's hub, h_i, as the city that appears more frequently in the direct connections of the network $\mathbf{x}_{it}$. And we define the airline's *hub-and-spoke ratio* (*HSR*) as the proportion of direct connections that include the airline's hub:

$$HSR_{it} = \frac{\sum_{m=1}^{M} x_{imt} \; 1\left\{\text{city } h_i \text{ is in city-pair } m\right\}}{\sum_{m=1}^{M} x_{imt}} \tag{16}$$

where $1\{.\}$ is the indicator function. A pure hub-and-spoke network has HSR equal to 1. In the other extreme, a point-to-point network connecting C cities has a ratio equal to $2/C$.

Table 4 presents, for each airline, the two airports with largest hub sizes (as measured by number of direct connections), and the hub-and-spoke ratio as defined in equation (16). Several interesting features appear in this table. *Pure* hub-and-spoke networks are very rare, and they are only observed in small carriers.[22] Southwest, the leader in number of passengers and active markets, has a hub-and-spoke ratio (9.3%) that is significantly smaller than any other airline and

[22] The only carriers with pure hub-and-spoke networks are Sun Country at Minneapolis (11 connections), Ryan at Atlanta (2 connections), and Allegiant at Las Vegas (3 connections).

very close to a pure point-to-point network. Among the largest carriers, the ones with largest hub-and-spoke ratios are Continental (36.6%), Delta (26.7%), and Northwest (25.6%). The largest hubs in terms of number of connections are Delta at Atlanta (53 connections), Continental at Houston (52), and American at Dallas (52).

Figure 1 presents the cumulative hub-and-spoke ratios for three large carriers: Southwest, American, and Continental. Using these cumulative ratios we can describe an airline as a combination of multiple hubs such that the cumulative ratio is equal to one. According to this, Continental airlines can be described as the combination of 5 hub-and-spoke networks. However, the description of American as a combination of hub-and-spoke networks requires 10 hubs, and for Southwest we need 20 hubs.

Table 5 presents different statistics that describe market structure and its dynamics. The first panel of this table (panel 5.1) presents the distribution of the 1,485 city-pairs by the number of incumbent airlines. More than one-third of the city-pairs have no incumbents, i.e., there are not direct flights between the cities. Typically, these are pairs of relative smaller cities which are far away of each other (e.g., Tulsa, OK, and Ontario, CA). Almost one-third of the markets are monopolies, and approximately 17% are duopolies. The average number of incumbents per market is only 1.4. Therefore, these markets are highly concentrated. This is also illustrated by the value of the Herfindahl index in panel 5.2. Panel 5.3 presents the number of monopoly markets for each of the most important carriers. Southwest, with approximately 150 markets, accounts for a large portion of monopoly markets, followed by Northwest and Delta with approximately 65 and 60 monopoly markets, respectively. Panels 5.4 and 5.5 present the distribution of markets by the number of new entrants and by the number of exits, respectively. It is interesting that, even for our quarterly frequency of observation, there is a substantial amount of entry and exit in these markets. The average number of entrants per market and quarter is 0.17 and the average number of exits is 0.12. As shown in section 4, this significant turnover provides information to identify fixed costs and entry costs parameters with enough precision.

Table 6 presents the transition matrix for the number of incumbent airlines in a city-pair.

We report the transition matrix from the second to the third quarter of 2004.[23] There is significant persistence in market structure, specially in markets with zero incumbents or in monopoly markets. Nevertheless, there is a non-negligible amount of transition dynamics.

4 Estimation of the structural model

Our approach to estimate the structural model proceeds in three steps. First, we estimate the parameters in the demand system using information on prices, quantities and product characteristics. In a second step, we estimate the parameters in the marginal cost function using the Nash-Bertrand equilibrium conditions. Steps 1 and 2 provide estimates of the effects of hub-size on demand and variable costs. Given these estimates of variable profits, we estimate the parameters in fixed costs and entry costs using the dynamic game of network competition.

4.1 Estimation of the demand system

The demand model can be represented using the regression equation:

$$\ln(s_{kt}) - \ln(s_{0t}) \;=\; W_{kt}\ \alpha + \left(\frac{-1}{\sigma_1}\right) p_{kt} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln(s^*_{kt}) + \xi^{(3)}_{kt} \tag{17}$$

The regressors in vector W_{kt} are the ones in equation (4): i.e., dummy for nonstop-flight, hub-size variables, distance, airline dummies, origin-city dummies $\times$ time dummies, and destination-city 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 $\ln(s^*_{kt})$ (see Berry, 1994, and Berry, Levinshon and Pakes, 1995). Equilibrium prices depend on the characteristics (observable and unobservable) of all products, and therefore the regressor p_{kt} is correlated with the unobservable demand shock $\xi^{(3)}_{kt}$. Similarly, the regressor $\ln(s^*_{kt})$ depends on unobserved characteristics and it is endogenous. In our model, there is other potential endogeneity problem in the estimation of the demand. The hub-size variables HUB^O_{kt} and HUB^D_{kt} (included in the vector W_{kt}) depend on the entry decisions of the airline in other city-pairs that include the origin or the destination cities

[23] The transition matrices from Q1 to Q2 and from Q3 to Q4 are very similar to the one reported in Table 6.

of the route in product k. These entry decisions may be correlated with the demand shock $\xi_{kt}^{(3)}$. For instance, if the demand shocks $\xi_{kt}^{(3)}$ are spatially correlated across markets, entry decisions in other nearby markets depend on $\{\xi_{kt}^{(3)}\}$, and therefore the hub-size variables are endogenous in the estimation of the demand model. The following assumption, together with the time-to-build assumption on entry-exit decisions, implies that the hub-size variables are not endogenous in the estimation of demand.[24]

ASSUMPTION D1: Idiosyncratic demand shocks $\{\xi_{kt}^{(3)}\}$ *are not serially correlated over time.*

Assumption D1 establishes that once we control for the observable variables in W_{kt}, including airline fixed effects $\xi_i^{(1)}$, and airport-time effects $\xi_{kt}^{(2)}$, the residual demand does not present any persistence or time-series correlation. Given that entry-exit decisions are taken a quarter before they become effective, if demand shocks $\{\xi_{kt}^{(3)}\}$ are not serially correlated, then they are not correlated with hub-size variables.

ASSUMPTION D2: The idiosyncratic demand shock $\{\xi_{kt}^{(3)}\}$ *is private information of the corresponding airline. Furthermore, the demand shocks of two different airlines at two different routes are independently distributed.*

Remember that the hub-size variables HUB_{kt}^{O} and HUB_{kt}^{D} depend on the entry decisions in city-pairs that include one of the cities in the origin or the destination of the route in product k, but they exclude the own city-pair of product k. Under Assumption D2, the hub-size variables of other airlines in the same route are not correlated with $\xi_{kt}^{(3)}$. Furthermore, by the equilibrium condition, prices depend on the hub-size of every active firm in the market. Therefore, we can use the hub-sizes of competing airlines as valid instruments for the price p_{kt} and the market share $\ln(s_{kt}^{*})$. We use as instruments the average value of the hub-sizes of the competitors. Note that Assumptions D1 and D2 are testable. Using the residuals from the estimation we can test for time-series correlation, and cross-airlines correlation in the idiosyncratic demand shocks $\xi_{kt}^{(3)}$.

Table 7 presents our estimates of the demand system. To illustrate the endogeneity problem,

[24] Sweeting (2007) considers a similar identifying assumption in the estimation of a demand system of radio listeners in the context of a dynamic oligopoly model of the commercial radio industry.

we report both OLS and IV estimation results. The estimated coefficient for the FARE variable in the IV estimation is significantly smaller than in the OLS estimation, which is consistent with the endogeneity of prices in the OLS estimation. The test of first order serial correlation in the residuals cannot reject the null hypothesis of no serial correlation. This result supports Assumption D1, and therefore the exogeneity of the hub-size variables.

We can obtain measures of willingness to pay for different product characteristics, in dollar amounts, by dividing the coefficient of the product characteristic by the coefficient of the FARE variable. We find that the willingness to pay for a non-stop flight is \$152 more than for a stop-flight. The estimated effects of hub-size are also plausible. Expanding the hub-size in the origin airport (destination airport) in one million people would increase consumers willingness to pay in \$1.97 (\$2.63). Finally, longer nonstop distance makes consumer more inclined to use airplane transportation than other transportation modes.

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 $\hat{c}_{kt} = p_{kt} - \hat{\sigma}_1(1 - \bar{s}_{kt})^{-1}$, where $\hat{\sigma}_1(1 - \bar{s}_{kt})^{-1}$ is the estimated price-cost margin of product k at period t. The marginal cost function can be represented using the regression equation $\hat{c}_{kt} = W_{kt}\ \delta + \omega_{kt}^{(3)}$, where the vector of regressors W_{kt} has the same definition as in the demand equation above.

As in the estimation of demand, the hub-size variables are potentially endogenous regressors in the estimation of the marginal cost function. These variables might be correlated with the cost shock $\omega_{kt}^{(3)}$. We consider the following identifying assumption.

ASSUMPTION MC1: Idiosyncratic shocks in marginal cost $\{\omega_{kt}^{(3)}\}$ *are not serially correlated over time.*

Assumption MC1 implies that the hub-size variables are exogenous regressors in the marginal cost function. Under this assumption, the vector of parameters δ can be estimated consistently by OLS.

Table 8 presents OLS estimates of the marginal cost function. The marginal cost of a non-stop flight is \$12 larger than the marginal cost of a stop-flight, but this difference is not statistically significant. Distance has a significantly positive effect on marginal cost. The airline scale of operation (or hub-size) at the origin and destination airports reduce marginal costs. However, these effects are relatively small. An increase of one million people in the hub-size of the origin airport (destination airport) would reduce the marginal cost (per passenger) in \$2.3 (\$1.6).

4.3 Estimation of the dynamic game

4.3.1 An alternative representation of the equilibrium mapping

As shown in section 2.4, a MPE of our dynamic game can be described as a vector $\mathbf{P}$ of *conditional choice probabilities* (CCPs) that solves the equilibrium fixed point problem $\mathbf{P} = \Psi(\mathbf{P})$, where Ψ is the best response probability mapping that we have defined in equation (13). Following the *Representation Lemma* in Aguirregabiria and Mira (2007, page 11), we can represent a MPE of our dynamic game as a fixed point of an alternative mapping that is more convenient for estimation. In order to describe this representation, it is useful to write the current profit of a local manager, Π_{imt}, as follows:

$$\Pi_{imt} = (1 - a_{imt}) \ \mathbf{z}_{imt}(0) \ \boldsymbol{\theta} + a_{imt} \ \mathbf{z}_{imt}(1) \ \boldsymbol{\theta} - a_{imt} \ \varepsilon_{imt} \tag{18}$$

$\boldsymbol{\theta}$ is a column vector with the structural parameters characterizing fixed and entry costs:

$$\begin{aligned} \boldsymbol{\theta} \quad \equiv \quad & \big(\, 1, \ \gamma_1^{FC}, \ \gamma_2^{FC}, \ \gamma_3^{FC}, \ \{\gamma_{4i}^{FC}\}, \{\gamma_{5c}^{FC}\} \\ & \quad \eta_1^{EC}, \ \eta_2^{EC}, \ \eta_3^{EC}, \ \{\eta_{4i}^{EC}\}, \{\eta_{5c}^{EC}\} \ \big)' \end{aligned} \tag{19}$$

where $\{\gamma_{4i}^{FC}\}$ and $\{\eta_{4i}^{EC}\}$ represent airline fixed-effects in fixed costs and entry costs, respectively, and $\{\gamma_{5c}^{FC}\}$ and $\{\gamma_{5c}^{EC}\}$ represent city fixed-effects. $\mathbf{z}_{imt}(0)$ and $\mathbf{z}_{imt}(1)$ are row vectors with the following definitions:

$$\begin{aligned} \mathbf{z}_{imt}(0) \quad & \equiv \quad (\ R_{imt}, \ \mathbf{0} \ ) \\ \mathbf{z}_{imt}(1) \quad & \equiv \quad \big(\ R_{imt}, \ 1, \ \overline{HUB}_{imt}, \ DIST_m, \ AIRDUM_i, \ CITYDUM_m \\ & \qquad (1 - x_{imt}) * \big[1, \ \overline{HUB}_{imt}, \ DIST_m, \ AIRDUM_i, \ CITYDUM_m\big]\big) \end{aligned} \tag{20}$$

$AIRDUM_i$ and $CITYDUM_m$ are vectors of airline dummies and city dummies, respectively.[25]

We can represent a MPE in this model as a vector $\mathbf{P} = \{P_{im}(\mathbf{w})\}$ of CCPs that solves the fixed point problem $\mathbf{P} = \Lambda(\boldsymbol{\theta}, \mathbf{P})$, where $\Lambda(\boldsymbol{\theta}, \mathbf{P}) \equiv \{\Lambda(\tilde{\mathbf{z}}_{imt}^{\mathbf{P}} \frac{\boldsymbol{\theta}}{\sigma_\varepsilon} + \tilde{e}_{imt}^{\mathbf{P}}) : \text{for every } (i, m, \mathbf{w}_{imt})\}$. $\Lambda()$ is the CDF of $\varepsilon_{imt}/\sigma_\varepsilon$, that in our model is the logistic function $\exp(.)/(1+\exp(.))$. The vector $\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}$ is equal to $\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}(1) - \tilde{\mathbf{z}}_{imt}^{\mathbf{P}}(0)$, where $\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}(a)$ represents the expected and discounted sum of current and future $\mathbf{z}$ vectors $\{\mathbf{z}_{imt+j}(a_{imt+j}) : j = 0, 1, 2, ...\}$ which may occur along all possible histories originating from the choice of $a_{imt} = a$ in state $\mathbf{w}_{imt}$, if player (i, m) behaves optimally in the future and the other players behave, now and in the future, according to their choice probabilities in $\mathbf{P}$. Similarly, $\tilde{e}_{imt}^{\mathbf{P}}$ is equal to $\tilde{e}_{imt}^{\mathbf{P}}(1) - \tilde{e}_{imt}^{\mathbf{P}}(0)$, where $\tilde{e}_{imt}^{\mathbf{P}}(a)$ has the same definition as $\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}(a)$ but for the expected and discounted sum of the stream $\{a_{imt+j}\ \varepsilon_{imt}/\sigma_\varepsilon : j = 1, 2, ...\}$ instead of $\mathbf{z}_{imt+j}(a_{imt+j})$. More formally,

$$
\begin{aligned}
\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}(a) &= \mathbf{z}_{imt}(a) + \beta \sum_{\mathbf{w}_{imt+1}} f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a, \mathbf{w}_{imt})\ V_{\mathbf{z},im}^{\mathbf{P}}(\mathbf{w}_{imt+1}) \\
\tilde{\mathbf{e}}_{imt}^{\mathbf{P}}(a) &= \beta \sum_{\mathbf{w}_{imt+1}} f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a, \mathbf{w}_{imt})\ V_{\mathbf{e},im}^{\mathbf{P}}(\mathbf{w}_{imt+1})
\end{aligned}
\tag{21}
$$

The matrix of valuations $\mathbf{V}_{\mathbf{z},im}^{\mathbf{P}} \equiv \{V_{\mathbf{z},im}^{\mathbf{P}}(\mathbf{w}_{im}) : \mathbf{w}_{im} \in W\}$ is equal to $(I - \beta \mathbf{F}_{im}^{\mathbf{w},\mathbf{P}})^{-1}((1 - \mathbf{P}_{im}) * \mathbf{Z}_{im}(0) + \mathbf{P}_{im} * \mathbf{Z}_{im}(1))$, where $\mathbf{P}_{im}$ is the column vector of choice probabilities $\{P_{im}(\mathbf{w}_{im}) : \mathbf{w}_{im} \in W\}$; $\mathbf{Z}_{im}(a)$ is the matrix $\{\mathbf{z}_{imt}(a) : \mathbf{w}_{imt} \in W\}$; and $\mathbf{F}_{im}^{\mathbf{w},\mathbf{P}}$ is a $W \times W$ matrix of transition probabilities with elements $(1 - P_{im}(\mathbf{w}_{imt})) f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|0, \mathbf{w}_{imt}) + P_{im}(\mathbf{w}_{imt}) f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|1, \mathbf{w}_{imt})$. Similarly, the vector of valuations $\mathbf{V}_{\mathbf{e},im}^{\mathbf{P}} \equiv \{V_{\mathbf{e},im}^{\mathbf{P}}(\mathbf{w}_{im}) : \mathbf{w}_{im} \in X\}$ is equal to $(I - \beta \mathbf{F}_{im}^{\mathbf{w},\mathbf{P}})^{-1} \mathbf{P}_{im} * \mathbf{e}_{im}$, where $\mathbf{e}_{im}$ is a a $W \times 1$ with elements $E(\varepsilon_{imt}/\sigma_\varepsilon | \mathbf{w}_{imt}, a_{imt} = 1 \text{ is the optimal choice})$. Given that ε_{imt} has a logistic distribution, the elements of $\mathbf{e}_{im}$ are equal to $Euler - \ln P_{im}(\mathbf{w}_{im})$, where $Euler$ represents Euler's constant.

For a fixed value of $\mathbf{P}$, the evaluation of the mapping $\Lambda(\boldsymbol{\theta}, \mathbf{P})$ for multiple values of $\boldsymbol{\theta}$ is very simple computationally because the values $\{\tilde{\mathbf{z}}_{imt}^{\mathbf{P}}\}$ and $\{\tilde{e}_{imt}^{\mathbf{P}}\}$ are fixed and they should not be recomputed. However, the evaluation of the mapping $\Lambda(\boldsymbol{\theta}, \mathbf{P})$ for multiple values of $\mathbf{P}$ is

[25] $AIRDUM_i$ is a vector of dimension $N - 1 = 21$ with a 1 at the position of airline i and zeroes elsewhere. Similarly, $CITYDUM_m$ is a vector of dimension $C - 1 = 54$ with $1's$ at the positions of the two cities in market m and zeroes elsewhere.

significantly more costly because the values $\{\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}\}$ and $\{\tilde{e}^{\mathbf{P}}_{imt}\}$ should be recalculated. The most costly tasks in recalculating these values are the computation of the transition probabilities $f^{\mathbf{w},\mathbf{P}}_{im}$ and of the inverse matrices $(I - \beta \mathbf{F}^{\mathbf{w},\mathbf{P}}_{im})^{-1}$. Note that we have to calculate these functions and matrices for every local manager (i, m), and there are $22 * 1,485 = 32,670$ local managers.[26]

For the computation of the values $\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}$ and $\tilde{e}^{\mathbf{P}}_{imt}$ we discretize the vector of state variables $\mathbf{w}_{imt} = (x_{imt},\ R_{imt},\ \overline{HUB}_{imt},\ n_{mt},\ \overline{HUB}_{mt})$. The incumbent status x_{imt} is already a binary variable. The number of incumbents, n_{mt}, is discretized in 5 values: $\{0, 1, 2, 3, 4\}$ where $n_{mt} = 4$ represents four or more incumbents. Figures 2 and 3 present the empirical distributions of the variables $\ln(R_{imt})$ and $\overline{HUB}_{imt}$, respectively. We discretize $\overline{HUB}_{imt}$ and $\overline{HUB}_{mt}$ using a uniform grid of 6 points in the interval $[0, 54]$. Similarly, we discretize $\ln(R_{imt})$ using a uniform grid of 11 points in the interval $[4, 18]$. These discretizations imply that the state space of $\mathbf{w}_{imt}$, W, has $2 * 11 * 6 * 5 * 6 = 3,960$ cells.

4.3.2 Estimators

For notational simplicity, we use $\boldsymbol{\theta}$ to represent $\boldsymbol{\theta}/\sigma_\varepsilon$. For arbitrary values of $\boldsymbol{\theta}$ and $\mathbf{P}$, define the likelihood function:

$$Q(\boldsymbol{\theta}, \mathbf{P}) \ \equiv \ \sum_{m=1}^{M} \sum_{t=1}^{T} \sum_{i=1}^{N} a_{imt} \ \ln \Lambda \left(\tilde{\mathbf{z}}^{\mathbf{P}}_{imt} \boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}_{imt} \right) + (1 - a_{imt}) \ \ln \Lambda \left(-\tilde{\mathbf{z}}^{\mathbf{P}}_{imt} \boldsymbol{\theta} - \tilde{e}^{\mathbf{P}}_{imt} \right) \tag{22}$$

For given $\mathbf{P}$, this is the log-likelihood function of a standard logit model where the parameter of one of the explanatory variables (i.e., the parameter associated to $\tilde{e}^{\mathbf{P}}_{imt}$) is restricted to be one.

Let $\boldsymbol{\theta}_0$ be the true value of the $\boldsymbol{\theta}$ in the population, and let $\mathbf{P}_0$ be the true equilibrium in the population. The vector $\mathbf{P}_0$ is an equilibrium associated with $\boldsymbol{\theta}_0$: i.e., in vector form, $\mathbf{P}_0 = \Lambda \left(\tilde{\mathbf{z}}^{\mathbf{P}_0} \boldsymbol{\theta} + \tilde{e}^{\mathbf{P}_0} \right)$. 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. Given $\hat{\mathbf{P}}$ and the constructed variables $\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}_{imt}$ and $\tilde{e}^{\hat{\mathbf{P}}}_{imt}$, the vector of parameters $\boldsymbol{\theta}_0$ is estimated using a standard logit model. However,

[26] However, we do not need to keep the probabilities $f^{\mathbf{w},\mathbf{P}}_{im}$ and P_{im}, and the matrix $(I - \beta \mathbf{F}^{\mathbf{w},\mathbf{P}}_{im})^{-1}$ in memory once we have calculated $\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}$ and $\tilde{e}^{\mathbf{P}}_{imt}$ for a local manager. Therefore, the memory requirements of this method are only of the order of magnitude of our sample size.

this two-step method suffers of several important limitations. First, the method should be initialized with a consistent estimator of $\mathbf{P}_0$. That consistent estimator may not be available in models with unobserved heterogeneity. Our model includes airline and city heterogeneity in fixed costs and entry costs. Conditional on (i, m) we have only $T = 4$ observations, and therefore it is not plausible to argue that we have a consistent nonparametric estimator of $\mathbf{P}_0$. However, note that given a consistent estimator of $\mathbf{P}_0$, the logit estimator of $\boldsymbol{\theta}_0$ in the second step is consistent despite the existence of unobserved airline and city heterogeneity. This logit estimator captures this heterogeneity by including airline dummies (22) and city dummies (55), but not city-pair dummies (i.e., we would have to include $1,485$ dummies). Without a parametric assumption that establishes how the city dummies enter into the model, we have that including city dummies is equivalent to include city-pair dummies. Therefore, the nonparametric estimator is not consistent. The second important limitation of the two-step method is that, even when consistent, the initial estimator $\hat{\mathbf{P}}$ typically suffers of the well-known *curse of dimensionality in nonparametric estimation*. When the number of conditioning variables is relatively large, the estimator $\hat{\mathbf{P}}$ can be seriously biased and imprecise in small samples. In a nonlinear model, both the bias and the variance of $\hat{\mathbf{P}}$ can generate serious biases in the second step estimator of $\boldsymbol{\theta}_0$.

Aguirregabiria and Mira (2007) proposed an alternative estimator that deals with the limitations of the two-step method. The Nested Pseudo Likelihood (NPL) estimator is defined as a pair $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ that satisfies the following two conditions:

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg\max_{\boldsymbol{\theta} \in \Theta} \; Q(\boldsymbol{\theta}, \hat{\mathbf{P}}) \\ \hat{\mathbf{P}} &= \Lambda\left(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}} \hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}}\right) \end{aligned} \tag{23}$$

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 $\hat{\boldsymbol{\theta}}$. The transition probabilities $f_{im}^{\mathbf{w},\hat{\mathbf{P}}}$, that we use to calculate $\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}$ and $\tilde{e}^{\hat{\mathbf{P}}}$, are equilibrium transition probabilities. This estimator has lower asymptotic variance and finite sample bias than the two-step estimator (see Aguirregabiria and Mira, 2007, and Kasahara and Shimotsu, 2008).

A recursive extension of the two-step method can be used as a simple algorithm to obtain the NPL estimator. We initialize the procedure with an initial vector of CCPs, say $\hat{\mathbf{P}}^0$. Note that $\hat{\mathbf{P}}^0$ is not necessarily a consistent estimator of $\mathbf{P}_0$. Then, at iteration $K \geq 1$, we update our estimates of $(\boldsymbol{\theta}_0, \mathbf{P}_0)$ by using the pseudo maximum likelihood (logit) estimator $\hat{\boldsymbol{\theta}}^K = \arg\max_{\boldsymbol{\theta}\in\Theta}$ $Q(\boldsymbol{\theta}, \hat{\mathbf{P}}^{K-1})$ and the policy iteration $\hat{\mathbf{P}}^K = \Lambda\left(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}^{K-1}}\hat{\boldsymbol{\theta}}^K + \tilde{e}^{\hat{\mathbf{P}}^{K-1}}\right)$, that is:

$$\hat{\mathbf{P}}_{im}^K(\mathbf{w}_{imt}) = \Lambda\left(\tilde{\mathbf{z}}_{imt}^{\hat{\mathbf{P}}^{K-1}}\hat{\boldsymbol{\theta}}^K + \tilde{e}_{imt}^{\hat{\mathbf{P}}^{K-1}}\right) \tag{24}$$

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 $\mathbf{P}$.

In our application, we initialize the procedure with a reduced-form estimation of the CCPs $P_{im}(\mathbf{w}_{imt}^*)$ based on a logit model that includes as explanatory variables airline dummies, city dummies, and a second order polynomial in $\mathbf{w}_{imt}^*$.

4.3.3 Estimation results

Table 9 presents our estimation results for the dynamic game of network competition. We have fixed a value of the quarterly discount factor, β, equal to 0.99 (i.e, a 0.96 annual discount factor). The estimates are measured in thousands of dollars. The estimated fixed cost, evaluated at the mean value of hub-size, distance, and airline and city dummies, is $\$119,000$. The sample median of the quarterly variable profit in the non-stop routes of a city-pair is around \$159,000. Thus, the mean value of the estimated fixed cost is 75% of that median variable profit. Perhaps not surprisingly for this industry, this value implies very substantial economies of scale. Fixed costs increase with the distance between the two cities: it increases \$4.64 per mile. Hub-size has also a significant effect on fixed costs. A unit increase in hub-size (i.e., an additional city connected) implies a $\$1,020$ reduction in fixed costs. This seems a non-negligible cost reduction.

The estimated entry cost, evaluated at the mean value of hub-size and distance, is $\$298,000$. This value represents 250% of the corresponding (quarterly) fixed cost, 187% of the median variable profit, and 7.5 times the (quarterly) operating profit (variable profit minus fixed cost) in a market with median variable profit, mean distance and mean hub-size. That is, it requires almost two years of profits to compensate the firm for its initial investment or entry cost. These costs do not depend significantly on flown distance. However, the effect of hub-size is very important. While an airline with the minimum hub-size (i.e., zero) has to pay an entry cost of $\$536,000$, an airline with the maximum hub-size in the sample (i.e., 50 cities connected) pays only $\$73,000$. A unit increase in hub-size implies a reduction of entry costs of more than $\$9,260$.

We have included airline fixed-effects and city fixed effects in all our estimations. Therefore, the effects that we have estimated cannot be spuriously capturing unobserved airline characteristics invariant across markets and over time, or unobserved city characteristics (e.g., better infrastructure and labor supply). The type of omitted variables that might introduce biases in our estimation results should have joint variation over airlines and city-pairs.

Using the estimated model, we have generated predictions for several statistics that describe market structure. To obtain these predictions, for every observation in the sample (i.e., every quarter-market-airline), we calculate CCPs using the estimated equilibrium probabilities evaluated at the actual values of the observed state variables. Then, we use these choice probabilities to generate, for each sample observation, a random draw of the decision variable. Finally, we use these random draws to calculate the predicted statistics of market structure.[27] Table 10 reports predicted and actual values of the statistics. Overall, the estimated model performs reasonably well. However, there are some significant biases in the predictions. The model over-predicts the proportion of markets with 1 and 2 incumbents, and it under-predicts the proportion of markets without incumbents. Interestingly, the model under-predicts the proportion of markets where Southwest is a monopolist. In the estimated model, it is very clear that Southwest has lower costs than any other airline, and that this feature makes it possible for Southwest to operate with profits in markets where the rest of the airlines would have losses. However, the model fails short to explain part of Southwest monopoly power. Finally, the model fits reasonably well the

[27] These predicted statistics contain a simulation error. However, for the statistics that we report here, which are averages over 1,485 markets, 3 quarters, and 22 airlines, this simulation error is very small even if we use just one simulation per observation. Given that the statistics are sample means, and that the simulation error is independently distribution across observations and it is averaged over a large number of observations, we have that the bias introduced by the simulation error is very small.

distributions of the number of exits and entries, with just a small over-prediction of the amount of market turnover.

5 Disentangling demand, cost and strategic factors

We use our estimated model to measure the contribution of demand, cost and strategic factors to explain airlines' propensity to operate using hub-and-spoke networks. We analyze how different parameters of the model contribute to explain the observed hub-and-spoke ratios. The parameters of interest are the ones that measure the effects of hub-size on demand (α_2 and α_3), variable costs (δ_2 and δ_3), fixed costs (γ_2^{FC}), and entry costs (η_2^{EC}). We implement four experiments. In experiment 1, we consider a counterfactual model with zero hub-size effects on demand and variable costs, i.e., $\alpha_2 = \alpha_3 = \delta_2 = \delta_3 = 0$. In experiment 2, the counterfactual model has zero hub-size effects on fixed costs, i.e., $\gamma_2^{FC} = 0$. In experiment 3, we fix the hub-size effects on entry costs at zero, i.e., $\eta_2^{EC} = 0$. Finally, in experiment 4 we want to measure the contribution of entry deterrence motive. We consider a counterfactual model where the local manager of a city-pair AB is only concerned with profits from non-stop routes AB and BA but not with profits from other (one-stop) routes that contain AB or BA as a segment. Under this counterfactual, local managers do not internalize the complementarity between profits at different local markets, and therefore there is not the entry deterrence motive that we consider in this paper.

Multiplicity of equilibria is an important problem when we use the estimated model to predict players' behavior in counterfactual scenarios such as a change in structural parameters. Here we propose an approach to deal with this problem. The main advantages of this approach are its simplicity and its minimum assumptions on the equilibrium selection mechanism. The main limitation is that it provides only a first order approximation. This approximation might be imprecise when the counterfactual structural parameters are far from the estimated values. We propose and implement a second method that tries to alleviate this limitation.

An equilibrium associated with $\boldsymbol{\theta}$ is a vector of choice probabilities $\mathbf{P}$ that solves the fixed point problem $\mathbf{P} = \Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}}\boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}\right)$. For a given value $\boldsymbol{\theta}$, the model may 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 equilibria associated with $\boldsymbol{\theta}$. We use $\boldsymbol{\pi}(\boldsymbol{\theta})$ to represent this (unique) selected equilibrium. Our approach here is 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 particular form for the 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 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 $\mathbf{P}_0 = \Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}_0}\boldsymbol{\theta}_0 + \tilde{e}^{\mathbf{P}_0}\right)$ and $\mathbf{P}_0 = \boldsymbol{\pi}(\boldsymbol{\theta}_{\mathbf{0}})$. Let $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ be a consistent estimator of $(\boldsymbol{\theta}_0,\mathbf{P}_0)$.[28] Let $\boldsymbol{\theta}^*$ be the vector of parameters under a counterfactual scenario. We want to obtain airlines' behavior and equilibrium outcomes under $\boldsymbol{\theta}^*$. That is, 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 $\boldsymbol{\pi}$. Given our model assumptions, the mapping $\Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}}\boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}\right)$ is continuously differentiable in $(\boldsymbol{\theta}, \mathbf{P})$. Our approach requires also the following assumption.

ASSUMPTION PRED: The equilibrium selection mechanism $\boldsymbol{\pi}(\boldsymbol{\theta})$ is a continuously differentiable function of $\boldsymbol{\theta}$ around $\hat{\boldsymbol{\theta}}_0$.

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 that is "closer" (in a Taylor-approximation sense) to the equilibrium estimated in the data. The data is not only useful to identify the equilibrium in the population but also to identify the equilibrium in the counterfactual experiments. We do not know the function $\boldsymbol{\pi}$ and, apparently, we do not know the Jacobian matrix $\partial\boldsymbol{\pi}(\hat{\boldsymbol{\theta}})/\partial\boldsymbol{\theta}'$ that is necessary to implement the Taylor approximation. However, we show here that the equilibrium condition can be used to obtain this Jacobian matrix. A

[28] Note that we do not know the function $\boldsymbol{\pi}(\boldsymbol{\theta})$. All what we know is that the point $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ belongs to the graph of this function $\boldsymbol{\pi}$.

Taylor approximation to $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$ around $\hat{\boldsymbol{\theta}}$ implies that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}) + \frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\theta}'}(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}) + O(\| \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}^2 \|) \tag{25}$$

Note that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}) = \hat{\mathbf{P}}$ and that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}) = \Lambda(\tilde{\mathbf{z}}^{\boldsymbol{\pi}(\hat{\boldsymbol{\theta}})}\hat{\boldsymbol{\theta}} + \tilde{e}^{\boldsymbol{\pi}(\hat{\boldsymbol{\theta}})})$. Differentiating this last expression with respect to $\boldsymbol{\theta}$ and solving for $\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}})/\partial \boldsymbol{\theta}'$, we can represent this Jacobian matrix in terms of Jacobians of $\Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}}\boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}\right)$ evaluated at the estimated values $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$. That is,

$$\frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}})}{\partial \boldsymbol{\theta}'} = \left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}})}{\partial \boldsymbol{\theta}'} \tag{26}$$

Solving expression (26) into (25), we have that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \hat{\mathbf{P}} + \left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}})}{\partial \boldsymbol{\theta}'}(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}) + O(\| \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}} \|^2) \tag{27}$$

Therefore, under the condition that $\| \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}} \|^2$ is small, the expression $\hat{\mathbf{P}} + (I - \partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}})/\partial \mathbf{P}')^{-1}\ \partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}})/\partial \boldsymbol{\theta}'\ (\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}})$ provides a good approximation to the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. Note that all the elements in this expression are known to the researcher.

In our application, this approach suffers of two limitations. The first limitation is computational. The dimension of the Jacobian matrix $\partial \Lambda/\partial \mathbf{P}'$ is $NM|W| \times NM|W|$, that in our application is equal to $130,244,400 \times 130,244,400$. Calculating all the elements of this matrix, and then inverting the matrix $I - \partial \Lambda/\partial \mathbf{P}'$ would be extremely costly. To deal with this problem we consider a Taylor approximation on a player-by-player basis such that, for every local manager, we approximate the $|W| \times 1$ vector $\boldsymbol{\pi}_{im}(\boldsymbol{\theta}^*)$ using the expression $\hat{\mathbf{P}}_{im} + (I_{|W|} - \partial \Lambda(\tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}_{im}^{\hat{\mathbf{P}}})/\partial \mathbf{P}'_{im})^{-1}$ $\partial \Lambda(\tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}_{im}^{\hat{\mathbf{P}}})/\partial \boldsymbol{\theta}'\ (\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}})$. In our model, it is possible to show that this expression is equal to $\hat{\mathbf{P}}_{im} + \hat{\mathbf{P}}_{im} * (\mathbf{1} - \hat{\mathbf{P}}_{im}) * (\tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}))$, where $*$ is the Hadamard or element-by-element product, and $\mathbf{1}$ is a column vector of ones.[29] A second important issue is the accuracy of the Taylor approximation. Our counterfactual experiments are far from being marginal changes in the parameters. Therefore, the approximation error might be large. To deal with this issue, we implement a

[29] To obtain this expression, first note that Proposition 2 in Aguirregabiria and Mira (2002, p. 1526) implies that in equilibrium the Jacobian matrix $\partial \Lambda(\tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}_{im}^{\hat{\mathbf{P}}})/\partial \mathbf{P}'_{im}$ is zero. Second, for the logistic function Λ, we have that $\partial \Lambda(\tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}\hat{\boldsymbol{\theta}} + \tilde{e}_{im}^{\hat{\mathbf{P}}})/\partial \boldsymbol{\theta}'$ is equal to $\hat{\mathbf{P}}_{im} * (\mathbf{1} - \hat{\mathbf{P}}_{im}) * \tilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}$.

second method. Suppose that the Taylor approximation is precise enough to be in the dominion of attraction of the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. This means that if we start with the Taylor approximation and then iterate in the equilibrium mapping, i.e., $\mathbf{P}_{k+1} = \Lambda(\tilde{\mathbf{z}}^{\mathbf{P}_k}\boldsymbol{\theta}^* + \tilde{e}^{\mathbf{P}_k})$, upon convergence, we will obtain the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. This is our second method for the counterfactual experiments.[30]

Table 11 presents the results of our counterfactual experiments. The top panel shows the results using the Taylor approximation approach, and the bottom panel reports the results the second method. Though there are significant differences in the magnitudes of the hub-and-spoke ratios, the two methods provide very similar pictures of the main qualitative implications. Hub-size effects on variable profits and fixed costs explain only a small portion of the observed hub-and-spoke ratios. However, hub-size effects on entry costs explain a very significant portion. Based on our estimates in Table 10, hub-size generates cost-savings in entry costs that are roughly equal to seven quarters of the cost-savings in fixed costs. Therefore, if airlines entering in a city-pair stayed operating in that market for at least seven quarters, hub-size effects on fixed costs would have more important effects on airlines' behavior than the effects on entry costs. There are at least two reasons why that is not the case here. First, there are non-negligible exit probabilities for most airlines and markets. The average probability of exit during the first quarter of operation in a city-pair is approximately 10%. This implies a significant discount rate on future fixed costs. Second, this discounting is much larger for those airlines that have large hub sizes in the market. These airlines have lower entry costs and therefore larger entry and exit rates. The larger probability of exit implies that they apply large discount rates on future profits.

The entry deterrence motive plays an important role for Northwest and Delta. Interestingly, Northwest and Delta are the airlines that, after Southwest, operate in a larger number of monopoly markets (see Table 4) and that have largest hub sizes (see panel 5.3 in Table 5). Interestingly, Southwest is by far the airline with the smallest contribution of the entry deterrence

[30] Note that the policy iterations $\mathbf{P}_{k+1} = \Lambda(\tilde{\mathbf{z}}^{\mathbf{P}_k}\boldsymbol{\theta}^* + \tilde{e}^{\mathbf{P}_k})$ require to recalculate the transition probabilities $f_{im}^{\mathbf{w},\mathbf{P}}$ using the method that we describe in the Appendix.

motive. This explains the empirical facts reported in Table 5.3 and Table 11 showing that the monopoly markets occupied by the Northwest and Delta are more likely connected to their hubs whereas those monopolized by Southwest tend to be isolated markets.

6 Conclusions

We have proposed and estimated a dynamic game of network competition in the US airline industry. An attractive feature of the model is that an equilibrium of the model is relatively simple to compute, and the estimated model can be used to analyze the effects of alternative policies. As it is common in dynamic games, the model has multiple equilibria and this is an important issue when using the model to make predictions. We have proposed and implemented a simple approach to deal with multiplicity of equilibria when using this type of model to predict the effects of counterfactual experiments.

We use this model and methods to study the contribution of demand, costs, and strategic factors to the adoption of hub-and-spoke networks by companies in the US airline industry. Though the scale of operation of an airline in an airport has statistically significant effects on variable profits and fixed operating costs, these effects seem to play a minor role to explain airlines' propensity to adopt hub-and-spoke networks. In contrast, our estimates of the effects of hub-size on entry costs are very substantial. While airlines without previous presence in an airport have to pay very significant entry costs to start their operation (i.e., around half a million dollars, according to our estimates), an airline with a large hub in the airport has to pay a negligible entry cost to operate an additional route. Eliminating these hub-size effects on entry costs reduces very importantly airlines propensity to adopt hub-and-spoke networks. In our model, these cost savings can be interpreted either as due to technological factors or to contractual agreements between airports and airlines. Investigating the specific sources of these cost savings is an important topic for further research. For some of the larger carriers, we also find evidence consistent with the hypothesis that a hub-and-spoke network can be an effective strategy to deter the entry of competitors in spoke markets.

APPENDIX. Random-Grid Method to Approximate the Transition Probability Functions $f_{im}^{\mathbf{w},\mathbf{P}}$.

We draw S independent random draws from the ergodic distribution of the vector $\mathbf{w}_t$. We use these random draws to construct a simulator (i.e., approximation) of the transition probability functions $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt}, \mathbf{w}_{imt})$. This simulator is consistent in the sense that it converges to the true transition probability as S goes to infinity. The procedure to compute this simulator can be described in four steps: (a) construction of the random-grids $W_{all}^{(S)}$ and $A^{(S)}$; (b) simulator of the conditional probability functions $\Pr(\mathbf{w}_{-imt}|\mathbf{w}_{imt}, \mathbf{P})$; (c) simulator of the probability functions $Q_{im}^{\mathbf{P}}(\boldsymbol{a}_{-(im)t}|\mathbf{w}_{imt})$; and (d) simulator of the transition probability functions $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt}, \mathbf{w}_{imt})$.

(a) Random Draws from the Ergodic Distribution of $\{\mathbf{w}_t\}$*.* We generate S independent random draws from the ergodic distribution $p^*(\mathbf{w}_t|\mathbf{P})$. Each draw is generated as follows. We start with an arbitrary value of $(\mathbf{x}, \mathbf{z})$, say $(\mathbf{x}_0, \mathbf{z}_0)$, and use the first order Markov structure of $\{\mathbf{x}_t, \mathbf{z}_t\}$ to generate a T-periods history starting from $(\mathbf{x}_0, \mathbf{z}_0)$. For T large enough, the last period of this history, $(\mathbf{x}_T, \mathbf{z}_T)$, provides a random draw from the ergodic distribution of $(\mathbf{x}, \mathbf{z})$ associated with $\mathbf{P}$. Then, we apply the functions $w_{im}(.)$ to obtain $\mathbf{w}_{imT} = w_{im}(\mathbf{x}_T, \mathbf{z}_T)$ for every (i, m). The following is a more detailed description:

(i) Given $(\mathbf{x}_0, \mathbf{z}_0)$, we obtain $\mathbf{w}_{im0} = w_{im}(\mathbf{x}_0, \mathbf{z}_0)$ for every local-manager (i, m).

(ii) We generate a random draw of next period vector $\mathbf{x}_1$. That is, for every local-manager (i, m), we generate a random draw of next-period incumbent status using the formula $x_{im1} = 1\{u \leq P_{im}(\mathbf{w}_{im0})\}$, where u is a random draw from a $U(0, 1)$ distribution.

(iii) We generate a random draw of next period vector $\mathbf{z}_1$. We use the (normal) density functions p_ξ and p_ω to generate random draws of demand and cost shocks.

(iv) Given $(\mathbf{x}_1, \mathbf{z}_1)$, we apply again (i)-(iii) to generate $(\mathbf{x}_2, \mathbf{z}_2)$, and so on T times until we generate $(\mathbf{x}_T, \mathbf{z}_T)$ and $\mathbf{w}_T$.

We use $W_{all}^{(S)}$ to denote the set of random draws from the ergodic distribution $p^*(\mathbf{w}_t|\mathbf{P})$. We index the elements of this set by s, such that $W_{all}^{(S)} = \{\mathbf{w}^{(s)} : s = 1, 2, ..., S\}$. Since the lagged action a_{imt-1} is a component of the vector $\mathbf{w}_{imt}$, the set of random draws defines also a grid in the space of players' actions, $\{0,1\}^{NM}$. We use $A^{(S)}$ to denote this random-grid in the action space. In our estimations and numerical experiments, we have used $T = 50$ and $S = 200,000$.

(b) Simulator of the conditional probability function $\Pr(\mathbf{w}_{-im}|\mathbf{w}_{im}, \mathbf{P})$. By definition, $\Pr(\mathbf{w}_{-(im)} \mid \mathbf{w}_{im}, \mathbf{P}) = p^*(\mathbf{w}_{im}, \mathbf{w}_{-(im)}|\mathbf{P})/p^*_{im}(\mathbf{w}_{im}|\mathbf{P})$, where $p^*(\mathbf{w}|\mathbf{P})$ and $p^*_{im}(\mathbf{w}_{im}|\mathbf{P})$ are the ergodic distributions of $\{\mathbf{w}_t\}$ and $\{\mathbf{w}_{imt}\}$, respectively, under the strategies in $\mathbf{P}$. Based on the random draws in $W_{all}^{(S)}$, we can construct the following frequency simulators of these ergodic distributions: $p^{(S)*}(\mathbf{w}|\mathbf{P}) = S^{-1}\sum_{s=1}^{S} 1\{\mathbf{w} = \mathbf{w}^{(s)}\}$, and $p^{(S)*}_{im}(\mathbf{w}_{im}|\mathbf{P}) = S^{-1}\sum_{s=1}^{S} 1\{\mathbf{w}_{im} = \mathbf{w}^{(s)}_{im}\}$. Therefore, our frequency simulator of $\Pr(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P})$ is:

$$\Pr{}^{(S)}(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P}) = \begin{cases} \dfrac{\sum_{s=1}^{S} 1\{(\mathbf{w}_{-(im)}, \mathbf{w}_{im}) = \mathbf{w}^{(s)}\}}{\sum_{s=1}^{S} 1\{\mathbf{w}_{im} = \mathbf{w}^{(s)}_{im}\}} & \text{if} \quad (\mathbf{w}_{-(im)}, \mathbf{w}_{im}) \in W_{all}^{(S)} \\ 0 & \text{if} \quad (\mathbf{w}_{-(im)}, \mathbf{w}_{im}) \notin W_{all}^{(S)} \end{cases}$$

Note that, $\Pr^{(S)}(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P})$ is a well-defined conditional probability function that sums to 1 when 'integrated' over all the values of $\mathbf{w}_{-(im)}$ in the random-grid $W_{all}^{(S)}$.

(c) Simulator of the probability functions $Q^{\mathbf{P}}_{im}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{im})$. In section 2.4, we have defined the probability functions $Q^{\mathbf{P}}_{im}$ as:

$$Q^{\mathbf{P}}_{im}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{im}) \equiv \sum_{\mathbf{w}_{-(im)}} \left[\prod_{(j,n)\neq(i,m)} P_{jn}(\mathbf{w}_{jn})^{a_{jn}} (1 - P_{jn}(\mathbf{w}_{jn}))^{1-a_{jn}} \right] \Pr(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P})$$

To obtain a consistent simulator of $Q^{\mathbf{P}}_{im}$, we just replace $\Pr(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P})$ by the simulator $\Pr^{(S)}(\mathbf{w}_{-(im)}|\mathbf{w}_{im}, \mathbf{P})$ defined in (b). That is, our simulator of $Q^{\mathbf{P}}_{im}$ is:

$$\begin{aligned} Q^{(S)\mathbf{P}}_{im}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{im}) &= \sum_{\mathbf{w}_{-(im)}} \left[\prod_{(j,n)\neq(i,m)} P_{jn}(\mathbf{w}_{jn})^{a_{jn}} (1 - P_{jn}(\mathbf{w}_{jn}))^{1-a_{jn}} \right] \frac{\sum_{s=1}^{S} 1\{(\mathbf{w}_{-(im)}, \mathbf{w}_{im}) = \mathbf{w}^{(s)}\}}{\sum_{s=1}^{S} 1\{\mathbf{w}_{im} = \mathbf{w}^{(s)}_{im}\}} \\ &= \sum_{s=1}^{S} \left[\prod_{(j,n)\neq(i,m)} P_{jn}(\mathbf{w}_{jn})^{a_{jn}} (1 - P_{jn}(\mathbf{w}_{jn}))^{1-a_{jn}} \right] \frac{1\{\mathbf{w}_{im} = \mathbf{w}^{(s)}_{im}\}}{\sum_{s=1}^{S} 1\{\mathbf{w}_{im} = \mathbf{w}^{(s)}_{im}\}} \end{aligned}$$

By replacing $\Pr(\mathbf{w}_{-(im)}|\mathbf{w}_{imt},\mathbf{P})$ with $\Pr^{(S)}(\mathbf{w}_{-(im)}|\mathbf{w}_{imt},\mathbf{P})$ we are also replacing the sum $\sum_{\mathbf{w}_{-(im)}}$ by the sum $\sum_{s=1}^{S}$ over the random-grid $W_{all}^{(S)}$. This is because $\Pr^{(S)}(\mathbf{w}_{-(im)t}|\mathbf{w}_{imt},\mathbf{P})$ has probability mass only at points in the random-grid.

The simulator $Q_{im}^{(S)\mathbf{P}}$ is a probability distribution with probability mass at every point in the action space of $\boldsymbol{a}_{-(im)}$, i.e., over the whole set $\{0,1\}^{NM-1}$. To obtain our simulator of $f_{im}^{\mathbf{w},\mathbf{P}}$ below, it is convenient to have a simulator of $Q_{im}^{\mathbf{P}}$ that has positive probability mass only at values of $\boldsymbol{a}_{-(im)}$ that belong to the random-grid in the action space, $A^{(S)}$. Therefore, we use the following re-weighted simulator of $Q_{im}^{\mathbf{P}}$ (see Rust, 1997):

$$\tilde{Q}_{im}^{(S)\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{im}) = \begin{cases} \dfrac{Q_{im}^{(S)\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{im})}{\sum_{s=1}^{S} Q_{im}^{(S)\mathbf{P}}(\boldsymbol{a}_{-(im)}^{(s)}|\mathbf{w}_{im})} & \text{if} \quad \boldsymbol{a}_{-(im)} \in A_{-(im)}^{(S)} \\ 0 & \text{if} \quad \boldsymbol{a}_{-(im)} \notin A_{-(im)}^{(S)} \end{cases}$$

where $\boldsymbol{a}_{-(im)}^{(s)}$ represents the value of $\boldsymbol{a}_{-(im)}$ for the s-th element in the random-grid $A^{(S)}$.

(d) Simulator of the probability functions $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt},\mathbf{w}_{imt})$. In section 2.4, we showed that $f_{im}^{\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt},\mathbf{w}_{imt}) \equiv \sum_{\boldsymbol{a}_{-(im)}} g_{im}^{\mathbf{w}}(\mathbf{w}_{imt+1}|a_{imt},\boldsymbol{a}_{-(im)})\, Q_{im}^{\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{imt})$, where $g_{im}^{\mathbf{w}}(\mathbf{w}_{imt+1}|\boldsymbol{a}_t) \equiv \sum_{\mathbf{z}_{t+1}\in Z} 1\{\mathbf{w}_{imt+1} = w_{im}(\boldsymbol{a}_t,\mathbf{z}_{t+1})\}\ p_{\mathbf{z}}(\mathbf{z}_{t+1})$. To obtain a consistent simulator of $f_{im}^{\mathbf{w},\mathbf{P}}$, we replace $Q_{im}^{\mathbf{P}}$ by the simulator $\tilde{Q}_{im}^{(S)\mathbf{P}}$ defined in (c), and replace $g_{im}^{\mathbf{w}}$ by the frequency simulator:

$$g_{im}^{(S)\mathbf{w}}(\mathbf{w}_{imt+1}|\boldsymbol{a}_t) = \frac{1}{S}\sum_{s=1}^{S} 1\left\{\mathbf{w}_{imt+1} = w_{im}(\boldsymbol{a}_t,\mathbf{z}^{(s)})\right\}$$

where $\{\mathbf{z}^{(s)} : s = 1,2,...,S\}$ are the values of $\mathbf{z}$ associated with the random-grid $W_{all}^{(S)}$. Therefore, our simulator of $f_{im}^{\mathbf{w},\mathbf{P}}$ is:

$$\begin{aligned} f_{im}^{(S)\mathbf{w},\mathbf{P}}(\mathbf{w}_{imt+1}|a_{imt},\mathbf{w}_{imt}) &= \sum_{\boldsymbol{a}_{-(im)}} g_{im}^{(S)\mathbf{w}}(\mathbf{w}_{imt+1}|a_{imt},\boldsymbol{a}_{-(im)})\ \tilde{Q}_{im}^{(S)\mathbf{P}}(\boldsymbol{a}_{-(im)}|\mathbf{w}_{imt}) \\ &= \sum_{s=1}^{S} g_{im}^{(S)\mathbf{w}}(\mathbf{w}_{imt+1}|a_{imt},\boldsymbol{a}_{-(im)}^{(s)})\ \tilde{Q}_{im}^{(S)\mathbf{P}}(\boldsymbol{a}_{-(im)}^{(s)}|\mathbf{w}_{imt}) \end{aligned}$$

Since $\tilde{Q}_{im}^{(S)\mathbf{P}}$ has positive probability mass only at points in the random-grid, replacing $Q_{im}^{\mathbf{P}}$ with $\tilde{Q}_{im}^{(S)\mathbf{P}}$ implies that we are also replacing the sum $\sum_{\boldsymbol{a}_{-(im)}}$ by the sum $\sum_{s=1}^{S}$ over the random-grid $W_{all}^{(S)}$.

References

[1] Aguirregabiria, V., and P. Mira (2007): "Sequential Estimation of Dynamic Discrete Games," *Econometrica,* 75, 1-53.

[2] Alam, I., and R. Sickles (2000): "A Time Series Analysis of Deregulatory Dynamics and Technical Efficiency: The Case of the U. S. Airline Industry," *International Economic Review*, 41, 203-218.

[3] Anderson, S., A. De Palma, and J-F. Thisse (1992): "Discrete Choice Theory of Product Differentiation," The MIT Press. Cambridge, Massachusetts.

[4] Bajari, P., L. Benkard and J. Levin (2007): "Estimating Dynamic Models of Imperfect Competition," *Econometrica*, 75, 1331-1370.

[5] Berry, S. (1990): "Airport Presence as Product Differentiation," *American Economic Review*, 80, 394-399.

[6] Berry, S. (1992): "Estimation of a model of entry in the airline industry", *Econometrica,* 60(4), 889-917.

[7] Berry, S. (1994): "Estimating Discrete-choice Models of Product Differentiation." *RAND Journal of Economics*, 25, 242–262.

[8] Berry, S, J. Levinsohn, and A. Pakes (1995). "Automobile Prices in Market Equilibrium." *Econometrica*, 63, 841–890.

[9] Berry, S., M. Carnall, and P. Spiller (2006): "Airline Hubs: Costs, Markups and the Implications of Customer Heterogeneity," in *Advances in Airline Economics, Vol. 1: Competition Policy and Antitrust*, D. Lee, ed. Elsevier Press. pp 183-214.

[10] Borenstein, S. (1989): "Hubs and high fares: Dominance and market power in the US airline industry", *Rand Journal of Economics,* 20(3), 344-365.

[11] Borenstein, S. (1992): "The Evolution of U.S. Airline Competition." *Journal of Economic Perspectives*, Vol. 6.

[12] Borenstein, S., and N. Rose (2007): "How Airline Markets Work...Or Do They? Regulatory Reform in the Airline Industry," NBER Working Paper #13452.

[13] Ciliberto, F. and E. Tamer (2009): "Market Structure and Multiple Equilibria in Airline Markets," *Econometrica*, forthcoming.

[14] Doraszelski, U., and Satterthwaite, M. (2007): "Computable Markov-Perfect Industry Dynamics: Existence, Purification, and Multiplicity," manuscript. Department of Economics. Harvard University.

[15] Ericson, R., and A. Pakes (1995): "Markov-Perfect industry dynamics: A framework for empirical work", *Review of Economic Studies,* 62, 53-82.

[16] Färe, R., S. Grosskopf, and R. Sickles (2007): "Productivity? of US Airlines After Deregulation," *Journal of Transport Economics and Policy*, 41, 93-112.

[17] Hendel, I., and A. Nevo (2006): "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74, 1637-73.

[18] Hendricks, K., M. Piccione, and G. Tan (1995): "The Economics of Hubs: The Case of Monopoly," *The Review of Economic Studies*, 62(1), 83-99.

[19] Hendricks, K., M. Piccione, and G. Tan (1997): "Entry and exit in hub-spoke networks," *Rand Journal of Economics*, 28(2), 291–303.

[20] Hendricks, K., M. Piccione, and G. Tan (1999): "Equilibria in Networks," *Econometrica*, 67, 1407-1434.

[21] Januszewski, J. and M. Lederman (2003): "Entry Patterns of Low-Cost Airlines ," manuscript, Rotman School of Management, University of Toronto.

[22] Judd, K. (1985): "Credible Spatial Preemption," *The RAND Journal of Economics*, 16(2), 153-166.

[23] Kahn, A. (2004): *Lessons from Deregulation: Telecommunications and Airlines After the Crunch*, Washington, DC: AEI-Brookings Joint Center for Regulatory Studies.

[24] Kasahara, H., and K. Shimotsu (2008): "Pseudo-likelihood Estimation and Bootstrap Inference for Structural Discrete Markov Decision Models," *Journal of Econometrics*, 146, 92-106.

[25] Lederman, M. (2008): "Are Frequent-Flyer Programs a Cause of the Hub Premium?" *Journal of Economics and Management Strategy,* 17, 35-66.

[26] Morrison, S. A. and C. Winston, (1995): *The Evolution of the Airline Industry*, Brookings, Washington, D.C.

[27] Morrison, S. A., and C. Winston. (2000): "The remaining role for government policy in the deregulated airline industry," in *Deregulation of network industries: What's next?*, edited by Sam Peltzman and Clifford Winston. Washington, DC: AEI-Brookings Joint Center for Regulatory Studies.

[28] Nevo, A., and F. Rossi (2008): "An Approach for Extending Dynamic Models to Settings with Multi-Product Firms," *Economics Letters*, 100, 49-52.

[29] Oum, T., A. Zhang, and Y. Zhang (1995): "Airline Network Rivalry," *Canadian Journal of Economics,* 28, 836-857.

[30] Pakes, A., M. Ostrovsky, and S. Berry (2007): "Simple estimators for the parameters of discrete dynamic games (with entry/exit examples)," *RAND Journal of Economics*, 38(2), 373-399.

[31] Sweeting, A. (2007): "Dynamic Product Repositioning in Differentiated Product Industries: The Case of Format Switching in the Commercial Radio Industry," NBER WP #13522.

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
Ranking of City-Pairs by Number of Passengers (Round-trip, Non-Stop) in 2004

	CITY PAIR		Total
1.	Chicago	New York	1,412,670
2.	Los Angeles	New York	1,124,690
3.	Atlanta	New York	1,100,530
4.	Los Angeles	Oakland	1,080,100
5.	Las Vegas	Los Angeles	1,030,170
6.	Chicago	Las Vegas	909,270
7.	Las Vegas	New York	806,230
8.	Chicago	Los Angeles	786,300
9.	Dallas	Houston	779,330
10.	New York	San Francisco	729,680
11.	Boston	New York	720,460
12.	New York	Tampa	713,380
13.	Chicago	Phoenix	706,950
14.	New York	Washington	680,580
15.	Los Angeles	Phoenix	648,510
16.	Miami	New York	637,850
17.	Los Angeles	Sacramento	575,520
18.	Atlanta	Chicago	570,500
19.	Los Angeles	San Jose	556,850
20.	Dallas	New York	555,420

Source: DB1B Database

Table 3
Airlines
Ranking by #Passengers and #City-Pairs in 2004

Airline (Code)	#Passengers[1] (in thousands)	#City-Pairs[2] (maximum = 1,485)
1. Southwest (WN)	25,026	373
2. American (AA)[3]	20,064	233
3. United (UA)[4]	15,851	199
4. Delta (DL)[5]	14,402	198
5. Continental (CO)[6]	10,084	142
6. Northwest (NW)[7]	9,517	183
7. US Airways (US)	7,515	150
8. America West (HP)[8]	6,745	113
9. Alaska (AS)	3,886	32
10. ATA (TZ)	2,608	33
11. JetBlue (B6)	2,458	22
12. Frontier (F9)	2,220	48
13. AirTran (FL)	2,090	35
14. Mesa (YV)[9]	1,554	88
15. Midwest (YX)	1,081	33
16. Trans States (AX)	541	29
17. Reno Air (QX)	528	15
18. Spirit (NK)	498	9
19. Sun Country (SY)	366	11
20. PSA (16)	84	27
21. Ryan International (RD)	78	2
22. Allegiant (G4)	67	3

Note (1): Annual number of passengers in 2004 for our selected markets
Note (2): An airline is active in a city-pair if it has at least
20 passengers/week in non-stop flights. This column refers to 2004-Q4.
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, their Hubs, and Hub-Ratios

	Airline (Code)	Name and Hub Size 1st largest hub(1)	Hub-Spoke Ratio (%) One Hub	Name and Hub Size 2nd largest hub(1)	Hub-Spoke Ratio (%) Two Hubs
1.	Southwest (WN)	Las Vegas (35)	9.3	Phoenix (33)	18.2
2.	American (AA)	Dallas (52)	22.3	Chicago (46)	42.0
3.	United (UA)	Chicago (50)	25.1	Denver (41)	45.7
4.	Delta (DL)	Atlanta (53)	26.7	Cincinnati (42)	48.0
5.	Continental (CO)	Houston (52)	36.6	New York (45)	68.3
6.	Northwest (NW)	Minneapolis (47)	25.6	Detroit (43)	49.2
7.	US Airways (US)	Charlotte (35)	23.3	Philadelphia (33)	45.3
8.	America West (HP)	Phoenix (40)	35.4	Las Vegas (28)	60.2
9.	Alaska (AS)	Seattle (18)	56.2	Portland (10)	87.5
10.	ATA (TZ)	Chicago (16)	48.4	Indianapolis (6)	66.6
11.	JetBlue (B6)	New York (13)	59.0	Long Beach (4)	77.3
12.	Frontier (F9)	Denver (27)	56.2	Los Angeles (5)	66.6
13.	AirTran (FL)	Atlanta (24)	68.5	Dallas (4)	80.0
14.	Mesa (YV)	Phoenix (19)	21.6	Washington DC (14)	37.5
15.	Midwest (YX)	Milwakee (24)	72.7	Kansas City (7)	93.9
16.	Trans States (AX)	St Louis (18)	62.0	Pittsburgh (7)	93.9
17.	Reno Air (QX)	Portland (8)	53.3	Denver (7)	100.0
18.	Spirit (NK)	Detroit (5)	55.5	Chicago (2)	77.7
19.	Sun Country (SY)	Minneapolis (11)	100.0	(0)	100.0
20.	PSA (16)	Charlotte (8)	29.6	Philadelphia (5)	48.1
21.	Ryan Intl. (RD)	Atlanta (2)	100.0	(0)	100.0
22.	Allegiant (G4)	Las Vegas (3)	100.0	(0)	100.0

(1) The hub-size of the 1st largest hub is equal to the number of direct connections of the airline from that airport. The hub-size of the 2nd largest hub is the number of direct connections of the airline from that airport, excluding the connection to the lst largest hub.

Table 5
Descriptive Statistics of Market Structure
1,485 city-pairs (markets). Period 2004-Q1 to 2004-Q4

	2004-Q1	2004-Q2	2004-Q3	2004-Q4	All Quarters
(5.1) Distribution of Markets by Number of Incumbents					
Markets with 0 airlines	35.79%	35.12%	35.72%	35.12%	35.44%
Markets with 1 airline	30.11%	29.09%	28.76%	28.28%	29.06%
Markets with 2 airlines	17.46%	16.71%	17.52%	18.06%	17.44%
Markets with 3 airlines	9.20%	10.83%	9.47%	9.88%	9.84%
Markets with 4 or more airlines	7.43%	8.25%	8.53%	8.67%	8.22%
(5.2) Herfindahl Index					
Herfindahl Index (median)	5344	5386	5286	5317	5338
(5.3) Number of Monopoly Markets by Airline					
Southwest	146	153	149	157	
Northwest	65	63	67	69	
Delta	58	57	57	56	
American	31	34	33	28	
Continental	31	26	28	24	
United	21	14	13	17	
(5.4) Distribution of Markets by Number of New Entrants					
Markets with 0 Entrants	-	82.61%	86.60%	84.78%	84.66%
Markets with 1 Entrant	-	14.48%	12.31%	13.33%	13.37%
Markets with 2 Entrants	-	2.44%	0.95%	1.69%	1.69%
Markets with 3 Entrants	-	0.47%	0.14%	0.20%	0.27%
(5.5) Distribution of Markets by Number of Exits					
Markets with 0 Exits	-	87.89%	85.12%	86.54%	86.51%
Markets with 1 Exit	-	10.55%	13.13%	11.77%	11.82%
Markets with 2 Exits	-	1.35%	1.56%	1.15%	1.35%
Markets with more 3 or 4 Exits	-	0.21%	0.21%	0.54%	0.32%

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	**93.83%**	**5.78%**	**0.39%**	0.00%	0.00%	0.00%	100.00% 519
1	**9.07%**	**79.53%**	**11.16%**	**0.23%**	0.00%	0.00%	100.00% 430
2	**0.81%**	**19.84%**	**68.42%**	**10.12%**	**0.81%**	0.00%	100.00% 247
3	**0.20%**	**3.76%**	**20.20%**	**52.28%**	**19.21%**	**4.36%**	100.00% 160
4	0.00%	**1.59%**	**6.35%**	**31.75%**	**46.03%**	**14.29%**	100.00% 63
>4	0.00%	0.00%	0.00%	**5.08%**	**33.90%**	**61.02%**	100.00% 59
Total	528	425	259	140	73	53	1,478

Table 7
Demand Estimation[1]
Data: 85,497 observations. 2004-Q1 to 2004-Q4

	OLS		**IV**	
FARE (in \$100) $\left(-\frac{1}{\sigma_1}\right)$	-0.329	(0.085)	-1.366	(0.110)
ln(s*) $\left(1-\frac{\sigma_2}{\sigma_1}\right)$	0.488	(0.093)	0.634	(0.115)
NON-STOP DUMMY	1.217	(0.058)	2.080	(0.084)
HUBSIZE-ORIGIN (in million people)	0.032	(0.005)	0.027	(0.006)
HUBSIZE-DESTINATION (in million people)	0.041	(0.005)	0.036	(0.006)
DISTANCE	0.098	(0.011)	0.228	(0.017)
σ_1 **(in \$100)**	3.039	(0.785)	0.732	(0.059)
σ_2 **(in \$100)**	1.557	(0.460)	0.268	(0.034)
Test of Residuals Serial Correlation				
m1$\sim N(0,1)$ **(p-value)**	0.303	(0.762)	0.510	(0.610)

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

Table 8

Marginal Cost Estimation[(1)]

Data: 85,497 observations. 2004-Q1 to 2004-Q4

Dep. Variable: Marginal Cost in $100

	Estimate	(Std. Error)
NON-STOP DUMMY	0.006	(0.010)
HUBSIZE-ORIGIN (in million people)	-0.023	(0.009)
HUBSIZE-DESTINATION (in million people)	-0.016	(0.009)
DISTANCE	5.355	(0.015)
Test of Residuals Serial Correlation		
m1$\sim N(0,1)$ **(p-value)**	0.761	(0.446)

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

Table 9

Estimation of Dynamic Game of Entry-Exit[1]

Data: 1,485 markets × 22 airlines × 3 quarters = 98,010 observations

	Estimate (in thousand \$)	**(Std. Error)**
Fixed Costs (quarterly):[2]		
$\gamma_1^{FC} + \gamma_2^{FC}$**mean hub-size** $+\gamma_3^{FC}$**mean distance (average fixed cost)**	119.15	(5.233)
γ_2^{FC} **(hub-size in # cities connected)**	-1.02	(0.185)
γ_3^{FC} **(distance, in thousand miles)**	4.04	(0.317)
Entry Costs:		
$\eta_1^{EC} + \eta_2^{EC}$**mean hub-size** $+\eta_2^{EC}$**mean distance (average entry cost)**	249.56	(6.504)
η_2^{EC} **(hub-size in # cities connected)**	-9.26	(0.140)
η_3^{EC} **(distance, in thousand miles)**	0.08	(0.068)
σ_ε	8.402	(1.385)
β	0.99	(not estimated)
Pseudo R-square	0.231	

(1) All the estimations include airline dummies, and city dummies.

(2) Mean hub size = 25.7 million people. Mean distance (nonstop flights) = 1996 miles

Table 10
Comparison of Predicted and Actual Statistics of Market Structure
1,485 city-pairs (markets). Period 2004-Q1 to 2004-Q4

		Actual (Average All Quarters)	Predicted (Average All Quarters)
	Herfindahl Index (median)	5338	4955
Distribution of Markets by Number of Incumbents	Markets with 0 airlines	35.4%	29.3%
	" " 1 airline	29.1%	32.2%
	" " 2 airlines	17.4%	24.2%
	" " 3 airlines	9.8%	8.0%
	" " $\geq$4 airlines	8.2%	6.2%
Number (%) of Monopoly Markets for top 6 Airlines	Southwest	151 (43.4%)	149 (38.8%)
	Northwest	66 (18.9%)	81 (21.1%)
	Delta	57 (16.4%)	75 (19.5%)
	American	31 (8.9%)	28 (7.3%)
	Continental	27 (7.7%)	27 (7.0%)
	United	16 (4.6%)	24 (6.2%)
Distribution of Markets by Number of New Entrants	Markets with 0 Entrants	84.7%	81.9%
	" " 1 Entrant	13.4%	16.3%
	" " 2 Entrants	1.7%	1.6%
	" " $\geq$3 Entrants	0.3%	0.0%
Distribution of Markets by Number of Exits	Markets with 0 Exits	86.5%	82.9%
	" " 1 Exit	11.8%	14.6%
	" " 2 Exits	1.4%	1.4%
	" " $\geq$3 Exits	0.3%	0.0%

Table 11
Counterfactual Experiments
Hub-and-Spoke Ratios when Some Structural Parameters Become Zero

		Method 1: Taylor Approximation			
Carrier	Observed	**Experiment 1** No hub-size effects in variable profits	**Experiment 2** No hub-size effects in fixed costs	**Experiment 3** No hub-size effects in entry costs	**Experiment 4** No complementarity across markets
Southwest	18.2	17.3	15.6	8.9	16.0
American	42.0	39.1	36.5	17.6	29.8
United	45.7	42.5	39.3	17.8	32.0
Delta	48.0	43.7	34.0	18.7	25.0
Continental	68.3	62.1	58.0	27.3	43.0
Northwest	49.2	44.3	36.9	18.7	26.6
US Airways	45.3	41.7	39.0	18.1	34.4

		Method II: Policy Iterations Starting from Taylor Approx.			
Carrier	Observed	**Experiment 1** No hub-size effects in variable profits	**Experiment 2** No hub-size effects in fixed costs	**Experiment 3** No hub-size effects in entry costs	**Experiment 4** No complementarity across markets
Southwest	18.2	16.9	14.4	8.3	16.5
American	42.0	37.6	34.2	16.6	24.5
United	45.7	40.5	37.3	15.7	30.3
Delta	48.0	41.1	32.4	17.9	22.1
Continental	68.3	60.2	57.4	26.0	42.8
Northwest	49.2	40.8	35.0	17.2	23.2
US Airways	45.3	39.7	37.1	16.4	35.2

Experiment 1: Counterfactual model: $\alpha_2 = \alpha_3 = \delta_2 = \delta_3 = 0$
Experiment 2: Counterfactual model: $\gamma_2^{FC} = 0$
Experiment 3: Counterfactual model: $\eta_2^{EC} = 0$
Experiment 4: Counterfactual model: Variable profit of local manager in city-pair AB ncludes only variable profits from non-stop routes AB and BA.

Figure 1: Cumulative Hub-and-Spoke Ratios

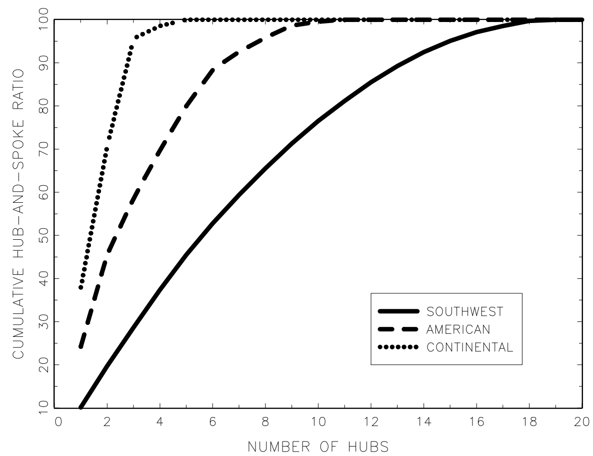

Figure 2: Histogram of the Logarithm of (Estimated) Variable Profits

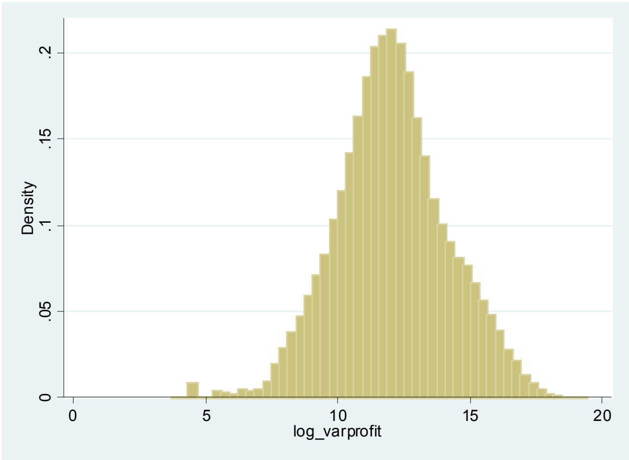

Figure 3: Histogram of Hub-Size (in million people)