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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 which may explain the adoption of hub-and-spoke networks: (1) travelers value the services associated with the scale of operation of an airline in the hub airport (e.g., more convenient check-in and landing facilities); (2) operating costs and entry costs in a route may decline with an airline's scale operation in 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 a methodological contribution, we propose and apply a simple method to deal with the problem of multiple equilibria when using the estimated model to predict the effects of changes in structural parameters. We find that the most important factor to explain the adoption of hub-and-spoke networks is that the cost of entry in a route declines very importantly with the scale of operation of the airline in the airports of the route. 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 charged.[1] Soon after deregulation, most airline companies adopted a hub-and-spoke system for the structure of their routes. In a hub-and-spoke network an airline concentrates most of its operations in one airport, 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. The arguments that have been proposed to explain the adoption of hub-and-spoke networks can be classified in three groups: demand factors, cost factors and strategic factors. Soon after deregulation, most airline companies adopted a hub-and-spoke system for the structure of their routes. In a hub-and-spoke network an airline concentrates most of its operations in one airport, 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. The arguments that have been proposed to explain the adoption of hub-and-spoke networks can be classified in three groups: demand factors, cost factors and strategic factors. Demand-side explanations argue that 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.[2] Cost-side explanations claim that some costs depend on the airline's scale of operation in an airport. For instance, it is well-known that larger planes are cheaper to fly on a per-seat basis: airlines can exploit these economies 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. [3] An airline's fixed operating cost, and

[1] Borenstein (1992) and Morrison and Winston (1995) 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] This demand factor is partly offset by the fact that consumers prefer non-stop flights to stop-flights.

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

its cost of entry in a route, may also decline with the airline's scale operation in the airports of the route. These cost savings may be due to technological reasons, but they may be also linked to contractual arrangements between airports and airlines. 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. Exit from a route between a hub-city and a spoke-city implies to stop 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.[4]

This paper develops an estimable dynamic structural model 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 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 (1,485 city-pairs).

This paper builds on an extends a significant literature in empirical IO on structural models of competition in the airline industry. The previous studies that are more closely

[4] 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.

related to this paper are Berry (1990 and 1992), Berry, Carnall, and Spiller (2006) and Ciliberto and Tamer (2006). 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 a methodological contribution to the recent literature on the econometrics of dynamic discrete games.[5] 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.

We find that the scale of operation of an airline in an airport (i.e., its hub-size) has

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

statistically significant effects on travelers' willingness to pay (positive effect) and on variable, fixed and entry costs (negative effect). Nevertheless, the most substantial impact is on the cost of entry. 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 important factor to explain hub-and-spoke networks.

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

2 Model

2.1 Framework

The industry is configured by N airline companies, A airports and C cities or metropolitan areas. Some cities have more than one airport. Airlines and airports are exogenously given in our model.[6] Following Berry (1992), we define a market in this industry as 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. An *airline network* at period t is the set of city-pairs for which the airline operates non-stop flights. Note that our market definition is not *directional*. Let $\boldsymbol{x}_{it} \equiv \{x_{imt} : m = 1, 2, ..., M\}$

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

be the network of airline i at period t, where $x_{imt} \in \{0,1\}$ is a binary indicator for the event "airline i operates non-stop flights in city-pair m". Therefore, $\boldsymbol{x}_{it}$ belongs to the set $X \equiv \{0,1\}^M$. This network also describes implicitly the city-pairs for which an airline provides stop-flights. For instance, consider an industry with 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. Then, if airline i's network is $\boldsymbol{x}_{it} \equiv \{x_{iABt}, x_{iACt}, x_{iADt}, x_{iBCt}, x_{iBDt}, x_{iCDt}\} = \{1,1,0,0,0\}$, then this airline operates non-stop flights in markets AB and AC, and stop-flights in market BC. The whole industry network is represented by the vector $\boldsymbol{x}_t \equiv \{\boldsymbol{x}_{it} : i = 1,2,...,N\} \in \{0,1\}^{NM}$.

Taken as given the network at period t, $\boldsymbol{x}_t$, and some exogenous state variables $\boldsymbol{z}_t \in Z$, airlines compete in prices. Price competition determines current profits for each airline and market. Section 2.1 describes consumers demand, Nash-Bertrand price competition, and variable profits. Let $R_i(\boldsymbol{x}_t, \boldsymbol{z}_t)$ be the indirect variable profit function for airline i that results from the Nash-Bertrand equilibrium. Every period (quarter), each airline decides its network 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 as $\boldsymbol{a}_{it} \equiv \{a_{imt} : m = 1,2,...,M\}$, 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 $\boldsymbol{x}_{i,t+1} = \boldsymbol{a}_{it}$, but it is convenient to use different letters to distinguish state and decision variables. The airline's total profit function is:

$$\Pi_i\left(\boldsymbol{a}_{it}, \boldsymbol{x}_t, \boldsymbol{z}_t, \boldsymbol{\varepsilon}_{it}\right) = R_i(\boldsymbol{x}_t, \boldsymbol{z}_t) - F_i(\boldsymbol{a}_{it}, \boldsymbol{x}_t, \boldsymbol{\varepsilon}_{it}) \tag{1}$$

where $F_i(.)$ represents the sum of fixed costs, entry costs and exit costs for airline i over all city-pairs. The term $\boldsymbol{\varepsilon}_{it}$ represents a vector of idiosyncratic shocks for airline i which are private information of this airline and are independently and identically distributed over airlines and over time with CDF G_ε. Section 2.2 describes our specification assumptions for fixed costs and entry costs.[7]

[7] There are two main reasons why we incorporate these private information shocks. As shown by Do-

Airlines maximize intertemporal profits, 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. Markets are interconnected through hub-size effects, such as entry-exit decisions in a market/city-pair have implications on airlines' profits at other city-pairs. In our model, airlines take into account these network 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 $\{\boldsymbol{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}\}$. Let $\boldsymbol{\sigma} \equiv \{\sigma_i(\boldsymbol{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}) : i = 1, 2, ..., N\}$ 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 $(\boldsymbol{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it})$ and taking as given other airlines' strategies.

Let $V_i^{\boldsymbol{\sigma}}(\boldsymbol{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it})$ 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:

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

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 $(\boldsymbol{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it})$ we have that:

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

That is, every airline strategy is the best response to the other airlines' strategies.

Given a set of strategy functions $\boldsymbol{\sigma}$ we can define a set of *Conditional Choice Probabilities (CCP)* $\mathbf{P} = \{P_i(\boldsymbol{a}_i|\mathbf{x}, \mathbf{z}) : (\boldsymbol{a}_i, \mathbf{x}, \mathbf{z}) \in X^2 \times Z\}$ such that $P_i(\boldsymbol{a}_i|\mathbf{x}, \mathbf{z})$ is the probability that

raszelski and Satterthwaite (2007), without private information shocks, this type of dynamic game may not have an equilibrium. However, Doraszelski and Satterthwaite show that, under mild regularity conditions, the incorporation of private information shocks implies that the game has at least one equilibrium. Furthermore, private information state variables independently distributed across players are convenient econometric errors in the sense that they can explain part of the heterogeneity in players' actions without generating endogeneity problems.

firm i chooses a network $\boldsymbol{a}_i$ given that the industry network at the beginning of the period is $\mathbf{x}$ and the value of the exogenous state variables is $\mathbf{z}$. By definition, these CCPs are obtained integrating decision rules over the distribution of private information shocks. That is,

$$P_i(\boldsymbol{a}_i|\mathbf{x},\mathbf{z}) \equiv \int I\left\{\sigma_i(\boldsymbol{x}_t,\mathbf{z}_t,\boldsymbol{\varepsilon}_{it}) = \boldsymbol{a}_i\right\}\; dG_\varepsilon(\boldsymbol{\varepsilon}_{it}) \tag{4}$$

where $I\{.\}$ is the indicator function. These probabilities represent the expected behavior of airline i from the point of view of the rest of the airlines. It is possible to show that the value functions $V_i^{\boldsymbol{\sigma}}$ depend on players' strategy functions only through players' choice probabilities.[8] To emphasize this point we will use the notation $V_i^{\mathbf{P}}$ instead $V_i^{\boldsymbol{\sigma}}$ to represent these value functions. Then, we can use the definition of MPE in expression (14) to represent a MPE in terms of CCPs. A set of CCPs $\mathbf{P}$ is a MPE if for every airline i, every state $(\mathbf{x},\mathbf{z})$, and every action $\boldsymbol{a}_i$, we have that:

$$P_i(\boldsymbol{a}_i|\mathbf{x},\mathbf{z}) = \int I\left\{\boldsymbol{a}_i = \arg\max_{\boldsymbol{a}_{it}} \Pi_i\left(\boldsymbol{a}_{it},\boldsymbol{x}_t,\boldsymbol{z}_t,\boldsymbol{\varepsilon}_{it}\right) + \beta\; E\left[V_i^{\mathbf{P}}(\boldsymbol{x}_{t+1},\mathbf{z}_{t+1},\boldsymbol{\varepsilon}_{it+1}) \mid \boldsymbol{x}_t,\mathbf{z}_t,\boldsymbol{a}_{it}\right]\right\} dG_\varepsilon(\boldsymbol{\varepsilon}_{it}) \tag{5}$$

If the density function of $\boldsymbol{\varepsilon}_{it}$ is absolutely continuous with respect to the Lebesgue measure, this dynamic game has at least one equilibrium.[9] Multiplicity of equilibria in this class of dynamic games is very common. 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.

The rest of this section describes the details of the model. Section 2.2 presents the demand system and the static model of price competition. Section 2.3 discusses the structure of fixed costs and entry costs. Section 2.4 deals with simplifying assumptions that reduce very significantly the dimensionality of the model.

[8] For more details, see sections 2.3 and 2.4 in Aguirregabiria and Mira (2007).

[9] See Doraszelski and Satterthwaite (2007), and Aguirregabiria and Mira (2007) for proofs of equilibrium existence.

2.2 Consumer demand and variable profits

In the dynamic game of network competition, we have defined a market as a non-directional city-pair. However, for the model of demand and price competition it is more realistic and convenient to consider a route as the appropriate market definition. We define a route as a directional round-trip between two cities, e.g., a round-trip from Chicago to Los Angeles. Of course, this means that to obtain the current profit of operating non-stop flights in a city-pair m (i.e., $x_{imt} = 1$) we have to consider demand and profits in all the routes including this city-pair. For notational simplicity, we omit the time subindex t for most of this subsection, but all the variables may vary over time. We index routes by r.

A product can be described in terms of three attributes: the route (r), the airline (i), and the indicator of non-stop flight (NS).[10] For simplicity, we use k instead of the triple (r, i, NS) to index products. 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; b_k is the "quality" or willingness to pay 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 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 scale of operation of the airline in the origin and destination airports. We consider the following specification of product quality:

$$\begin{aligned} b_k &= \alpha_1 \; NS_k + \alpha_2 \; HUB_k^O + \alpha_3 \; HUB_k^D + \alpha_4 \; (1 - NS_k) HUB_k^C + \alpha_5 \; DIST_k \\ &+ \; \xi_i^{(1)} + \xi_r^{(2)} + \xi_r^{(3)} + \xi_k^{(4)} \end{aligned} \tag{6}$$

α_1 to α_5 are parameters. NS_k is a dummy variable for "non-stop flight". $DIST_k$ is the distance between the origin and destination cities. This variable is a proxy of the value of

[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.

air transportation relative to the outside alternative, i.e., air travelling is a more attractive transportation mode when distance is larger. $\xi_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in quality which are constant over time and across markets. $\xi_r^{(2)}$ (and $\xi_r^{(3)}$) represents the interaction of origin-airport dummies (destination airport dummies) and time dummies. These terms account for demand shocks, such as seasonal effects, which can vary across cities and over time. $\xi_k^{(4)}$ is a demand shock that is airline and route specific. The variables HUB_k^O, HUB_k^D and HUB_k^C are indexes that represent the scale of operation or "hub size" of airline i in the origin, destination and connecting (if any) airports of route r, respectively. Therefore, the terms associated with 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 the hub-size of an airline in an airport as the sum of the population in the cities that the airline serves from this airport (see Section 3 for more details).

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 demands 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 demands depends on our assumption 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 which 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]

$$\ln(s_k) - \ln(s_0) \quad = \quad \frac{\alpha_k - p_k}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right) \ln(s_k^*) \tag{7}$$

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 and at the local market level. The variable profit of airline i in route r is:

$$\pi_{ir} = (p_{ir0} - c_{ir0})\ q_{ir0} + (p_{ir1} - c_{ir1})\ q_{ir1} \tag{8}$$

where c_k is the marginal cost of product k, that is constant with respect to the quantity sold. Our specification of the marginal cost is similar to the one of product quality:

$$\begin{aligned} c_k \quad &= \quad \delta_1\ NS_k + \delta_2\ HUB_k^O + \delta_3\ HUB_k^D + \delta_4\ (1 - NS_k) HUB_k^C + \delta_5\ DIST_k \\ &+ \quad \omega_i^{(1)} + \omega_r^{(2)} + \omega_r^{(3)} + \omega_k^{(4)} \end{aligned} \tag{9}$$

δ_1 to δ_5 are parameters. $\omega_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in marginal costs. $\omega_r^{(2)}$ and $\omega_r^{(3)}$ capture time-variant, airport-specific shocks in costs which are common for all the airlines. $\omega_k^{(4)}$ is a shock in the marginal cost that is airline, route and time specific.

Given quality indexes $\{\alpha_k\}$ 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]

$$p_k - c_k = \frac{\sigma_1}{1 - \bar{s}_k} \tag{10}$$

where $\bar{s}_k = (e_{ir0} + e_{ir1})^{\sigma_2/\sigma_1}[1 + \sum_{j=1}^{N}(e_{jr0} + e_{jr1})^{\sigma_2/\sigma_1}]^{-1}$, $e_k \equiv I_k \exp\{(\alpha_k - p_k)/\sigma_2\}$, and I_k is the indicator of the event "product k is available in route r". Equilibrium prices depend on the qualities and marginal costs of the active airlines and products.

An airline total variable profits is the some of the profits $\{\pi_{ir}\}$ over all the possible routes that the airline serves given its network $\boldsymbol{x}_{it}$.

[12] The nested logit model implies the following relationships. Define $e_k \equiv I_k \exp\{(\alpha_k - p_k)/\sigma_2\}$, 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 $\bar{s}_{ir} = (e_{ir0} + e_{ir1})^{\sigma_2/\sigma_1}[1 + \sum_{j=1}^{N}(e_{jr0} + e_{jr1})^{\sigma_2/\sigma_1}]^{-1}$.

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

2.3 Fixed costs and sunk entry costs

The total fixed cost and entry cost of airline i at quarter t is:

$$F_{it} = \sum_{m=1}^{M} a_{imt} \ (FC_{imt} + \varepsilon_{imt} + (1 - x_{imt}) \ EC_{imt}) \tag{11}$$

where $FC_{imt} + \varepsilon_{imt}$ and EC_{imt} represent fixed operating 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:

$$\begin{aligned} FC_{imt} &= \gamma_1^{FC} + \gamma_2^{FC} \ \overline{HUB}_{imt} + \gamma_3^{FC} DIST_m + \gamma_{4i}^{FC} + \gamma_{5c}^{FC} \\ EC_{imt} &= \eta_1^{EC} + \eta_2^{EC} \ \overline{HUB}_{imt} + \eta_3^{EC} DIST_m + \eta_{4i}^{EC} + \eta_{5c}^{EC} \end{aligned} \tag{12}$$

$\gamma' s$ and $\eta' s$ are parameters. $\overline{HUB}_{imt}$ represents the average hub-size of airline i in the airports of city-pair m. γ_{5i}^{FC} and η_{5i}^{EC} are airline fixed-effects. γ_{6c}^{FC} and η_{6c}^{EC} are city fixed-effects.

2.4 Reducing the dimensionality of the dynamic game of network competition

The estimation and solution of the dynamic game of network competition that we have described in section 2.1 is extremely challenging from a computational point of view. Given the number of cities and airlines in our empirical analysis,[14] the space of possible values of the industry network $\mathbf{x}_t$ is really huge: i.e., $|X| = 2^{NM} \simeq 10^{10,000}$. We consider several simplifying assumptions that reduce very significantly the dimension of the dynamic game and make its estimation and solution very manageable.

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

Suppose that each airline has M local managers, one for each market or city-pair. A local manager decides whether to operate or not non-stop flights in his local-market: i.e., he chooses a_{imt}. Let R_{imt} be the sum of airline i's variable profits over all the routes that include city-pair m.

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 $\Pi_{imt} \equiv x_{imt} R_{imt} - a_{imt}\left(FC_{imt} + \varepsilon_{imt} + (1 - x_{imt}) EC_{imt}\right)$.

ASSUMPTION NET-2: The shocks $\{\varepsilon_{imt}\}$ are private information of the local manager of airline i at market 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 this decentralized decision-making can still generate the type of entry deterrence suggested by Hendricks, Piccione and Tan (1997), and that we have described in the Introduction. A local manager of a city-pair takes into account that exit from this 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.

To complete the model we follow a similar approach to Hendel and Nevo (2006) and Nevo and Rossi (2008) to reduce the dimensionality of the decision problem. First, note the following feature of the model: for local-manager (i, m), the current profit at any period t can be described in terms of only three time-varying variables: the indicator of incumbent status, x_{imt}; the variable profit, R_{imt}; and the hub-size measure, $\overline{HUB}_{imt}$.[15] Let $\mathbf{x}^*_{imt}$ represent the vector (x_{imt},R_{imt},$\overline{HUB}_{imt}$). We consider the following assumption.

ASSUMPTION NET-3: Consider the decision problem of local-manager (i, m). Let $\mathbf{P}_{-im}$ be the vector with the CCPs of all airlines other than i, and all local-managers of airline i

[15]Variable profit R_{imt} is well-defined regardless the airline is active in market m or not. That is, R_{imt} represents the potential variable profit of airline i in market m. The actual variable profit is $x_{imt} R_{imt}$.

other than (i,m). Given $\mathbf{P}_{-im}$, the vector $\mathbf{x}^*_{imt} \equiv (x_{imt}, R_{imt}, \overline{HUB}_{imt})$ follows a first-order controlled Markov Process with control variable a_{imt}. That is,

$$\Pr\left(\mathbf{x}^*_{im,t+1} \mid \mathbf{x}^*_{imt}, a_{imt}, \mathbf{x}_t, \mathbf{z}_t; \mathbf{P}_{-im}\right) = \Pr\left(\mathbf{x}^*_{im,t+1} \mid \mathbf{x}^*_{imt}, a_{imt}; \mathbf{P}_{-im}\right) \tag{13}$$

Under this assumption, and for a given $\mathbf{P}_{-im}$, the vector of payoff-relevant state variables for local-manager (i,m) is $(x_{imt}, R_{imt}, \overline{HUB}_{imt})$. We use X^* to represent the space of $(x_{imt}, R_{imt}, \overline{HUB}_{imt})$.

Given these assumptions, we redefine a Markov Perfect Equilibrium (MPE) in our dynamic game of network competition. Let $\boldsymbol{\sigma} \equiv \{\sigma_{im}(\mathbf{x}^*_{imt}, \varepsilon_{imt}) : i = 1,2,...,N;\ m = 1,2,...,M\}$ be a set of strategy functions, one for each local-manager, such that σ_{im} is a function from $X^* \times \mathbb{R}$ into $\{0,1\}$. A Markov Perfect Equilibrium (MPE) in this game is a set of strategy functions such that each local manager's strategy maximizes the value of the airline in his local market taken as given the strategies of the other airlines as well as the strategies other local managers of the same airline. More formally, $\boldsymbol{\sigma}$ is a MPE if for every local manager (i,m) and every state $(\mathbf{x}^*_{imt}, \varepsilon_{imt})$ we have that:

$$\{\sigma_{im}(\mathbf{x}^*_{imt}, \varepsilon_{imt}) = 1\} \Leftrightarrow$$

$$\left\{\varepsilon_{imt} \leq -FC_{imt} - (1 - x_{imt})EC_{imt} + \beta E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, a_{imt} = 1\right] - \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, a_{imt} = 0\right]\right\} \tag{14}$$

A MPE can be described in the space of *conditional choice probabilities (CCPs).* Let $\mathbf{P} = \{P_{im}(\mathbf{x}^*)\}$ be a vector of CCPs for every local manager, and every value of $\mathbf{x}^* \in X^*$. Then, $\mathbf{P}$ is a MPE if for every $(i, m, \mathbf{x}^*_{imt})$:

$$P_{im}(\mathbf{x}^*_{imt}) = G_\varepsilon\left(-FC_{imt} - (1 - x_{imt})EC_{imt} + \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 1\right] - \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 0\right]\right) \tag{15}$$

To complete the model we have to specify the transition probability function of the vector of state variables: i.e., $\Pr\left(\mathbf{x}^*_{im,t+1} \mid \mathbf{x}^*_{imt}, a_{imt}; \mathbf{P}_{-im}\right)$. First, it is clear that the transition of x_{imt} is deterministic, i.e., $x_{im,t+1} = a_{imt}$. Therefore, we have to specify only the probability $\Pr\left(R_{im,t+1}, \overline{HUB}_{im,t+1} \mid \mathbf{x}^*_{imt}, a_{imt}; \mathbf{P}_{-im}\right)$. We consider a VAR model with varying coefficients.

$$\begin{array}{rcl}\log\left(R_{im,t+1}\right) & = & \lambda_{R0}(x_{imt},a_{imt})+\lambda_{RR}(x_{imt},a_{imt})\ \log\left(R_{imt}\right) \\ & + & \lambda_{RH}(x_{imt},a_{imt})\ \log\left(\overline{HUB}_{imt}\right)+u_{R,im,t+1} \\ \log\left(\overline{HUB}_{im,t+1}\right) & = & \lambda_{H0}(x_{imt},a_{imt})+\lambda_{HR}(x_{imt},a_{imt})\ \log\left(R_{imt}\right) \\ & + & \lambda_{HH}(x_{imt},a_{imt})\ \log\left(\overline{HUB}_{imt}\right)+u_{H,im,t+1}\end{array} \tag{16}$$

Given that (x_{imt}, a_{imt}) can take only four values, $\{(0,0),(0,1),(1,0),(1,1)\}$, each $\lambda(.)$ function can be represented in terms of 4 parameters. The variables $u_{R,im,t+1}$ and $u_{H,im,t+1}$ represent error terms which include airline fixed-effects, city fixed-effects, and pure idiosyncratic innovations which are independently distributed over time.

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, and it is divided into 3 parts, namely DB1B-Coupon, DB1B-Market and DB1B-Ticket. 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.[16] 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 year 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 market is a round-trip travel between two cities, an origin city and a destination city. These

[16] 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.

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 (2006) with the only difference that they consider airport-pairs instead of city-pairs. The main reason why we consider city-pairs instead of airport-pairs is to allow for substitution in the demand (and in the supply) of routes that involve airports located in the same city. In the demand, we distinguish different types of products within a market. The type of product depends on whether the flight is non-stop or stop, and on the origin and destination airports. Thus, the itineraries New York (La Guardia)-Los Angeles, New York (JFK)-Los Angeles, and New York (JFK)-Las Vegas-Los Angeles are three different products in the New York-Los Angeles route-market.

(b) Selection of markets. We started selecting the 75 largest US cities in terms of population in 2004. We use city population estimates from the Population Estimates Program in the Bureau of Statistics to find out the 75 largest US cities in 2004.[17] For each city, we use 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 cities or metropolitan areas and 63 airports. Table 1 presents the list of "cities" with their airports and population.[18] 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) Definition of carrier. There may be more than one airline or carrier involved in a ticket. The DB1B distinguishes three types of carriers: operating carrier, ticketing carrier, and reporting carrier. The operating carrier is an airline whose aircraft and flight crew are used

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

[18] 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.

in air transportation. The ticketing carrier is the airline that issued the air ticket. And the reporting carrier is the one that submits the ticket information to the Office of Airline Information. According to the directives of the Bureau of Transportation Statistics (Number 224 of the Accounting and Reporting Directives), the first operating carrier is responsible for submitting the applicable survey data as reporting carrier. For more than 70% of the tickets in this database the three variables are the same. For the construction of our working sample, we use the *reporting carrier* to identify the airline and assume that this carrier pays the cost of operating the flight and receives the revenue for providing this service.

(e) Selection of tickets. We apply several selection filters on tickets in the DB1B database. We eliminate all those 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*.

(f) Airlines. According to DB1B, there are 31 airlines operating in our selected markets in 2004. However, not all these airlines can be considered as independent because some of them belong to the same corporation or have very exclusive code-sharing agreements.[19] We take this into account in our analysis. Table 3 presents our list of 22 airlines. The notes in the table explains how some of these "airlines" combine several carriers. The table also reports, for each airline, the number of passengers and the number of city-pairs in which the 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 nonstop flights (373 of a maximum of 1,485). American, United and Delta, in this order, follow in the ranking, but they serve significantly fewer city-pairs (with non-stop flights) than Southwest.

(g) 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

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

quarter) in non-stop flights for that city-pair.

(h) Construction of quantity and price data. A ticket/record in the DB1B database may correspond to more than one passenger. The DB1B-Ticket dataset reports the number of passengers in a ticket. Our quantity measure q_k is the number of passengers in the DB1B survey at quarter t that corresponds to airline i, route r and product 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.

(i) Measure of hub size. For each airport and airline, we construct a measure of the scale of operation, or *hub-size*, of the airline at the airport. Following Berry (1990) and Berry, Carnall and Spiller (2006), we measure the hub-size of an airline-airport as the sum of the population in other markets that the airline serves with nonstop flights from this airport. The reason to weight routes by the number of passengers travelling in the route is that more popular routes are more valued by consumers and therefore this hub measure takes into account this service to consumers.

Our working dataset is an unbalanced panel with 1,485 city-pairs, 2,970 routes, 22 airline, and 4 quarters. The number of observations is 249,530.

3.2 Descriptive statistics

Table 4 presents, for each airline, the two airports with largest hub sizes. The largest hubs are Delta Airlines at Atlanta (48.5 million people) and Tampa (46.9), Northwest at Detroit (47.6) and Minneapolis-St. Paul (47.1), Continental at Washington International (46.9) and Cleveland (45.6), American at Dallas-Fort Worth (46.7) and Chicago-O'Hare (44.4), and United at Denver (45.9) and San Francisco (45.8). Note that Southwest, though it flies more passengers and is active in more markets than any other airline, has significantly smaller hubs than most other airlines.

Tables 5 presents different statistics that describe market structure and its dynamics.

The first panel of the 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 non-stop flights between the pair of cities. Typically, these are pairs of relative small 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, as it 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 less than 70 monopoly markets each. 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, which is very similar to the transition matrices from Q1 to Q2 or from Q3 to Q4. 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. For this third step, we use a recursive pseudo maximum likelihood estimator as proposed in Aguirregabiria and Mira (2007).

4.1 Estimation of the demand system

The demand model can be represented using the regression equation:

$$\ln(s_{kt}) - \ln(s_{0t}) = W_{kt}\ \alpha + \left(\frac{-1}{\sigma_1}\right) p_{kt} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln(s_{kt}^{*}) + \xi_{kt}^{(4)} \tag{17}$$

The regressors in vector W_{kt} are the ones in equation (6): i.e., dummy for nonstop-flight, hub-size variables, distance, airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies.

It is well-known that an important econometric issue in the estimation of this demand system is the endogeneity of prices and conditional market shares $\ln(s_{kt}^{*})$ (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 $\xi_{kt}^{(4)}$. Similarly, the regressor $\ln(s_{kt}^{*})$ depends on unobserved characteristics and it is endogenous. In our model, there is another potential endogeneity problem in the estimation of the demand. The hub-size variables HUB_{kt}^{O} and HUB_{kt}^{D} (included in the vector W_{kt}) depend on the entry decisions of the airline in city-pairs connected with the origin or the destination of the route in product k (though excluding the city-pair of product k). These variables may be correlated with the demand shock $\xi_{kt}^{(4)}$. Suppose that the local managers of city-pairs that include the origin or the destination cities of the route in product k know the demand shock $\{\xi_{kt}^{(4)}\}$ and they take it into account when deciding whether to be active or not. If that is the case, the entry-exit decisions of these local managers, and therefore HUB_{kt}^{O} and HUB_{kt}^{D}, depend on $\{\xi_{kt}^{(4)}\}$, and the hub-size variables are endogenous in the estimation of the demand model.

The following identifying assumption implies that the hub-size variables are not endogenous in the estimation of demand.[20]

ASSUMPTION D1: The idiosyncratic demand shock $\{\xi_{kt}^{(4)}\}$ *is independently distributed 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 $\xi_{kt}^{(2)}$ and $\xi_{kt}^{(3)}$, the residual demand left 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 $\{\xi_{kt}^{(4)}\}$ are independently distributed over time, they are not correlated with hub-size variables.

ASSUMPTION D2: The idiosyncratic demand shock $\{\xi_{kt}^{(4)}\}$ *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}^{O} depend on the entry decisions in city-pairs that include one of the cities in the origin or the destination of 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 $\xi_{kt}^{(4)}$. 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 (Assumption D1), and cross-airlines correlation in the idiosyncratic demand shocks $\xi_{kt}^{(4)}$.

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

[20]Sweeting (2007) has also considered this type of 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.

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, according to the model, the estimated price-cost margin of product k at period t. The marginal cost function can be represented using the regression equation $\hat{c}_{kt} = W_{kt}\ \delta + \omega_{kt}^{(4)}$. The vector of regressors W_{kt} has the same interpretation as in the demand equation: dummy for nonstop-flight, hub-size variables, distance, airline dummies, origin-airport dummies $\times$ time dummies, and destination-airport dummies $\times$ time dummies.

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

ASSUMPTION MC1: The idiosyncratic shock in marginal cost $\{\omega_{kt}^{(4)}\}$ is independently distributed 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 we have described in section 2.4, a MPE of our dynamic game can be described as a vector $\mathbf{P} = \{P_{im}(\mathbf{x}^*)\}$ of *conditional choice probabilities (CCPs)* such that for every $(i, m, \mathbf{x}^*_{imt})$:

$$P_{im}(\mathbf{x}^*_{imt}) = G_\varepsilon \left(-FC_{imt} - (1 - x_{imt})EC_{imt} + \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 1\right] - \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 0\right]\right) \tag{18}$$

Following Aguirregabiria and Mira (2007), we can get a simple and useful representation of the expression $-FC_{imt} - (1 - x_{imt})EC_{imt} + \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 1\right] - \beta\ E\left[V^{\mathbf{P}}_{im,t+1} | \mathbf{x}^*_{imt}, 0\right]$. In order to describe this representation, it is convenient to write the current profit of a local manager, Π_{imt}, as follows:

$$\Pi_{imt} = (1 - a_{imt})\ \mathbf{z}_{imt}(0)'\boldsymbol{\theta} + a_{imt}\ \mathbf{z}_{imt}(1)'\boldsymbol{\theta} - a_{imt}\ \varepsilon_{imt} \tag{19}$$

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

$$\begin{aligned} \boldsymbol{\theta}\ \ \equiv\ \ & \big(\ 1,\ \gamma_1^{FC},\ \gamma_2^{FC},\ \gamma_3^{FC},\ \{\gamma_{4i}^{FC}\}, \{\gamma_{5c}^{FC}\} \\ & \eta_1^{EC},\ \eta_2^{EC},\ \eta_3^{EC},\ \{\eta_{4i}^{EC}\}, \{\eta_{5c}^{EC}\}\ \big)' \end{aligned} \tag{20}$$

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 column vectors with the following definitions:

$$\begin{array}{rcl} \mathbf{z}_{imt}(0) & \equiv & (\ x_{imt}R_{imt},\ \mathbf{0}\ )' \\ \mathbf{z}_{imt}(1) & \equiv & (\ x_{imt}R_{imt},\ 1,\ \overline{HUB}_{imt},\ DIST_m,\ AIRDUM_i,\ CITYDUM_m \\ & & (1-x_{imt}),\ (1-x_{imt})\overline{HUB}_{imt},\ (1-x_{imt})DIST_m, \\ & & (1-x_{imt})AIRDUM_i,\ (1-x_{imt})CITYDUM_m\ )' \end{array} \tag{21}$$

$AIRDUM_i$ and $CITYDUM_m$ are vectors of airline dummies and city dummies, respectively.[21]

Given this vector notation, we can represent a MPE in this model as a vector $\mathbf{P} = \{P_{im}(\mathbf{x}^*)\}$ of CCPs such that for every $(i, m, \mathbf{x}^*_{imt})$:

$$P_{im}(\mathbf{x}^*_{imt}) = \Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}{}'\frac{\boldsymbol{\theta}}{\sigma_\varepsilon} + \tilde{e}^{\mathbf{P}}_{imt}\right) \tag{22}$$

where we have assumed that ε_{imt} is a random variable with logistic distribution and variance σ^2_ε, $\Lambda(.)$ is the logistic function $\exp(.)/(1+\exp(.))$, and:

$$\begin{array}{rcl} \tilde{\mathbf{z}}^{\mathbf{P}}_{imt} & \equiv & \sum_{j=0}^{\infty}\beta^j E\left\{\left(1-P_{im}(x^*_{im,t+j})\right)\mathbf{z}_{im,t+j}(0) + P_{im}(x^*_{im,t+j})\mathbf{z}_{im,t+j}(1)\ |x^*_{imt}, 1\right\} \\ & - & \sum_{j=0}^{\infty}\beta^j E\left\{\left(1-P_{im}(x^*_{im,t+j})\right)\mathbf{z}_{im,t+j}(0) + P_{im}(x^*_{im,t+j})\mathbf{z}_{im,t+j}(1)\ |x^*_{imt}, 0\right\} \\ \tilde{e}^{\mathbf{P}}_{imt} & \equiv & \sum_{j=0}^{\infty}\beta^j E\left\{P_{im}(x^*_{im,t+j})\ \left(Euler - \ln P_{im}(x^*_{im,t+j})\right)\ |x^*_{imt}, 1\right\} \\ & - & \sum_{j=0}^{\infty}\beta^j E\left\{P_{im}(x^*_{im,t+j})\ \left(Euler - \ln P_{im}(x^*_{im,t+j})\right)\ |x^*_{imt}, 0\right\} \end{array} \tag{23}$$

The expression of $\tilde{e}^{\mathbf{P}}_{imt}$ is based on the assumption that ε_{imt} is a logistic random variable. Though these expressions of $\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}$ and $\tilde{e}^{\mathbf{P}}_{imt}$ involve infinite sums, these values can be calculated solving a system of linear equations with the same dimension as the space of the vector of state variables $\mathbf{x}^*_{imt}$ (see Aguirregabiria and Mira, 2007, for further details).

For the computation of the values $\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}$ and $\tilde{e}^{\mathbf{P}}_{imt}$ we discretize the variables $(R_{imt}, \overline{HUB}_{imt})$. Figures 1 and 2 present the empirical distributions of the variables $\ln(R_{imt})$ and $\overline{HUB}_{imt}$. We discretize $\ln(R_{imt})$ using a uniform grid of 31 points in the interval $[4, 18]$. Similarly, we discretize $\overline{HUB}_{imt}$ using a uniform grid of 26 points in the interval $[0, 50]$. These discretizations imply that the state space of $(x_{imt}, R_{imt}, \overline{HUB}_{imt})$ has $31 * 26 * 2 = 1,612$ cells.

[21] $AIRDUM_i$ is a vector of dimension $N = 22$ with a 1 at the position of airline i and zeroes elsewhere. Similarly, $CITYDUM_m$ is a vector of dimension $C = 55$ with $1's$ at the positions of the two cities in market m and zeroes elsewhere.

This determines the order of the system of linear equations that we have to solve to obtain $\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}$ and $\tilde{e}^{\mathbf{P}}_{imt}$. Note that we have to solve this system for every local manager (i, m). There are $22 * 1,485 = 32,670$ local managers. Therefore, we have to solve $32,670$ systems of linear equations with dimension $1,612$ each. This is the main computational burden in the estimation of this model.

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:

$$Q(\boldsymbol{\theta}, \mathbf{P}) \equiv \sum_{m=1}^{M}\sum_{t=1}^{T}\sum_{i=1}^{N} a_{imt} \ \ln\Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}{}'\boldsymbol{\theta}+\tilde{e}^{\mathbf{P}}_{imt}\right) + (1-a_{imt}) \ \ln\Lambda\left(-\tilde{\mathbf{z}}^{\mathbf{P}}_{imt}{}'\boldsymbol{\theta}-\tilde{e}^{\mathbf{P}}_{imt}\right) \tag{24}$$

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, 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. A second important of the two-step method is that, even if 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 very 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:

$$\begin{aligned} \hat{\boldsymbol{\theta}} &= \arg\max_{\boldsymbol{\theta}\in\Theta}\ Q(\boldsymbol{\theta}, \hat{\mathbf{P}}) \\ \hat{\mathbf{P}} &= \Lambda\left(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}\prime}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}}\right) \end{aligned} \tag{25}$$

That is, $\hat{\boldsymbol{\theta}}$ maximizes the pseudo likelihood given $\hat{\mathbf{P}}$ (as in the two-step estimator), and $\hat{\mathbf{P}}$ is an equilibrium associated with $\hat{\boldsymbol{\theta}}$. This estimator has lower asymptotic variance and finite sample bias than the two step estimator (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 $\hat{\mathbf{P}}^K = \Lambda\left(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}^{K-1}\prime}\hat{\boldsymbol{\theta}}^K + \tilde{e}^{\hat{\mathbf{P}}^{K-1}}\right)$, that is:

$$\hat{\mathbf{P}}_{im}^K(\mathbf{x}_{imt}^*) = \Lambda\left(\tilde{\mathbf{z}}_{imt}^{\hat{\mathbf{P}}^{K-1}\prime}\hat{\boldsymbol{\theta}}^K + \tilde{e}_{imt}^{\hat{\mathbf{P}}^{K-1}}\right) \tag{26}$$

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 $P_{im}(x^*_{imt})$ based on a logit model that includes as explanatory variables airline dummies, city dummies, and a second order polynomial in $(R_{imt}, \overline{HUB}_{imt})$ where the terms of this polynomial are interacted with the incumbent status dummy x_{imt}.

4.3.3 Estimation results

Table 9 presents our estimation results for the dynamic game of network competition. The estimates are measured in thousands of dollars. The estimated fixed cost, evaluated at the mean value of hub-size and distance, is $\$117,000$. Since the median variable profit in the sample is around \$159,000, we have that this fixed cost is 73% of the median variable profit. Not surprisingly for this industry, this value implies 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 million people increase of hub-size implies a $\$1,610$ reduction in fixed costs. This is a non-negligible cost reduction.

The estimated entry cost, evaluated at the mean value of hub-size and distance, is $\$242,000$. This value represents 207% of the corresponding (quarterly) fixed cost, 152% of the median variable profit, and 5.8 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 six quarters 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 $\$501,000$, and airline with the maximum hub-size in the sample (i.e., 50 million people) pays only $\$12,000$. A one million people increase in hub-size implies a reduction of entry costs of more than $\$10,000$.

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 consider a simple measure of this propensity, that we define as an airline's $hub - ratio$. Airlines' hub ratios can be obtained from the data. Then, we analyze how different parameters of the model contribute to the observed hub-ratios. The parameters of interest are the ones that measure the effects hub-size on demand, variable costs, fixed costs and entry costs. We use the estimated model to calculate the counterfactual hub-ratio if some of these parameters becomes zero. We distinguish two different types of counterfactual experiments: an experiment where the behavior of the other airlines remains the same; and an experiment where the other airlines change their behavior in the new equilibrium. The comparison between the two types of experiments provides a measure of the importance of strategic factors in the adoption of hub-and-spoke networks.

5.1 Empirical hub-ratios

To obtain our measure of an airline propensity to operate using a hub-and-spoke network, we start assuming that each airline has two hub airports. These hub airports are the two airports with the largest values of hub-size for the airline. For the most important carriers, this 'empirical' definition of a hub-airport coincides with the self-reported hubs. Table 4 presents the list of hub-airports using our definition of hubs. Then, an airline hub-ratio is defined as:

$$hub - ratio_{it} = \frac{\sum_{m=1}^{M} x_{imt} \; I\left\{\text{city-pair } m \text{ involves a hub airport of airline } i\right\}}{\sum_{m=1}^{M} x_{imt}} \tag{27}$$

Of those city-pairs in which the airline is active (with nonstop flights), the hub-ratio is the proportion of these city-pairs that involve a hub airport.

Table 10 presents the hub ratios of the top 12 airlines. Southwest hub-ratio (15.6%) is substantially smaller than those of any other airline in the industry. Within the other large carriers, Continental (with 61.3%), Northwest (49.2), and American (40.1) are the ones with largest hub ratios. Interestingly, we find very large hub ratios among some of regional carriers such as Alaska (90.6%), ATA (66.7), Frontier (62.5%), and America West (60.2%).

5.2 A simple method to deal with multiple equilibria in counterfactual experiments

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 advantage of this approach is its simplicity, and that it makes minimum assumptions on the equilibrium selection mechanism. Its 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.

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 can have multiple equilibria. The model can be completed with an equilibrium selection mechanism. This mechanism can be represented as a function that, for given $\boldsymbol{\theta}$, selects one equilibrium within the set of equilibria associated with $\boldsymbol{\theta}$. We use $\boldsymbol{\pi}(\boldsymbol{\theta})$ to represent this (unique) selected equilibrium. Our approach here (both for the estimation and for counterfactual experiments) is 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 (and the population) come from a unique equilibrium associated with $\boldsymbol{\theta}_0$. Let $\mathbf{P}_0$ be the equilibrium in the population. By definition, $\mathbf{P}_0$ is such that $\mathbf{P}_0 = \Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}_0}{}'\boldsymbol{\theta}_0 + \tilde{e}^{\mathbf{P}_0}\right)$ and $\mathbf{P}_0 = \boldsymbol{\pi}(\boldsymbol{\theta}_\mathbf{0})$. Let $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$ be a consistent estimator of $(\boldsymbol{\theta}_0,\mathbf{P}_0)$. Note that we do not know the function $\boldsymbol{\pi}(\boldsymbol{\theta})$. All what we know is that the point $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$ belongs to the graph of this function $\boldsymbol{\pi}$. 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 $\Lambda\left(\tilde{\mathbf{z}}^{\mathbf{P}\prime}\boldsymbol{\theta} + \tilde{e}^{\mathbf{P}}\right)$ 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 which is "closer" (in a Taylor-approximation sense) to the equilibrium estimated in t0he data. The data is not only useful to identify the equilibrium in the population but also to identify the equilibrium in the counterfactual experiments. A Taylor approximation to $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$ around $\hat{\boldsymbol{\theta}}_0$ implies that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) + \frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'}\left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) + O\left(\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2\right) \tag{28}$$

Note that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) = \hat{\mathbf{P}}_0$ and that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) = \Lambda(\tilde{\mathbf{z}}^{\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)})$. Differentiating this last expression with respect to $\boldsymbol{\theta}$ we have that

$$\frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'} = \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \boldsymbol{\theta}'} + \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \mathbf{P}'}\ \frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'} \tag{29}$$

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

$$\frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'} = \left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \boldsymbol{\theta}'} \tag{30}$$

Solving expression (30) into (28) we have that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \hat{\mathbf{P}}_0 + \left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0\prime}\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \boldsymbol{\theta}'}\left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) + O\left(\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2\right) \tag{31}$$

Therefore, under the condition that $\left\|\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right\|^2$ is small, the term $\left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0}{}'\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0}{}'\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \boldsymbol{\theta}'} \left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right)$ provides a good approximation to the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. Note that all the elements in $\left(I - \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0}{}'\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Lambda(\tilde{\mathbf{z}}^{\hat{\mathbf{P}}_0}{}'\hat{\boldsymbol{\theta}}_0 + \tilde{e}^{\hat{\mathbf{P}}_0})}{\partial \boldsymbol{\theta}'} \left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right)$ are known to the researcher.

5.3 Results

Table 11 presents the results of our counterfactual experiments. Hub-size effects on variable profits and fixed costs explain only a small portion of the observed hub-ratios. However, hub-size effects on entry costs explain a very significant portion. Furthermore, for Northwest and Delta, strategic factors play an important role in explaining the hub-ratio. Interestingly, after Southwest, these are the airlines that operate in a larger number of monopoly markets (see panel 5.3 in Table 5).

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 therefore 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 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 hub-and-spoke networks are used to deter the entry of competitors in spoke markets.

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Table 1. Cities, Airports and Population

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

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

Table 2. Ranking of City-Pairs by Number of Passengers (Round-trip, Non-Stop) in 2004

	CITY *A*	CITY *B*	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

	Airline (Code)	# Passengers[1] (in thousands)	# City-Pairs in 2004-Q4[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.

Note (3): American (AA) + American Eagle (MQ) + Executive (OW)

Note (4): United (UA) + Air Wisconsin (ZW)

Note (5): Delta (DL) + Comair (OH) +Atlantic Southwest (EV)

Note (6): Continental (CO) + Expressjet (RU)

Note (7): Northwest (NW) + Mesaba (XJ)

Note (8): On 2005, America West merged with US Airways.

Note (9): Mesa (YV) + Freedom (F8)

Table 4
Airlines and their Hubs (2004-Q4)

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

(1) Hub-size is measured in millions of people.

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)**	116.98	(5.931)
γ_2^{FC} **(hub-size, in million people)**	-1.61	(0.404)
γ_3^{FC} **(distance, in thousand miles)**	4.64	(0.322)
Entry Costs:		
$\eta_1^{FC} + \eta_2^{FC}$**mean hub-size** $+\eta_2^{FC}$**mean distance (average entry cost)**	241.87	(6.047)
η_2^{FC} **(hub-size, in million people)**	-10.06	(0.108)
η_3^{FC} **(distance, in thousand miles)**	0.07	(0.417)
σ_ε	8.402	(1.385)
Pseudo R-square	0.289	

(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
Hub Ratios of Top 12 Airlines (2004-Q4)

	Airline (Code)	Hub Cities	Hub-Ratio (%)
1.	Southwest (WN)	Kansas City; Baltimore	15.55
2.	American (AA)	Detroit; Chicago	42.06
3.	United (UA)	Denver; San Francisco	30.65
4.	Delta (DL)	Atlanta; Tampa	32.32
5.	Continental (CO)	Houston; Cleveland	61.27
6.	Northwest (NW)	Detroit; Minneapolis	49.18
7.	US Airways (US)	Charlotte; Boston	32.67
8.	America West (HP)	Phoenix; Las Vegas	60.18
9.	Alaska (AS)	Seattle; Portland	90.63
10.	ATA (TZ)	Indianapolis; Chicago	66.67
11.	JetBlue (B6)	Long Beach; Oakland	36.36
12.	Frontier (F9)	Denver; Portland	62.50

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

Carrier	Observed	No hub-size effects in variable profits		No hub-size effects in fixed costs		No hub-size effects in entry costs	
		No Strat.	*Strategic*	*No Strat.*	*Strategic*	*No Strat.*	*Strategic*
Southwest	**15.6**	14.9	14.8	14.1	13.5	9.7	7.6
American	**42.1**	40.8	39.2	38.8	36.8	24.2	17.6
United	**30.7**	29.7	28.5	27.0	26.4	18.8	12.1
Delta	**32.3**	30.1	29.5	29.4	**23.2**	19.9	**12.6**
Continental	**61.3**	59.4	56.1	55.4	52.4	34.8	24.6
Northwest	**49.2**	47.4	44.4	44.5	**37.1**	29.3	**15.1**
America West	**60.2**	58.9	55.9	54.1	52.5	34.4	24.1
Alaska	**90.6**	87.0	84.8	81.5	78.5	50.2	36.8

Figure 1: Histogram of the Logarithm of (Estimated) Variable Profits

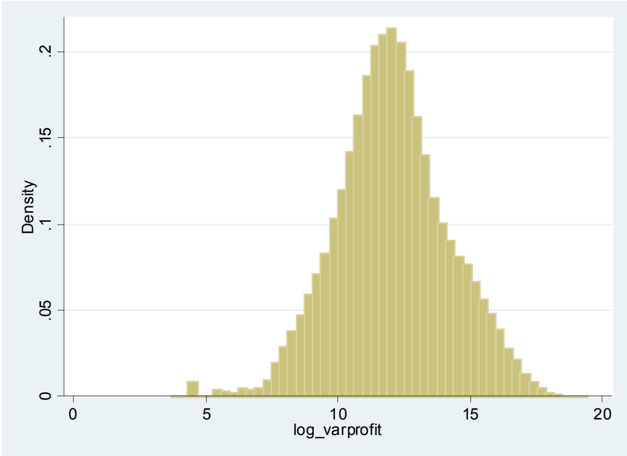

Figure 2: Histogram of Hub-Size (in million people)