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 game of network competition 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 of the paper, 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 implementing counterfactual experiments. Our empirical results show that the most important factor to explain the adoption of hub-and-spoke networks is that the sunk cost of entry in a route declines importantly with the number of cities that the airline connects from the origin and destination airports of the route. For some carriers, the entry deterrence motive is the second most important factor to explain hub-and-spoke networks.

Keywords: Airline industry; Hub-and-spoke networks; Industry dynamics; Estimation of dynamic games; Network competition; Counterfactual experiments.

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

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1 Introduction

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 adopted hub-and-spoke networks to organize their routes. In a hub-and-spoke network an airline concentrates most of its operations in an airport called the *hub* such that all the other cities in the network (the *spokes*) have non-stop flights only to the hub. Different hypotheses have been suggested to explain airlines' adoption of hub-and-spoke networks. According to demand-side explanations, some travelers value the services associated with the scale of operation of an airline in the hub airport, e.g., more convenient check-in and landing facilities, higher flight frequency.[2] According to cost-side explanations, an airline can exploit economies of scale and scope by concentrating most of its operation in a hub airport. For instance, larger planes are cheaper to fly, on a per-passenger basis, and airlines can exploit these economies of scale by seating in a single plane, flying to the hub city, passengers with different final destinations.[3] There may be also economies of scope. Some costs of operating a route, such as aircraft maintenance and labor costs, may be common for different routes in the same airport.[4] Another 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 (see Hendricks, Piccione and Tan, 1997). The main argument is that a hub-and-spoke airline is willing to operate non-stop flights between two cities even if profits from this city-pair are negative, as long as these losses are compensated by the positive profits from other routes that have this city-pair as a segment. This willingness to operate in a city-pair with negative profits may deter the entry of airlines that do not have hub-and-spoke networks or that have smaller networks.[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

[1] Borenstein (1992), Morrison and Winston (1995), and Borenstein and Rose (2007) provide excellent overviews of the US airline industry. For studies that evaluate the effects of the deregulation, see Alam and Sickles (2000), Morrison and Winston (2000), Kahn (2004), and Färe, Grosskopf, and Sickles (2007).

[2] The willingness to pay for these services can be offset by consumers' preference of non-stop flights over stop-flights.

[3] These economies of scale can be offset by the larger distance travelled with the hub-and-spoke system.

[4] Some of these cost savings may not be only technological but they may be linked to contractual arrangements between airports and airlines. 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 the size of 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 (subgame perfect) 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.

knowledge, this is the first study that estimates a dynamic game of network competition. In our model, airline companies decide every period the city-pairs where they operate non-stop flights, and the fares for each route-product they serve. The structure of our model is similar to the one in a well-known class of models of industry dynamics studied by Ericson and Pakes (1995). In particular, we have that: (i) direct strategic interactions between firms occur only through the effect of prices on demand; (ii) price competition is static; and (iii) a firm's entry decisions in city-pairs is dynamic or forward looking and it affects other firms' profits only indirectly through its effect on equilibrium prices.

The model is estimated using data from the *Airline Origin and Destination Survey* of the US Bureau of Transportation Statistics (BTS). We use 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 answer our empirical questions on the sources of hub-and-spoke networks, we need to measure airline costs at the route level. Though there is plenty of public information available on the balance sheets and costs of airline companies, this information is not at the airline-route level or even at the airline-airport level. 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 use 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 Reiss and Spiller (1989), 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 (2009) 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 endogenizes the existence of hubs and, more generally, the structure of airlines' networks. Treating hub size as a variable that is endogenously determined in the equilibrium of the model is important for some predictions and counterfactual experiments using these structural models. Second, 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), and to study the hypothesis that hub-and-spoke networks deter entry of competitors.

The paper presents also two methodological contributions to the recent literature on the econometrics of dynamic discrete games.[6] First, we propose a method to reduce the dimension of the state space in dynamic games. Our method extends to dynamic games the inclusive-values approach in Hendel and Nevo (2006) and Nevo and Rossi (2008). The main contribution of our approach to model inclusive-values is that we endogenize the transition probabilities of the inclusive-values such that we can use the estimated model to make counterfactual experiments that take into account how these transition probabilities depend on the strategies of all the players, and therefore how they change in the counterfactual scenario. Second, we implement the procedure proposed in Aguirregabiria (2009) to deal with multiple equilibria when conducting counterfactual experiments with the estimated model. Under the assumption that the equilibrium selection mechanism is a smooth function of the structural parameters, we show how to obtain an approximation to the counterfactual equilibrium.

Our empirical results show that an airline's scale of operation in an airport (as measured by the number of cities that the airline connects from that airport) has a statistically significant effect on travelers' willingness to pay, on unit (per-passenger) costs, on fixed operating costs, and on the cost of starting a new route (i.e., route entry costs). Nevertheless, the most substantial impact is on the cost of entry in a route. Given the estimated model, we implement counterfactual experiments to decompose the contribution of demand, costs, and strategic interactions to each airline's propensity to use a hub-and-spoke network. These experiments show that eliminating the effect of the number of connections in an airport on route entry costs would reduce very substantially airlines' propensity to hubbing. We also find that, 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. Section 2 presents our model and assumptions, as well as 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. We assume that each city has only one airport. Airlines and airports are exogenously given in our model. An airline's *network* is the set of city-pairs that the airline connects via non-stop flights. From the

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

point of view of an airline's entry and exit decisions, a market in this industry is a *not directional city-pair*, i.e., if an airline operates flights from A to B, then it should operate flights from B to A. Therefore, there are $M \equiv C(C-1)/2$ markets or *city-pairs*. Travelers are concerned about *routes*. A *route* is a directional round-trip between two cities, e.g., a round-trip from Chicago to Los Angeles. The number of all possible routes is $C(C-1) = 2M$. We index time by t, airlines by i, city-pairs by m, and routes by r. Let $x_{imt} \in \{0,1\}$ be the binary indicator of the event "airline i operates non-stop flights in city-pair m at period t". The network or route map of airline i at period t can be represented using the vector of M binary indicators $\mathbf{x}_{it} \equiv \{x_{imt} : m = 1, 2, ..., M\}$. This network describes implicitly all the routes that the airline serves, either with non-stop or with stop flights. We use $L(\mathbf{x}_{it})$ to represent the set with all routes associated with network $\mathbf{x}_{it}$.[7] The vector $\mathbf{x}_t \equiv \{\mathbf{x}_{it} : i = 1, 2, ..., N\}$, that belongs to the set $X \equiv \{0,1\}^{NM}$, denotes the whole industry network.

Every period (quarter) t, airlines compete in prices taking as given the current industry network $\mathbf{x}_t$ and the value of exogenous variables that affect demand and costs and that we represent with the vector $\mathbf{z}_t \in Z$. Each airline chooses prices for all the routes in its route-set $L(\mathbf{x}_{it})$. Price competition determines current profits for every airline and route. Section 2.2 presents the details of our model of consumer demand and price competition. Every quarter, airlines also choose their networks for next period. We assume that it takes one quarter to build up the inputs needed to start operating non-stop flights between two cities. Fixed costs and startup costs are paid at quarter t but entry-exit decisions are not effective until quarter $t+1$. We represent this network choice 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 $t+1$". By definition, we have that $\mathbf{x}_{i,t+1} = \boldsymbol{a}_{it}$, but it is convenient to use different letters to distinguish state and decision variables. An airline's total profit is:

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

$R_{ir}(\mathbf{x}_t, \mathbf{z}_t)$ is the variable profit of airline i that results from equilibrium price competition in route r at period t. F_{imt} represents the sum of fixed costs and entry costs for airline i in city-pair m and quarter t. Section 2.3 describes our assumptions on fixed costs and entry costs. We anticipate here two important features. First, fixed and entry costs depend on the airline's scale of operation in the airports of the city-pair, as measured by the number of other non-stop connections that the airline has in the two cities. This cost structure implies that markets are interconnected through hub-size effects. A second feature in the specification of the cost F_{imt} is that it depends on a shock

[7] For instance, consider an industry with four cities, say A, B, C, and D. The industry has 6 city-pairs that we represent as AB, AC, AD, BC, BD, and CD. The number of possible routes is 12. Suppose that 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 city-pairs AB and AC, and it serves six routes, the non-stop routes AB, BA, AC, and CA, and the stop routes BC and CB.

ε_{imt} that is private information of the airline at period t. We assume that the vector with the shocks of airline i at every market, $\boldsymbol{\varepsilon}_{it} \equiv \{\varepsilon_{imt} : m = 1, 2, ..., M\}$, is independently and identically distributed over airlines and over time with distribution function G_{ε}.[8]

Airlines are forward-looking, maximize intertemporal profits, and take into account the implications of their current network choices on future profits and on the future reaction of competitors. Airlines also take into account that operating non-stop flights in a city-pair have implications on the firm's profits in many different routes, i.e., route network effects. 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 $\{\mathbf{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}\}$. Let $\boldsymbol{\sigma} \equiv \{\sigma_i(\mathbf{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it}) : i = 1, 2, ..., N\}$ be a vector of strategy functions, one for each airline. A Markov Perfect Equilibrium (MPE) in this game is a vector of strategy functions $\boldsymbol{\sigma}$ such that each airline's strategy maximizes the value of the airline for each possible state $(\mathbf{x}_t, \mathbf{z}_t, \boldsymbol{\varepsilon}_{it})$ and taking as given other airlines' strategies.

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

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

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

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

That is, every airline is using its best response to the other airlines' strategies. An equilibrium in this dynamic game provides a description of the dynamics of airlines' route networks and, combined with the equilibrium in price competition, of the dynamics of prices and quantities for every route between the C cities.

2.2 Consumer demand and price competition

Consider a *route*, defined as a directional round-trip between two cities. Let H_{rt} be the number of travelers in route r at quarter t. Each traveler demands only one trip per period, and can select between several differentiated products. We index products by j. These products can be described in terms of five characteristics: (i) the route, that we represent as r_j or simply r, and includes

[8] There are two main reasons why we incorporate private information shocks. First, including private information shocks guarantees that the game has at least one equilibrium in pure strategies (see Doraszelski and Satterthwaite, 2010). And second, private information state variables, independently distributed across players and over time, are convenient econometric errors because they can explain part of the heterogeneity in players' actions without generating endogeneity problems.

features such as the distance between the two cities, and the origin and destination airports; (ii) the airline, that we represent as i_j or simply i; (iii) the binary indicator for *non-stop flight*, d_j; (iv) the scale of operation or "hub size" of the airline in the origin and destination airports of the route, HUB_{irt}^{O} and HUB_{irt}^{D}, respectively; and (v) other product characteristics valued by travelers but unobserved to us as researchers, that we represent as $\xi_{jt}^{(3)}$.[9]

The indirect utility of a traveler who purchases product j at period t is $U_{jt} = b_{jt} - p_{jt} + v_{jt}$, where p_{jt} is the price of the product, b_{jt} is the "quality" or willingness to pay for the product of the average consumer in the market, and v_{jt} is a consumer-specific component that captures consumer heterogeneity in preferences. The value $j = 0$ of the product index represents the choice of the *outside alternative,* that in this case corresponds to the traveler's decision of not travelling by air. Quality and price of the outside alternative are normalized to zero.[10]

Product quality b_{jt} depends on the product characteristics that we have mentioned above. We consider the following specification of product quality:

$$b_{jt} \quad = \quad \alpha_1 \; d_j + \alpha_2 \; HUB_{irt}^{O} + \alpha_3 \; HUB_{irt}^{D} + \alpha_4 \; DIST_r + \xi_i^{(1)} + \xi_{rt}^{(2)} + \xi_{jt}^{(3)} \tag{4}$$

α_1 to α_4 are parameters. The parameter α_1 associated with the indicator of non-stop flight measures the utility premium for non-stop flights for the average traveler. $DIST_r$ is the distance between the origin and destination cities of route r 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 routes. $\xi_{rt}^{(2)}$ represents the interaction of (origin and destination) city dummies and time dummies. These dummies account for demand shocks that are common for all the products in the same city, e.g., quality and congestion of the city airport(s), seasonal effects. $\xi_{jt}^{(3)}$ is a demand shock that is product specific. The "hub size" variables HUB_{irt}^{O} and HUB_{irt}^{D} capture consumer willingness to pay for the services associated with the scale of operation of an airline in an airport. Our measure of the hub-size of an airline in an airport is equal to the number of cities that the airline serves from this airport (see Section 3 for more details).

A consumer purchases product j if and only if the utility U_{jt} is greater than the utilities of any other product available for route r, including the outside alternative. This condition characterizes the unit demand of an individual consumer. To obtain aggregate demand, q_{jt}, we have to integrate individual demands over the consumer-idiosyncratic variables v_{jt}. The form of the aggregate demand depends on the probability distribution of this consumer heterogeneity. We consider a nested logit model with two nests. The first nest represents the decision of which airline (or outside

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

[10] Therefore, b_{jt} should be interpreted as willingness to pay relative to the value of the outside alternative.

alternative) to patronize. The second nest consists of the choice of stop versus non-stop flight. We have that $v_{jt} = \sigma_1 \, v_{irt}^{(1)} + \sigma_2 \, v_{jt}^{(2)}$, where $v_{irt}^{(1)}$ and $v_{jt}^{(2)}$ are independent Type I extreme value random variables, and σ_1 and σ_2 are parameters, with $\sigma_1 \geq \sigma_2$.[11] Let s_{jt} be the market share of product j in route r, i.e., $s_{jt} \equiv q_{jt}/H_{rt}$. And let s_{jt}^* be the market share of product j within the products of airline i in route r, i.e., $s_{jt}^* \equiv s_{jt}/\sum_{j' \in J_{irt}} s_{j't}$, where J_{irt} is the set of products of airline i in route r at period t.[12] A property of the nested logit model is that the demand system can be represented using the following closed-form demand equations:[13]

$$\ln(s_{jt}) - \ln(s_{0t}) \quad = \quad \frac{b_{jt} - p_{jt}}{\sigma_1} + \left(1 - \frac{\sigma_2}{\sigma_1}\right) \; \ln\left(s_{jt}^*\right) \tag{5}$$

where s_{0t} is the share of the outside alternative in route r, i.e., $s_{0t} \equiv 1 - \sum_{i=1}^{N} \sum_{j \in J_{irt}} s_{jt}$.

Travelers' demand and airlines' price competition in this model are static.[14] The variable profit of airline i in route r is $R_{irt} = \sum_{j \in J_{irt}} (p_{jt} - c_{jt}) q_{jt}$, where c_{jt} is the unit cost or cost per passenger of product j, that is assumed constant with respect to the quantity sold. Our specification of this marginal cost has the same components as product quality:

$$c_{jt} \quad = \quad \delta_1 \; d_j + \delta_2 \; HUB_{irt}^{O} + \delta_3 \; HUB_{irt}^{D} + \delta_4 \; DIST_r + \omega_i^{(1)} + \omega_{rt}^{(2)} + \omega_{jt}^{(3)} \tag{6}$$

δ_1 to δ_4 are parameters. $\omega_i^{(1)}$ is an airline fixed-effect that captures between-airlines differences in marginal costs. $\omega_{rt}^{(2)}$ captures between-cities differences in marginal costs which are common for all the airlines. $\omega_{jt}^{(3)}$ is a shock in the marginal cost that is product specific.

Given quality indexes $\{b_{jt}\}$ and marginal costs $\{c_{jt}\}$ for all the products available in route r at period t, airlines compete in prices a la Nash. The Nash-Bertrand equilibrium is characterized by the system of price equations $p_{jt} - c_{jt} = \sigma_1 (1 - \bar{s}_{jt})^{-1}$, where $\bar{s}_{jt}$ has been defined in footnote 13 above.[15]

[11] A random coefficients model would be a more flexible specification of the demand system. See Berry, Carnall, and Spiller (2006) and Berry and Jia (2009) for applications of random coefficients demand models for the airline industry. The main reason why we have used a simpler specification, such as the nested logit, is the computational cost in the solution of the Nash-Bertrand equilibrium. For the estimation of the dynamic game of entry-exit, we need to calculate the equilibrium of the pricing game not only for the route-level market structures (i.e., configuration of active products in a route) that we observe in the data, but also for every possible counterfactual route-level market structure. For each route, there are millions of possible market structures. Therefore, we need a model of price of competition that provides flexible enough price elasticities, but also that is simple enough such that we can compute very quickly a Nash-Bertrand equilibrium. In this context, we believe that the nested logit model provides a good compromise between flexibility and computational cost.

[12] In our model, the set of products that an airline provides in a route can take four possible values: no products; only non-stop flights; only stop flights; and both stop and non-stop flights.

[13] The nested logit model implies the following relationships. Define $e_{jt} \equiv I_{jt} \exp\{(b_{jt} - p_{jt})/\sigma_1\}$, where I_{jt} is the indicator of the event "product j is available in route r at period t". Then, $s_{jt} = s_{jt}^* \; \bar{s}_j$ where $s_{jt}^* = e_{jt}/\sum_{j' \in J_{irt}} e_{j't}$, and $\bar{s}_{jt} = (\sum_{j' \in J_{irt}} e_{j't})^{\sigma_2/\sigma_1} [1 + \sum_{i'=1}^{N} (\sum_{j' \in J_{i'rt}} e_{j't})^{\sigma_2/\sigma_1}]^{-1}$.

[14] Capacity constraints and intertemporal price discrimination may generate dynamics in the pricing strategies of airlines. However, this type of pricing dynamics is short-run and at the level of individual flights. Therefore, we expect that these factors should play a very minor role in the configuration and in the dynamics of airlines' networks.

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

2.3 Fixed costs and route entry costs

The sum of fixed costs and startup or entry costs of airline i at city-pair m 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 next period, 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. The component ε_{imt} is private information of the airline. This private information shock is assumed to be independently and identically distributed over firms, markets, and 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. $\{\gamma_{4i}^{FC}, \eta_{4i}^{EC}\}$ and $\{\gamma_{4c}^{FC}, \eta_{4c}^{EC}\}$ are airline and city fixed-effects, respectively.[16]

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 $\{\mathbf{x}_t, \mathbf{z}_t\}$. Given the number of cities and airlines in our empirical analysis,[17] we have that the dimension of the space of the industry network $\mathbf{x}_t$ is $|X| = 2^{NM} \simeq 10^{10,000}$. Solving exactly for an equilibrium of a dynamic game with this state space 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. We make two main assumptions: (1) an airline's choice of network is decentralized in terms of the separate decisions of the airline's local managers (Assumptions NET-1 and NET-2); and (2) the state variables in the decision problem of a local manager can be aggregated into a vector of inclusive-values that belongs to a space with a much smaller dimension than the original state space (Assumption NET-3).

Suppose that every airline has M local managers, one for each city-pair. A local manager decides whether or not to operate non-stop flights in his local market, i.e., local manager (i, m)

[16] More precisely, in the specification of FC_{imt} and EC_{imt} we include a dummy for each city in city-pair m.

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

chooses variable a_{imt}. We assume that a local manager is concerned with the maximization of the expected discounted value of the firm's profits from a particular local sub-network of the airline.

ASSUMPTION NET-1: The local manager (i,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 $\Pi^*_{imt} \equiv R^*_{imt} - a_{imt}\left(FC_{imt} + \varepsilon_{imt} + (1-x_{imt})EC_{imt}\right)$, and R^*_{imt} is 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:

$$R^*_{imt} \equiv \sum_{r} 1\{m \in \mathcal{M}_r\} \left[\sum_{j \in J_{irt}} (p_{jt} - c_{jt}) q_{jt} \right] \tag{9}$$

where $1\{.\}$ is the indicator function, and $\mathcal{M}_r$ is the set of city-pairs that are segments of route r.[18]

We assume that R^*_{imt} is the *variable profit that local manager (i,m) is concerned with.* To illustrate this concept, consider as an example the local manager of American Airlines in the city-pair Boston-Chicago. The variable profit R^*_{imt} of this local manager consists of the profits from all routes and products that include Boston-Chicago as a segment. The following table includes all these routes and products.

Routes and Products in the Variable Profit of a Local Manager in the city-pair Boston-Chicago

Routes	Products
Boston → Chicago (1 route)	{ non-stop Boston→Chicago (1 product) one-stop Boston→City X→Chicago ($C-2$ products)
Chicago → Boston (1 route)	{ non-stop Chicago→Boston (1 product) one-stop Chicago→City X→Boston ($C-2$ products)
Boston → City X ($C-2$ routes)	{ one-stop Boston→Chicago→City X ($C-2$ products) -
City X → Boston ($C-2$ routes)	{ one-stop City X→Chicago→Boston ($C-2$ products)
Chicago → City X ($C-2$ routes)	{ one-stop Chicago→Boston→City X ($C-2$ products) -
City X → Chicago ($C-2$ routes)	{ one-stop City X→Boston→Chicago ($C-2$ products) -
Total of $4C-6=214$ routes	Total of $6C-10=320$ products

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 profit in a route is the result of the Nash-Bertrand equilibrium described in Section 2.2, and it

[18] For computational simplicity, our definition of R^*_{imt} includes only non-stop and one-stop routes. However, this restriction has a negligible incidence in our empirical results because routes with more than one stop represent a very small fraction of tickets and of total revenue in our data.

depends on which airlines are active in the route. Therefore, the variable profit of a local-manager depends on the incumbent status 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 Boston-Chicago local manager of American Airlines. This is because AA will see reduced its profit from the routes Madison-Boston and Boston-Madison with stop at Chicago.

ASSUMPTION NET-2: The shock $\{\varepsilon_{imt}\}$ is private information of local manager (i, m). This shock is unknown to the local managers of airline i at city-pairs other than m.

Assumptions NET-1 and NET-2 establish a degree of decentralization in airline's network choice. 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 property 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 product 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 solving exactly a dynamic programming problem in this state space is computationally intractable. To deal with this issue, we impose restrictions on the form of players' strategies in this dynamic game. We assume that the strategy function of a player, say local manager (i, m), depends on the state variables $\{\mathbf{x}_t, \mathbf{z}_t\}$ only through a vector $\mathbf{w}_{imt}$ that aggregates the information in $\{\mathbf{x}_t, \mathbf{z}_t\}$ and has a much smaller set of possible values. More specifically, the strategy of local-manager (i, m) depends on ε_{imt} and on the vector of payoff-relevant variables

$$\mathbf{w}_{imt} \equiv \left\{x_{imt},\, R^*_{imt},\, \overline{HUB}_{imt},\, n_{mt},\, \overline{HUB}_{mt}\right\} \in W \tag{10}$$

where n_{mt} is the number of incumbent airlines at city-pair m and period t; $\overline{HUB}_{mt}$ is the average hub-size of all the active airlines at city-pair m and period t; and the variables x_{imt}, R^*_{imt}, and $\overline{HUB}_{imt}$ have been defined above.

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

Each local manager has his "own" vector of state variables, $\mathbf{w}_{imt}$. Then, apparently, it might look like that each manager is solving a single-agent dynamic decision problem, and that the model does not incorporate dynamic strategic interactions. However, the vector of state variables of a local manager depends on previous period entry and exit decisions of other local managers. For instance, the vector of state variables $\mathbf{w}_{imt}$ includes the variable profit of this local manager at period t, i.e., R^*_{imt}. This variable profit depends on which airlines are operating at each of the 214 routes involved in the definition of R^*_{imt}. Therefore, R^*_{imt} depends on the entry and exit decisions of many different local managers at period $t-1$. Other components of the state vector $\mathbf{w}_{imt}$, such as the number of airlines operating in city-pair m (n_{mt}), or the average hub-size of the active airlines in the city-pair ($\overline{HUB}_{mt}$), also depend on the entry-exit decisions of many local managers at $t-1$.

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

$$P_{im}(\mathbf{w}) \equiv \Pr\left(\sigma_{im}(\mathbf{w}_{imt}, \varepsilon_{imt}) = 1 \mid \mathbf{w}_{imt} = \mathbf{w}\right) \tag{11}$$

Given the vector of CCPs $\mathbf{P}$, let $f^{\mathbf{P}}_{im}(\mathbf{w}_{imt+1}|a_{imt}, \mathbf{w}_{imt})$ be the Markov transition probability function of the vector $\{\mathbf{w}_{imt}\}$ induced by the vector of strategy functions $\mathbf{P}$. The transition probability function $f^{\mathbf{P}}_{im}$ captures the dynamic strategic interactions between the local managers of this dynamic game. We now describe the structure of this transition probability function $f^{\mathbf{P}}_{im}$. It is important to emphasize that this function depends on players' strategies and therefore it is not a primitive of the model but an equilibrium outcome. The variables in the vector $\mathbf{w}_{imt}$ are deterministic functions of the state variables in the original problem, $\mathbf{x}_t$. That is, $\mathbf{w}_{imt} = (x_{imt},\ R^*_{imt},\ \overline{HUB}_{imt},\ n_{mt},\ \overline{HUB}_{mt})$, where: $n_{mt} \equiv \sum_{j=1}^{N} x_{jmt}$; $\overline{HUB}_{imt} = \sum_{m' \in C_m} x_{imt}$, with C_m being the set of city-pairs 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 profits from different routes, which is a function of $\mathbf{x}_t$. We use the vector valued function $w_{im}(.)$ to represent in a more compact form the relation between $\mathbf{w}_{imt}$ and the state vector $\mathbf{x}_t$, i.e., $\mathbf{w}_{imt} = w_{im}(\mathbf{x}_t)$. More precisely, we assume that the variables R^*_{imt}, $\overline{HUB}_{imt}$, and $\overline{HUB}_{mt}$ in the vector $\mathbf{w}_{imt}$ are discrete, and the vector valued function $w_{im}(.)$ incorporates also this discretization. We assume that the discrete model is the "true" model. Let $\{\mathbf{w}_{(k)} : k = 1, 2, ..., K\}$ be the set of values that define the discrete space of $\mathbf{w}_{imt}$. For any vector of values $(\mathbf{w}_{(k')}, a, \mathbf{w}_{(k)})$ in the discrete space of ($\mathbf{w}_{imt+1}$,a_{imt},$\mathbf{w}_{imt}$), the probability $f^{\mathbf{P}}_{im}(\mathbf{w}_{(k')}|a,\ \mathbf{w}_{(k)})$ is defined by the following expression:

$$f^{\mathbf{P}}_{im}\left(\mathbf{w}_{(k')}|a, \mathbf{w}_{(k)}\right) = \sum_{\mathbf{x}_{t+1}} 1\left\{w_{im}(\mathbf{x}_{t+1}) = \mathbf{w}_{(k')}\right\}\ \Pr\left(\mathbf{x}_{t+1} \mid a_{imt} = a, \mathbf{w}_{imt} = \mathbf{w}_{(k)};\ \mathbf{P}\right) \tag{12}$$

Taking into account that $\mathbf{x}_{t+1} = \boldsymbol{a}_t = (a_{imt}, \boldsymbol{a}_{(-im)t})$, where $\boldsymbol{a}_{(-im)t}$ is the vector with the actions of all the local managers other than (i, m), we have that:

$$f^{\mathbf{P}}_{im}\left(\mathbf{w}_{(k')}|a, \mathbf{w}_{(k)}\right) = \sum_{\boldsymbol{a}_{(-im)t}} 1\left\{w_{im}(a, \boldsymbol{a}_{(-im)t}) = \mathbf{w}_{(k')}\right\}\ \Pr\left(\boldsymbol{a}_{(-im)t} \mid \mathbf{w}_{imt} = \mathbf{w}_{(k)};\ \mathbf{P}\right) \tag{13}$$

where $\Pr(\boldsymbol{a}_{-(im)t}|\mathbf{w}_{imt}, \mathbf{P})$ is the probability distribution of other players' actions given their strategies in the vector $\mathbf{P}$ and from the point of view of player (i, m) who observes only $\mathbf{w}_{imt}$. Therefore, to obtain the transition probabilities $f^{\mathbf{P}}_{im}$ we should calculate the distribution of $\Pr(\boldsymbol{a}_{-(im)t}|\mathbf{w}_{imt}, \mathbf{P})$

that comes from the ergodic distribution of the state variables $\mathbf{x}_t$ induced by the CCPs in $\mathbf{P}$. Computing exactly the transition probabilities $\{f_{im}^{\mathbf{P}}\}$ is not trivial, and in fact it suffers of a curse of dimensionality. To deal with this computational problem, we use Monte Carlo simulation to approximate the transition probability functions $\{f_{im}^{\mathbf{P}}\}$. We describe the details of our Monte Carlo simulator in the Appendix.

The best response of a local-manager is the solution of a dynamic programming problem. We assume that ε_{imt} has a logistic distribution with dispersion parameter σ_ε. Let $V_{im}^{\mathbf{P}}(\mathbf{w}_{imt})$ be the (integrated) value function in the dynamic programming problem that defines the best response of player (i, m). This value function is the unique solution to the (integrated) Bellman equation $V = \Gamma_{im}^{\mathbf{P}}(V)$, where $\Gamma_{im}^{\mathbf{P}}(.)$ is the following Bellman operator:

$$\begin{aligned} \Gamma_{im}^{\mathbf{P}}(V)(\mathbf{w}_{imt}) &\equiv \int \max_{a \in \{0,1\}} \left\{ \Pi_{imt}^{*}(a) - a\ \varepsilon_{imt} + \beta \sum_{\mathbf{w}'} V(\mathbf{w}')\ f_{im}^{\mathbf{P}}(\mathbf{w}'|a, \mathbf{w}_{imt}) \right\} dG_\varepsilon(\varepsilon_{imt}) \\ &= \sigma_\varepsilon \ln \left(\sum_{a \in \{0,1\}} \exp \left\{ \frac{\Pi_{imt}^{*}(a) + \beta \sum_{\mathbf{w}'} V(\mathbf{w}')\ f_{im}^{\mathbf{P}}(\mathbf{w}'|a, \mathbf{w}_{imt})}{\sigma_\varepsilon} \right\} \right) \end{aligned} \tag{14}$$

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

$$\varepsilon_{imt} \leq -FC_{imt} - (1 - x_{imt})EC_{imt} + \beta \sum_{\mathbf{w}'} V_{im}^{\mathbf{P}}(\mathbf{w}')\ \left[f_{im}^{\mathbf{P}}(\mathbf{w}'|1, \mathbf{w}_{imt}) - f_{im}^{\mathbf{P}}(\mathbf{w}'|0, \mathbf{w}_{imt}) \right] \tag{15}$$

The best response probability function is just the best response function integrated over the distribution of the private information shock ε_{imt} and it is equal to:

$$\Lambda \left(\frac{-FC_{imt} - (1 - x_{imt})EC_{imt} + \beta \sum_{\mathbf{w}'} V_{im}^{\mathbf{P}}(\mathbf{w}')\ \left[f_{im}^{\mathbf{P}}(\mathbf{w}'|1, \mathbf{w}_{imt}) - f_{im}^{\mathbf{P}}(\mathbf{w}'|0, \mathbf{w}_{imt}) \right]}{\sigma_\varepsilon} \right) \tag{16}$$

where $\Lambda(.)$ is the logistic function $\exp(.)[1 + \exp(.)]^{-1}$. A Markov Perfect Equilibrium (MPE) in our dynamic game of network competition is a vector of CCPs, $\mathbf{P} = \{P_{im}(\mathbf{w}) \text{ for every } i, m, \mathbf{w}\}$, such that $P_{im}(\mathbf{w})$ is a best response:

$$P_{im}(\mathbf{w}) = \Lambda \left(\frac{-FC_{im}(\mathbf{w}) - (1 - x_{im})EC_{im}(\mathbf{w}) + \beta \sum_{\mathbf{w}'} V_{im}^{\mathbf{P}}(\mathbf{w}')\ \left[f_{im}^{\mathbf{P}}(\mathbf{w}'|1, \mathbf{w}) - f_{im}^{\mathbf{P}}(\mathbf{w}'|0, \mathbf{w}) \right]}{\sigma_\varepsilon} \right) \tag{17}$$

2.5 An alternative representation of the equilibrium mapping

As described in previous section, 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 (16). 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 dimension 157×1 that contains the structural parameters characterizing fixed and entry costs:[19]

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

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. $\mathbf{z}_{im}(0, \mathbf{w}_{imt})$ and $\mathbf{z}_{imt}(1, \mathbf{w}_{imt})$ are row vectors with dimension 1×157 and with the following definitions:

$$\begin{aligned} \mathbf{z}_{imt}(0, \mathbf{w}_{imt}) \ &\equiv \ (\ R_{imt},\ \mathbf{0}_{156}\ ) \\ \mathbf{z}_{imt}(1, \mathbf{w}_{imt}) \ &\equiv \ \big(\ R_{imt},\ 1,\ \overline{HUB}_{imt},\ DIST_m,\ AIRDUM_i,\ CITYDUM_m \\ &\qquad (1 - x_{imt}) * \big[1,\ \overline{HUB}_{imt},\ DIST_m,\ AIRDUM_i,\ CITYDUM_m\big]\big) \end{aligned} \tag{20}$$

$AIRDUM_i$ and $CITYDUM_m$ are vectors of airline dummies and city dummies, respectively.[20]

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

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

[19] The dimension 157×1 comes from (22 airlines $-1) * 2$ + (55 cities $-1) * 2 + 7 = 157$.

[20] $AIRDUM_i$ is a vector of dimension 1×21 (the number of airlines minus one) with a 1 at the position of airline i and zeroes elsewhere. Similarly, $CITYDUM_m$ is a vector of dimension 1×54 (the number of cities minus one) with $1's$ at the positions of the two cities in market m and zeroes elsewhere.

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

For a fixed value of $\mathbf{P}$, the evaluation of the mapping $\Psi(\boldsymbol{\theta}, \mathbf{P})$ for multiple values of $\boldsymbol{\theta}$ is computationally simple because the values $\{\widetilde{\mathbf{z}}^{\mathbf{P}}_{im}(\mathbf{w})\}$ and $\{\widetilde{e}^{\mathbf{P}}_{im}(\mathbf{w})\}$ are fixed and they should not be recomputed. The evaluation of the mapping $\Psi(\boldsymbol{\theta}, \mathbf{P})$ for multiple values of $\mathbf{P}$ is significantly more costly because the values $\{\widetilde{\mathbf{z}}^{\mathbf{P}}_{im}(\mathbf{w})\}$ and $\{\widetilde{e}^{\mathbf{P}}_{im}(\mathbf{w})\}$ should be recalculated. The most costly tasks in recalculating these values are the computation of the transition probabilities $f^{\mathbf{P}}_{im}$ and of the inverse matrices $(I - \beta \mathbf{F}^{\mathbf{P}}_{im})^{-1}$. Note that we have to calculate these functions and matrices for every local manager (i, m).[21]

For the computation of the values $\widetilde{\mathbf{z}}^{\mathbf{P}}_{im}(\mathbf{w})$ and $\widetilde{e}^{\mathbf{P}}_{im}(\mathbf{w})$ 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. 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 $[0, 20]$. These discretizations imply that our state space for $\mathbf{w}_{imt}$ has $2 * 11 * 6 * 5 * 6 = 3,960$ cells.

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.[22] 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

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

[22] This dataset does not contain information on the flight number, the day or week of the flight, or ticket restrictions such as 7 or 14 days purchase in advance.

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 that have used the same database.

(a) Definition of a market and a product. From the point of view of airlines' entry and exit decisions, a market is a non-directional city-pair. For the model of demand and price competition, a route is a directional round-trip between an origin city and a destination city. These definitions are the same as in Berry (1992) and Berry, Carnall and Spiller (2006), among others, and similar to the ones used by Borenstein (1989) or Ciliberto and Tamer (2009) with the only difference that they consider airport-pairs instead of city-pairs.[23]

(b) Selection of markets. We started selecting the 75 largest US cities in 2004 based on population estimates from the Bureau of Statistics.[24] 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.[25] As measure of market size we use 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 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.[26] In our dataset, more than 70% of the tickets have the same airline as the operating, ticketing, and reporting carrier. 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 operating in our selected markets in 2004. However,

[23] In these models, selecting the city (versus the airport) as the geographic unit for the definition of markets and products has its relative advantages and limitations. By using cities, we implicitly assume perfect substitution in demand and supply between two routes with the same cities but different airports. In contrast, using airports as geographic unit restricts, sometimes too much, the degree of substitution between airports within the same city.

[24] 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".

[25] 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.

[26] 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.

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.[27] We take this into account to aggregate these 31 carriers into 22 airlines that we treat as separate firms in our analysis. Table 3 presents our list of 22 airlines. The footnotes in that table explain how some of these airlines are a combination of the original carriers. The table also reports for each airline the annual number of passengers in 2004, and the number of city-pairs with non-stop flights 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: one-way tickets, and tickets that are neither one-way nor round-trip; more than 6 coupons (a coupon is equivalent to a segment or boarding pass); foreign carriers; and 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 for product j at quarter t, q_{jt}, is the number of passengers in the DB1B survey at quarter t that corresponds to the airline, route, and value of the non-stop flight indicator associated to product j. The DB1B-Ticket dataset reports the total itinerary fare. We construct the price variable p_{jt} (measured in dollars-per-passenger) as the ratio between the sum of fares from all those tickets that belong to product j and the number of passengers q_{jt}.

(g) Measure of the scale of operation (hub size) of an airline in a city. For each city and airline, we construct two measures of the scale of operation or *hub-size* of the airline in the city. The first measure is the number of destinations that the airline connects with this city using non-stop flights. This hub size measure 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 connects with nonstop flights from this city. The reason to weigh connections by city population is that more populated cities are typically more valued by consumers and therefore this hub measure takes into account this higher willingness to pay.

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

(h) Airlines' hubs. We define the *first hub* of airline i, denoted as $h_{it}^{(1)}$, as the city with the largest number of non-stop connections in the network of airline i, as represented by the vector $\mathbf{x}_{it}$. Similarly, we define the *k-th hub* of airline i, denoted as $h_{it}^{(k)}$, as the city with the $k-th$ largest number of non-stop connections in the network of that airline.[28]

(i) 'Hubbing' Concentration Ratio. To measure the propensity of an airline to use a hub-and-spoke network we use the following *'hubbing' concentration ratio, $CR^{(1)}$.* This ratio measures the degree of concentration of non-stop flights of an airline in its first hub. More specifically, $CR_{it}^{(1)}$ is the ratio between the number of non-stop connections of airline i that include its first hub over the total number of non-stop connections of the airline, i.e., $CR_{it}^{(1)} \equiv [\sum_{m=1}^{M} x_{imt}\ 1\{h_i^{(1)}$ is in city-pair $m\}]$ / $[\sum_{m=1}^{M} x_{imt}]$. For a *pure* hub-and-spoke network with a single hub, this concentration ratio is equal to 1. At the other extreme, for a pure point-to-point network connecting C cities, this ratio is equal to $2/C$.[29] Similarly, we can define the *'hubbing' concentration ratio* of order 2, $CR^{(2)}$, that represents the ratio between the number of non-stop connections in hubs 1 and 2 over the total number of non-stop connections of the airline. For an airline with a network characterized by two hubs-and-spokes, we have that $CR^{(1)}$ is greater or equal than 0.5 and lower than 1, and $CR^{(2)}$ is equal to one. In general, the larger these concentrations ratios the stronger is the propensity of an airline to concentrate its operation using hub-and-spoke networks.

Our working dataset for the estimation of the entry-exit game is a balanced panel of $32,670$ local managers (i.e., 22 airlines times $1,485$ city-pairs) 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

Table 4 presents the first and second hubs of each airline in 2004, with their respective numbers of non-stop connections. We also report the *hubbing concentration ratios* of order 1 and 2. *Pure* single hub-and-spoke networks are rare, and they are observed only in small carriers.[30] *Southwest*, the leader in number of passengers and non-stop connections, has hubbing concentration ratios (9.3% and 18.2%) that are significantly smaller than those of any other airline, and very close to those of a pure point-to-point network. Among the largest carriers, the ones with largest hub-and-spoke ratios are *Continental* (36.6% and 68.3%), *Delta* (26.7% and 48.0%), and *Northwest* (25.6% and

[28] In principle, the ranking of hubs of an airline can change over time. However, during our sample period, all the airlines have maintained their first and second hubs.

[29] The total number of non-stop connections in a point-to-point network with C cities is $1+2+3+...+(C-1) = C(C-1)/2$. The number of non-stop connections for any city is $C-1$. Therefore, $CR^{(1)} = (C-1)/\ [C(C-1)/2] = 2/C$.

[30] 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).

49.2%). The largest airlines' hubs are *Delta* at Atlanta with 53 connections (out of 54), *Continental* at Houston with 52, and *American* at Dallas also with 52 connections.

Figure 1 presents curves with the hubbing concentration ratios of order 1 to 20 for three large carriers: *Southwest*, *American*, and *Continental*. These curves provide a closer look at the degree of concentration of the number of connections of an airline. The three airlines present very different degrees of hubbing. *Continental* can be described as a combination of 5 hubs that account for all the connections of this airline. In contrast, we need 10 hubs and 20 hubs to account for all the connections of *American* and *Southwest*, respectively.

Table 5 presents different statistics that describe market structure and its dynamics. The first panel (panel 5.1) presents the distribution of the 1,485 city-pairs by the number of airlines with non-stop flights. More than one-third of these city-pairs do not have direct (non-stop) flights. Typically, these are pairs of small cities which are far away of each other (e.g., Tulsa, OK and Ontario, CA). Almost one-third of the city-pairs have only one airline providing non-stop service, and approximately 17% of the city pairs have two airlines. The average number of airlines with non-stop flights per market is only 1.4. Therefore, from the point of view of non-stop services, these markets are highly concentrated. This pattern is also illustrated by the value of the Herfindahl index in panel 5.2. Panel 5.3 presents the number of "monopoly" markets for the largest carriers.[31] *Southwest*, with approximately 150 city-pairs, accounts for a large portion of monopoly markets, followed by *Northwest* and *Delta* with approximately 65 and 58 monopoly markets, respectively. Note that *Delta* and *Northwest* are only 4th and 6th, respectively, in the ranking of number of passengers and number of city-pairs, but they are 2nd and 3rd in the ranking of monopoly markets, far away of *American* or *United* that have monopolies in only 28 and 17 city-pairs, respectively. One of our goals in the estimation of our structural model is to explain these significant differences in airlines' ability to avoid direct competition.

Panels 5.4 and 5.5 present the distribution of city-pairs by number of new entrants and by number of exits, respectively. It is interesting that, even with the quarterly frequency of our data, there is substantial amount of entry and exit in these city-pairs. The average number of entrants per city-pair-quarter is 0.17 and the average number of exits is 0.12. As shown in section 4, this significant turnover provides useful information to identify separately fixed costs and entry costs parameters.

Table 6 presents the transition matrix for the number of active (non-stop) airlines in a city-pair. We only report the transition matrix from the second to the third quarter of 2004, as the transition matrices for the other quarters are very similar. There is significant persistence in market structure, especially in markets with zero incumbents or in monopoly markets. Nevertheless, there

[31] These airlines are not really monopolies in the routes between these city-pairs because they may be competing with other airlines that provide stop flights. However, given that stop and non-stop flights are not perfect substitutes, these measures of market structure are relevant and potentially related to firms' profits.

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. 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 linear-in-parameters system of equations:

$$\ln(s_{jt}) - \ln(s_{0t}) = W_{jt}\ \alpha + \left(\frac{-1}{\sigma_1}\right) p_{jt} + \left(1 - \frac{\sigma_2}{\sigma_1}\right)\ \ln\left(s^*_{jt}\right) + \xi^{(3)}_{jt} \tag{22}$$

where W_{jt} is a vector of regressors that, according to our demand model in equation (4), includes a dummy for nonstop-flight, hub-size variables, route distance, airline dummies, and city dummies interacted with time dummies. An important econometric issue in the estimation of this demand system is the endogeneity of prices and conditional market shares $\ln\left(s^*_{jt}\right)$. In equilibrium, prices depend on product characteristics (observable and unobservable). Therefore, the regressor p_{jt} is correlated with the error term $\xi^{(3)}_{jt}$. For the same reason, the regressor $\ln\left(s^*_{jt}\right)$ is also correlated with $\xi^{(3)}_{jt}$. In our model, there is another potential problem of endogeneity in the estimation of this demand system. Hub-size variables HUB^O_{irt} and HUB^D_{irt} (included in the vector W_{jt}) depend on the airline's entry-exit decisions at city-pairs that share either the origin city or the destination city of the route in product j. And these entry-exit decisions depend on unobserved demand shocks $\xi^{(3)}$ at many different routes, included the shock $\xi^{(3)}$ of product j. Therefore, hub-size variables HUB^O_{irt} and HUB^D_{irt} may be endogenous regressors in our demand system.

We start the description of our approach for the estimation of demand by providing sufficient conditions for independence between the contemporaneous values of hub-size variables and the error term. The following assumption, together with the assumption of time-to-build in airlines' entry decisions, implies this independence.[32]

ASSUMPTION ID-ξ. Product-specific demand shocks $\{\xi^{(3)}_{jt}\}$ are independently distributed over time.

Assumption *ID-ξ* establishes that after controlling for airline fixed effects $\{\xi^{(2)}_{i}\}$ and for city-dummies interacted with time-dummies $\{\xi^{(2)}_{ct}\}$, the remaining error term or unobserved demand of

[32] Sweeting (2011) 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.

a product does not have any dependence over time. Remember that we have also assumed that an airline's network at quarter t (that determines the value of hub-size variables HUB^O_{irt} and HUB^D_{irt}) is chosen at quarter $t-1$, before demand shocks at quarter t are known. This time-to-build assumption together with assumption *ID-ξ* implies that regressors HUB^O_{irt} and HUB^D_{irt} are independent of the error term $\xi^{(3)}_{jt}$. Note that Assumption *ID-ξ* is testable using our model and data. Given residuals $\{\hat{\xi}^{(3)}_{jt}\}$ from the GMM estimation of the demand system, we can construct a statistic of residual serial correlation that can be used to test Assumption *ID-ξ* as a null hypothesis.

Assumption *ID-ξ* has another important implication in the estimation of the demand system. Following the seminal work by Berry (1994) and Berry, Levinshon and Pakes (1995), the most common method for the estimation of demand of differentiated products is a GMM where the instrumental variables for equation (22) are the exogenous observable characteristics of the other products in the same route. In our model, these observable product characteristics are the hub-sizes and the non-stop-flight dummies of the other products competing in the same route. Assumption *ID-ξ* implies that the hub-sizes of other airlines at quarter t (that are determined in quarter $t-1$) are independent of the demand shock $\xi^{(3)}_{jt}$ and are valid instruments for price p_{jt} and market share $\ln\left(s^*_{jt}\right)$.

Table 7 presents our estimates of the demand system. Our set of instrumental variables consists of: the average value of hub-sizes of all the other carriers active in the route; the average value of hub-sizes of all the *legacy carriers* active in the route; the average value of the non-stop dummy for all the other carriers in the route; and the dummy for the presence of *Southwest*. Standard errors are robust of heteroscedasticity and serial correlation. To illustrate the endogeneity problem, we report both OLS and IV estimates. The IV estimate of the coefficient for the FARE variable is significantly smaller than the OLS estimate. This result is consistent with the endogeneity of prices in the OLS estimation. The test of first order serial correlation of the residuals cannot reject the null hypothesis of no serial correlation. This result supports Assumption *ID-ξ* and the exogeneity of the hub-size variables.

We can obtain dollar amount estimates of the willingness-to-pay for different product characteristics by dividing the coefficient of a 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 the hub-size variables seem also plausible. Expanding the hub-size in the origin airport in one million people would increase consumers willingness to pay in \$1.97. The same increase in hub-size at the destination airport raises consumer willingness to pay by \$2.63. Finally, longer distance makes consumer more inclined to use airplane transportation than other transportation modes.

4.2 Estimation of variable costs

Given our estimates of demand parameters and the Nash-Bertrand equilibrium condition for prices, we can obtain estimates of marginal costs as $\hat{c}_{jt} = p_{jt} - \hat{\sigma}_1(1 - \bar{s}_{jt})^{-1}$. We use these estimates of marginal costs as the dependent variable in the regression equation for the estimation of the marginal cost function in equation (6). This regression equation is $\hat{c}_{jt} = W_{jt}\ \delta + \omega_{jt}^{(3)}$, where the vector of regressors W_{jt} has the same definition as in the demand equation above, except that now the hub size variables are measured in number of connections and not in terms of population in the connected cities.

For the same reason as in the estimation of demand, the hub-size variables included in W_{jt} are potentially correlated with the error term in the marginal cost equation, $\omega_{jt}^{(3)}$. We consider a similar identification assumption as in the estimation of demand.

ASSUMPTION ID-ω: Product-specific shocks in marginal cost $\{\omega_{jt}^{(3)}\}$ are independently distributed over time.

Assumption *ID-ω*, together with the time-to-build assumption in airlines' choice of network, implies that 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. Standard errors are robust of heteroscedasticity and serial correlation. We cannot reject the null hypothesis of no serial correlation in the residuals of the marginal cost equation. As for the values of the estimated parameters, 'Distance' between the origin and destination cities is the explanatory variable with the strongest and most significant effect. An increase of distance by 100 miles implies that the marginal cost per passenger goes up by \$53.4. Ceteris paribus, 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. The airline scale of operation (or hub-size) at the origin and destination airports reduces marginal costs. However, this effect is small. An increase of one connection in the hub-size of the origin airport (destination airport) reduces marginal cost (per passenger) by \$2.3 (\$1.6).

4.3 Estimation of the dynamic game

4.3.1 Estimators

For the asymptotics of the estimators in our application, we assume that the number of markets or city-pairs M goes to infinity, and the number of airlines N and time periods T are fixed.[33] For

[33] The number of city-pairs M is equal to $C(C-1)$ where C is the number of cities. Therefore, when we assume that $M \to \infty$ we are also assuming that the number of cities goes to infinity. Our specification of demand and cost functions include city fixed effects. Therefore, apparently we may have an incidental parameters problem, i.e., the number of parameters of the model increases with sample size M. However, note that the number of city fixed-effect parameters per observation is $\frac{C}{M} = \frac{1}{C-1}$, that goes to zero as $C \to \infty$. That is, to estimate the fixed effect of a

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:

$$Q(\boldsymbol{\theta},\mathbf{P}) \equiv \sum_{m,i,t} a_{imt} \ \ln\Lambda\left(\widetilde{\mathbf{z}}_{im}^{\mathbf{P}}(\mathbf{w}_{imt})\boldsymbol{\theta}+\widetilde{e}_{im}^{\mathbf{P}}(\mathbf{w}_{imt})\right) + (1-a_{imt}) \ \ln\Lambda\left(-\widetilde{\mathbf{z}}_{im}^{\mathbf{P}}(\mathbf{w}_{imt})\boldsymbol{\theta}-\widetilde{e}_{im}^{\mathbf{P}}(\mathbf{w}_{imt})\right) \tag{23}$$

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 $\widetilde{e}_{im}^{\mathbf{P}}(\mathbf{w}_{imt})$) is restricted to be one. Let $\boldsymbol{\theta}_0$ be the true value of $\boldsymbol{\theta}$ 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, $\mathbf{P}_0 = \Psi\left(\boldsymbol{\theta}_0, \mathbf{P}_0\right)$. 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 $\widetilde{\mathbf{z}}_{im}^{\hat{\mathbf{P}}}(\mathbf{w}_{imt})$ and $\widetilde{e}_{im}^{\hat{\mathbf{P}}}(\mathbf{w}_{imt})$, the vector of parameters $\boldsymbol{\theta}_0$ is estimated using a standard logit model.

The two-step method has two important limitations that are relevant in our application. First, for the consistency of this method, the initial nonparametric estimator of $\mathbf{P}_0$ should be consistent. However, consistent nonparametric estimation of $\mathbf{P}_0$ may not be possible in dynamic models with serially correlated or time invariant unobserved heterogeneity. That is the case in this empirical application. Our model allows for time-invariant airline and city heterogeneity in costs. Given our parametric specification of the profit function, where airline and city fixed-effects enter in an additively separable form, we can estimate airline and city fixed effects consistently in our parametric model by simply including airline dummies and city dummies in the vector of explanatory variables $\mathbf{z}_{imt}$. However, the nonparametric specification of $\mathbf{P}_0$ does not take into account this structure of the profit function. In the nonparametric estimation, every local manager (i, m) has its own unrestricted CCP function $P_{im}(\mathbf{w})$. Since we only have 3 quarters/observations for each local manager, it is obvious that we cannot claim to have consistent nonparametric estimates of the CCP functions $P_{im}(.)$. Therefore, the two-step estimator of $\boldsymbol{\theta}_0$ is inconsistent. Second, even if the model did not have unobserved heterogeneity and we could have a nonparametric estimator of $\mathbf{P}_0$, this estimator would be very imprecise, and this noisy estimation of CCPs implies large biases in the two-step estimator of the structural parameters.

The *Nested Pseudo Likelihood (NPL) estimator* (Aguirregabiria and Mira, 2007) deals with these limitations of the two-step method. The *NPL mapping* $\varphi(.)$ is the composition of the equilibrium or best response mapping $\Psi\left(\boldsymbol{\theta}, \mathbf{P}\right)$ and the mapping that provides the pseudo maximum likelihood estimator of $\boldsymbol{\theta}$ for a given arbitrary vector of CCPs $\mathbf{P}$. That is, the NPL mapping is defined as $\varphi(\mathbf{P}) \equiv \Psi\left(\hat{\theta}(\mathbf{P}), \mathbf{P}\right)$ where $\hat{\theta}(\mathbf{P}) \equiv \arg\max_{\boldsymbol{\theta}} Q(\boldsymbol{\theta}, \mathbf{P})$. An *NPL fixed point* is a vector of probabilities $\hat{\mathbf{P}}$ that solves the fixed point problem $\hat{\mathbf{P}} = \varphi(\hat{\mathbf{P}})$. We can also define an *NPL fixed*

city, we can average observations over all the other cities such that we can apply standard law of large numbers and central limit theorems to prove consistency and asymptotic normality of fixed-effect estimators.

point as a pair $(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})$ that satisfies the following two conditions: (a) $\hat{\boldsymbol{\theta}}$ maximizes the pseudo likelihood $Q(\boldsymbol{\theta}, \hat{\mathbf{P}})$ given $\hat{\mathbf{P}}$; and (b) $\hat{\mathbf{P}}$ is an equilibrium associated to $\hat{\boldsymbol{\theta}}$. The *NPL estimator* is defined as the NPL fixed point with the maximum value of the pseudo likelihood function. This estimator is consistent under standard regularity conditions (Aguirregabiria and Mira, 2007, Proposition 2), and it does not rely on the existence of an initial consistent nonparametric estimator of CCPs.

To compute the NPL fixed point we can use successive iterations in the NPL mapping $\varphi(.)$. That is, we can generate a sequence of vectors $\{\hat{\boldsymbol{\theta}}^K, \hat{\mathbf{P}}^K : K \geq 1\}$ such that: (a) $\hat{\mathbf{P}}^0$ is an initial vector of CCPs, and it is not necessarily a consistent estimator of $\mathbf{P}_0$; (b) at every iteration $K \geq 1$, we update $\boldsymbol{\theta}$ using the pseudo maximum likelihood $\hat{\boldsymbol{\theta}}^K = \hat{\theta}(\hat{\mathbf{P}}^{K-1}) \equiv \arg\max_{\boldsymbol{\theta}\in\Theta} Q(\boldsymbol{\theta}, \hat{\mathbf{P}}^{K-1})$; and (c) at every iteration $K \geq 1$, we update $\mathbf{P}$ using the NPL iteration $\hat{\mathbf{P}}^K = \varphi(\hat{\mathbf{P}}^{K-1}) \equiv \Psi\left(\hat{\boldsymbol{\theta}}^K, \hat{\mathbf{P}}^{K-1}\right)$. This algorithm, upon convergence, finds an NPL fixed point. In case there are multiple NPL fixed points, the researcher needs to start the NPL algorithm from different CCP's and selects the fixed point with the largest value of the likelihood function. This situation is similar to using a gradient algorithm, designed to find a local root, in order to obtain an estimator which is defined as a global root. Of course, this global search aspect of the method makes it significantly more costly than just finding one NPL fixed point. Note, however, that this global search can be parallelized in a computer with multiple processors. Finally, it is also important to note that this algorithm finds the consistent estimator only if the equilibrium that generates the data is Lyapunov stable such that the NPL mapping $\varphi(.)$ is also Lyapunov stable around the true equilibrium in the population. See Kasahara and Shimotsu (2009) and Aguirregabiria and Nevo (2010) for discussions of this issue.

To initialize the NPL iterations, we use a vector of CCPs $\hat{\mathbf{P}}^0 = \{\hat{P}^0_{im}(\mathbf{w})$: for every local manager (i,m) and every state $\mathbf{w}\}$ that comes from the estimation of a reduced form logit model where the set of explanatory variables includes airline dummies, city dummies, and a third order polynomial in $\mathbf{w}_{imt}$. To check the sensitivity of the NPL fixed point to this initial value for CCPs, we also calculate NPL fixed points starting with alternative initial values. The alternative initial CCPs are chosen as $\hat{P}^0_{im}(\mathbf{w}) = \hat{P}^{logit}_{im}(\mathbf{w})^{1-\lambda}\ U_{im}(\mathbf{w})^{\lambda}$, where $\hat{P}^{logit}_{im}(\mathbf{w})$ represents the estimated probabilities from the reduced form logit model, $\lambda \in (0,1)$ is a parameter that represents the magnitude of the perturbation, and $U_{im}(\mathbf{w})$ is an iid over $(i,m,\mathbf{w})$ random draw from a Uniform $(0,1)$ distribution.[34]

[34] For our estimation of the dynamic game, we have used a machine with twelve 3.33 GHz Intel Xeon processors, and code written in *GAUSS* language version 10. Most of the CPU time of an iteration in the NPL mapping comes from the computation of the present values $\{\widetilde{\mathbf{z}}^{\mathbf{P}}_{imt}\}$ for each of the local managers. The calculation of these present values for a single local-manager took only 0.8 seconds. Without using parallel (multi-thread) programming, that calculation for all the local managers took more than 5 hours. However, the calculation of these present values can be performed separately (in parallel) over local managers. In this context, parallel computing yields very substantial savings of CPU time. Exploiting multi-thread programming in GAUSS reduced CPU time of one NPL iteration from more than 5 hours to less than 1 hour. The total waiting time to calculate an NPL fixed point was always lower than 20 hours.

4.3.2 Estimation results

Table 9 presents our estimation results for the dynamic game of network competition. The quarterly discount factor, β, is fixed at 0.99 (that implies an annual discount factor of 0.96). All the estimated parameters are measured in thousands of dollars. As explained above, the estimated model includes airlines and city fixed effects both in the fixed cost and in the entry cost. We report the average value of estimated fixed costs and entry costs, averaged over all the local managers, as well as the effects of hub-size and distance on these costs. The average estimated fixed cost is $\$119,000$, that represents 75% of the median value of quarterly variable profit in the non-stop routes of a city-pair (that is approximately $\$159,000$ in our sample). This high value of the ratio between fixed costs and variable profits shows very substantial economies of scale in the airline industry. Fixed costs increase significantly with distance between the two cities: they increase by \$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 with a non-stop connection) implies a $\$1,020$ reduction in fixed costs, which seems a non-negligible cost reduction. The average estimated entry cost is $\$298,000$, that represents 250% of the average estimated (quarterly) fixed cost, 187% of the median variable profit, and 7.5 times the (quarterly) median operating profit (i.e., variable profit minus fixed cost). Therefore, for the average local manager, it takes almost two years of profits (7.5 quarters) to amortize the initial investment or entry cost. These entry costs do not depend significantly on flown distance. However, the effect of hub-size is very important. A unit increase in hub-size implies a reduction of entry costs of more than $\$9,260$. To have a better idea of the magnitude of this effect, note that an airline with the minimum hub-size in the city-pair (i.e., zero non-stop connections in the two cities) has to pay an entry cost of $\$536,000$, while an airline with the maximum hub-size in the sample (i.e., 53 non-stop connections in each city) pays only $\$45,000$.

We have included airline and city fixed-effects in all our estimations. Therefore, it seems plausible to claim that the effects that we have estimated do not capture spuriously the effects of unobserved heterogeneity in airline characteristics that is 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 join variation over airlines and city-pairs.

Using the estimated model, we have generated predictions for several statistics that describe market structure. Table 10 reports predicted and actual values of the statistics.[35] Overall, the estimated model performs reasonably well. However, there are some biases in the predictions. The model over-predicts the proportion of markets with 1 and 2 incumbents, and it under-predicts the

[35] To obtain the predicted statistics, we have generated simulations of the entry-exit decision variables $\{a_{imt}\}$ using the estimated CCPs evaluated at the actual values of the vector of state variables in the sample $\{\mathbf{w}_{imt}\}$. Then, we have average these simulated values of $\{a_{imt}\}$ over the Monte Carlo simulations and over the sample.

proportion of markets without incumbents. Interestingly, the model under-predicts the proportion of markets where *Southwest* is a monopolist. According to our estimates, *Southwest* has lower costs than any other airline, and this airline can make positive profits in many markets where the rest of the airlines would have losses. Despite this finding, our estimated model fails to explain why *Southwest* is the only airline that operates non-stop flights in many markets. It seems that our model misses some aspects of the higher profitability associated with this airline company. Finally, the model fits reasonably well the 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 measure how different parameters of the model contribute to explain the *hubbing concentration ratios* that we have defined in section 3.1. The main 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 experiments 1 to 3, we shut down hub-size effects in variable profits (experiment 1), fixed costs (experiment 2), and entry costs (experiment 3).[36] In experiment 4 we want to measure the contribution of the entry deterrence motive. The entry deterrence argument that we study in this paper is based on the complementarity of the total variable profit function of a hub-and-spoke airline with respect to the airline's entry-exit decisions at two city-pairs. Therefore, in experiment 4, 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 scenario, local managers do not internalize the complementarity between profits at different local markets, and the entry deterrence motive is not present.[37]

When implementing these counterfactual experiments, we should deal with multiplicity of equilibria in the counterfactual specification of the model. Here we implement an approach to deal with this problem proposed in Aguirregabiria (2009). The main advantages of this approach are its simplicity and its minimum assumptions on the equilibrium selection mechanism. An equilib-

[36] The description of these experiments in terms of the counterfactual values of structural parameters is the following: in experiment 1, $\alpha_2 = \alpha_3 = \delta_2 = \delta_3 = 0$; in experiment 2, $\gamma_2^{FC} = 0$; and in experiment 3, $\eta_2^{EC} = 0$.

[37] To illustrate this point, suppose an industry with three cities (A, B, and C) and consider the decision problem of the local manager of an airline at city-pair AB. The total variable profit of this local manager is $R^*_{AB} = x_{AB}$ $(R^{ns}_{AB} + R^{ns}_{BA}) + (x_{AB} x_{AC})$ $(R^s_{AC} + R^s_{CA}) + (x_{AB} x_{BC})$ $(R^s_{AB} + R^s_{BC})$, where R^{ns}_r and R^s_r represent variable profits in route r for non-stop and stop flights, respectively. If $(R^s_{AC} + R^s_{CA}) > 0$, this profit function is supermodular with respect to the airline's entry decisions at city-pairs AB and AC. Similarly, if $(R^s_{AB} + R^s_{BC}) > 0$, the profit function is supermodular with respect to entry decisions at city-pairs AB and BC. In our counterfactual experiment 4, we shut down this complementarity and assume that this local manager is only concerned with profits from routes AB and BA, such that its variable profit is $R^*_{AB} = x_{AB}$ $(R^{ns}_{AB} + R^{ns}_{BA})$.

rium associated with $\boldsymbol{\theta}$ is a vector of choice probabilities $\mathbf{P}$ that solves the fixed point problem $\mathbf{P} = \Psi(\boldsymbol{\theta}, \mathbf{P})$. 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 key assumption is that $\boldsymbol{\pi}(\boldsymbol{\theta})$ is a smooth function of $\boldsymbol{\theta}$ in a neighborhood of our estimated value of this vector of parameters. In other words, we assume that the equilibrium selection mechanism does not "jump" between different types of equilibrium when we move along the space of the structural parameters.

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 $\mathbf{P}_0 = \Psi(\boldsymbol{\theta}_0, \mathbf{P}_0)$ and $\mathbf{P}_0 = \boldsymbol{\pi}(\boldsymbol{\theta}_\mathbf{0})$. Let $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$ be our consistent estimates of $(\boldsymbol{\theta}_0,\mathbf{P}_0)$.[38] Let $\boldsymbol{\theta}^*$ be the vector of parameters under a counterfactual scenario. We want to obtain airlines' equilibrium choice probabilities 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 assumptions, the mapping $\Psi(\boldsymbol{\theta}, \mathbf{P})$ 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 $\hat{\boldsymbol{\theta}}_0$. This Taylor approximation implies that:

$$\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) + \frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'}(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0) + O(\parallel \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0 \parallel^2) \tag{24}$$

We do not know the function $\boldsymbol{\pi}$ and, apparently, we do not know the Jacobian matrix $\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)/\partial \boldsymbol{\theta}'$ that is necessary to implement the Taylor approximation. However, the equilibrium condition can be used to obtain this Jacobian matrix. We know that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) = \hat{\mathbf{P}}_0$ and that $\boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0) = \Psi\left(\hat{\boldsymbol{\theta}}_0, \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)\right)$. Differentiating this last expression with respect to $\boldsymbol{\theta}$ and solving for $\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)/\partial \boldsymbol{\theta}'$, we can represent this Jacobian matrix in terms of Jacobians of $\Psi(\boldsymbol{\theta}, \mathbf{P})$ evaluated at the estimated values $(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)$. That is,

$$\frac{\partial \boldsymbol{\pi}(\hat{\boldsymbol{\theta}}_0)}{\partial \boldsymbol{\theta}'} = \left(\mathbf{I} - \frac{\partial \Psi\left(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0\right)}{\partial \mathbf{P}'}\right)^{-1} \frac{\partial \Psi\left(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0\right)}{\partial \boldsymbol{\theta}'} \tag{25}$$

Solving expression (25) into (24), we have that $\boldsymbol{\pi}(\boldsymbol{\theta}^*) = \hat{\mathbf{P}}^* + O(\parallel \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0 \parallel^2)$, where $\hat{\mathbf{P}}^*$ is our

[38] 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 $\boldsymbol{\pi}$.

estimation or approximation to the counterfactual $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$, and it has the following expression:

$$\hat{\mathbf{P}}^* \equiv \hat{\mathbf{P}}_0 + \left(\mathbf{I} - \frac{\partial\Psi\left(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0\right)}{\partial\mathbf{P}'}\right)^{-1} \frac{\partial\Psi\left(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0\right)}{\partial\boldsymbol{\theta}'} \left(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0\right) \tag{26}$$

Under the condition that $\| \boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0 \|^2$ is small, the vector $\hat{\mathbf{P}}^*$ provides a good approximation to the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. Note that all the elements involved in the definition of $\hat{\mathbf{P}}^*$ are known to the researcher.

To implement this method in our empirical application, we have to deal with two important issues. The first issue is computational. The dimension of the Jacobian matrix $\partial\Psi/\partial\mathbf{P}'$ is equal to the number of local managers $(32,670)$ times the number of states in the space of the state variables W $(3,960)$. Calculating all the elements of this matrix, and then inverting the matrix $I - \partial\Psi/\partial\mathbf{P}'$ 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 $\hat{\mathbf{P}}^*_{im} \equiv \hat{\mathbf{P}}^0_{im} + (\mathbf{I}_{|W|} - \partial\Psi_{im}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)/\partial\mathbf{P}'_{im})^{-1}\ \partial\Psi_{im}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)/\partial\boldsymbol{\theta}'\ (\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0)$, where Ψ_{im} represents the best response mapping of local manager (i, m). In our logit model, it is possible to show that $\hat{\mathbf{P}}^*_{im}$ has the following simple closed-form expression:[39]

$$\hat{\mathbf{P}}^*_{im} = \hat{\mathbf{P}}^0_{im} + \hat{\mathbf{P}}^0_{im} * (\mathbf{1} - \hat{\mathbf{P}}^0_{im}) * (\widetilde{\mathbf{z}}^{\hat{\mathbf{P}}^0}_{im}(\boldsymbol{\theta}^* - \hat{\boldsymbol{\theta}}_0)) \tag{27}$$

where $*$ is the Hadamard or element-by-element product, and $\mathbf{1}$ is a column vector of ones. We call this method *Taylor approximation without strategic interactions* because this method takes into account how the change in $\boldsymbol{\theta}$ affects the behavior of a player only through the *direct* effect on his profit function but not the *indirect* effect through the change in behavior of the competitors. A second important issue is the accuracy of this Taylor approximation. Our counterfactual experiments are far from being marginal changes in the parameters. Therefore, the approximation error might be large. Furthermore, ignoring strategic interactions may introduce an additional approximation error that can be significant in some applications. To deal with this issue, we implement a second method. This method requires the additional assumption that the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$ is Lyapunov stable and that the Taylor approximation $\hat{\mathbf{P}}^*$ is precise enough to lie in the dominion of attraction of this stable equilibrium. Under this condition, if we start with the Taylor approximation and then iterate in the counterfactual equilibrium mapping (i.e., $\mathbf{P}_{k+1} = \Psi(\boldsymbol{\theta}^*, \mathbf{P}_k)$), then we should converge to the counterfactual equilibrium $\boldsymbol{\pi}(\boldsymbol{\theta}^*)$. This is our second method to implement the counterfactual experiments.[40]

[39] To obtain this expression, first note that Proposition 2 in Aguirregabiria and Mira (2002, p. 1526) implies that in equilibrium the Jacobian matrix $\partial\Psi_{im}(\hat{\boldsymbol{\theta}}, \hat{\mathbf{P}})/\partial\mathbf{P}'_{im}$ is zero. Therefore, $(\mathbf{I}_{|W|} - \partial\Psi_{im}(\hat{\boldsymbol{\theta}}_0, \hat{\mathbf{P}}_0)/\partial\mathbf{P}'_{im})^{-1} = \mathbf{I}_{|W|}$. Second, for the logistic function Λ, we have that $\partial\Lambda(\widetilde{\mathbf{z}}^{\hat{\mathbf{P}}}_{im}\hat{\boldsymbol{\theta}} + \tilde{e}^{\hat{\mathbf{P}}}_{im})/\partial\boldsymbol{\theta}'$ is equal to $\hat{\mathbf{P}}_{im} * (\mathbf{1} - \hat{\mathbf{P}}_{im}) * \widetilde{\mathbf{z}}^{\hat{\mathbf{P}}}_{im}$.

[40] Note that the policy iterations $\mathbf{P}_{k+1} = \Psi(\boldsymbol{\theta}^*, \mathbf{P}_k)$ require recalculating the transition probabilities $f^{\mathbf{P}}_{im}$ using the simulation method that we describe in the Appendix.

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 using the second method. Though there are differences between the magnitudes of the hubbing concentration ratios predicted by the two methods, they provide very similar pictures of the main implications. Hub-size effects on variable profits and fixed costs explain only a small portion of the observed hubbing concentration ratios. In contrast, hub-size effects on entry costs explain a very significant part. For *Continental*, eliminating hub-size effects in entry costs implies a reduction in CR-2 from 68.3% to 27.3% using the first method and to 26.0% using the second method.

The entry deterrence motive explains a non negligible part of the hubbing concentration ratios of some airlines. For all of the legacy airlines, eliminating the entry deterrence motive implies a significant reduction in the concentration ratio CR-2. The contribution of this factor is particularly important for *Northwest* and *Delta*. Eliminating the entry deterrence motive reduces the CR-2 of *Northwest* from 49.2% to 23.2%, and of *Delta* from 48.0% to 22.1%. Interestingly, as shown in Table 5, *Northwest* and *Delta* are the airlines with the second and third largest number of 'monopoly' city-pairs. *Southwest* is, by far, the airline with the smallest contribution of the entry deterrence motive. The immediate explanation of this result is that *Southwest* prefers not using a hub-and-spoke network but a network that is close to point-to-point. Why does not *Southwest* use a hub-and-spoke network? According to our estimates, *Southwest* is the airline with the lowest values of the exogenous components of marginal cost, fixed cost, and sunk entry cost (i.e., the components that do not depend on hub size) . Therefore, it seems that reducing costs by increasing hub-size, or deterring entry by using a hub-and-spoke network, is less attractive and profitable for *Southwest* than for other airlines.

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 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 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 in explaining airlines' propensity to 'hubbing'. In contrast, our estimates of the effects of hub-size on entry costs are very substantial. While airlines with a small number connections in an airport have to pay a large sunk entry cost to operate an additional route (i.e., around half a million dollars on average), airlines with many connections should pay negligible entry costs for that additional route. Eliminating these hub-size effects on entry costs reduces substantially airlines' propensity to adopt hub-and-spoke networks. In our model, these cost savings can be interpreted as either due to technological factors or to contractual agreements between airports and airlines. Investigating the 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 networks can deter entry of competitors in spoke markets. In this paper, we do not model entry in the airline industry and the number of airlines is exogenous and fixed. However, the *entry deterrence motive* of hub-and-spoke networks applies also to potential entrants in the industry. Investigating the importance of this additional entry deterrence motive is also a relevant research topic.

APPENDIX: Monte Carlo Simulator of the Transition Probabilities $f^{\mathbf{P}}_{im}$

Let $\{(\boldsymbol{a}^{(s)}, \mathbf{w}^{(s)}) : s = 1, 2, ..., S\}$ be S independent random draws from the ergodic distribution of $(\boldsymbol{a}_t, \mathbf{w}_t)$. Each of these random draws is generated as follows. We start with an arbitrary value of $\mathbf{x}$, say $\mathbf{x}_0$, and use the first order Markov structure of $\mathbf{x}_t$ to generate a T-periods history starting from $\mathbf{x}_0$. For T large enough, the last period of this history, $\mathbf{x}_T$, provides a random draw from the ergodic distribution of $\mathbf{x}_t$ associated with $\mathbf{P}$. Then, we apply the vector valued functions $w_{im}(.)$ to obtain $\mathbf{w}_{imT} = w_{im}(\mathbf{x}_T)$ for every (i, m). The following is a more detailed description:

(i) Given $\mathbf{x}_0$, we apply the vector valued function $w_{im}(.)$ to obtain $\mathbf{w}_{im0} = w_{im}(\mathbf{x}_0)$ 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 $x_{im1} = 1\{u_{im1} \leq P_{im}(\mathbf{w}_{im0})\}$, where $\{u_{im1}\}$ are independent random draws from a $U(0, 1)$ distribution.

Given $\mathbf{x}_1$, we apply again steps (i) and (ii) to generate $\mathbf{x}_2$, and so on T times until we generate $\mathbf{x}_T$ and $\mathbf{w}_T$. We repeat this procedure S times to generate S independent random draws: $\{\mathbf{x}^{(s)}, \boldsymbol{a}^{(s)}, \mathbf{w}^{(s)} : s = 1, 2, ..., S\}$. We maintain the same set of random draws $\{u_{imt}\}$ to calculate simulators of $f^{\mathbf{P}}_{im}$ for different values of the vector of CCPs $\mathbf{P}$. Keeping the same random draws is important to have that our simulator of $f^{\mathbf{P}}_{im}$ is a continuous function of $\mathbf{P}$ (see McFadden, 1989).

Let $(\mathbf{w}_{(k')}, a, \mathbf{w}_{(k)})$ be a value in the discrete space of $(\mathbf{w}_{imt+1}, a_{imt}, \mathbf{w}_{imt})$. Given our random draws, we approximate the probability $f^{\mathbf{P}}_{im}(\mathbf{w}_{(k')}|a, \mathbf{w}_{(k)})$, using the following *L-Nearest-Neighbors simulator,*

$$\widetilde{f^{\mathbf{P}}_{im}}\left(\mathbf{w}_{(k')}|a, \mathbf{w}_{(k)}\right) = \frac{1}{L} \sum_{s=1}^{S} 1\left\{w_{im}\left(a, \boldsymbol{a}^{(s)}_{(-im)}\right) = \mathbf{w}_{(k')}\right\} \ 1\left\{\mathbf{w}^{(s)}_{im} \in NN_{im}(\mathbf{w}_{(k)})\right\} \tag{A.1}$$

where $\{\boldsymbol{a}^{(s)}_{(-im)}, \mathbf{w}^{(s)}_{im}\}$ come from the S random draws $\{\boldsymbol{a}^{(s)}, \mathbf{w}^{(s)}\}$, and $NN_{im}(\mathbf{w})$ is the subset of $L < S$ random draws of $\mathbf{w}_{im}$ that are closest to $\mathbf{w}$. For the selection of these *nearest neighbors* we use the following distance: for any pair of vectors $\mathbf{w}^{A}_{im}$ and $\mathbf{w}^{B}_{im}$ the distance between them is $\sqrt{(\mathbf{w}^{A}_{im} - \mathbf{w}^{B}_{im})' \ \Omega_S^{-1} \ (\mathbf{w}^{A}_{im} - \mathbf{w}^{B}_{im})}$, where Ω_S is the variance-covariance matrix of $\mathbf{w}_{im}$ based on the S random draws. If L goes to infinity and L/S goes to zero as the number of simulations S goes to infinity, then, for our discrete model, the simulator in (A.1) is root-S consistent and the proof is based on the application of a pretty standard Law of Large Numbers (see for instance Delgado and Mora, 1995). In our estimations and numerical experiments, we have used $T = 50$ and $S = 200,000$, and for the nearest neighbors we have used $L = 20$.

Note that the conditions for the consistency of the simulator $\widetilde{f^{\mathbf{P}}_{im}}$ in our model with a discrete state space are weaker than those in a model with continuous state variables. Rust (1997) studies the properties of Monte Carlo simulation methods in the problem of approximating the solution of dynamic decision processes with continuous state variables. In the continuous state case, to have a root-S consistency simulator (and to obtain the self-approximating property of the simulator) one needs stronger conditions than in our discrete problem. In particular, in the continuous case the integrand function should be continuous everywhere. For our discrete model, we do not need a self-approximating simulator, and we do not need the integrand function to be continuous everywhere.

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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 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 'Hubbing' Concentration Ratios

	Airline (Code)	Name and Hub Size 1st largest hub(1)	Concentration Ratio (%) CR-1	Name and Hub Size 2nd largest hub(1)	Concentration Ratio (%) CR-2
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 a city is the number of non-stop connections of the airline from that city.

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 City-Pairs by # of Airlines with Non-Stop Flights					
City-Pairs with 0 airlines	35.79%	35.12%	35.72%	35.12%	35.44%
City-Pairs with 1 airline	30.11%	29.09%	28.76%	28.28%	29.06%
City-Pairs with 2 airlines	17.46%	16.71%	17.52%	18.06%	17.44%
City-Pairs with 3 airlines	9.20%	10.83%	9.47%	9.88%	9.84%
City-Pairs 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 City-Pairs by Number of New Entrants					
City-Pairs with 0 Entrants	-	82.61%	86.60%	84.78%	84.66%
City-Pairs with 1 Entrant	-	14.48%	12.31%	13.33%	13.37%
City-Pairs with 2 Entrants	-	2.44%	0.95%	1.69%	1.69%
City-Pairs with 3 Entrants	-	0.47%	0.14%	0.20%	0.27%
(5.5) Distribution of City-Pairs by Number of Exits					
City-Pairs with 0 Exits	-	87.89%	85.12%	86.54%	86.51%
City-Pairs with 1 Exit	-	10.55%	13.13%	11.77%	11.82%
City-Pairs with 2 Exits	-	1.35%	1.56%	1.15%	1.35%
City-Pairs with more 3 or 4 Exits	-	0.21%	0.21%	0.54%	0.32%

Table 6
Transition Probability Matrix of Market Structure (Quarter 2 to 3)(1)

# Airlines in Q2	# Airlines in Q3: 0	1	2	3	4	>4	Total # city-pairs
0	93.8%	5.8%	0.4%	-	-	-	516 (100%)
1	9.1%	79.5%	11.2%	0.2%	-	-	430 (100%)
2	0.8%	19.9%	68.4%	10.1%	0.8%	-	247 (100%)
3	0.2%	3.8%	20.2%	52.3%	19.2%	4.3%	160 (100%)
4	-	1.6%	6.4%	31.7%	46.0%	14.3%	63 (100%)
>4	-	-	-	5.1%	33.9%	61.0%	59 (100%)
Total # city-pairs	525	425	259	140	73	53	1,475

Note (1): An entry in this matrix, say entry for row r and column c, represents the frequency ratio between the the number of city-pairs with r incuments in quarter Q2 and c in quarter Q3 and the total number of city-pairs city-pairs with r incuments in quarter Q2, i.e., $\frac{\text{\#city-pairs with r incuments in quarter Q2 and c incumbents in quarter Q3}}{\text{\#city-pairs with r incuments in quarter Q2}}$.

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

	OLS		IV	
Variable	Estimate	(S.E.)	Estimate	(S.E.)
FARE (in $100) **[Parameter $\frac{-1}{\sigma_1}$]**	-0.329	(0.085)	-1.366	(0.110)
[Implied estimate of σ_1 (in $100)]	3.039	(0.785)	0.732	(0.059)
ln(s*) **[Parameter $1-\frac{\sigma_2}{\sigma_1}$]**	0.488	(0.093)	0.634	(0.115)
[Implied estimate of σ_2 (in $100)]	1.557	(0.460)	0.268	(0.034)
NON-STOP DUMMY	1.217	(0.058)	2.080	(0.084)
HUB SIZE-ORIGIN (in million people)	0.032	(0.005)	0.027	(0.006)
HUB SIZE-DESTINATION (in million people)	0.041	(0.005)	0.036	(0.006)
DISTANCE (in thousand miles)	0.098	(0.011)	0.228	(0.017)
Airline Dummies	YES		YES	
City Dummies × Time Dummies	YES		YES	
Test of Residual Serial Correlation				
m1$\sim N(0,1)$ **(p-value)**	0.303	(0.762)	0.510	(0.610)

Note: All the estimations include airline dummies, and city dummies × time dummies. Stadard errors in parentheses. Standard errors are robust of heteroscedasticity and serial correlation.

Table 8
Marginal Cost Estimation
Data: 85,497 observations. 2004-Q1 to 2004-Q4
Dep. Variable: Marginal Cost Estimate (in $100)

Variable	Estimate	(S.E.)
NON-STOP DUMMY	0.006	(0.010)
HUB SIZE-ORIGIN (in # connections)	-0.023	(0.009)
HUB SIZE-DESTINATION (in # connections)	-0.016	(0.009)
DISTANCE (in thousand miles)	5.355	(0.015)
Airline Dummies	YES	
City Dummies × Time Dummies	YES	
Test of Residual Serial Correlation		
m1$\sim N(0,1)$ **(p-value)**	0.761	(0.446)

Note: All the estimations include airline dummies and city dummies × time dummies. Standard errors, in parentheses, are robust of heteroscedasticity and serial correlation.

Table 9

Estimation of Dynamic Game of Entry-Exit[1]

Data: 32,670 local managers × 3 quarters = 98,010 observations

	Estimates (in thousand $) **(Std. Error)**
Fixed Costs (quarterly):	
Average value of fixed cost[2]	119.156
(in thosand dollars)	(5.233)
γ_2^{FC}**: Effect of hub-size on fixed cost**	-1.022
(in thousand dollars per non-stop connection)	(0.185)
γ_3^{FC}**: Effec of distance on fixed cost**	4.046
(in thousand dollars per thousand miles)	(0.319)
Entry Costs:	
Average value of entry cost[2]	249.561
(in thosand dollars)	(6.504)
η_2^{FC}**: Effect of hub-size on entry cost**	-9.260
(in thousand dollars per non-stop connection)	(0.140)
η_3^{FC}**: Effec of distance on entry cost**	0.008
(in thousand dollars per thousand miles)	(0.007)
σ_ε : **Standard deviation error term**	8.402
	(1.385)
β : **Discount factor** (fixed)	0.99
Pseudo R-square	0.231

Note 1: All the estimations include airline dummies, and city dummies.

Note 2: Let $\widehat{FC}_{imt}$ be the estimated fixed cost for local manager (i, m) at quarter t. According to our specification, $\widehat{FC}_{imt} = \hat{\gamma}_1^{FC} + \hat{\gamma}_2^{FC} \overline{HUB}_{imt} + \hat{\gamma}_3^{FC} DIST_m + \hat{\gamma}_{4i}^{FC} + \hat{\gamma}_{5c}^{FC}$. The average value of estimated fixed cost is $(MNT)^{-1} \sum_{i,m,t} \widehat{FC}_{imt}$. Similarly, the average estimated entry cost is $(MNT)^{-1} \sum_{i,m,t} \widehat{EC}_{imt}$, where $\widehat{EC}_{imt}$ is the estimated entry cost for local manager (i, m) at quarter t.

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

		Actual (Avg. All Quarters)	Predicted (Avg. All Quarters)
	Herfindahl Index (median)	5338	4955
Distribution of City-Pairs by Number of Airlines with Non-Stop Flights	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%
	" " ≥4 airlines	8.2%	6.2%
Number (%) of 'Monopoly' City-Pairs 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 City-Pairs 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%
	" " ≥3 Entrants	0.3%	0.0%
Distribution of City-Pairs by Number of Exits	Markets with 0 Exits	86.5%	82.9%
	" " 1 Exit	11.8%	14.6%
	" " 2 Exits	1.4%	1.4%
	" " ≥3 Exits	0.3%	0.0%

Table 11
Counterfactual Experiments
'Hubbing' Concentration Ratios CR-2

Method I: Taylor approximation without strategic interactions

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 between city-pairs
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 between city-pairs
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: Curves with Hubbing Concentration Ratios of Order 1 to 20