Exchanges of Cost Information in the Airline Industry.

Olivier Armantier* and Oliver Richard†

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Abstract

We analyze exchanges of cost information in a multimarket model with complement goods. We propose a model of Cournot competition with entry and incomplete information on marginal costs of production. We develop an algorithm to solve numerically the Bayesian Nash Equilibrium. The model is applied to the American Airlines and United Airlines duopoly at Chicago O'Hare. We estimate the structural model of supply decisions. Results provide probabilities of entry, expected quantities, prices, and profits on each market. Given the estimated parameters, we simulate competition under a hypothetical alliance on costs exchanges. Expected profits and social welfare rise. Expected consumer surplus does not vary significantly overall and actually increases on most markets. Hence, exchanges of costs information would benefit airlines without hurting consumers.

Keywords: Cost Exchanges, Entry, Incomplete Information, Structural Estimation, Network, Airline Industry

JEL Classifications : L11, D82, C15, C51, L93, R41

* Dept of Economics, S621 SBS Building, SUNY Stony Brook, Stony Brook NY, 11794. E-mail: olivier.armantier@sunysb.edu.

† Simon School of Business, University of Rochester, Rochester, NY 14627; E-mail: richard@ssb.rochester.edu

1. Introduction

In the past ten years, the airline industry has witnessed a proliferation of marketing alliances. Airlines within alliances market and sell tickets on their partner's flights, and share revenues on joint flights. These practices, known as code sharing, require exchanges of information on production processes and, in particular, on costs of production. Given recent major alliances between U.S. carriers (e.g. Continental Airlines and Northwest Airlines, American Airlines and US Airways, both in 1998), the implications of exchanges of cost information have become highly relevant. In particular, policy makers may wonder how such exchanges affect social welfare and consumer surplus.

Fried (1984), Gal-Or (1986), and Shapiro (1986) study exchanges of cost information in single-market models of Cournot competition with linear demand. They find that while expected aggregated welfare increases when oligopolist truthfully exchange cost information, expected consumer surplus is lower. Armantier & Richard (2000) show that this result does not necessarily hold in multi-market settings. Namely, both expected social welfare and consumer surplus can be higher when firms truthfully exchange cost information. This issue is of significance since courts in antitrust cases traditionally consider consumer surplus as the deciding factor. In the airline industry where firms compete across multiple markets, the question remains as to the effects of exchanges of cost information on consumer surplus and social welfare. In the present paper, we estimate an empirical model and run some simulations to answer this question.

The empirical models in the airline literature analyze decisions on a single-market basis (given decisions across all other markets) and under complete information (Reiss & Spiller (1989), Berry (1992), Berry, Carnall & Spiller (1995), Richard (2000)). Both hypotheses are empirically questionable as firms rarely observe accurately their rivals' costs, and entry (or production) on a market typically affects the state of other markets within the network. We consider a more realistic empirical framework with entry on interdependent markets and incomplete information. This model allows for the analysis of exchanges of cost information.

Namely, we propose a static model of simultaneous entry decisions for N symmetric firms across M markets. Goods are complements across markets and, thus, a firm's revenues on a market are a function of decisions across all other markets. Demand functions are common knowledge and exogenously determined with respect to firms' decisions. Marginal cost are assumed to be random private signals (known to the firm but not its opponents) drawn from a joint distribution which is common knowledge. Firms decide simultaneously whether to enter and how much to produce on each of the M markets, based upon their cost vector and the distribution of costs. In particular, a firm has to commit on quantity on a market without knowing, ex-ante, how many firms will compete on that market and how much they will produce. This model, although simple, defines a complex optimization problem. It is analytically intractable and we propose an algorithm to determine numerically the Bayesian Nash Equilibrium.

We apply the model to the airline industry. We consider the entry and production decisions of American Airlines (AA) and United Airlines (UA) at Chicago O'Hare. The sample data, from the third quarter of 1993, includes 83 markets with flights from at least one of AA or UA, and 17 major markets with no flights. We first estimate the demand functions as these are assumed to be exogenous to the structural model. Then we estimate the structural parameters of the theoretic model (previously outlined) with the inference method proposed by Florens et al. (1997). We find an average cost per passenger/mile of \$0.165. This figure is consistent with trade publications. The method provides also probabilities of entry, expected quantities of passengers, prices, and profits. Our simple model yields results that closely match observed values.

Finally, we assume that AA and UA form an hypothetical alliance under which they reveal cost information to each other. In this scenario, the two airlines compete under complete information. Using the estimated distribution of marginal costs, we simulate and compare the airlines' equilibrium decisions under both information regimes (i.e., incomplete and complete information). As expected, the results show that expected profits increase on every market when AA and UA choose to truthfully exchange cost information. Interestingly, such exchanges leave expected consumer surplus essentially unchanged and consumers are actually better off on a majority of markets (57%).

The paper is structured as follows. Section 2 introduces the theoretic model. We propose an algorithm to solve the Bayesian Nash Equilibrium in section 3. Section 4 discusses the application to the airline industry. The structural estimation method and the results are presented in section 5. Exchanges of cost information are analyzed in section 6. Section 7 concludes.

2. A Model of Firms' Decisions

There are N symmetric firms ($i = 1, .., N$) and M markets ($m = 1, ..., M$). Firms decide simultaneously whether to enter and how much to produce on each of the M markets.

There is incomplete information on marginal costs of production. Each firm i is endowed with a vector of private types $c_i = (c_{i,1}, ..., c_{i,m}, ..., c_{i,M})$ where $c_{i,m}$ is firm i's constant marginal cost of production on market m. Firms know their own marginal costs, but they do not observe their rivals' $c_{-i} = (c_1, .., c_{i-1}, c_{i+1,}, .., c_N)$ when deciding upon an optimal strategy. Cost values $c_{i,m}$ are independently and identically distributed (hereafter i.i.d.) across firms and independently distributed across markets. Let $f(.|\theta)$ denote the probability density function (p.d.f.) of $c_{i,m}$ indexed by the vector $\theta \in \Re^k$. The p.d.f. $f(.)$ and the parameter θ are common knowledge among firms. Finally, we assume that there are no fixed costs of production.

The demand function on a market is common knowledge and exogenously determined. It is linear and symmetric across firms. Goods on a market are initially (prior to production on other markets) perceived by consumers as perfect substitutes across firms. Goods across markets are complements. The price for a representative customer of firm i on market m, $P_{i,m}$, is a non-negative function of quantity choices across all M markets:

$$P_{i,m} = \alpha_m + \beta_m \sum_{m' \neq m}^{M} q_{i,m'} + \lambda_m \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} q_{j,m'} - \gamma_m \sum_{j=1}^{N} q_{j,m} \tag{2.1}$$

where $q_{i,m}$ is firm i's quantity on market m and $\alpha_m, \beta_m, \lambda_m, \gamma_m$ are parameters verifying

$\alpha_m > 0$, $\gamma_m > \beta_m \geq \lambda_m > 0$. This specification allows for the level of complementarity to differ across firms (i.e., $\beta_m \geq \lambda_m$). Namely, a consumer who purchases a good from a firm may have a higher willingness to pay for a different good from the same firm. Brand loyalty or compatibility problems across brands may explain this behavior.[1] Hence, consumers may have different willingness to pay for goods which would be considered perfect substitutes if there were no complementarities. We also assume that firm $i's$ price on a market m is equally affected by an increase in quantity on any market $m' \neq m$, even when m' is a new market.[2] We can interpret β_m and λ_m as the average increase in a consumer's willingness to pay for good m due to one more unit supplied on a market $m' \neq m$.

Given their marginal costs, firms simultaneously decide whether to enter and how much to produce on each of the M markets. In other words, given c_i, firm i maximizes expected profits across all M markets by selecting non-negative quantities $q_i^* = \left(q_{i,1}^*, .., q_{i,m}^*\right)$ such that

$$\begin{aligned} q_i^* &= \varphi_i\left(c_i, \theta\right) = \underset{\{q_{i,m}\}_{m=1,..,M}}{Arg\max} \sum_{m=1}^{M} E\left[\left(P_{i,m} - c_{i,m}\right) q_{i,m} \middle| \theta\right] \\ & \qquad \text{subject to} \qquad q_{i,m} \geq 0 \qquad \forall m = 1, ..., M \end{aligned} \tag{2.2}$$

where $\varphi_i\left(c_i, \theta\right)$ is firm $i's$ equilibrium strategy function. We do not impose that profits nor expected profits are positive on a given market. In the subsequent simulations, firms have positive expected profits on every market even if, sometimes, they incur losses. We also implicitly assume non-negative prices; this assumption is non-binding in the simulations.

[1] Unlike Regibeau & Matutes (1989), we do not attempt to model the strategic decisions associated with brand loyalty or brand compatibility.

[2] Our objective is to develop the simplest structural model, with the least ad hoc assumptions, which provides realistic results. The linear specification, although overly simplistic on a theoretical level, provides an excellent structural model. Hence, we did not identify a *need* to select a nonlinear, concave specification by which the effects from adding one unit on $m' \neq m$ would be larger when m' is a new market.

Substituting (2.1) into (2.2), we have that

$$\begin{aligned} q_i^* \quad = & \quad \underset{\{q_{i,m}\}_{m=1,\dots M}}{Arg\max} \sum_{m=1}^{M} \left(\alpha_m + \beta_m \sum_{m' \neq m}^{M} q_{i,m'} + \lambda_m \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} E\left[q_{j,m'} | \theta, c_i\right] \right. \\ & \qquad \left. -\gamma_m \sum_{j \neq i}^{N} E\left[q_{j,m} | \theta, c_i\right] - \gamma_m q_{i,m} - c_{i,m} \right) q_{i,m} \qquad (2.3) \\ & \text{subject to} \qquad q_{i,m} \geq 0 \qquad \forall m = 1, ..., M \end{aligned}$$

Subsequent to their quantity choices, firms observe the realizations of prices and profits on each of the M markets.

3. Computing the Bayesian Nash Equilibrium Solution

The Kuhn-Tucker conditions for the constrained optimization problem in (2.3) are:

$$\begin{aligned} V_{i,m} = \alpha_m + \sum_{m' \neq m}^{M} \left(\beta_m + \beta_{m'}\right) q_{i,m'} + \lambda_m \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} E\left[q_{j,m'} | \theta, c_i\right] \\ -\gamma_m \sum_{j \neq i}^{N} E\left[q_{j,m} | \theta, c_i\right] - 2\gamma_m q_{i,m} - c_{i,m} \leq 0 \\ q_{i,m} V_{i,m} = 0 \qquad and \qquad q_{i,m} \geq 0 \qquad \forall m = 1, ..., M \qquad \forall i = 1, ..., N \qquad (3.1) \end{aligned}$$

where $V_{i,m}$ is the partial derivative of (2.3) with respect to $q_{i,m}$.[3]

Since firms are ex-ante symmetric and private signals are i.i.d. across firms, we have that at the equilibrium: $E\left[q_{j,m} | \theta, c_i\right] = E\left[q_{j',m} | \theta, c_{i'}\right] = E\left[q_m | \theta\right] \quad \forall j \neq i \quad \forall i \neq i' \; or \; \forall j \neq j'$. We then write

$$V_{i,m} = \alpha_m + \sum_{m' \neq m}^{M} \left(\beta_m + \beta_{m'}\right) q_{i,m'} + \lambda'_m \sum_{m' \neq m}^{M} E\left[q_{m'} | \theta\right] - \gamma'_m E\left[q_m | \theta\right] - 2\gamma_m q_{i,m} - c_{i,m} \qquad (3.2)$$

[3] The optimization problem is not well-defined if the number of markets, M, is sufficiently large. Indeed, there exists M_0 such that $\forall M > M_0 \lim_{q_{i,m} \to \infty} V_{im} > 0 \; \forall i$ and $\forall m$; i.e., the marginal profit on any market is positive for infinite quantities. We do not encounter this problem in our application as M is not large enough.

where $\lambda'_m = \lambda_m(N-1)$ and $\gamma'_m = \gamma_m(N-1)$. The Kuhn-Tucker conditions are invariant to a permutation of player indices and equilibrium strategies are symmetric across firms: $\varphi_i(.,\theta) = \varphi_j(.,\theta) = \varphi(.,\theta) \quad \forall j \neq i$. We thus focus on the decisions of a representative firm i.

When $q_{i,m} = 0$, the Kuhn-Tucker conditions require that $V_{i,m} \leq 0$ or, equivalently,

$$\begin{aligned} &q_{i,m} = 0 \quad \Rightarrow \quad c_{i,m} \geq \overline{c}_{i,m}(c_{i,-m}) \qquad \forall m = 1, ...M \qquad where \\ &\overline{c}_{i,m}(c_{i,-m}) = \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) q_{i,m'} + \lambda'_m \sum_{m' \neq m}^{M} E[q_{m'}|\theta] - \gamma'_m E[q_m|\theta] \end{aligned} \tag{3.3}$$

with $c_{i,-m} = (c_{i,1}, .., c_{i,m-1}, c_{i,m+1,}, .., c_{i,M})$. Firm i only enters on market m if its marginal cost $c_{i,m}$ is below $\overline{c}_{i,m}(c_{i,-m})$. Note that the threshold value $\overline{c}_{i,m}(c_{i,-m})$ is a function of firm $i's$ marginal costs on every market $m' \neq m$. Given the model's demand and cost functions are linear in quantities, the value $\overline{c}_{i,m}(c_{i,-m})$ is uniquely defined on each market m.

The solution to the optimization problem (2.3) then verifies:

$$\begin{aligned} q_{i,m} \;\; = \;\; & \frac{1}{2\gamma_m} [\alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) q_{i,m'} + \lambda'_m \sum_{m' \neq m}^{M} E[q_{m'}|\theta] \\ & -\gamma'_m E[q_m|\theta] - c_{i,m}] \, I_{\{c_{i,m} \leq \overline{c}_{i,m}(c_{i,-m})\}} \qquad \forall m = 1, ...M \end{aligned} \tag{3.4}$$

where $I_{\left\{c_{i,m} \leq \overline{c}_{i,m}\left(c_{i,-m}\right)\right\}}$ is the indicator function defined as

$$I_{\{x \leq 0\}} = \begin{Bmatrix} 1 & when \ x \leq 0 \\ 0 & otherwise \end{Bmatrix}$$

If we insert equation (3.3) in equation (3.4) we obtain

$$q_{i,m} = \left(\frac{\overline{c}_{i,m}(c_{i,-m}) - c_{i,m}}{2\gamma_m} \right) I_{\{c_{i,m} \leq \overline{c}_{i,m}(c_{i,-m})\}} \qquad \forall m = 1, ...M \tag{3.5}$$

and if we insert equation (3.5) into equation (3.3), then

$$\begin{aligned} 0 &= \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) \left(\frac{(\overline{c}_{i,m'} (c_{i,-m'}) - c_{i,m'})}{2\gamma_{m'}} \right) I_{\{c_{i,m'} \leq \overline{c}_{i,m'}(c_{i,-m})\}} \\ &+ \lambda'_m \sum_{m' \neq m}^{M} E[q_{m'}|\theta] - \gamma'_m E[q_m|\theta] - \overline{c}_{i,m}(c_{i,-m}) \qquad \forall m = 1, ...M \qquad (3.6) \end{aligned}$$

To determine equilibrium quantities, one needs to solve the system of equations (3.6) and then (3.5). Note that (3.6) depends upon $E[q_m|\theta]$ $\forall m = 1, ..., M$. Unlike in a complete information setting, firms cannot predict the exact quantities their rivals produce at the Nash solution. Firms can only rely upon their rivals' expected quantities, $E[q_m|\theta]$, to determine their best strategies. However, there is no analytically tractable way to calculate $E[q_m|\theta]$. To determine the Nash Equilibrium, we propose to replace $E[q|\theta] = (E[q_1|\theta], ..., E[q_M|\theta])$ by a Monte Carlo approximation $\widehat{E}[q|\theta]$.

The numerical algorithm consists in five steps. First, given θ, we simulate S vectors of private types[4] (using the Common Random Number technique) for the representative firm i, $\{\widetilde{c}_{i,s}\}_{s=1,...,S}$. Second, we consider an initial value for $E[q_m|\theta]$, say ε_m, on each market. Third, given $\varepsilon = (\varepsilon_1, ..., \varepsilon_M)$ and $\widetilde{c}_{i,s}$, we solve the system of equations (3.6) to obtain the vector $\{\overline{c}_{i,m,s}(\widetilde{c}_{i,-m,s})\}_{m=1,...M}$. Using the set of equations (3.5), we then calculate the equilibrium quantities $\{\widetilde{q}_{i,m,s}\}_{m=1,...M}$. Fourth, we repeat step 3 for the S simulations and we compute the empirical mean of the simulated quantities on each market:

$$\overline{q_{i,m}} = \frac{1}{S} \sum_{s=1}^{S} \widetilde{q}_{i,m,s}$$

Fifth, given the symmetry of the model, we compare ε_m to $\overline{q_{i,m}}$. If ε_m is a reasonable approximation of the expected quantity $E[q_m|\theta]$, then it should be close to its simulated empirical counterpart. The approximation $\widehat{E}[q|\theta]$ is then defined as

$$\widehat{E}[q|\theta] = \underset{\{\varepsilon_m\}_{m=1,...M}}{Arg\min} \sum_{m=1}^{M} [\varepsilon_m - \overline{q_{i,m}}]^2 \qquad \forall m = 1, ...M$$

[4] In practice, we select $S = 5000$.

The calculation of $\widehat{E}\left[q|\theta\right]$ is time consuming but it is not computationally challenging. To obtain the approximation of $\widehat{E}\left[q|\theta\right]$, we use an optimization technique that requires to solve numerically the system of equations (3.6) for any value of θ and for each of the S Monte Carlo simulations. These equations are linear up to an indicator function and there exist numerous numerical procedures to solve these systems in a matter of seconds.

Once $\widehat{E}\left[q_m|\theta\right]\ \forall m$ has been determined, we can calculate the equilibrium quantities for a given cost vector $\{c_{i,m}\}_{m=1,\dots M}$. Symmetrically, we can invert the strategy function and calculate $\{c_{i,m}, \overline{c}_{i,m}\left(c_{i,-m}\right)\}_{m=1,\dots M}$ for a vector of observed equilibrium quantities. The econometric technique which we use for the application to the airline industry requires the inversion of the equilibrium strategy (see section 5).

4. An Application to the Airline Industry

4.1. American Airlines and United Airlines at Chicago O'Hare

We define an airline market as a pair of U.S. airports which can be linked by nonstop flights (hereafter flights).[5] A good on a market is a seat on a flight. If at least a firm produces on a market, the market is said to be active. We consider the competition between American Airlines (AA) and United Airlines (UA) at Chicago O'Hare. Following Reiss & Spiller (1989) and Brander & Zhang (1990), we justify the maintained hypotheses of the model developed in section 2 by the following facts:

(i) Chicago O'Hare is a major hub for both airlines.[6] By nature, a hub is at the center of a self-contained network with demand complementarities across markets (c.f. Morrison & Winston (1995), Hendricks, Piccione & Tan (1997)).

(ii) AA and UA can be viewed as symmetric firms. They are major U.S. carriers with similar network-wide cost structures and brand images. Their network of active markets is comparable at Chicago O'Hare.

(iii) AA and UA are in duopoly competition at O'Hare. They jointly account for

[5] Markets are assumed to be non-directional.

[6] We consider the existence of a hub airport at Chicago O'Hare as given.

89.5% of passenger enplanements at O'Hare and, together, they are present on all 127 active markets at Chicago O'Hare. By comparison, Delta Airlines, the third largest airline at O'Hare, has only 3.1% of passenger enplanements at O'Hare and offers flights on just 8 markets.

(iv) Airlines decide on the number of passengers they fly on each of the sample markets. Quantity seems to be the appropriate decision variable since, in practice, airlines frequently and almost costlessly modify prices. Note that we do not model capacity and flight frequency choices.

(v) There is incomplete information on costs. Average costs per passenger per mile for a given airline are available ex-post on a network-wide basis (e.g., The Airline Monitor (1994)). While AA and UA have information on each other's leasing and servicing contracts, details of operating costs on a market remain private information.

(vi) A static analysis of entry seems appropriate for this sample of markets. The number of Chicago markets with flights, the number of flights per Chicago market, and the number of U.S. airlines with flights from O'Hare are stable through 1993-1994.

4.2. Data

The data come from three databases: Databank 1A, Databank DS T-100, and the Official Airline Guide (OAG) publications. Databank 1A, from the Department of Transportation (DOT), is a 10% random sample of all airlines tickets sold quarterly. It provides the itinerary and the price per mile for each passenger.[7] We consider itineraries that include nonstop flights between O'Hare and a US airport and flights connecting two US airports with a stop at O'Hare. To determine $P_{i,m}$, we multiply the mileage of market m with the average price per mile for all passengers flying with airline i on market m. Databank DS T-100 provides the number of passengers per major airline and per month on a market.

The sample data for our paper are from the 3^{rd} quarter of 1993. There are $M = 100$

[7]Following Borenstein (1989) and Hurdle et al. (1989), we filter Databank 1A data for excessive fares (see Richard (2000) for details on the preparation of the price data in our sample).

Chicago markets in our sample data (c.f. Appendix). Eighty-three have flights from at least one of AA or UA. The other 17 are major markets without flights from any airline.[8] The sample does not include 44 Chicago markets with flights. Seventeen markets are excluded for lack of data. The remaining 27 excluded markets are not part of the duopoly competition over the hub network for one of the following reasons: (i) a different airline dominates the market, (ii) the market links Chicago to a hub airport of another competitor, (iii) AA and UA have different numbers of hub airports on the market. The inclusion of these markets would require to model the overall competition with every possible airline and every potential market. Such task is known to be next to impossible. Summary statistics of the 100 sample markets are presented in table 1.

[Table 1 roughly here]

4.3. Demand and Cost Specifications

The demand functions are assumed to be known to the firms and exogenously determined. Therefore, we have to estimate the demand function prior to the estimation of the structural model. We use data on the sample Chicago markets across seven consecutive quarters: 1^{th} quarter 1993 through 3^{th} quarter 1994. The inverse demand function faced by airline i on a market m in quarter t is equal to:

$$\begin{aligned} P_{i,m,t} &= \alpha_0 + \alpha_1 INC_m + \alpha_2 POP_m + \alpha_3 \ln(POP_m) + \alpha_4 MILES_m + \alpha_5 DPOP_m \\ &\quad + \alpha_6 QTR_t + \beta \sum_{m' \neq m}^{M} q_{i,m',t} + \lambda \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} q_{j,m',t} - \gamma \sum_{j=1}^{N} q_{j,m,t} \end{aligned} \tag{4.1}$$

where $\alpha_0, ..., \alpha_6, \beta, \gamma$ are parameters known to the airlines. $MILES_m$ is the mileage of market m, INC_m and POP_m are, respectively, the median household income and the population for the metropolitan area paired to Chicago on market m. $DPOP_m$ is a dummy variable equal to 1 if that metropolitan area has more than 2,600,000 inhabitants (source: 1990 Census data). QTR_t is AA and UA's average number of passengers in

[8] A market is said to be a major market if both metropolitan areas are larger than 350,000 inhabitants.

quarter t on U.S. markets (other than the 100 markets in our sample) active during all seven quarters.

The theoretic model is sequential since firms choose quantities and then observe realized prices. Therefore, there is no endogeneity problem between prices and quantities. To allow for correlations between unobservable variables on duopoly markets, we use the Feasible Generalized Least–Squares method. A preliminary estimation of (4.1) reveals that λ (the level of complementarity across firms) is insignificant (at a 5% level). This result is consistent with Morrison and Winston (1995) who find that, by 1994, less than 1% of all passengers switch airlines in their path of travel. We re-estimate the inverse demand function under the constraint that $\lambda = 0$. Results are presented in Table 2. Firms' optimal strategy are subsequently derived using this estimated demand function.

[Table 2 roughly here]

AA and UA have long-term leases on their facilities at O'Hare and we consider fixed airport costs (i.e., administrative costs, costs of leasing facilities and ground equipment) as sunk prior to the sample period. Following Brander & Zhang (1990) and Hendricks, Piccione & Tan (1997), we assume that marginal operating costs per passenger on a market are constant. We define the marginal cost of airline i on market m as $c_{i,m} = cpm_{i,m} \times MILES_m$ where $cpm_{i,m}$ is the cost per passenger per mile.[9] $cpm_{i,m}$ is assumed to be log-normally distributed on $]0,\infty[$ with mean $\mu_m = \mu_0 - \mu_1 MILES_m$ and standard deviation σ. The mean of $cpm_{i,m}$ is known to decline with the mileage as most costs are incurred during take-off (c.f. Brander & Zhang (1990)). The distribution of the private types $cpm_{i,m}$ is estimated in the following section with the structural econometric model.

[9] While there is some evidence of economies of density in the airline industry (c.f. Caves, Christensen & Tretheway (1984), Brueckner & Spiller (1994)), we found no significant relation between marginal costs and quantities in our sample (see section 5.2).

5. Estimation of the Structural Model of Firms' Decisions

5.1. Inference Method

The estimation of the distribution of private costs requires non standard econometric techniques. Indeed, in models of incomplete information, unobserved private types are transformed into observed actions by means of strategies which depend upon the underlying distribution of the types. This creates an identification problem in that we cannot jointly estimate the functional form of players' strategies and the distribution of types from the sole observation of actions. We solve this identification problem by imposing that strategies are Nash Equilibrium solutions of the model.

We then estimate the distribution of unobserved types using the generic estimation principle proposed by Florens et al. (1997).[10] Within this estimation framework, one initially selects an 'unfeasible' estimator $\widetilde{\theta}(c)$, whereby one could estimate θ if the cost vectors for all firms on all markets, $c = (c_1, ...c_i, ..., c_N)$, were known. The corresponding 'feasible' estimator $\left(\widehat{\theta}(q), \widehat{c}(q)\right)$ of (θ, c) (where $q = (q_1, ...q_i, ..., q_N)$) is defined as the fixed point solution to

$$\widehat{\theta}(q) = \widetilde{\theta}(\widehat{c}(q)) \qquad and \qquad \widehat{c}(q) = \varphi^{-1}\left(q; \widehat{\theta}(q)\right) \qquad i : 1 \to N \tag{5.1}$$

where $\varphi^{-1}\left(q; \widehat{\theta}(q)\right)$ is the inverse strategy function calculated using the algorithm in section 3.[11] In practice, the computation of this fixed point solution necessitates iterating between the two equations in (5.1) until convergence obtains (see Armantier & Richard (1998) for additional numerical considerations). The unfeasible estimator is given by

[10]The algorithm to determine numerically the Nash Equilibrium requires to simulate the first moment of the quantity produced on each market. This suggests to estimate the underlying structural parameters with the method of simulated moments. However, the optimal weighting matrix was quite time consuming to calculate and we opted for the Florens and al. (1997) technique.

[11]Conditions for the local identification of θ from the sole observation of q and for the existence and (local) unicity of a fixed joint solution are found in Florens et al. (1997), together with characterizations of the asymptotic distributions of $\widehat{\theta}$ and $\widehat{c}$.

the censored Maximum Likelihood estimator:

$$L(\theta|\widehat{c}(q)) = \prod_{i,m}\left(1 - F\left(\overline{cpm}_{i,m}|\,\theta\right)\right)^{I\{q_{i,m}=0\}}\left[f\left(\widehat{cpm}_{i,m}(q)\,|\theta\right)\right]^{I\{q_{i,m}>0\}} \tag{5.2}$$

where $\theta = (\mu_0, \mu_1, \sigma) \in \Re\times]0,\infty[^2$, $\overline{cpm}_{i,m} = \overline{c}_{i,m}/MILES_m$, $\widehat{cpm}_{i,m}(q) = \widehat{c}_{i,m}(q)/MILES_m$, and $f(.)$ and $F(.)$ are, respectively, the log-normal probability density function and cumulative distribution.

Computing is of the order of 274 minutes of CPU time on a recent SUN workstation. Standard deviations for the estimates are computed with a Monte Carlo simulation of size 5000.

5.2. Estimation Results

The estimates for the parameters of the cost distribution are $\widehat{\theta} = (\widehat{\mu_0}, \widehat{\mu_1}, \widehat{\sigma}) = (0.217$, $6.85\text{E}10^{-5}$, $2.084)$ with a standard deviation of ($3.94\text{E}10^{-2}$,$6.10\text{E}10^{-6}$,$8.32\text{E}10^{-4}$). This corresponds to an aggregate average cost per passenger/mile of \$0.165 with a standard deviation of \$0.043. It is difficult to find benchmarks to compare the estimated average cost per passenger/mile on a market basis; however, \$0.165 appears consistent with network-wide averages (c.f. The Airline Monitor (1994)). Note that the standard deviation of $cpm_{i,m}$ is non-negligeable. This indicates that network-wide averages are an imperfect measure of the marginal cost on a given market. This finding reinforces our assumption of incomplete information at the market level.

The simulations within the algorithm provide, for each market, expected quantities, prices, profits and the probability that a firm enters (see table 3).[12] The estimated probabilities of entry are consistent with the observed number of active firms on a sample market. Namely, the average probability that a firm enters a market is equal to 0.84 across markets in duopoly in our sample, 0.66 across sample markets in monopoly, and 0.36 across inactive sample markets. Estimated quantities and prices fit well the

[12] Detailed results are available upon request.

observations and are well within one standard deviation of observed values. The difference between observed quantities (prices) and estimated expected quantities (prices) is -4.7% (1.4%) across sample markets in duopoly, -6% (-0.7%) across sample markets in monopoly, and -5.5% (0.3%) overall. Conditional upon observed entry decisions, we estimate that AA earned expected profits of $34,120,907, while UA earned $43,897,404, during the sample period. Note that these figures do not include all fixed costs assumed sunk prior to the sample period. Finally, a regression indicates that expected quantities do not have a significant effect on estimated marginal costs (the p-value=0.58). This result confirms that there are no economies of density on our sample markets.

[Table 3 roughly here]

6. Exchanges of Cost Information in Airline Alliances

Fried (1984), Gal-Or (1986), and Shapiro (1986) (hereafter FGS) analyze exchanges of cost information in single-market models of Cournot competition with linear demand and incomplete information on the constant marginal costs of production. They find that expected profits and welfare increase when oligopolist choose to truthfully exchange cost information. Exchanges increase efficiency by raising the market shares of lower cost firms and reducing the variability of aggregated output. However, the reduction of output volatility decreases expected consumer surplus since the latter is a convex function of output.

Armantier & Richard (2000) show that this latter result need not hold in multi-market models with entry and complementarities across markets. Complementarities affect both the entry and production decisions. When complementarities are large enough, these changes may yield greater expected consumer surplus when firms choose to truthfully exchange cost information. The authors also find that consumers on smaller markets tend to benefit more.

Following Shapiro (1986) we assume that, before observing their own cost vector, firms enter in an agreement to exchange cost information.[13] Under this agreement, firms truthfully reveal to each other their costs vector c_i and then compete in complete information by selecting an output level for each of the M markets. Following FGS, we assume that firms can transfer and verify each other's reports at no cost. All previous assumptions regarding demand and costs are maintained. The Nash Equilibrium under complete information obtains numerically from the first-order conditions. We simulate competition under the agreement over the 100 sample markets to estimate expected profits and consumer surplus. Private signals are simulated from the distribution estimated in section 5.2. Simulations results are summarized in table 4 and compared to those in table 3.

[Table 4 roughly here]

The probability that a market is active is larger under complete information. Markets with a low probability of entry under incomplete information see the largest relative increases. Markets are more likely to be in monopoly and less likely to be in duopoly under complete information. Expected profits are larger on every market under complete information (expected aggregated profits increase by 39%). Hence, firms should enter in an agreement to exchange cost information. Expected aggregated consumer surplus decreases by only 0.06% under complete information. However, if we do not account for the largest market (Chicago to Washington Reagan National with an expected quantity per firm of 108,510), expected consumer surplus increases by 6.9% under complete information. Besides, consumer surplus is larger on most markets (57%) under complete information. Consumers on small markets (i.e., markets with low expected quantities) benefit the most since these markets are active more often. Hence, exchanges of cost information improve expected profits and actually increase consumer surplus on a majority of markets.

[13] This agreement is purely hypothetical and we are not aware of any plans by AA and UA to form a marketing alliance on the U.S. market.

7. Conclusion

Tables

Table 1. Descriptive Sample Statistics

	State of the Market			
	Monopoly (only 1 firm enters)	Duopoly (2 firms enter)	Active (at least 1 firm enters)	Overall (with non-entry)
Number of Markets	43	40	83	100
Average Quantity per Firm	17366.67	33969.15	25367.86	21055.33
	(8809.43)	(22066.86)	(18466.34)	(19343.43)
Average Price	123.35	127.91	125.55	.
	(52.44)	(65.19)	(58.61)	
Average Mileage of Markets	652.233	698.17	674.37	715.28
	(433.42)	(556.02)	(493.76)	(493.73)

Note: Mean values are listed with standard deviations in parentheses.

Table 2. Estimates for the Demand Specification.

Variable	*Constant*	*INC*	*POP*	*ln(POP)*	*MILES*
Parameter	α_0	α_1	α_2	α_3	α_4
Estimate	-34.21	1.72E10-3	1.03E10-5	9.66	0.109
(Std error)	(25.98)	(2.15E10-4)*	(1.75E10-6)*	(1.73)*	(1.90E10-3)*
Variable	*DPOP*	*QTR*			
Parameter	α_5	α_6		β	γ
Estimate	37.30	-2.28E10-3		3.05E10-6	-6.47E10-4
(Std error)	(7.97)*	(3.60E-4)*		(1.23E-6)*	(5.19E-5)*

R-square value: 0.896 (Greene (1997)).

* denotes significance at a 5% level.

Table 3. Simulation Results for Competition Under Incomplete Information on Marginal Costs.

	State of the Market			
	Monopoly (only 1 firm enters)	Duopoly (2 firms enter)	Active (at least 1 firm enters)	Overall (with non-entry)
Probability of	0.28	0.54	0.82	
	(0.20)	(0.37)	(0.29)	
Expected Quantity per Firm	28050	28031	28038	19161
	(20938)	(20902)	(20918)	(18250)
Expected price	134.14	120.17	123.65	.
	(61.71)	(56.58)	(58.61)	
Expected Profit per Firm	801348	389471	488019	353311
	(1202672)	(582153)	(659507)	(532420)
Expected Consumer Surplus				1048235
				(2521641)

Note: Mean values are listed with standard deviations in parentheses.

Table 4. Simulation Results for Competition Under Complete Information.

	State of the Market			
	Monopoly (only 1 firm enters)	Duopoly (2 firms enter)	Active (at least 1 firm enters)	Overall (with non-entry)
Probability of	0.50	0.45	0.95	
	(0.24)	(0.32)	(0.21)	
Expected Quantity per Firm	42262	25140	33693	22226
	(27655)	(19874)	(24657)	(16535)
Expected price	129.70	125.86	127.16	.
	(60.29)	(57.96)	(58.26)	
Expected Profit per Firm	1313348	570149	820316	582527
	(1606157)	(823149)	(1041073)	(763672)
Expected Consumer Surplus				1047632
				(1991809)

Note: Mean values are listed with standard deviations in parentheses.

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Appendix

Table. The 100 Chicago Markets in Our Sample.

#	Market with flights from 1 airline	Airline with flights	Miles	#	Markets with flights fro AA and UA	Miles	#	Markets with no flights	Miles
1	Albuquerque, NM	AA	1118	44	Albany, NY	723	84	Wilkes-Barre/Scranton, PA	631
2	Bloomington, IL	AA	116	45	Austin, TX	972	85	Fresno, CA	1730
3	Champaign, IL	AA	135	46	Kalamazoo, MI	122	86	Greensville, SC	577
4	Dubuque, IA	AA	147	47	Hartford, CT	783	87	Bakersfield, CA	1732
5	El Paso, TX	AA	1236	48	Buffalo, NY	473	88	Little Rock, AR	552
6	Evansville, IN	AA	273	49	Iowa City, IA	196	89	Mobile, AL	779
7	Fargo, ND	AA	557	50	Columbus, OH	296	90	Tri-City Airport, TN	481
8	Flint, MI	AA	223	51	Wausau, WI	213	91	Chattanooga, TN	501
9	Lafayette, IN	AA	119	52	Dayton, OH	240	92	Bridgeport, CT	767
10	La Crosse, WI	AA	215	53	Washington National, DC	612	93	Baton Rouge, LA	810
11	Muskegon, MI	AA	118	54	Des Moines, IA	299	94	Melbourne, FL.	1040
12	Rochester, MN	AA	268	55	Sioux Falls, SD	462	95	Augusta, GA	677
13	Toledo, OH	AA	214	56	Fort Wayne, IN	157	96	Beaumont/Pt. Arthur, TX	897
14	Tucson, AZ	AA	1437	57	Green Bay, WI	174	97	Mc. Allen, TX	1238
15	Allentown, PA	UA	654	58	Grand Rapids, MI	137	98	Daytona Beach, FL	962
16	Appletown, WI	UA	160	59	Westchester County, NY	738	99	Santa Barbara, CA	1803
17	Bangor, ME	UA	978	60	Indianapolis, IN	177	100	Youngstown, OH	378
18	Birmingham, AL	UA	584	61	New-York Laguardia, NY	733			
19	Boise, ID	UA	1437	62	Kansas City, MO	403			
20	Burlington, VT	UA	763	63	Harrisburg, PA	594			
21	Columbus, SC	UA	666	64	Moline, IL	139			
22	Akron/Canton, OH	UA	344	65	Madison, WI	109			
23	Charleston, SC	UA	760	66	New Orleans, LA	837			
24	Colorado Springs, CO	UA	911	67	Oklahoma City, OK	693			
25	Ft. Lauderdale, FL	UA	1182	68	Omaha, NE	416			
26	Spokane, WA	UA	1498	69	Ontario, CA	1700			
27	Greensboro, NC	UA	590	70	Portland, OR	1739			
28	Huntsville/Decatur, AL	UA	510	71	Peoria, IL	130			
29	New Haven, CT	UA	778	72	Providence, RI	849			
30	Wichita, KS	UA	588	73	Rochester, NY	528			
31	Jacksonville, FL.	UA	865	74	San Diego, CA	1723			
32	Lexington, KY	UA	323	75	San Antonio, TX	1041			
33	Lincoln, NE	UA	466	76	Seattle/Tacoma, WA	1721			
34	Saginaw, MI	UA	222	77	San Jose, CA	1829			
35	Manchester, NH	UA	843	78	Sacramento, CA	1781			
36	Oakland, CA	UA	1835	79	Orange County, CA	1726			
37	Norfolk/ VA Beach, VA	UA	717	80	St. Louis, MO	258			
38	Portland, ME	UA	900	81	Syracuse, NY	607			
39	Richmond/Wmbg. VA	UA	642	82	Tampa/St. Petersburg, FL	1012			
40	Fort Myers, FL	UA	1120	83	Tulsa, OK	585			
41	Savannah, GA	UA	773						
42	Louisville, KY	UA	286						
43	Knoxville, TN	UA	475						