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Exchanges of cost information in the airline industry

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We empirically analyze exchanges of cost information in a multimarket oligopoly model for the airline industry with entry and incomplete information on marginal costs. We develop an algorithm to solve the Nash equilibrium numerically. We estimate the structural model of supply decisions using data on the American Airlines and United Airlines duopoly at Chicago O'Hare airport. Our results provide probabilities of entry, expected quantities, prices, and profits in each market. Given the estimated parameters, we simulate competition under a hypothetical agreement to exchange cost information. We find that such exchanges would benefit airlines while only moderately costing consumers.

1. Introduction

■ In the past ten years, the airline industry has witnessed a proliferation of marketing alliances. Within these alliances, airlines may market tickets on their partners' flights, and they may coordinate flight schedules, frequent-flyer programs, and joint promotional campaigns.[1] These activities may also include exchanges of information on production processes, particularly on costs of production. In the wake of proposed alliances between major U.S. carriers, the welfare implications of such activities have become highly relevant to economists (see Bamberger, Carlton, and Neuman, 2000, and Brueckner, 2001). We focus on a specific aspect of airline alliances; namely, we examine how exchanges of information on costs of production in the airline industry may affect consumer welfare.

Armantier and Richard (2001) find that although exchanges of cost information raise expected

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[1] A marketing alliance may be characterized as an arm's-length contract between two firms that does not involve any commingling of assets. The marketing of tickets on a partner's flight may be part of an interlining agreement whereby flights on an itinerary are listed by the operating airline's code, or a code-sharing agreement whereby all flights are listed under a common airline code (see GRA Transportation Advisor at www.gra-inc.com for more detail).

profits in multimarket settings like the airline industry, expected consumer surplus may increase or decrease depending upon the model's parameters. This issue is significant, since policy makers and courts in antitrust cases traditionally consider consumer surplus the deciding factor. In this article we estimate the structural parameters of a multimarket model of airline competition, and run some simulations to analyze how cost exchanges affect consumer surplus.

In the airline literature, the existing empirical models by Reiss and Spiller (1989), Berry (1992), and Berry, Carnall, and Spiller (1996) analyze decisions in single markets under complete information. We expand on the findings of the earlier literature as we recognize that firms rarely observe their rivals' costs accurately, and entry into a market typically affects the state of other markets. Namely, to analyze exchanges of cost information, we propose a static oligopoly model with incomplete information on costs and simultaneous entry decisions across multiple markets with demand complementarities. There are no fixed costs, and marginal costs are assumed to be random private signals, known to the firm but not its rivals. The marginal costs are drawn from a joint distribution, which is common knowledge among firms. Our model is analytically intractable, and we propose an algorithm, based upon Monte Carlo simulations, to determine the Bayesian Nash equilibrium numerically.

We apply this model to American Airlines' (AA) and United Airlines' (UA) duopoly competition at Chicago O'Hare airport. The data sample, 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. First, we estimate the demand functions, which we assume to be exogenous to the structural model. We then estimate the distribution of marginal costs with the method of simulated moments. We find an average cost per passenger mile of \$.158. This figure is consistent with trade publications. Our method also provides probabilities of entry, expected quantities of passengers, prices, and profits. The results closely match observed values.

Finally, we assume that AA and UA agree to exchange cost information truthfully. 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 incomplete and complete information. As expected, average profits increase in every market when AA and UA exchange cost information. Interestingly, these exchanges lower expected consumer surplus only moderately, and consumers typically benefit in a majority of markets (61%). Hence, a marketing alliance between AA and UA, with the sole objective of exchanging cost information, would be advantageous to airlines without significantly hurting consumers.

The article is structured as follows. We introduce the theoretic model in Section 2. We propose an algorithm to solve the Bayesian Nash equilibrium in Section 3. Section 4 discusses the application to the airline industry. In Section 5 we discuss the structural estimation method and present our findings. Section 6 then analyzes exchanges of cost information. Section 7 concludes.

2. A model of firms' decisions

■ To analyze exchanges of cost information in the airline industry, we expand on the existing literature by proposing a multimarket model with entry, incomplete information, and demand complementarities across markets. We maintain, however, the hypotheses of a static model with linear demand that are standard to the literature on exchanges of information (see Raith, 1996, and Vives, 1999). These simplifying assumptions are necessary to obtain an amenable, yet realistic, structural model.

There are N symmetric firms ($i = 1, \dots, N$) and M markets ($m = 1, \dots, M$). Firms decide simultaneously whether to enter and how much to produce in each of the M markets. There are no fixed costs, and marginal costs of production are constant. We assume incomplete information on marginal costs. Each firm i is endowed with a vector of private types $c_i = (c_{i,1}, \dots, c_{i,m}, \dots, c_{i,M})$, where $c_{i,m}$ is firm i's constant marginal cost of production in market m. Firms know their own marginal costs, but they do not observe their rivals' $c_{-i} = (c_1, \dots, c_{i-1}, c_{i+1}, \dots, c_N)$ when deciding upon an optimal strategy. Cost values $c_{i,m}$ are independently distributed across markets, and i.i.d. distributed across firms within a market.[2] Let $f_m(\cdot \mid \theta)$ denote the probability density function of $c_{i,m}$ indexed by the vector $\theta \in \mathbb{R}^k$. The p.d.f. $f_m(\cdot)$ and the parameter θ are common knowledge among firms.

The demand function in a market is common knowledge and exogenously determined. The demand is assumed to be linear and symmetric across firms. If production is limited to one market, then goods in that market are perceived to be perfect substitutes across firms. Goods across markets are complements and expressed in a common unit. The price for a representative customer of firm i in market m, $P_{i,m}$, is a nonnegative function of quantity choices across all M markets:

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

where $q_{i,m}$ is firm i's quantity in market m and α_m, β_m, λ_m, and γ_m are parameters verifying $\alpha_m > 0$ and $\gamma_m > \beta_m \geq \lambda_m > 0$. 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 may be more willing to buy another good from the same firm than from another firm. Brand loyalty or compatibility problems across brands may explain this behavior.[3] Hence, consumers' willingness to pay for goods that would be considered perfect substitutes if there were no complementarities may vary. We also assume that firm i's price in a market m is equally affected by an increase in quantity in any market $m' \neq m$, even when m' is a new market. We can interpret β_m and λ_m as the marginal increase in a consumer's willingness to pay for good m due to one more unit supplied in a market $m' \neq m$.

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

$$q_i^* = \varphi_i(c_i, \theta) = \underset{\{q_{i,m}\}_{m=1,\ldots,M}}{\operatorname{argmax}} \sum_{m=1}^{M} E\left[\left(P_{i,m} - c_{i,m}\right) q_{i,m} \mid \theta, c_i\right] \tag{2}$$

subject to $q_{i,m} \geq 0 \forall m = 1, \ldots, M$,

where $\varphi_i(c_i, \theta)$ is firm i's equilibrium strategy function. We do not impose that profits or expected profits are positive in a given market. In the subsequent simulations, firms have positive expected profits in every market even if they sometimes incur losses. Note as well that the nonnegativity constraints on prices are nonbinding in the simulations.

Substituting (1) into (2), we have that

$$\begin{aligned} q_i^* = \underset{\{q_{i,m}\}_{m=1,\ldots,M}}{\operatorname{argmax}} \sum_{m=1}^{M} \Bigg(& \alpha_m + \beta_m \sum_{m' \neq m}^{M} q_{i,m'} + \lambda_m \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} E\left[q_{j,m'} \mid \theta, c_i\right] \\ & - \gamma_m \sum_{j \neq i}^{N} E\left[q_{j,m} \mid \theta, c_i\right] - \gamma_m q_{i,m} - c_{i,m} \Bigg) q_{i,m} \end{aligned} \tag{3}$$

subject to $q_{i,m} \geq 0 \ \forall \ m = 1, \ldots, M$.

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

[2] Armantier and Richard (2002) find that the results in the present article are robust, in a single-market context, to slight correlations in costs. A multimarket model with correlated costs is, however, significantly more complex and not amenable to empirical analysis.

[3] Unlike Matutes and Regibeau (1988), we do not attempt to model the strategic decisions associated with brand loyalty or brand compatibility.

3. Computing the Bayesian Nash equilibrium solution

■ To analyze exchanges of cost information, we need to derive the Bayesian Nash equilibrium. We find that there is no analytical solution to the problem, and we propose an algorithm, based upon Monte Carlo simulations of the game, to find the equilibrium solution numerically. This numerical technique is central to our analysis. We use it both to estimate the structural model and to quantify the effects of exchanges of cost information on consumer surplus.

□ **The Kuhn-Tucker conditions.** The Kuhn-Tucker conditions for the constrained optimization problem in (3) are as follows:

$$\begin{aligned} V_{i,m} &= \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) q_{i,m'} + \lambda_m \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} E\left[q_{j,m'} \mid \theta, c_i\right] \\ &\quad - \gamma_m \sum_{j \neq i}^{N} E\left[q_{j,m} \mid \theta, c_i\right] - 2\gamma_m q_{i,m} - c_{i,m} \leq 0 \\ q_{i,m} V_{i,m} &= 0 \quad \text{and} \quad q_{i,m} \geq 0 \qquad \forall m = 1, \ldots, M \; \forall i = 1, \ldots, N, \end{aligned} \tag{4}$$

where $V_{i,m}$ is the partial derivative of (3) with respect to $q_{i,m}$.[4]

Since firms are *ex ante* symmetric and private signals are i.i.d. across firms on a given market, we find that at the equilibrium $E[q_{j,m} \mid \theta, c_i] = E[q_{j',m} \mid \theta, c_{i'}] = E[q_m \mid \theta]\ \forall j \neq i\ \forall i \neq i'$ or $\forall j \neq j'$. We then write

$$V_{i,m} = \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) q_{i,m'} + \lambda'_m \sum_{m' \neq m}^{M} E\left[q_{m'} \mid \theta\right] - \gamma'_m E\left[q_m \mid \theta\right] - 2\gamma_m q_{i,m} - c_{i,m}, \tag{5}$$

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 $\varphi_i(\cdot, \theta) = \varphi_j(\cdot, \theta) = \varphi(\cdot, \theta)\ \forall j \neq i$. We thus focus on the decisions of a representative firm i. The Kuhn-Tucker conditions imply that

$$\begin{aligned} &q_{i,m} > 0 \iff c_{i,m} < \bar{c}_{i,m}\left(c_{i,-m}\right) \qquad \forall m = 1, \ldots, M, \qquad \text{where} \\ &\bar{c}_{i,m}\left(c_{i,-m}\right) = \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) q_{i,m'} + \lambda'_m \sum_{m' \neq m}^{M} E\left[q_{m'} \mid \theta\right] - \gamma'_m E\left[q_m \mid \theta\right], \end{aligned} \tag{6}$$

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

Inserting (6) into (5), we find that the solution to the optimization problem (3) verifies the following:

$$\varphi_i\left(c_i, \theta\right) = q_{i,m} = \left(\frac{\bar{c}_{i,m}\left(c_{i,-m}\right) - c_{i,m}}{2\gamma_m}\right) I_{\left\{c_{i,m} \leq \bar{c}_{i,m}\left(c_{i,-m}\right)\right\}} \qquad \forall m = 1, \ldots, M, \tag{7}$$

[4] 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 in any market is positive for infinite quantities. We do not encounter this problem in our application, as M is not large enough.

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

$$I_{\{x \leq 0\}} = \begin{cases} 1 & \text{when } x \leq 0 \\ 0 & \text{otherwise.} \end{cases}$$

Now, inserting (7) into (6) leads to

$$0 = \alpha_m + \sum_{m' \neq m}^{M} (\beta_m + \beta_{m'}) \left(\frac{\left(\bar{c}_{i,m'}\left(c_{i,-m'}\right) - c_{i,m'}\right)}{2\gamma_{m'}} \right) I_{\{c_{i,m'} \leq \bar{c}_{i,m'}(c_{i,-m'})\}}$$

$$+ \lambda'_m \sum_{m' \neq m}^{M} E\left[q_{m'} \mid \theta\right] - \gamma'_m E\left[q_m \mid \theta\right] - \bar{c}_{i,m}\left(c_{i,-m}\right) \qquad \forall m = 1, \dots, M. \tag{8}$$

To determine equilibrium quantities, we need to solve the system of equations (8) and then (7). Note that (8) depends upon $E[q \mid \theta] = (E[q_1 \mid \theta], \dots, E[q_M \mid \theta])$. In this case, unlike a complete-information setting, firms cannot predict the exact quantities that their rivals produce at the Nash solution. To determine their best strategies, firms can rely only upon their rivals' expected quantities, $E[q \mid \theta]$. There is no analytically tractable way, however, to calculate $E[q \mid \theta]$.

□ **A numerical solution.** To determine the Nash equilibrium, we propose to replace $E[q \mid \theta]$ by an approximation $\hat{E}[q \mid \theta]$. Intuitively, $\hat{E}[q \mid \theta]$ is the fixed-point solution of a problem matching a potential expected quantity to its empirical counterpart as calculated across Monte Carlo simulations.

For a given θ, we simulate S vectors of private types (using the Common Random Number technique) for the representative firm i, $\{\tilde{c}_{i,s}\}_{s=1,\dots,S}$ with $\tilde{c}_{i,s} = (\tilde{c}_{i,s,1}, \dots, \tilde{c}_{i,s,M})$.[5] The approximation $\hat{E}[q \mid \theta]$ is then the solution of

$$\min_{\varepsilon} \|\varepsilon - \overline{q_i}(\varepsilon)\|, \tag{9}$$

where $\varepsilon = (\varepsilon_1, \dots, \varepsilon_M)$ is a potential value for $E[q \mid \theta]$; $\overline{q_i}(\varepsilon) = (1/S)\sum_{s=1}^{S} \tilde{q}_{i,s}(\tilde{c}_{i,s}, \varepsilon)$ is the empirical mean of simulated quantities; and $\tilde{q}_{i,s}(\tilde{c}_{i,s}, \varepsilon)$ is the numerical solution of the system of equations (8) and (7) given $E[q \mid \theta] = \varepsilon$ and $c_i = \tilde{c}_{i,s}$. Once $\hat{E}[q \mid \theta]$ has been determined, we can calculate from (8) and (7) the equilibrium quantities for a given cost vector c_i.

In practice, (9) is solved numerically with the simplex method. $\hat{E}[q \mid \theta] = \varepsilon$ is a reasonable approximation of the expected quantity $E[q \mid \theta]$ when ε becomes arbitrarily close to its simulated empirical counterpart $\overline{q_i}(\varepsilon)$. The calculation of $\hat{E}[q \mid \theta]$ is time consuming but not computationally challenging. The equations to be solved numerically are linear up to an indicator function, and there exist numerous numerical procedures that solve these systems in a matter of seconds.

As is often the case in games of incomplete information, one cannot formally prove the uniqueness of the equilibrium, since it relies upon a set of nonlinear implicit equations. Two factors, however, strongly suggest that the equilibrium is unique. First, we ran 10^6 simulations of the numerical algorithm with a random selection of starting values. All simulations converged (in quadratic norm) toward the same equilibrium up to an $\varepsilon = 10^{-8}$. Second, the subsequent structural model has been estimated with two methods: a method of simulated moment and a semiparametric technique. The first estimator requires that we specify an equilibrium solution. The second estimator is based upon the first-order condition of the problem and, therefore, does not rely upon a given equilibrium strategy. The estimation results generated by these two techniques cannot be statistically differentiated.[6] This suggests that firms' actual behavior is not inconsistent with the numerical solution derived with our algorithm.

[5] In practice, we select $S = 5{,}000$.

[6] A detailed description of the semiparametric technique, as well as the test results, may be found at http://www.simon.rochester.edu/fac/richard/.

4. An application to the airline industry

■ **American Airlines and United Airlines at Chicago O'Hare.** In this section we examine how our model applies to the airline industry. We define an airline market as a pair of U.S. airports that can be linked by nonstop flights (hereafter flights).[7] A good in a market is a seat on a nonstop flight. If at least one carrier flies in a market, the market is said to be active. In the discussion that follows, we consider the competition between American Airlines (AA) and United Airlines (UA) at Chicago O'Hare. We justify the maintained hypotheses of Section 2's model according to the following facts:

(i) Chicago O'Hare is a major hub for both airlines.[8] By nature, a hub is at the center of a self-contained network with demand complementarities across markets, as discussed by Morrison and Winston (1995) and Hendricks, Piccione, and Tan (1997). The complementarities are essentially rooted in the feeder structure of the hub-and-spoke system, whereby O'Hare is the hub for passenger flows from spoke airports. Borenstein (1989, 1991) argues that complementarities may also be generated by frequent-flyer programs, as these programs create an option on future travel that increases in value with the extensiveness of the airline's service from its hub.

(ii) Following Brander and Zhang (1990, 1993), AA and UA can be viewed as symmetric firms. They are major U.S. carriers with similar network-wide cost structures and brand images. In addition, their network of active markets is comparable at Chicago O'Hare.[9]

(iii) At O'Hare, AA and UA are in duopoly competition, as assumed by Brander and Zhang (1990, 1993).[10] They jointly account for 90% of passenger enplanements and, together, are present on all of approximately 125 active markets at the airport. By comparison, Delta Airlines, the third-largest airline at O'Hare, has only 3.1% of passenger enplanements and offers flights in just eight markets.[11]

(iv) The internal structure of airline companies is such that a marketing group first determines the aggregate number of passengers that fly in each of the sample markets. In practice, changes in aggregated quantities are rare and costly, while price fluctuations are numerous. This is reasonably consistent with a Cournot model in which firms commit to quantities and then prices adjust through a tâtonnement process. The Cournot assumption is common to most empirical studies on the airline industry (e.g., Reiss and Spiller, 1989). In addition, Brander and Zhang (1990) find empirical support for the hypothesis of Cournot competition between AA and UA at Chicago O'Hare. Our model remains nevertheless a simplication of airline behavior because we do not include, for instance, capacity and flight frequency choices.

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[7] Markets are assumed to be nondirectional.

[8] We take the existence of a hub at Chicago O'Hare as given.

[9] Aircraft landing and takeoff slots at Chicago O'Hare are a potential source of asymmetry. Indeed, AA has sued UA, arguing that UA has an unfair advantage in slot allocation at O'Hare (see *Frequent Flyer*, September 1992, pp. 22–24). This issue remains contentious and we leave its analysis for future work.

[10] In particular, we assume that there are no substitutes competing with flights offered by AA and UA over the self-contained network of sample markets. The inclusion of potential substitutes would require us to consider every airport and every airline with flights with one or more stops, as well as other means of transportation. Such an analysis is beyond the scope of the present article.

[11] Only six of our sample markets have flights from Midway, the other airport located in the Chicago area. In addition, over 80% of passenger enplanements at Midway are on low-price airlines that may reasonably be said to target a different clientele from AA and UA. In that context, following Borenstein (1989) and Brander and Zhang (1990, 1993), we assume that flights to Midway and O'Hare airports are in separate markets.

(v) There is incomplete information on costs. Average costs per passenger per mile for a given airline are made public *ex post* on a networkwide basis (see, e.g., *The Airline Monitor,* 1994). Although AA and UA have information on each other's leasing and servicing contracts, information about a market's main operating costs remains private. It is accepted in the literature that mileage is the primary determinant of average costs in a market (see Caves, Christensen, and Tretheway, 1984; Borenstein, 1992; and Morrison and Winston, 1995). Actual costs in a market, however, are also affected by firm-specific idiosyncratic factors such as aircraft allocation and/or routing. In that context, quarterly operating costs may reasonably be considered to be independent across markets and i.i.d. across firms.

□ **Data.** Our data come from three databases: Databank 1A, Databank DS T-100, and the Official Airline Guide (OAG) publications. Databank 1A, from the U.S. Department of Transportation (DOT), is a 10% random sample of all airline tickets sold quarterly. It provides the itinerary and the price per mile for each passenger.[12] We consider itineraries that include nonstop flights between O'Hare and another U.S. airport and flights connecting two U.S. 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 in market m. Databank DS T-100 provides the number of passengers per major airline and per month in a market.

The sample data for our article are from the 3rd quarter of 1993. There are $M = 100$ Chicago markets in our sample data (see Appendix A). Eighty-three have flights from one or both AA and UA. The other 17 are major markets without flights from any airline.[13] The sample does not include every Chicago market with flights. For lack of data, 17 markets are excluded. Another 27 markets are excluded because they 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 another competitor's hub, or (iii) AA and UA have different numbers of hub airports in the market. The inclusion of these markets would require us to consider every possible airline and every potential market. Such a task is beyond the scope of the present article. In Table 1, we present summary statistics of the 100 sample markets. Note that the average quantity and prices for AA and UA are slightly different. In an incomplete-information framework, these differences are not incompatible with an assumption of symmetry.

□ **Demand and cost specifications.** We now turn to a discussion of the demand and cost specifications in the Chicago markets. We assume that the demand functions are known to the firms and exogenously determined. Therefore, we need 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: the 1st quarter of 1993 through the 3rd quarter of 1994. The inverse-demand function faced by airline i in a market m in quarter t is equal to

$$\begin{aligned} P_{i,m,t} &= \alpha_0 + \alpha_1 INC_m + \alpha_2 POP_m + \alpha_3 \ln(POP_m) + \alpha_4 MILES_m + \alpha_5 DPOP_m \\ &\quad + \alpha_6 QTR_t + \beta \sum_{m' \neq m}^{M} q_{i,m',t} + \lambda \sum_{m' \neq m}^{M} \sum_{j \neq i}^{N} q_{j,m',t} - \gamma \sum_{j=1}^{N} q_{j,m,t} + \varepsilon_{i,m,t}, \end{aligned} \tag{10}$$

where $\alpha_0, \ldots, \alpha_6$, β, λ, and γ are parameters known to the airlines, $\varepsilon_{i,m,t}$ is the error term, and the parameter β (λ) represents the complementarities between products within the same airline (across 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 in market m (source: 1990 Census data). $DPOP_m$ is a dummy variable accounting for larger markets and is equal to one if that metropolitan area has more than 2,600,000 inhabitants. These market

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

[13] A market is said to be a major market if both metropolitan areas have more than 350,000 inhabitants.

TABLE 1 Summary Statistics of Sample Data

State of the Market		Number of Markets	Average Quantity per Firm	Average Price	Average Mileage
Monopoly	American	14	13,586.61	92.74	441.14
(only one firm enters)			(8,055.24)	(62.93)	(463.91)
	United	29	19,191.53	138.13	754.13
			(8,699.98)	(39.90)	(385.78)
	Total	43	17,366.67	123.35	652.23
			(8,809.43)	(52.44)	(433.42)
Duopoly	American	40	31,302.64	127.91	—
(two firms enter)			(20,481.25)	(65.19)	
	United	40	36,635.66	128.71	—
			(26,628.18)	(63.44)	
	Total	40	33,969.15	128.31	698.17
			(22,066.86)	(64.13)	(556.02)
Active	American	54	26,709.59	118.79	631.53
(at least one firm enters)			(19,646.95)	(65.88)	(541.49)
	United	69	29,304.07	132.67	721.69
			(22,650.92)	(54.64)	(489.25)
	Total	83	25,367.86	125.74	674.37
			(18,466.34)	(58.06)	(668.51)
Overall		100	—	—	715.28
(100 markets)					(493.74)

Standard errors in parentheses.

characteristics—namely, mileage and alternate measures of population and income (e.g., logs, geometric means, etc.)—are standard in the estimation of demand functions in the empirical airline literature (see Reiss and Spiller, 1989, and Brueckner, Dyer, and Spiller, 1992). QTR_t is AA's and UA's average number of passengers in quarter t in U.S. markets (other than the 100 markets in our sample) active during all seven quarters. This time-effect variable controls for unobserved fluctuations in demand for AA and UA products. We also tested for, and failed to reject at a 5% level, each of the hypotheses of symmetry (across airlines) in the level of complementarities within firms (i.e., $H_0 : \beta_{AA} = \beta_{UA}$) and in the demand-slope parameters (i.e., $H_0 : \gamma_{AA} = \gamma_{UA}$).

The theoretic model is sequential, since firms choose quantities and then observe realized prices. Under the model's assumptions, quantities are therefore predetermined with regard to prices. We tested this hypothesis with the augmented regression approach outlined in Davidson and MacKinnon (1993). The test was performed using the instrumental variables $AMI_{m,t}$ and $API_{m,t}$, representing, respectively, the total number of active markets and the average number of passengers in active markets in period t across all airlines at the airport paired to O'Hare in market m.[14] We failed to reject the null hypothesis that the parameters of our demand model are consistently estimated (p-value is .58).

To allow for correlations between unobservable variables on duopoly markets, we use the feasible generalized-least-squares method. A preliminary estimation of (10) 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 reestimate the inverse-demand function under the constraint that $\lambda = 0$. We present our results in Table 2. Note that the parameter β is significantly greater than zero, which confirms that the hub-feeder effect and frequent-flyer programs generate complementarities

[14] The correlation between $\sum_{j=1}^{N} q_{j,m,t}$ and $AMI_{m,t}$ ($API_{m,t}$) is .71 (.54).

TABLE 2 Estimates for the Demand Specification

Variable	Parameter	Estimate	Standard Errors
Constant	α_0	−34.21	26.39
INC	α_1	1.72E10-3*	2.19E10-4
POP	α_2	1.03E10-5*	1.78E10-6
ln(POP)	α_3	9.66*	1.76
MILES	α_4	.11*	1.93E10-3
DPOP	α_5	37.30*	8.10
QTR	α_6	−2.28E10-3*	3.66E10-4
	β	3.05E10-6*	1.25E10-6
	γ	6.48E10-4*	5.27E10-5
$R_G^2 = .852$			

*Significant at the .05 level.

in demand across markets within a firm. We subsequently derive firms' optimal strategies using this estimated demand function.

AA and UA have long-term leases on their facilities at O'Hare, and we consider fixed airport costs (i.e., administrative costs, takeoff and landing slots, and costs for leasing facilities and ground equipment) as sunk prior to the sample period. Following Brander and Zhang (1990) and Hendricks, Piccione, and Tan (1997), we assume that marginal operating costs per passenger in a market are constant. We define the marginal cost of airline i in market m as $c_{i,m} = cpm_{i,m} \times MILES_m$, where $cpm_{i,m}$ is the cost per passenger per mile.[15] $cpm_{i,m}$ 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 takeoff (see Brander and Zhang, 1990). We estimate the distribution of the private types $cpm_{i,m}$ in the next section, using the structural econometric model.

5. Estimation of the structural model of firms' decisions

■ **Inference method.** The objective is to estimate the unknown parameter of the distribution of airlines' private costs $\theta = (\mu_0, \mu_1, \sigma) \in \Theta$, where $\Theta = \mathbb{R} \times]0, \infty[^2$. To do so, we apply the method of simulated moments (MSM) as originally introduced by McFadden (1989) and Pakes and Pollard (1989).

Consider the i.i.d sequence of observations $(q_m, z_m), m = 1, \ldots, M$, where $q_m = (q_{1,m}, q_{2,m})$ is the endogenous variable, $q_{i,m}$ is the quantity produced by firm $i = 1, 2$ in market m, and $z_m = MILES_m$ is the exogenous variable. Let us define the vectors $H(q_m)' = (q_{1,m}+q_{2,m}, I_{\{q_{1,m}>0\}} + I_{\{q_{2,m}>0\}})$ and $h(z_m, \theta) = (h_1(z_m, \theta), h_2(z_m, \theta)) = E_\theta[H(q_m) \mid z_m]$. In other words, $h_1(z_m, \theta)$ represents the expected total quantity supplied in market m, while $h_2(z_m, \theta)$ is the expected number of active firms on market m.

We consider the matrix

$$g(z_m)' = \begin{pmatrix} 1 & 0 & z_m & 0 \\ 0 & 1 & 0 & z_m \end{pmatrix}$$

to generate four moment conditions:

$$E_\theta [g(z_m)(H(q_m) - h(z_m, \theta))] = 0. \tag{11}$$

The generalized-method-of-moments (GMM) estimator is based upon the empirical counterpart

[15] There is some evidence of economies of density in the airline industry (see Caves, Christensen, and Tretheway, 1984, and Brueckner and Spiller, 1994), but we found no significant relation between marginal costs and quantities in our sample (see Section 5).

of the previous orthogonality conditions:

$$\hat{\theta}_{GMM} = \underset{\theta \in \Theta}{\operatorname{argmin}}[A_1' \Omega A_1], \qquad \text{where } A_1 = \sum_{m=1}^{M} g(z_m)(H(q_m) - h(z_m, \theta)), \tag{12}$$

and Ω is a 4×4 symmetric positive semidefinite matrix that may be chosen in order to minimize the variance of the estimator. Note that the model is overidentified, as we specify four moment conditions to estimate a parameter of only dimension three.

In our article, the GMM estimator is not directly implementable, since the expectations $h(z_m, \theta)$ cannot be derived analytically. Following the MSM technique, we propose to replace $h(z_m, \theta)$ by a Monte Carlo approximation

$$\overline{h}_{MC}(z_m, \theta) = (1/MC) \sum_{\ell=1}^{MC} \tilde{H}(\tilde{c}_\ell(m), z_m, \theta),$$

where $\tilde{H}(\cdot) = (\tilde{H}_1(\cdot), \tilde{H}_2(\cdot))$ and

$$\begin{aligned} \tilde{H}_1(\tilde{c}_\ell(m), z_m, \theta) &= \sum_{i=1}^{2} \varphi\left(\tilde{c}_{i,\ell}(m), \theta\right), \\ \tilde{H}_2(\tilde{c}_\ell(m), z_m, \theta) &= \sum_{i=1}^{2} I_{\left\{\varphi\left(\tilde{c}_{i,\ell}(m), \theta\right) > 0\right\}}. \end{aligned} \tag{13}$$

MC is the size of the Monte Carlo simulation, $\varphi(\cdot, \theta)$ is the symmetric equilibrium strategy derived in Section 3, and $\tilde{c}_\ell(m) = (\tilde{c}_{1,\ell}(m), \tilde{c}_{2,\ell}(m))$ are simulated pairs of costs randomly generated from the distribution $f(\cdot \mid \theta, z_m)$. Note that the derivation of the MSM estimator does not significantly increase the computational burden, since the vector $\overline{h}_{MC}(z_m, \theta)$ is previouly calculated, for each value of θ, in the approximation algorithm presented in Section 3.

Gourieroux and Monfort (1996) show that when MC is fixed, the MSM estimator is strongly consistent and asymptotically normal. In addition, the authors show that the optimal matrix Ω^*, which minimizes the variance of the estimator, is given by

$$\left(\Omega^*\right)^{-1} = \operatorname{var}_\theta\left[g(z_m)(H(q_m) - h(z_m, \theta))\right] + \frac{1}{MC} \operatorname{var}_\theta\left[g(z_m)\left(\tilde{H}(c_m, z_m, \theta) - h(z_m, \theta)\right)\right].$$

However, Ω^* depends upon the unknown distribution and cannot be derived directly. Following Gourieroux and Monfort (1996), Ω^* is replaced in practice by a sequence of consistent estimators

$$\begin{aligned} \left(\hat{\Omega}_{t+1}^*\right)^{-1} = {} & \frac{1}{M} \sum_{m=1}^{M} g(z_m) B_1\left(q_m, z_m, \hat{\theta}_t\right) B_1\left(q_m, z_m, \hat{\theta}_t\right)' g(z_m)' \\ & + \frac{1}{M \cdot MC} \sum_{m=1}^{M} g(z_m) B_2\left(q_m, z_m, \hat{\theta}_t\right) B_2\left(q_m, z_m, \hat{\theta}_t\right)' g(z_m)', \end{aligned}$$

where

$$\begin{aligned} B_1\left(q_m, z_m, \hat{\theta}_t\right) &= H(q_m) - \frac{1}{MC_2} \sum_{\ell=1}^{MC_2} \tilde{H}\left(\check{c}_\ell(m), z_m, \hat{\theta}_t\right) \\ B_2\left(q_m, z_m, \hat{\theta}_t\right) &= \tilde{H}\left(\tilde{c}_1(m), z_m, \hat{\theta}_t\right) - \frac{1}{MC_2} \sum_{\ell=1}^{MC_2} \tilde{H}\left(\check{c}_\ell(m), z_m, \hat{\theta}_t\right). \end{aligned}$$

$\tilde{c}_1(m)$ is the first element of the sequence $\{\tilde{c}_\ell(m)\}_{\ell=1,\ldots,MC}$; $\{\check{c}_\ell(m)\}_{\ell=1,\ldots,MC_2}$ is a new sequence of MC_2 pairs of simulated costs randomly generated from the distribution $f(\cdot \mid \hat{\theta}_t, z_m)$; $\hat{\theta}_t$ $(\forall t \geq 1)$ is the MSM estimator calculated with $\hat{\Omega}^*_{t-1}$; and $\hat{\Omega}^*_0$ is the identity matrix.

In practice, we consider $t = 5$, $MC = 10^6$, and $MC_2 = 10^9$. Computing is on the order of 88 minutes of CPU time on a recent SUN workstation. Standard deviations for the estimates are computed with a bootstrap technique of size 10^4.

□ **Estimation results.** We find the estimates for the parameters of the cost distribution to be $\hat{\theta} = (\hat{\mu_0}, \hat{\mu_1}, \hat{\sigma}) = (.193, 5.059\text{E}10^{-5}, 1.874\text{E}10^{-2})$ with a standard deviation of $(6.345\text{E}10^{-2}, 1.651\text{E}10^{-6}, 2.207\text{E}10^{-4})$. This corresponds to an aggregate average cost per passenger mile of \$.158 with a standard deviation of \$.025. It is difficult to find benchmarks to compare these figures on a market basis; \$.158, however, appears consistent with networkwide averages (see *The Airline Monitor*, 1994). Note that the standard deviation of $cpm_{i,m}$ is nonnegligible. This indicates that networkwide averages are an imperfect measurement of the marginal cost in a given market. This finding reinforces our assumption of incomplete information at the market level in the case of the airline industry.

The simulations within the algorithm provide, for each market, expected quantities, prices, profits, and the probability that a firm will enter (see Tables 3 and 4).[16] The estimated probabilities of entry are consistent with the observed number of active firms in a sample market. Namely, the average probability that a firm enters a market is equal to .86 across markets in duopoly in our sample, .68 across sample markets in monopoly, and .39 across inactive sample markets. As shown in Table 4, estimated quantities and prices fit the observations for AA and UA well. We also estimate that AA earned expected profits of \$36,654,003 and UA earned \$41,092,663 during the sample period, conditional upon observed entry decisions. Note that these figures do not include all sunk costs and that they are consistent with previous studies (see Borenstein, 1989, and Brander and Zhang, 1990). A market's consumer surplus is equal to $\gamma\,(q_{AA} + q_{UA})^2/2$, where q_{AA} (q_{UA}) is the quantity AA (UA) produced in that market. The disparity in expected quantities across markets explains the large standard deviation associated with the average consumer surplus in Table 3. Finally, a regression indicates that expected quantities do not have a significant effect on estimated marginal costs (the p-value equals .61). This result confirms that there are no economies of density in our sample markets.

TABLE 3 **Incomplete Information Simulation Results: Average Across All Markets**

	State of the Market			
	Monopoly (Only One Firm Enters)	Duopoly (Two Firms Enter)	Active (At Least One Firm Enters)	Overall (100 markets)
Probability that the market is	.32	.54	.86	—
	(.19)	(.36)	(.28)	
Expected quantity per firm	27,429.00	27,130.17	27,199.00	18,992.84
	(20,657.04)	(20,772.13)	(20,386.48)	(14,282.98)
Expected price	133.56	121.00	123.89	—
	(61.46)	(57.07)	(57.84)	
Expected profit per firm	804,538.52	392,865.68	486,968.57	340,725.41
	(1,184,272,21)	(584,678.93)	(699,237.09)	(488,335.02)
Expected consumer surplus	302,607.07	2,014,144.56	1,127,444.41	981,921.02
	(448,104.03)	(3,485,116.57)	(2,572,921.30)	(2,367,420.58)

Standard errors in parentheses.

[16] Detailed results are available upon request.

TABLE 4 Comparison Between Observations and Simulations

		Relative Difference Between Actual and Simulated Expected	
		Quantity (in %)	Price (in %)
Sample markets in monopoly	American	−.51	−2.46
		(14.31)	(14.72)
	United	.03	.30
		(16.14)	(9.29)
	Total	−.15	−.60
		(15.40)	(11.24)
Sample markets in duopoly	American	−5.40	.41
		(28.81)	(9.97)
	United	5.44	1.79
		(25.46)	(11.13)
	Total	.02	1.27
		(10.36)	(9.74)
Active sample markets	American	−4.13	−.34
		(25.80)	(11.31)
	United	3.17	1.17
		(22.05)	(10.35)
	Total	−3.65	.30
		(12.63)	(10.52)
Overall	Per firm	−.07	.30
		(13.13)	(10.52)

Standard errors in parentheses.

6. Exchanges of cost information in airline alliances

■ We now quantify the effects of exchanges of cost information as they pertain to the AA/UA duopoly at O'Hare.

Fried (1984), Gal-Or (1986), and Shapiro (1986) analyze exchanges of cost information in single-market models of Cournot competition with linear demand and incomplete information on constant marginal costs of production. They find that expected profits and welfare increase when oligopolists choose to exchange cost information truthfully. Such exchanges increase efficiency by raising the market shares of lower-cost firms and reducing the variability of aggregated output. The reduction of output volatility, however, decreases expected consumer surplus, because the latter is a convex function of output.[17]

Armantier and Richard (2001) show that this result need not hold in multimarket models with entry and complementarities across markets. When complementarities are different across firms, changes in production decisions may yield greater expected consumer surplus for firms that exchange cost information (see an example in Appendix B). The authors also find that consumers in smaller markets tend to benefit more.

Following Shapiro (1986), we assume that firms, before observing their own cost vector, agree to exchange cost information.[18] Under this agreement, firms truthfully reveal to each other their cost vector c_i and then compete under complete information by selecting an output

[17] Armantier and Richard (2002) extend these analyses to examine the effects of exchanges of cost information on entry decisions.

[18] 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.

TABLE 5 Complete Information Simulation Results: Average Across All Markets

	State of the Market			
	Monopoly (Only One Firm Enters)	Duopoly (Two Firms Enter)	Active (At Least One Firm Enters)	Overall (100 markets)
Probability that the market is	.52	.46	.98	—
	(.25)	(.30)	(.21)	
Expected quantity per firm	41,170.47	24,577.39	30,564.647	22,004.37
	(25,847.47)	(19,314.73)	(21,474.42)	(15,452.03)
Expected price	130.16	127.04	128.08	—
	(59.55)	(59.04)	(58.96)	
Expected profit per firm	1,176,839.39	516,927.94	754,974.62	544,199.725
	(1,626,334.05)	(751,433.30)	(1,030,123.59)	(744,184.14)
Expected consumer surplus	333,348.38	1,893,240.42	1,085,103.58	978,405.64
	(450,119.43)	(3,160,894.11)	(2,338,940.18)	(2,149,882.41)

Standard errors in parentheses.

level for each of the M markets. Following Fried, Gal-or, and Shapiro, we assume that firms can transfer and verify each other's reports at no cost. All previous assumptions regarding demand and costs are maintained. Under complete information, the Nash equilibrium obtains numerically from the first-order conditions of the firms' optimization problem. To estimate expected profits and consumer surplus, we simulate competition under the agreement over the 100 sample markets. Private signals are simulated from the distribution estimated in Section 5. The results of these simulations are summarized in Table 5 and compared to those in Table 3.

There is a larger probability that a market is active under complete information. Markets are more likely to be in a monopoly and less likely to be in a duopoly under complete information. Expected aggregated profits are consequently larger in every market (by 27% on average). Hence, firms benefit by entering into an agreement to exchange cost information. Under complete information, expected aggregated consumer surplus decreases by only 3.6%. Consumer surplus is also larger in most markets (61%) under complete information. Consumers in small markets (i.e., markets with low expected quantities) benefit the most, since these markets are more likely to be active. In summary, exchanges of cost information improve expected profits and increase consumer surplus in a majority of markets.

7. Concluding remarks

■ Our objective in this study was to extend the existing literature by analyzing the effect of exchanges of cost information in the airline industry. We have considered a multimarket model of competition with entry, incomplete information, and demand complementarities across markets. In addition, we have developed a numerical method to calculate the equilibrium solution. The subsequent structural estimation and simulations reveal that exchanges of cost information increase profits, only moderately lower the consumer surplus, and actually benefit consumers in a majority of markets. This result contrasts with previous findings in single-market industries.

Our results are limited to a hypothetical cost-sharing agreement in a symmetric duopoly setting, and they presuppose the existence of a mechanism to truthfully and costlessly exchange information. Such a mechanism may be difficult to implement in practice. Airlines may further face incomplete information on the demand side that may affect incentives to share information and benefits to consumers (see Vives, 1999). Although we identify some benefits to consumers of cost sharing, we recognize that cost sharing is only a small part of airline alliances. Marketing alliances are actually complex, multifaceted agreements that include other components, such as coordination of flight schedules and frequent-flyer programs, that we did not attempt to account for.

Our research indicates that agreements to exchange cost information may have a positive effect on consumer surplus in multimarket settings. Policy makers should therefore determine the nature of this effect before approving any such exchanges. The combination of theory, econometrics, and numerical analysis in the present article provides a powerful tool to quantify precisely how exchanges of cost information affect consumer surplus. Our analysis of competition under incomplete information can be extended to the structural estimation of models with asymmetric firms, endogenous demand and/or dynamic decision making. The methodology can also be applied to other multimarket industries with demand complementarities, such as, for instance, the home electronics and software industries.

Appendix A

TABLE A1

#	Market with Flights from 1 Airline	Airline	Miles	#	Market with Flights from AA and UA	Miles	#	Markets with No Flights	Miles
1	Albuquerque, NM	AA	1,118	44	Albany, NY	723	84	Wilkes-Barre/Scranton, PA	631
2	Bloomington, IL	AA	116	45	Austin, TX	972	85	Fresno, CA	1,730
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	1,732
5	El Paso, TX	AA	1,236	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	1,040
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	1,437	57	Green Bay, WI	174	97	McAllen, TX	1,238
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	1,803
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	1,437	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	1,182	68	Omaha, NE	416			
26	Spokane, WA	UA	1,498	69	Ontario, CA	17,003			
27	Greensboro, NC	UA	590	70	Portland, OR	1,739			
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	61	San Diego, CA	1,723			
32	Lexington, KY	UA	323	75	San Antonio, TX	1,041			
33	Lincoln, NE	UA	466	76	Seattle/Tacoma, WA	1,721			
34	Saginaw, MI	UA	222	77	San Jose, CA	1,829			
35	Manchester, NH	UA	843	78	Sacramento, CA	1,781			
36	Oakland, CA	UA	1,835	79	Orange County, CA	1,726			
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	1,012			
40	Fort Myers, FL	UA	1,120	83	Tulsa, OK	585			
41	Savannah, GA	UA	773						
42	Louisville, KY	UA	286						
43	Knoxville, TN	UA	475						

Appendix B

■ The following example illustrates that expected profits and consumer surplus can be higher in multimarket models when firms truthfully exchange cost information.

There are two markets ($m = 1, 2$) and two symmetric firms ($i = 1, 2$). The inverse-demand function for firm i in market m is common knowledge and linear: $p_{im} = 1 + .45q_{i,-m} + .1q_{-i,-m} - (q_{i,m} + q_{-i,m})$, where $q_{i,m}$ is firm i's quantity in market m and p_{im} is firm i's price in market m. The cost function of firm i in market m is given by $C(q_{i,m}) = c_{i,m}q_{i,m}$, where $c_{i,m}$ is uniformly and independently distributed over the interval $[0, 1]$. The distribution of marginal costs is common knowledge. The two firms simultaneously decide whether to enter and how much to produce in each of the two markets. We consider two scenarios: in the incomplete-information scenario, $(c_{i,1}, c_{i,2})$ is known only to firm i, while in the complete-information scenario, firms truthfully exchange cost information so that $c_{i,m}$ is common knowledge $\forall i, m = 1, 2$. The optimization problem under each scenario is solved numerically with the algorithm introduced in Section 3. Table B1 summarizes 50,000 Monte Carlo simulations. Under complete information, expected profits and expected consumer surplus increase by 32% and 8%, respectively. Note also that under complete information, the probability that a firm is in monopoly (duopoly) increases (decreases) and the quantity produced by a monopolistic (duopolistic) firm sharply increases (decreases).

TABLE B1 **Simulation Results**

	State of the Market			
	Monopoly (Only 1 Firm Enters)	Duopoly (Firms 1 and 2 Enter)	Active (At Least 1 Firm Enters)	Overall
Complete-Information				
Probability that the market is	.599	.401	1.000	—
Expected cost per firm	.342	.421	.374	.499
Expected quantity per firm	.572	.285	.457	.286
Expected price	.673	.579	.635	—
Expected profit per firm	.207	.067	.151	.089
Expected consumer surplus per market	.177	.178	.178	.178
Incomplete-Information				
Probability that the market is	.213	.770	.983	—
Expected cost per firm	.443	.445	.444	.499
Expected quantity per firm	.295	.291	.292	.255
Expected price	.841	.575	.633	—
Expected profit per firm	.137	.057	.075	.059
Expected consumer surplus per market	.057	.197	.167	.164

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