Flight Frequency and Mergers in Airline Markets

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Abstract

The welfare consequences of airline mergers have been analyzed almost exclusively in terms of ticket price. However, when flight frequency decisions are endogenized in a model, we can estimate measures of the relative importance of price and flight frequency in customer decisions. Hence, in a merger analysis, we can not only predict changes in flight frequency, but also the consequences of those changes on consumer welfare. In this paper, merger simulations suggest that while passenger volume and consumer surplus decrease on the aggregate, some markets benefit from welfare gains once merger-induced changes in flight frequency are factored in.

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1. Introduction

Studies of airline mergers have focused almost exclusively on ticket price when determining consumer welfare, often suggesting that because mergers tend to raise ticket prices, consumers are harmed (e.g. Borenstein (1990), Kim and Singal (1993)).[1] This approach, however, is based on the notion that consumers value only price and omits additional considerations that affect consumer choices, such as flight frequency. Indeed, consumers value the convenience of a flight schedule with multiple departure times, because they are then more able to find a flight that is closer to their desired departure time. To jointly incorporate valuation of ticket price and flight frequency requires a model with endogenous flight decisions, which this paper provides and estimates on a sample of U.S. markets.[2] Hence, I can predict not only changes in flight frequency in a merger, but also the relative consequences of those changes on consumer welfare.

I find that even though the net consumer surplus, as it relates to passengers on nonstop flights, falls by 20% on average following a merger, it increases in 11% of the sample markets. In those markets, consumers benefit despite the reduced competition, once increases in flight frequency following the merger are factored in, a result that derives from the comprehensiveness of the model. The importance of getting a full

[1] See, as well, Werden, Joskow, and Johnson (1991), Brueckner, Dyer and Spiller (1992), Morrison (1996), and the U.S. General Accounting Office (e.g. GAO/RCED90-102, Washington D.C.) for insighful discussions of fare changes, using hedonic regressions on pre- and post-merger ticket prices. Topics reviewed include TWA's purchase of Ozark Airlines, and the Northwest/Republic Airlines and US Airways/Piedmont Airlines mergers in 1985-1988. Papers by Brueckner (2001) and Bamberger, Carlton and Neuman (2000) provide valuable insights on price changes in airline alliances during the 1990's.

[2] While the empirical work of Berry (1990), Morrison and Winston (1995), and Berry, Carnall, and Spiller (1997) provides interesting structural models where several factors are considered in consumer decisions, these do not endogenize airlines' frequency decisions.

picture of consumer welfare is particularly clear in the airline industry, where policy makers now consider consumer welfare the deciding factor in antitrust cases.

The paper is structured as follows. Section 2 introduces the model and Section 3 describes the application and data. Section 4 outlines the functional forms and estimation methodology. Section 5 discusses the estimation results. Section 6 analyzes the consumer welfare consequences of hypothetical mergers. Section 7 concludes.

2. A Model of Firms' Decisions

Consider a market with two airlines ($i = 1, 2$) with nonstop flights (hereafter flights), where a market is defined as a pair of U.S. airports without reference to an origin and destination. For example, the pairs of airports Miami-Chicago O'Hare and Chicago O'Hare-Miami are the same market. In the market, let f_i be airline i's number of flights (or flight frequency); q_i be the number of tickets sold by airline i (i.e., its passenger volume); and p_i be the airline's ticket price. Finally, let q_0 be the numeraire good; that is, a composite good that represent all commodities other than those under consideration.

To develop the simplest structural model, and to endogenize flight frequency decisions, I assume that there is, on the demand side, a single representative consumer with a utility function that is quasilinear in the numeraire good and quadratic in the number of airline tickets that the consumer purchases:

$$U(q_0, q_1, q_2) = q_0 + \sum_{i=1}^{2} \alpha_i q_i - \frac{1}{2}\beta \left(\sum_{i=1}^{2} q_i^2 + 2\theta q_1 q_2 \right) \quad , \tag{2.1}$$

where α_i, β and θ are parameters, with α_i, $\beta \geq 0$ and $-1 \leq \theta \leq 1$.[3] In (2.1), airline products may be imperfect substitutes and, to the extent that the valuation parameters α_i differ across airlines, the consumer may prefer one brand to the other.

The effective price of airline i's good to the consumer is assumed to be additively separable in the airline's ticket price and the consumer's cost of schedule delay with airline i. Following Douglas and Miller (1972), this cost represents the dollar value of the time difference between the consumer's desired departure time and the closest scheduled departure time on airline i. This time difference is specified as inversely proportional to airline i's flight frequency. I assume that airline i's effective price, P_i, is equal to $p_i + \frac{\gamma}{\sqrt{f_i}}$, where γ is a parameter and $\frac{\gamma}{\sqrt{f_i}}$ is the consumer's cost of schedule delay on airline i.[4] Airline models with effective prices include, among others, Panzar (1979), Lederer (1993), Morrison and Winston (1995), and Brueckner and Zhang (2001).[5]

The representative consumer maximizes $U(q_0, q_1, q_2) - q_0 - \sum_{i=1}^{2} P_i q_i$, and this op-

[3] The model may be modified to include many consumers of the same type with utility as in (2.1). For example, to include K consumers while maintaining aggregate output of product i at q_i (i.e. each consumer ultimately buys q_i/K), we may rescale β to βK in (2.1) and write airline i's profits in (2.3) as $\sum_{k=1}^{K} (p_i - c_{i,q})\ q_{i,k} - c_{i,f}\ f_i$, where $q_{i,k}$ is the quantity of product i purchased by consumer k. The first-order conditions are comparable to (2.4)-(2.5), and the welfare analysis in my paper is unchanged.

[4] If flights are located at equal time intervals (along the 24-hr circle) and desired departure times are uniformly distributed, then the distance from the closest scheduled departure time on airline i is on average proportional to $\frac{1}{f_i}$. However, as Borenstein and Netz (1999) remark, an airline actually groups some of its departure times, so that a specification of $\frac{1}{\sqrt{f_i}}$, which is less convex in the flight frequency, is more appropriate. Empirically, a square root specification yields a better fit than a linear one.

[5] Alternative interpretations of the cost of schedule delay have been offered in the literature. For instance, a consumer may be willing to pay a higher price for an airline with multiple daily flights since he knows he gets priority seating on another flight of this airline should his original flight be cancelled. The consumer may also value frequent flyer miles, in which case a schedule with a higher number of daily flights affords the consumer greater flexibility in future travel plans. Note that Panzar (1979), Lederer (1993) and Brueckner and Zhang (2001) are theoretical analyses of location of flight departure times, while Morrison and Winston (1995) provide an in-depth empirical overview of the industry.

timization problem yields the following system of linear inverse demand functions:

$$P_i = \alpha_i - \beta q_i - \beta\theta q_{-i} \qquad i = 1, 2 \quad , \tag{2.2}$$

where goods are substitutes, independent, or complements according to $\theta \gtreqless 0$.

Following Reiss and Spiller (1989), Brander and Zhang (1990) and Hendricks, Piccione, and Tan (1997), I assume that airlines have constant marginal costs. Let $c_{i,q}$ denote airline i's marginal cost per passenger and $c_{i,f}$ be its marginal cost per flight.

The two airlines simultaneously maximize profits by selecting their number of flights and of passengers for these flights. In other words, firm i maximizes its profits by selecting a flight frequency f_i^* and a quantity q_i^* such that:

$$\begin{aligned} (q_i^*, f_i^*) &= Arg \max_{q_i, f_i} (p_i - c_{i,q})\ q_i - c_{i,f}\ f_i \\ &= Arg \max_{q_i, f_i} \left(\alpha_i - \beta q_i - \beta\theta q_{-i} - \frac{\gamma}{\sqrt{f_i}} - c_{i,q} \right) q_i - c_{i,f}\ f_i \ . \end{aligned} \tag{2.3}$$

The first-order conditions (hereafter FOC) to the problem in (2.3) are:

$$\frac{\gamma q_i}{2 f_i \sqrt{f_i}} - c_{i,f} = 0 \qquad , \tag{2.4}$$

$$\alpha_i - 2\beta q_i - \beta\theta q_{-i} - \frac{\gamma}{\sqrt{f_i}} - c_{i,q} = 0 \qquad i = 1, 2 \ , \tag{2.5}$$

where equation (2.4) is the FOC with respect to f_i and (2.5) is the FOC with respect to

q_i. Substituting (2.4) in (2.5), I obtain that:

$$\alpha_i - 2\beta q_i - \beta\theta q_{-i} = c_{i,q} + \frac{\gamma^{2/3}(2c_{i,f})^{1/3}}{q_i^{1/3}} \ . \tag{2.6}$$

Equation (2.6) shows that the model may be re-interpreted in terms of economies of density; that is, all else equal, the marginal *cost* per passenger (here, a composite of airline and consumer costs) decreases with the number of passengers. Such specifications are common to the airline literature (see Caves, Christensen, Tretheway (1984), Brueckner and Spiller (1991, 1994), Berry, Carnall and Spiller (1997)) and are typically introduced from cost-based conjectures.[6] My model highlights that such economies may likewise obtain from a consumer's valuation of time delays. In other words, there are economies of schedule delay, indexed by the parameter γ, on the demand side.

3. An Application

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

In this paper, I examine the decisions of American Airlines (hereafter AA) and United Airlines (UA) in markets at Chicago O'Hare airport (ORD). I justify the maintained hypotheses of Section 2's model according to the following facts:

(i) At O'Hare, AA and UA are in duopoly competition, as assumed by Brander and Zhang (1990, 1993). This airport is a major hub for AA and UA. These two airlines

[6] The traditional conjecture is that a larger passenger volume can be accomodated with larger aircraft which have a lower cost per passenger. See Brueckner and Spiller (1991, 1994) and Brueckner (2001) for interesting applications of this concept to the analysis of, respectively, airline mergers and alliances.

jointly account for 90% of passenger enplanements at O'Hare and, together, they 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 on just 8 markets. In this context, the implicit hypothesis that there are no substitutes competing with flights offered by AA and UA over the sample hub markets is reasonable.[7]

(ii) The internal structure of airline companies is such that Marketing and Fleet Assignment Groups at the airlines first simultaneously determine the aggregate number of passengers and flights on each of the sample markets. In practice, changes in aggregated quantities and flights are rare and costly, while price fluctuations are numerous. This is reasonably consistent with a Cournot model where firms commit to quantities and then prices adjust along the reaction curves. The Cournot assumption is common to most empirical studies on the airline industry (e.g. Reiss and Spiller (1989), Armantier and Richard (2002)). In addition, Brander and Zhang (1990) find empirical support for the hypothesis of Cournot competition between AA and UA at Chicago O'Hare. My model remains nevertheless a simplification of airline behavior as I do not consider, for instance, capacity choices and issues of aircraft landing and take-off slots at O'Hare.

[7] The inclusion of potential substitutes would require that I 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 this paper.

3.2. Data

I have monthly passenger, frequency, and cost data for the year 1993. The Databank 28DS T-100, maintained by the U.S. Department of Transportation, reports the monthly number of nonstop flights and passengers per market and per major airline. It indicates the mix of aircraft types used, but it provides no flight scheduling information. The Aircraft Operating Costs and Statistics, from AVMARK Inc., provide network-wide operating costs per type of jet aircraft and per major airline. As airlines primarily base aircraft assignment on mileage and network-wide routing, I assume that the mix of aircraft types used in a market is invariant to frequency choices. I then combine the aircraft data in the two databases to create airline cost variables.[8]

The sample data consist of duopoly (i.e. AA and UA) markets with Chicago-O'Hare and each of 26 different U.S. airports, across each of the 12 months of 1993. There are thus 312 markets with two airlines in the sample data for a total 624 airline observations. The non-O'Hare airports are in large metropolitan areas (e.g. New York, San Diego), in hub cities of AA and UA (e.g. San Francisco, Nashville), and in midsize Midwestern and Eastern metropolitan areas that feed into AA and UA's O'Hare hub (e.g. Rochester (NY), Grand Rapids (MI)).[9] A complete listing of the sample markets is provided in

[8]Since markets are defined as non-directional, the quantity and frequency values in a market are calculated by averaging values across both directions in the market (e.g. O'Hare-Rochester and Rochester-O'Hare). Values for the cost variables are computed as a weighted average across the types of aircraft used each month between two airports. The cost data are for the first quarter of 1993 and figures are then adjusted to yield monthly data based on the monthly index for the cost of jet fuel. Note that the source of the cost data is the Form 41 database, maintained by the U.S. Department of Transportation.

[9]Subsidiaries of AA and UA are associated with their parent company. Some subsidiaries at O'Hare do not report to Databank 28DS T-100. Markets with these airlines are identified using the Official Airline Guides and they are excluded from the sample due to lack of data.

Appendix 1 and descriptive sample statistics are provided in Table 1.

[Table 1 here]

4. Estimation of the Model of Firms' Decisions

I propose to estimate the system of first-order conditions (2.4)-(2.5). As I do not observe the firms' marginal costs or demand functions, I specify in this Section their functional forms and I outline the estimation methodology.

4.1. Functional Forms

Given the monthly data, the decision variables in Section 2's model (i.e. flight frequency, quantity) are defined on a monthly basis. I index the sample markets by the subscript t, where $t = 1, ..., 312$, so that $f_{i,t}$ represents airline i's number of flights (or flight frequency) in market t, and $q_{i,t}$ is its total number of tickets sold in that market (i.e. its passenger volume).

Firm i's marginal cost per flight in equation (2.4) is specified as follows:

$$\begin{aligned} c_{i,f,t} &= \lambda_{0,i} + \lambda_1 MILES_t + \lambda_2 COST_{i,t} + \lambda_3 FUEL_{i,t} + \lambda_4 CASM_{i,t} \\ &\quad + \lambda_5 WINTER_t + \varepsilon_{i,f,t} \qquad i = AA, UA, \quad t = 1, .., 312, \end{aligned} \tag{4.1}$$

where $\varepsilon_{i,f,t}$ is the error term, $\lambda_{0,i}, ..., \lambda_5$ are the parameters, and $\lambda_{0,i}$ (i.e. the intercept) is specific to each airline to account for fixed unobserved differences in frequency costs across airlines. $MILES_t$ is the mileage between the airports in the market. $COST_{i,t}$ is a measure of airline i's crew and insurance operating costs, and $FUEL_{i,t}$ is a measure of its fuel costs. I expect positive coefficients on these variables. $CASM_{i,t}$ denotes the operating cost per available seat-mile for airline i. As the cost per available seat-mile is lower for larger aircraft and larger aircraft are more costly to fly, I expect a negative coefficient for $CASM_{i,t}$. $WINTER_t$ is a dummy variable equal to 1 for markets in the months of November, December, January and February, and equal to 0 for all other markets. This variable controls for weather-related fluctuations in frequency costs.[10] The error term $\varepsilon_{i,f,t}$ then accounts for residual unobserved idiosyncratic factors that may affect costs in a market, such as high winds.

Firm i's marginal cost per passenger in equation (2.5) is given by:

$$c_{i,q,t} = \omega_{0,i} + \omega_1 MILES_t + \omega_2 CASM_{i,t} + \varepsilon_{i,q,t} \qquad i = AA, UA, \quad t = 1, .., 312, \quad (4.2)$$

where $\varepsilon_{i,q,t}$ is the error term, $\omega_{0,i}, ..., \omega_2$ are the parameters, and $\omega_{0,i}$ (i.e., the intercept) is specific to each airline to account for fixed unobserved differences in passenger costs across airlines. The marginal cost per passenger rises with the airline's cost per available seat-mile, and I expect a positive coefficient on $CASM_{i,t}$ in (4.2).

As a consumer's dollar valuation of time delays is a function of her income, I specify that the cost of schedule delay associated with airline i in market t is in fact equal to $\frac{\gamma INC_t}{\sqrt{f_{i,t}}}$, where INC_t is the median household income at the non-Chicago metropolitan area in the market (source: Census data for metropolitan areas, 1990). After substituting

[10] The $WINTER$ variable was added following tests on the presence of fixed effects for individual months. Within each of the $WINTER$ and non-$WINTER$ months, coefficients on the dummy variables for individual months do not significantly differ from each other.

for the effective price in the inverse demand function for firm i in (2.2), the empirical inverse demand function is written as follows:

$$\begin{aligned} p_{i,t} &= \alpha_{0,i} + \alpha_1 MILES_t + \alpha_2 POP_t + \alpha_{3,i} HUB_{i,t} + \alpha_4 INC_t + \alpha_5 MONTH_t \\ &\quad -\beta q_{i,t} - \beta\theta q_{-i,t} - \frac{\gamma INC_t}{\sqrt{f_{i,t}}} + \varepsilon_{i,d,t} \qquad i = AA, UA, \quad t = 1,..,312, \quad (4.3) \end{aligned}$$

where $\varepsilon_{i,d,t}$ is the error term, and $\alpha_{0,i}, ..., \alpha_5, \beta, \theta, \gamma$ are the parameters. POP_t is the population of the non-Chicago metropolitan area in the market, and $HUB_{i,t}$ is equal to the population of the non-Chicago area if the non-ORD airport is also a major hub for airline i. In the sample, these airports are Nashville and Raleigh-Durham for AA, and San Franscico, Seattle and Washington D.C. for UA. $MONTH_t$ is defined, in each sample month, as the sum of AA and UA's average number of passengers in that month in U.S. markets (other than the markets in the sample) with flights during all twelve months of 1993. This variable controls for monthly variations in consumer demand. The error term $\varepsilon_{i,d,t}$ accounts for unobserved residual idiosyncratic factors that may affect demand in a market, such as conventions or special cultural events.

Hence, the consumer's valuation for airline travel in (4.3) depends upon an airline-specific dummy variable (i.e., the intercept $\alpha_{0,i}$ is specific to each airline), unobserved factors ($MONTH_t$, $\varepsilon_{i,d,t}$), and demographics of the market and its non-Chicago metropolitan area ($MILES_t$, POP_t, INC_t, and $HUB_{i,t}$). Here, I recognize that larger, wealthier metropolitan areas tend to be major administrative, financial, and economic centers, and a consumer in these markets may have higher valuation for airline service. Markets linking O'Hare to another hub airport of AA and UA may also be more valuable to the consumer, as they afford greater flexibility in travel opportunities beyond the market itself. The range of these opportunities increases with the hub's size, which is itself proportional to the population of the city. This explains the variable $HUB_{i,t}$ in (4.3) and, given the disparity in the size of the non-O'Hare hub cities across airlines, the coefficient of $HUB_{i,t}$ is airline-specific (i.e., parameter $\alpha_{3,i}$). Similarly, the consumer may value the travel opportunities afforded by AA and UA's hub networks at O'Hare. As these hub networks are (essentially) invariant in 1993, their characteristics may be proxied for with an airline-specific dummy variable in the demand intercept, as I have done in (4.3) (i.e., $\alpha_{0,i}$).[11] These airline dummy variables may, as well, proxy for the consumer's valuation of AA and UA's frequent flyer programs and related marketing devices (see Borenstein (1990), Morrison and Winston (1995)).

Substituting the specifications (4.1)-(4.3) in the FOC (2.4)-(2.5), I obtain the following system of equations: $\forall\ i = AA, UA,\ t = 1, .., 312,$

$$\frac{\gamma INC_t q_{i,t}}{2 f_{i,t}\sqrt{f_{i,t}}} - (\lambda_{0,i} + \lambda_1 MILES_t + \lambda_2 COST_{i,t} + \lambda_3 FUEL_{i,t} + \lambda_4 CASM_{i,t} + \lambda_5 WINTER_t + \varepsilon_{i,f,t}) = 0 \quad , \tag{4.4}$$

$$(\alpha_{0,i} - \omega_{0,i}) + (\alpha_1 - \omega_1)\, MILES_t + \alpha_2 POP_t + \alpha_{3,i} HUB_{i,t} + \alpha_4 INC_t + \alpha_5 MONTH_t - \omega_2 CASM_{i,t} - 2\beta q_{i,t} - \beta\theta q_{-i,t} - \frac{\gamma INC_t}{\sqrt{f_{i,t}}} + (\varepsilon_{i,d,t} - \varepsilon_{i,q,t}) = 0\ . \tag{4.5}$$

[11]Indeed, we may consider adding to (4.3) characteristics of all adjacent markets at O'Hare, such as average population and income at all non-O'Hare metropolitan areas accessible from O'Hare with nonstop flights. As AA and UA's networks of markets at O'Hare do not vary in any significant fashion in 1993, adding these characteristics is equivalent to adding an airline dummy variable to (4.3).

The parameters of the system (4.4)-(4.5) can only be identified up to a constant of proportionality, and the pairs of parameters $(\alpha_{0,i}, \omega_{0,i})$ and (α_1, ω_1) cannot be separately identified. Hence, I propose to rewrite the FOC as follow: $\forall\ i = AA, UA,\ t = 1, .., 312$,

$$\frac{INC_t q_{i,t}}{2f_{i,t}\sqrt{f_{i,t}}} - (\lambda_{0,i}^* + \lambda_1^* MILES_t + \lambda_2^* COST_{i,t} + \lambda_3^* FUEL_{i,t} + \lambda_4^* CASM_{i,t} + \lambda_5^* WINTER_t + \varepsilon_{i,f,t}) = 0 \quad , \tag{4.6}$$

$$\alpha_{0,i}^* + \alpha_1^* MILES_t + \alpha_2^* POP_t + \alpha_{3,i}^* HUB_{i,t} + \alpha_4^* INC_t + \alpha_5^* MONTH_t - \omega_2^* CASM_{i,t} - q_{i,t} - \frac{\theta}{2} q_{-i,t} - \frac{\gamma^* INC_t}{\sqrt{f_{i,t}}} + \varepsilon_{i,dq,t} = 0 \ , \tag{4.7}$$

where $\lambda_k^* = \frac{2\lambda_k}{\gamma}$, $\alpha_j^* = \frac{(\alpha_j - \omega_j)}{2\beta}$ for $j = 0, 1$, $\alpha_k^* = \frac{\alpha_k}{2\beta}$ for $j \geq 3$, $\omega_2^* = \frac{\omega_2}{2\beta}$, $\gamma_k^* = \frac{\gamma}{2\beta}$, and $\varepsilon_{i,dq,t}$=($\varepsilon_{i,d,t}$-$\varepsilon_{i,q,t}$). The parameters in (4.6)-(4.7) can now be identified, and I assume that the residual error terms $\varepsilon_{i,f,t}$ and $\varepsilon_{i,dq,t}$ have mean zero and are independent across markets.[12]

4.2. Estimation Methodology

I estimate the parameters in equations (4.6)-(4.7) with the Nonlinear Three-Stage Least Squares method (see Appendix 2 for details). The instrumental variables are the model's exogenous variables. I find no evidence of heteroskedasticity in the estimated residuals. Given the estimated parameters, I compute predicted flight frequencies and passenger quantities on a market by the bootstrap method using a random draw of 100 residuals.

[12]Having controlled for fixed monthly effects in (4.6) with the variable $WINTER_t$, I tested for the inclusion of dummy variables for individual months in (4.7), which already includes the control variable $MONTH_t$. The coefficients on these variables were not significantly different from 0 at a 10% level, and these variables were not included, for parsimony.

Estimation and prediction results are listed in Table 2.

[Table 2 roughly here]

5. Estimation Results

The range and moments of the predicted values match closely with the sample data (see Table 2). In particular, correlations between observed and predicted flight frequencies and passenger quantities are, respectively, 0.91 and 0.94. This attests to the goodness of fit of the model and provides support for the specification choices.

The estimated value for the cost of schedule delay parameter γ^* is positive and significantly different from zero at a 1% level. In other words, the data suggest that the airline consumer significantly values the convenience of a flight schedule with multiple departure times. The second-order conditions to the firms' optimization problem in (2.3) require that $3q_{i,t}\sqrt{f_{i,t}} > \widehat{\gamma}^* INC_t$ for $i = AA, UA$ (i.e. $\gamma^* = \gamma/2\beta$). These conditions hold for each airline across all sample markets at the estimated value for γ^*, providing additional support for the model.

In the cost estimates, the cost per flight is found to increase with the mileage of the market, with crew and insurance costs, and with fuel expenses (i.e., $MILES_t$, $COST_{i,t}$, $FUEL_{i,t}$). It is estimated to be lower in the winter months (i.e., $WINTER_t$). This may be due to lower industry-wide consumption of jet fuel in those months, as airlines tend to scale back their flight schedules in the winter. The cost per flight is higher for aircraft with a lower cost per available seat-mile (i.e., $CASM_{i,t}$ in (4.6) in Table 2). As these aircraft are typically the larger ones, this finding is consistent with larger aircraft being more expensive to fly. The marginal cost per passenger rises, however, with the cost-per-passenger mile, as expected (i.e., $CASM_{i,t}$ in (4.7) in Table 2).

Finally, the demand estimates reveal that the customer's valuation for airline travel increases with the mileage of the market and with the presence of a second hub airport in the market (i.e., coefficients on $HUB_{AA,t}$ and $HUB_{UA,t}$ are positive and significant at 1%). AA and UA's products are also found to be imperfect substitutes, as $\widehat{\theta} = 0.51$. This estimate is both significantly different from 1 (i.e., perfect substitutes) and from 0 (i.e., independent products) at the 1% level.

6. Application to Merger and Welfare Analysis

I now quantify the effects of a merger among the two airlines on a market. My focus is on examining the extent to which changes in flight frequency affect passenger volumes and consumer welfare. I do not explore the incentives of firms to merge.[13]

I assume that the two airlines (i.e. AA and UA) on a market merge into a single entity. The demand and costs for the new firm are, respectively, the higher demand and lower costs of the two previous competitors. The new monopoly firm thus selects its

[13] See Perry and Porter (1985) for a discussion of firms' incentives to merge in Cournot models with regards to changes in productive capacity.

optimal frequency, f_t, and quantity of passengers, q_t, according to the following FOC:

$$\frac{INC_t q_t}{f_t\sqrt{f_t}} - \min_{i=AA,UA}(\widehat{\lambda}_{0,i}^* + \widehat{\lambda}_1^* MILES_t + \widehat{\lambda}_2^* COST_{i,t} + \widehat{\lambda}_3^* FUEL_{i,t} + \widehat{\lambda}_4^* CASM_{i,t} \\ + \widehat{\lambda}_5^* WINTER_t + \widehat{\varepsilon}_{i,f,t}) = 0 \quad , \tag{6.1}$$

$$\max_{i=AA,UA}(\widehat{\alpha}_{0,i}^* + \widehat{\alpha}_1^* MILES_t + \widehat{\alpha}_2^* POP_t + \widehat{\alpha}_{3,i}^* HUB_{i,t} + \widehat{\alpha}_4^* INC_t + \widehat{\alpha}_5^* MONTH_t \\ - \widehat{\omega}_2^* CASM_{i,t} + \widehat{\varepsilon}_{i,dq,t}) - q_t - \frac{\widehat{\gamma}^* INC_t}{\sqrt{f_t}} = 0 \quad , \tag{6.2}$$

where $\widehat{\lambda}_k^*$, $\widehat{\alpha}_k^*$, $\widehat{\omega}_k^*$, $\widehat{\gamma}^*$ and $\widehat{\varepsilon}_{i,f,t}$, $\widehat{\varepsilon}_{i,dq,t}$ are, respectively, the estimated parameter values and residual values. Based on equations (6.1)-(6.2), I simulate the predicted frequency and passenger quantity for the new firm. These predictions are computed by the bootstrap method using the same residual draws as for the predictions in Table 2.[14]

I then calculate changes in the consumer surplus following the merger.[15] In the model of Section 2, the net consumer surplus in a duopoly is equal to:

$$CS^d = CS(q_0, q_1, q_2) = U(q_0, q_1, q_2) - q_0 - \sum_{i=1}^{2} P_i q_i = \frac{\beta}{2}\left[(q_1)^2 + 2\theta q_1 q_2 + (q_2)^2\right] \ ,$$

where the second equality follows from (2.1) and (2.2). When firm 1 is, say, in a monopoly, the net consumer surplus is given by $CS^m = CS(q_0, q_1, 0)$. If $CS^m > CS^d$, then consumers are said to benefit from the merger. Note that the change in flight frequency in the merger affects consumer welfare indirectly by affecting chosen quantities

[14]In 67% of the simulations, there is a net gain in demand or costs for the new firm; i.e., if the new firm's costs in (6.1) are from AA, then the demand & cost term in (6.2) is from UA, and vice-versa.

[15]The numbers I provide subsequently are likely to be a lower bound on the true change as some consumers may ultimately choose alternate means or paths of transportation.

through its impact on the effective price. The interpretation of a gain then implicitly assumes that even though the monopolist may offer fewer total flights than the duopolists combined, its flight schedule reduces the cost of schedule delay of the representative consumer. This would be the case, for instance, if the two former airlines had similar departure times for their flights. Indeed, the new airline would then have the flexibility to match those times and add new ones, thus benefiting the consumer. Borenstein and Netz (1999) show that competitive hub airlines, such as AA and UA at ORD, schedule flight departures at similar times, and the interpretation of a gain in consumer surplus is therefore reasonable. Prediction and welfare results are found in Table 3.

[Table 3 here]

I find that the monopolist offers a higher flight frequency than each of the two previous competitors, individually, across all sample markets (see Table 3). Given that the model is Cournot with linear demands and (essentially) non-increasing marginal costs (see (2.6)), this result is expected.

Under the merger, the predicted passenger volume averages to 80% of the predicted total passenger volume under a duopoly structure. To put that number in perspective, note that when the cost of schedule delay parameter γ is equal to 0 (i.e., the number of flights in a market does not affect demand), then the ratio of the equilibrium quantity in a monopoly/merger to the total quantity in a duopoly is equal to:

$$\frac{q_1^m}{q_1^d + q_2^d} = \frac{(2+\theta)\left(\max\left\{\alpha_1,\alpha_2\right\} - \min\left\{c_{1,q}, c_{2,q}\right\}\right)}{2\left(\alpha_1 + \alpha_2 - c_{1,q} - c_{2,q}\right)} \geq \frac{(2+\theta)}{4} \quad . \tag{6.3}$$

At the estimated value $\widehat{\theta} = 0.51$, the lower bound on the ratio in (6.3) is equal to 0.628.[16] As $\widehat{\gamma}^{*} > 0$, the monopolist achieves a greater reduction in the cost of schedule delay, and the lower bound in the sample data (achieved in the Los Angeles and New York markets) is slightly higher, at 65.3%. In that context, an average ratio of 80% suggests non-trivial valuation of increases in flight frequency on the part of consumers across markets.

In fact, if the net consumer surplus decreases by 20% on average in a sample market, it increases in 34 of the 312 markets by an average of 19%. These gains obtain in some of the smaller sample markets (e.g. Harrisburg (PA), Syracuse (NY)) which benefit most from increases in flight frequency, as the cost of schedule delay specification is decreasing and convex in the flight frequency. In these markets, the consumer benefits in a merger despite the reduced competition, once the reduction in the cost of schedule delay following an increase in flight frequency is factored in, a result that derives from the comprehensive scope of the model.

7. Conclusion

I have proposed an analysis that recognizes that the airline consumer values not only ticket price, but also the convenience of a flight schedule with multiple departure times. As my model endogenizes flight frequency decisions, I can then predict changes in flight frequency and their effect on consumer welfare. The results from the structural estimation suggest significant valuation of flight frequency on the part of consumers. The

[16] When $\gamma = 0$, optimal total quantity in the monopoly and duopoly are, respectively, equal to $q_1^m = (\max\{\alpha_1, \alpha_2\} - \min\{c_{1,q}, c_{2,q}\}) \div 2\beta$ and $q_1^d + q_2^d = (\alpha_1 + \alpha_2 - c_{1,q} - c_{2,q}) \div (2+\theta)\,\beta$. Setting $\alpha_1 = \alpha_2$ and $c_{1,q} = c_{2,q}$, the ratio in (6.3) is equal to 0.628. This figure is meaningful in this paper as $\alpha_1 \approx \alpha_2$ and $c_{1,q} \approx c_{2,q}$ at the estimated parameter values.

subsequent merger simulations reveal that, while passenger volume and consumer welfare decrease on the aggregate, increases in flight frequency following the merger benefit consumers in some of the smaller markets.

This analysis therefore suggests that consumers' valuation of a convenient flight schedule is an important issue that warrants greater focus in policy analyses of consumer welfare. The structural estimation in this paper provides a valuable tool for quantifying, with simulations, how mergers may affect frequency decisions and consumers. Although the analysis here focuses only on flight frequency, extensions to models with additional quality measures or passenger types would be worthwhile. An extension to a multimarket model with entry would also make it possible to analyze how entry decisions at hub airports may factor in. Our recent work (see Armantier and Richard (2002)) in the context of exchanges of cost information provides a blueprint for a broader analysis of this type.

8. Tables

Table 1.
Descriptive Sample Statistics.

	Mean	Std. Dev.	Minimum	Maximum
Flight frequency $_{i,t}$	172	88	78	511
Passenger quantity $_{i,t}$	15771	11253	3408	66912
Total passenger quantity $_{t}$	31543	19869	10602	103503
MILES $_{t}$	862	547	137	1846
COST $_{i,t}$ (in $)	1213.53	239.85	836.89	2266.95
FUEL $_{i,t}$ (in $)	997.58	266.30	540.01	2100.80
CASM $_{i,t}$ (in $)	0.045	0.009	0.029	0.075
POP $_{t}$	2238232	2113984	392928	8863052
HUB $_{i,t}$	0.096	0.295	0.000	1.000
INC $_{t}$ (in $)	33216	5962	24442	48115
MONTH $_{t}$	18837	1686	15760	21439

Note: The frequency and quantity values are reported on a one-way basis.

Table 2.
Estimation and Prediction Results for the Sample Duopoly Markets.

Estimation results:

FOC for flight frequency: equation (4.6)			FOC for passenger quantity: equation (4.7)		
Variable	Estimate	Std. Error	Variable	Estimate	Std. Error
$CONST_{AA}$	242.3	23.0	$CONST_{AA}$	-10508	3025
$CONST_{UA}$	252.8	23.3	$CONST_{UA}$	-9577	3039
$MILES_t$	0.075	0.006	$MILES_t$	1.160	0.550
$COST_{i,t}$ #	0.345	0.037	POP_t	0.0043	0.0003
$FUEL_{i,t}$	0.056	0.012	$HUB_{AA,t}$	0.0082	0.0012
$CASM_{i,t}$	-4543	427.7	$HUB_{UA,t}$	0.0033	0.0002
$WINTER_t$	-25.94	5.46	INC_t	0.210	0.072
			$MONTH_t$	1.247	0.117
			$CASM_{i,t}$ ##	85780	18300
			γ *	3.203	1.018
			θ	0.515	0.065

Prediction results:

Square root of flight frequency			Passenger quantity		
	Observed	Predicted		Observed	Predicted
Mean	12.79	12.47	Mean	15771	15220
Std. Error	2.92	2.62	Std. Error	11253	10946
Min	8.80	7.33	Min	3408	1198
Max	22.61	20.37	Max	66912	58326
Correlation ### = 0.908			Correlation ### = 0.945		

Notes: All estimates are significantly different from zero at a 5% level. CONST denotes the intercept.
The minimized criterion value for the Nonlinear Three-Stage Least Squares estimation is equal to 308.
To lessen multicolinearity, FUEL is subtracted from COST prior to the estimation, and the estimate I report for the coefficient on COST applies to the variable (COST-FUEL).
I report the value for ω_2, the coefficient on CASM in equation (4.2). The negative of ω_2 enters in equation (4.7).
Correlation between observed and predicted values.

Table 3.
Merger (Monopoly) Predictions and Comparison to Predictions when Market is in a Duopoly.

	Duopoly	Monopoly	Difference	Ratio of Monopoly to Duopoly		
Prediction results:	Mean	Mean	Mean	Mean	Min	Max
Square root(flight frequency $_{i,t}$) #	13.17	15.53	2.36	1.190	1.015	1.491
Flight frequency $_{i,t}$ ##	181.0	247.9	66.9			
Total passenger quantity $_t$	30440	23256	-7184	0.800	0.653	1.251
Consumer surplus $_t$				0.800	0.537	1.456

For duopoly: Highest predicted flight frequency value amongst the two competitors.
Based on predicted values for the square root of flight frequency.

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10. Appendix 1

The non-ORD airports in the data are: Albany (NY), Buffalo (NY), Columbus (OH), Des Moines (IN), Grand Rapids (MI), Harrisburg (PA), Hartford (CT), Kansas City (KS), Los Angeles LAX (CA), Miami (FL), Nashville (TN), New Orleans (LA), New York Laguardia (NY), Omaha (NE), Portland (OR), Providence (RI), Raleigh-Durham (NC), Rochester (NY), San Diego (CA), San Francisco (CA), Seattle (WA), San Jose (CA), St Louis (MO), Syracuse (NY), Tampa Bay (FL), and Washington National (D.C.).

11. Appendix 2

I estimate a system of four equations: one of equations (4.6)-(4.7) per airline. There are restrictions on the parameters across the two equations (4.6) and the two equations (4.7). Hence, in the estimation, I update the variance-covariance matrix of the residuals as follows: Let $\widehat{\varepsilon_{AA,f}}, \widehat{\varepsilon_{UA,f}}, \widehat{\varepsilon_{AA,dq}}, \widehat{\varepsilon_{UA,dq}}$ be the vectors of first-stage residuals, with $\widehat{\varepsilon_{i,k}}' = \begin{pmatrix} \widehat{\varepsilon_{i,k,1}} & ... & \widehat{\varepsilon_{i,k,m}} & ... & \widehat{\varepsilon_{i,k,312}} \end{pmatrix}$ for $i = AA, UA, \quad k = f, dq,$

$$Var\left(\widehat{\varepsilon_{i,k}}\right) = \sum_{j=1}^{2} \widehat{\varepsilon_{j,k}}'\widehat{\varepsilon_{j,k}} \;/624 \quad ,$$

$$Cov\left(\widehat{\varepsilon_{i,k}}\ \widehat{\varepsilon_{-i,k}}\right) = \left(\widehat{\varepsilon_{1,k}} - \sum_{m=1}^{312}\left(\widehat{\varepsilon_{1,k,m}}\right)/312\right)'\left(\widehat{\varepsilon_{2,k}} - \sum_{m=1}^{312}\left(\widehat{\varepsilon_{2,k,m}}\right)/312\right)\ /312 \quad ,$$

$$Cov\left(\widehat{\varepsilon_{i,k}}, \widehat{\varepsilon_{i,-k}}\right) = \sum_{j=1}^{2} \widehat{\varepsilon_{j,f}}'\widehat{\varepsilon_{j,d}} \;/624 \quad , \quad Cov\left(\widehat{\varepsilon_{i,k}}, \widehat{\varepsilon_{-i,-k}}\right) = \sum_{j=1}^{2} \widehat{\varepsilon_{j,f}}'\widehat{\varepsilon_{-j,d}} \;/624 \quad ,$$

since $\sum_{m=1}^{312}\left(\widehat{\varepsilon_{AA,k,m}} + \widehat{\varepsilon_{UA,k,m}}\right) = 0.$