Appendix

CAN PRIVATE AIRPORT COMPETITION IMPROVE RUNWAY PRICING?

THE CASE OF SAN FRANCISCO BAY AREA AIRPORTS

Jia Yan — **Washington State University**

Clifford Winston — **Brookings Institution**

This appendix provides a comprehensive treatment of the technical issues raised in the text.

Equilibrium Concept of the Three-Stage Airport Privatization Game

By backward induction, we first characterize the SPE to the two-stage airline price and service competition given airport charges. Let $\mathbf{T} \equiv \{T_{sf}\}_{s,f} \in \Upsilon_{\mathbf{T}}$ denote a vector of carriers' spoke capacities; $\mathbf{P} \in \Upsilon_{\mathbf{P}}$ denote a vector of air product prices in all markets; $BE(\mathbf{T})$ denote the set of Bertrand-Nash equilibrium prices in all markets given the spoke capacities; and $f_p : \Upsilon_{\mathbf{T}} \to \Upsilon_{\mathbf{P}}$.

Definition A1: *A SPE to the two-stage game of airline competition constitutes a vector* $(\mathbf{T}^*, \mathbf{P}^*)$ *that satisfies the following conditions:*

1. $\mathbf{T}^*$ *is a fixed-point of* $\mathbf{H}(\cdot)$*, that is,* $\mathbf{T}^* = \mathbf{H}(\mathbf{T}^*)$*; and*
2. $\mathbf{P}^* = f_p(\mathbf{T}^*) \in BE(\mathbf{T}^*)$ *such that* $\mathbf{P}^*$ *satisfies equation (3)of the text given* $\mathbf{T}^*$.

Moving backward to the first stage of the game, the three airports engage in Bertrand competition with the expectation of the equilibrium outcomes of airline competition given airport charges. The SPE to the airport privatization game is defined as follows.

Definition A2: *Let* $\boldsymbol{\varsigma}^* \equiv \left(\varsigma_{SFO}^{A\;*}, \varsigma_{SJC}^{A\;*}, \varsigma_{OAK}^{A\;*}\right)$ *denote a vector of airport charges;* $\mathbf{P}^*$ *denote a vector of product prices in city-pair markets connected to SF airports with the size of the vector* l *;* $\mathbf{T}^*$ *denote a vector of airline capacities on the spoke routes they serve that are connected to the three SF airports with the size of the vector* k*; and* $\mathrm{O}(\varsigma)$ *denote the set of equilibria to the service-price subgame of airlines given a set of airport charges* ς *as in Definition A1. The vector* $(\varsigma^*, \mathbf{T}^*, \mathbf{P}^*)$ *is a SPE to the oligopoly airport price competition if* $(\mathbf{T}^*, \mathbf{P}^*) \in \mathrm{O}(\varsigma^*)$ *and for all* $\varsigma \geq 0$ *and for all* n *,*

$$\pi_n^A\left(\varsigma_n^{A^*}, \varsigma_{-n}^{A\,*}, \mathbf{T}^*, \mathbf{P}^*\right) \geq \pi_n^A\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}, \mathbf{T}\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}\right), \mathbf{P}\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}\right)\right) \; \forall \varsigma_n^A \geq 0$$

in which $\varsigma_{-n}^{A\,*}$ *is the subset of* ς^* *by excluding airport* $n \in \{SFO, OAK, SJC\}$ *and* $\left(\mathbf{T}\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}\right), \mathbf{P}\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}\right)\right) \in \mathrm{O}\left(\varsigma_n^A, \varsigma_{-n}^{A\,*}\right)$.

Model Parameterization

Discrete Choice Demand. As indicated in the text, we specify the price coefficient of the random utility function in equation (7) in terms of a simple binary random distribution, which enables us to broadly capture the difference between those travelers who are primarily traveling for business and those who are primarily traveling for leisure, namely

$$\alpha_i = \begin{cases} \alpha^B & \text{with the prob. } \rho \\ \alpha^L & \text{with the prob. } 1 - \rho \end{cases} \tag{A1}$$

Given our nested-logit model, this specification of demand implies that the market share of product j in a given market (we drop market subscript for simplicity) is

$$S_j = \rho \cdot S_j^B + (1-\rho) \cdot S_j^L \quad , \tag{A2}$$

where S_j^B and S_j^L are the market shares of business and leisure travelers. For *g= B or L*

$$\begin{aligned} S_j^g &= \frac{\exp\left(\dfrac{X_j\beta + \alpha^g p_j + \phi d_j + \gamma_f t_j^f + \gamma_a t_j^a + \gamma_l t_j^l + \xi_j}{\lambda}\right)}{\exp\left(I^g\right)} \cdot \frac{\exp\left(\lambda \cdot I^g\right)}{1 + \exp\left(\lambda \cdot I^g\right)} \\ &= S_{j|A}^g\left(1 - S_0^g\right) \end{aligned} \tag{A3}$$

and

$$I^g = \ln \sum_{j'=1}^{J} \exp\left(\frac{X_{j'}\beta + \alpha^g p_{j'} + \phi d_{j'} + \gamma_f t_{j'}^f + \gamma_a t_{j'}^a + \gamma_l t_{j'}^l + \xi_{j'}}{\lambda}\right); \tag{A4}$$

λ is the nested-logit parameter measuring the correlation of unobserved components of utility across air travel products. It must have a value between 0 and 1 for the choice model to be consistent with utility maximization. In the second equality in equation (A3), the term $S_{j|A}^g$ is the market share of product j for air travel products denoted A for type g travelers (for example, $S_{j|A}^B = 0.05$ if 5% of business air travelers choose air product j); the second term is the total share of air travel in the market (S_0^g is the market share of the outside product in a given market for type g travelers). Because the market shares of the air travel products respond differently in the business and leisure segments to a change in an air travel product's attributes, those shares are not constrained by the conventional logit model's IIA property. The demand for product j is then $q_j = S_j \cdot M_m$ with M_m denoting the market size.

Based on this specification, we calculate the change (denoted as *Pre* to *Post*) in consumers' surplus due to private airport competition using the "log-sum" rule for a nested-logit demand model given by Choi and Moon (1997):

$$CS = \sum_{g=B,L} M^g \frac{\rho^g}{\alpha^g}\left(\log\left[1+\lambda \cdot \exp\left(I^g_{\text{Post}}\right)\right] - \log\left[1+\lambda \cdot \exp\left(I^g_{\text{Pre}}\right)\right]\right) \quad \text{(A5)}$$

where M^g is the size of type g travelers; ρ^g equals ρ if $g = B$ and equals $1-\rho$ otherwise; and I^g_{Post} and I^g_{Pre} are values of equation (A4) based on the product attributes after and before private airport competition.

Airline Spoke Costs. Let $z_f\left(K_{sf}\right)$ be the unit aircraft operating cost function (in dollars per block hour for an aircraft) of carrier f on spoke s; K_{sf} denotes the average aircraft size (number of seats) of the carrier on the spoke. We parameterize $z_f\left(K_{sf}\right)$ in Cobb-Douglas form and obtain the following OLS regression results:

$$\ln z_{if} = \underset{(0.2821)}{4.4715} + \underset{(0.0566)}{0.6982}\ln\left(K_i\right) + \varepsilon^z_{if}, \quad \text{Adj. } R^2 = 0.55 \quad \text{(A6)}$$

where z_{if} is the operating costs per block hour for aircraft type i operated by carrier f and K_i is the number of seats of aircraft type i. We also included airline fixed effects to control for variables such as pilots' and flight attendants' average wages.

We can therefore express total aircraft operating costs (AOC) of the carrier on the spoke as

$$AOC_{sf} = \frac{Q_{sf}}{\theta_{sf} \cdot K_{sf}}\left(h_{sf} + \delta_s\right) \cdot \exp\left(4.5715 + 0.6982 \cdot \ln\left(K_{sf}\right) + \varepsilon^z_{if}\right). \quad \text{(A7)}$$

Total delay on a spoke route includes delay at both the departure and arrival airports; thus, in equation (A7) $\delta_s = departure \;\; delay + arrival \;\; delay$. Delays at non-SF airports are held constant in our analysis (Assumption 2) and delay at each of the three SF airports is modeled as a function of the total traffic volume (number of flights) at each airport. Total traffic volume at airport n is then

$$V_n = \sum_{s \in \Xi_n} \left\{ \sum_f \left(\frac{\sum_m \sum_{j \in \Psi_{sf}} q_{jm}}{\theta_{sf} \cdot K_{sf}} \right) \right\} \quad . \tag{A8}$$

Airport delay is specified as a function of the volume-capacity ratio, $\delta_n = D_n\left(\frac{V_n}{RW_n}\right)$, where RW_n is the number of active runways at airport n. We parameterize the function by a translog form and use traffic delays recorded in the FAA's Aviation System Performance Metrics (ASPM) database noted in the test to estimate the following regression equation

$$\ln \delta_n = b_{0n} + b_{1n} \ln\left(\frac{V_n}{RW_n}\right) + b_{2n}\left(\ln\left(\frac{V_n}{RW_n}\right)\right)^2 + \varepsilon_n^{\delta}, \tag{A9}$$

where the dependent variable is the log of average aircraft departure or arrival delay (minutes per aircraft) in a 15-minute interval on a representative day of travel in 2007 and the explanatory variables are the log of the volume-capacity ratio and its square in the 15-minute interval. Table A1 presents the parameter estimates of this equation for the SF airports and we plot the estimated delay functions in figure A1, which indicate that for a given number of flights, departure delays tend to exceed arrival delays at each of the airports and that SFO has the largest departure delays and OAK has the largest arrival delays. The shape of the curves can be convex and then concave because in response to an increase in flights above a certain threshold, an airport may vary the number of active runways and the allocation of runways for departures and arrivals.

U.S. airports charge aircraft weight-based landing fees, with a representative value of \$2 per 1,000 pounds of landing weight. The three SF Bay area airports charge different landing fees in 2007: \$3.01 per thousand pounds at SFO, \$2.14 per thousand pounds at SJC, and \$1.21 per thousand pounds at OAK (according to the annual reports of these airports). We estimated landing fee charges by using data on aircraft manufacturer websites to calculate the average aircraft landing weight per seat for aircraft with fewer than 100 seats (940 lbs/seat), 101–199 seats (940 lbs/seat), 200–299 seats (1,240 lbs/seat), 300–399 seats (1,350 lbs/seat), and greater than 400 seats (1,580 lbs/seat). (Note an aircraft is not charged when it takes off from an airport.) If $\tau(K_{sf})$ is the average aircraft landing weight per seat (as a function of aircraft size K_{sf}) of carrier f on spoke s, then the carrier's total landing fee expenditures (LF_{sf}), including fees paid at a connecting airport, are given by equation (9) in the text.

Data and Variables

We include only roundtrip itineraries in the DB1B dataset and exclude the following observations:

- Itineraries that involve tickets from multiple carriers
- Itineraries with fares that are less than $25 or that are unreasonably high
- Itineraries that require more than one connection.

We follow Berry and Jia (2010) and define ticket classes by using the following fare dispersion bins to avoid having an excessive number of products: increments of $50 are used for all tickets under $500; increments of $100 are used for all tickets above $500 and under $1000; and increments of $500 are used for all tickets above $1000. We explored the robustness of the demand estimates by using larger and smaller sizes for the fare bins.

Using the DB1B data, we determined the price (passenger-fare) and market share of each air travel product $\left(S_{j|A}\right)$. The market size, which is used to determine the share of the outside product, is estimated as the geometric mean of the populations at the end-point cities.

The travel time components associated with each product include airborne time, airport delays, airport transfer time, and schedule delay. Carriers' airborne or flying times between the origins and destinations in our sample were obtained from the U.S. Department of Transportation T-100 Domestic Segment Data. Traffic delays at the 71 airports are recorded in the FAA's Aviation System Performance Metrics (ASPM) database, which contains scheduled operations every 15 minutes for 23 specific airlines (22 U.S. network and commuter airlines plus Air Canada) plus one composite "other" category for all other commercial airlines. Because the data do not include general aviation operations, we do not include that airport user classification in our initial assessment of the effects of private airport competition but we later extend our framework to include general aviation to complete our assessment. We calculated average departure delay and average arrival delay for each airport in the third quarter 2007 (obtained by averaging across all carriers for each of the 15-minute segments and then averaging across all time segments). Flight frequency for each travel product is constructed from Back Aviation Solutions' schedule data. For nonstop flights, we aggregate all departures over all ticketing carriers. For connecting flights, we follow Berry and Jia (2010) and restrict the range of connecting time (transfer time) from 45 minutes to 4 hours; we include only the shortest layover time when multiple feasible connections exist. To measure schedule delay, we need flight frequency, aircraft size, and load factor. The flight frequency data from Back Aviation Solutions also records the size (number of seats) of each of the scheduled flights on a segment. The aircraft size of a non-stop product is then the average aircraft size of the carriers on the segment. The aircraft size of a connecting product is constructed by averaging the average aircraft sizes of the carriers on the two segments. Given the flight frequency and aircraft size for each product, we calculated schedule delay by assuming an 80 percent load factor.[1]

In addition to the preceding variables, we included a dummy variable indicating a long transfer time (defined as 1 if the transfer time of a connecting flight exceeds 1.5 hours; 0 otherwise), a dummy variable indicating whether a product involved a connecting flight (to capture the "fixed costs" of a transfer such as switching departure gates, having luggage transferred to a different plane, and so on), a carrier's airport presence (cities served) at both the origin and destination airport, and unobserved product attributes, such as the time it takes to travel to an airport from various residential locations and the quality of an airline's frequent flier program, which are captured by airline and airport dummies. Finally, the market characteristics in the demand specification include a vacation destination dummy for Florida or Nevada cities, the distance of the origin from the destination, and a dummy indicating whether a flight involves a slot-controlled airport (Chicago O'Hare, New York Kennedy and LaGuardia, and Washington, DC Reagan National). Data sources and summary statistics for the demand variables are presented in Table A2.

Two-Step Estimation of the Discrete Choice Demand Model and Airline Costs

We estimated parameters in the discrete choice demand model and airline costs in two steps. In the first step, as we noted, we estimated aircraft operating costs and landing fee charges, which are the two components of airline spoke costs. Given the first-step estimates, we estimated the demand parameters in equation (7) of the text and the remaining airline cost parameters in equation (11) of the text jointly by using the BLP approach.

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[1] The most recent functional expression that we are aware of to calculate schedule delay is from Douglas and Miller (1974). Our assumption of an 80 percent load factor is based on recent average industry load factors and reflects the fact that observed schedule delay is affected by all traffic. Assuming a somewhat higher or lower load factor did not affect our findings. We plugged the values of the relevant variables in our sample into Douglas and Miller's functional expression, which is given by:

$$d_j = 92 \cdot \text{Daily Departures}^{-0.456} + \left(\frac{12010}{\text{Daily Departures}}\right) \cdot \left(\text{Aircraft Size} \times \text{Load Factor}\right)^{0.5725} \cdot \left[\text{Aircraft Size} \times \left(1 - \text{Load Factor}\right)\right]^{-1.79}$$

BLP Approach

Let $\Gamma_D\left(Z_{jm}^D\right)$ and $\Gamma_C\left(Z_{jm}^C\right)$ denote the vector-valued functions of the instruments; the moment condition in equation (12) of the text implies $E\left(\xi_{jm}\cdot\Gamma_D\left(Z_{jm}^D\right)\right)=0$ and $E\left(\eta_{jm}\cdot\Gamma_C\left(Z_{jm}^C\right)\right)=0$ such that a GMM estimator can be constructed by the following empirical analog of the moment conditions

$$\chi_D(\Theta)=M^{-1}\sum_{m=1}^{M}\sum_{j=1}^{N_m}\xi_{jm}(\Theta)\cdot\Gamma_D\left(Z_{jm}^D\right) \quad \text{and} \quad \chi_C(\Theta)=M^{-1}\sum_{m=1}^{M}\sum_{j=1}^{N_m}\eta_{jm}(\Theta)\cdot\Gamma_C\left(Z_{jm}^C\right) \tag{A10}$$

where Θ denotes the vector of unknown parameters (demand parameters and the remaining marginal cost parameters). For some weighting matrix Σ, the BLP GMM estimator of the unknown parameters, Θ_{GMM}^{BLP}, is the solution to the minimization problem

$$\Theta_{GMM}^{BLP}=\arg\min_{\Theta}\begin{bmatrix}\chi_D(\Theta)\\ \chi_C(\Theta)\end{bmatrix}'\cdot\Sigma\cdot\begin{bmatrix}\chi_D(\Theta)\\ \chi_C(\Theta)\end{bmatrix}. \tag{A11}$$

To evaluate the GMM objective function, it is necessary to invert the share equation in equation (10) of the text to express the unobservables in demand, ξ, as a function of the observed data and unknown parameters. Following Berry and Jia (2010), we can solve $\boldsymbol{\xi}_{\mathbf{m}}\equiv\left(\xi_{1m},\xi_{2m},\ldots,\xi_{J_m m}\right)$ by iterating the contraction mapping

$$\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t+1}}=\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t}}+\lambda\cdot\left[\ln\left(\mathbf{S}_{\mathbf{m}}^{*}\right)-\ln\left(\mathbf{S}_{\mathbf{m}}\left(\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t}},\Theta,data\right)\right)\right] \tag{A12}$$

until $\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t+1}}$ and $\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t}}$ are sufficiently close. In equation (A3), $\mathbf{S}_{\mathbf{m}}^{*}\equiv\left(S_{1m}^{*},\ldots,S_{J_m m}^{*}\right)'$ is the vector of observed product market shares in market m and $\mathbf{S}_{\mathbf{m}}\left(\boldsymbol{\xi}_{\mathbf{m}}^{\mathbf{t}},\Theta,data\right)$ is the vector of predicted markets shares that is calculated using equation (A2) of the appendix.

We employ the nested-fixed point (NFP) algorithm in Berry, Levinsohn, and Pakes (1995) to implement BLP GMM estimation of the model.

Algorithm 1: The NFP algorithm of BLP GMM estimation

Initialization. Make an initial guess Θ^0

Inner loop. Given any Θ^0,

Step 1: Solve the demand shocks given Θ^0 denoted by $\boldsymbol{\xi}_\mathbf{m}(\Theta^0) \equiv (\xi_{1m}(\Theta^0), \ldots, \xi_{J_m m}(\Theta^0))$. The solution can be obtained by starting from a guess $\boldsymbol{\xi}_\mathbf{m}^\mathbf{0}$ and iterating the contraction mapping in equation (A3) until $\max\left\{\left|\xi_{1m}^{t+1} - \xi_{1m}^t\right|, \ldots, \left|\xi_{J_m m}^{t+1} - \xi_{J_m m}^t\right|\right\} \le \varepsilon_{Inner}$.

Step 2: Compute the mark-ups (the third term of the left hand side of equation (11) in the text) for each carrier in each market given Θ^0 and $\boldsymbol{\xi}_\mathbf{m}(\Theta^0)$.

Step 3: Compute the cost shocks $\boldsymbol{\eta}_\mathbf{m}(\Theta^0) \equiv (\eta_{1m}(\Theta^0), \ldots, \eta_{J_m m}(\Theta^0))$ from equation (11) in the text.

Step 4: Interact demand and cost shocks with instruments to obtain the moment functions in equation (A10).

Outer loop. Search for the Θ that solves the minimization problem in equation (A11). The minimization problem is solved by MATLAB's unconstrained nonlinear optimization package, which implements the BFGS Quasi-Newton method with a cubic line search procedure. The convergence tolerance of the outer loop is denoted by ε_{Outer}.

Recent papers by Knittel and Metaxoglou (2008, 2011) and Dube, Fox, and Su (2011) have raised several numerical issues associated with the NFP algorithm, which we address here.

Numerical errors in the inner loop. In the NFP algorithm, the optimization procedure in the outer loop maximizes an objective function that is constructed by the demand and cost shocks that are solved from the inner loop. The solutions from the inner loop are subject to numerical errors because demand shocks are solved by iterating the contraction mapping and because numerical errors associated with the solution are determined by the chosen tolerance ε_{Inner}. Dube, Fox, and Su (2011) point out that a loose inner loop tolerance may cause the optimization procedure in the outer loop not to converge or to converge to a point that is not a valid local minimum under a loose outer loop tolerance. Following their suggestion, we chose stringent tolerances for both the inner and outer loops. Specifically, we set $\varepsilon_{Inner} = 10^{-12}$ and $\varepsilon_{Outer} = 10^{-5}$ in the estimation. We also tried $\varepsilon_{Inner} = 10^{-14}$ and $\varepsilon_{Outer} = 10^{-6}$ and the estimation results were virtually unaffected. However, the optimization procedure converged to a different point under the tolerances $\varepsilon_{Inner} = 10^{-12}$ and $\varepsilon_{Outer} = 10^{-3}$, indicating that the objective function of the estimation has an irregular surface and that a loose tolerance in the outer loop may lead to inaccurate results**.**

Multiple local minimums and saddle points. The minimization problem in BLP GMM estimation is highly nonlinear and has many parameters. Knittel and Metaxoglou (2008) found that in practice BLP GMM estimation usually involves multiple local minimums and saddle points. Thus estimation results can be sensitive to the initial guess of the parameters and to the employed optimization algorithm. Those numerical concerns are partly addressed by the stringent tolerances that we chose. We also address the concerns by randomly varying the initial guess of the parameters and by employing a more robust optimization procedure—the Nelder-Mead simplex (direct search) method. Under the stringent tolerances that are chosen, our estimation results are robust to the different starting values of the parameters and to the optimization algorithms.

Existence and uniqueness of a pure-strategy Nash equilibrium to the Bertrand game. In the BLP GMM estimation, the objective function of the minimization problem includes moment conditions from both the demand and cost side. The moment conditions from the cost side are derived from the first-order conditions of Bertrand competition. Such an exercise requires the existence of a pure-strategy equilibrium for Bertrand competition in each market. As we indicate later, we are not aware of a result that shows the existence of a pure-strategy equilibrium for the airline price competition that we are considering. If a pure-strategy equilibrium for the Bertrand game does not exist, then incorporating moment conditions that are derived from the first-order conditions would lead to estimates that are not consistent with the observed market outcomes.

We addressed this concern in two ways. First, similar to Berry and Jia (2010), we dropped the cost-side moment conditions from the estimation to see how the demand estimates would be affected and we did not find any significant changes in those parameter estimates. Second, we used the estimation results to compute the pure-strategy Nash equilibrium of Bertrand competition in each of the 120 city-pair markets given the observed flight frequencies. The computation procedure follows step 3 of Algorithm 1 in this appendix. The computation of a firm's best response to the prices of the products offered by other firms requires us to solve a system of non-linear equations defined by the first-order conditions in equation (5) of the text. We used MATLAB's *fsolve* function, which implements a dogleg trust-region version of Newton's method (Nocedal and Wright (1999)), and used a stringent termination tolerance (1e-6) and tried multiple starting values. The computational procedure always converged to the same equilibrium for every market in those experiments. More importantly, the convergent equilibrium outcomes in the 120 city-pair markets replicated the observed prices and demands very closely. Thus the results suggest that the model estimates from the BLP GMM estimation are consistent with the existence of a unique equilibrium. Although a unique equilibrium is not essential for model estimation, it is essential for our policy simulations.

Instruments used in the BLP approach. We follow the literature (Nevo (2000), Berry and Jia (2010)) closely to select the instruments for endogenous price and schedule delay in the demand model. Specifically, variables in Z_{jm}^{D} include exogenous product attributes and instruments for the endogenous variables in the demand model. Variables in Z_{jm}^{C} include exogenous regressors in equation (11) and exogenous instruments for demand that affect the mark-up $\left(\Delta_{mf}^{j}\right)^{-1} q_{mf}$. Price and schedule delay are endogenous because they are likely to be correlated with an airline's unobserved product attributes. We use three sets of variables to obtain instruments for price. First, we followed the common strategy of using variables that capture rival product attributes and that indicate the competitiveness of the market environment, including the number of carriers in a market, the number of alternative routes offered by rivals in a market, the percentage of rivals' routes that are nonstop routes, and the average presence of rivals (number of connected cities) at the origin airport. Because those variables are largely determined by the size of a market and because they are unlikely to respond to the same shocks that affect prices, it is reasonable to assume that they are predetermined and uncorrelated with unobserved product characteristics.

Route characteristics constitute another set of variables that can be used as instruments, including a dummy if the origin or destination is a carrier's hub, the temperature difference between the origin and destination airports in January, and the temperature difference between January and July at the two endpoint airports. Given the other variables that we control for in the model, those variables affect the product price by affecting costs, such as time and money expenditures on de-icing, but not demand. Finally, a third set of variables captures the extent of competition from low-cost carriers, including a dummy variable indicating if a low-cost carrier serves a route, a dummy variable indicating if Southwest

Airlines serves the route, and a dummy variable indicating if Southwest Airlines is a potential competitor on the route, which occurs when Southwest serves the end-point airports but does not serve the route connecting the two airports.[2] Historically, low-cost carriers tend to enter markets with characteristics that are consistent with their operating "philosophy," such as Southwest's attraction to markets that do not have highly congested airports, and they are unlikely to react to the same shocks that affect prices. To be sure, low-cost carriers' growing market shares raise questions whether their operating philosophies have recently changed and whether it is appropriate to use them to construct instruments. We found that our parameter estimates were not affected very much when we did not include this third set of variables among the instruments.

Schedule delay is determined by an airline's flight frequency and aircraft size. We obtained an instrument for schedule delay by first regressing flight frequency and aircraft size on exogenous market characteristics, including flight distance, market size as defined previously, mean household income, the number of runways at the departure, arrival, and, if applicable, connecting airports, a dummy variable indicating whether the San Francisco Bay Area is the origin of a market, the temperature difference between the end-point cities in July and January, a vacation dummy variable defined previously, a dummy variable if the airports are subject to slot controls, a hub route dummy, and airline and airport dummies. The fitted frequency and aircraft size variables were then used as instruments for schedule delay in the final estimation.

The first stage regressions of endogenous price and schedule delay on their instruments, which are plausibly excluded from demand, produced high R-squares and statistically significant coefficients.

Sources of data variation to achieve identification. Identification of the demand and cost parameters relies on variation in the data both within and across markets; identification of the demand parameter ρ, the share of traveler type, relies on the variation across markets in the substitution patterns among travel products; and identification of the nested-logit parameter λ relies on the variation across markets in the substitution pattern between air products.

Estimation results. BLP GMM estimation results of travelers' demand are presented in table A3. We allowed the price coefficient to vary to capture preference heterogeneity that is likely to arise for business and leisure travelers by drawing on the available evidence and assuming that the percentage of

[2] Goolsbee and Syverson (2008) provide evidence that incumbent carriers cut their fares on a route when Southwest Airlines serves the end-point airports that define the route but does not serve the route.

business travelers in our markets is 45%.[3] Generally, the coefficients are precisely estimated and have the expected signs: market shares of leisure and business travelers are inversely related to price with business travelers attaching less disutility than leisure travelers attach to a price increase, market shares of all travelers are inversely related to the components of travel time, while they are positively related to airlines' presence at the origin and destination airports.[4] The carrier dummies indicate that holding attributes such as price, frequency, and service time constant, travelers' carrier preferences relative to their preference for United Airlines are frequently negative, perhaps because of United's valued frequent flier program. The airport dummies indicate travelers' airport preferences in multi-airport cities, capturing the advantage of an airport's location among other considerations, with positive preferences for SFO, ORD (Chicago O'Hare), JFK (New York JFK), IAH (Houston George Bush Intercontinental), DFW (Dallas Fort Worth), IAD (Washington Dulles), and LAX (Los Angeles). Air travel demand increases with route distance because other travel alternatives such as driving become less attractive, but it does so at a decreasing rate. Air travel demand decreases because of airport slot controls and in markets with tourist cities, perhaps because of intermodal competition on routes connecting the Bay Area and Nevada cities, but the effect is statistically imprecise. The estimated value of λ, 0.74, is consistent with utility maximizing behavior and the value of $1-\lambda = 0.26$ indicates the correlation of the unobserved utility of the air travel products.

As a robustness check, we followed Berry and Jia (2010) and explored how the demand estimates were affected by our assumption on airline price competition by dropping the cost-side moment conditions when we performed BLP GMM estimation. We did not find any notable changes to the parameter estimates. For sensitivity purposes, in table A4 we compare price demand elasticities and value of time components from the baseline demand estimates with the ones based on coefficients

[3] We are not aware of a recent estimate of the share of business travelers in the San Francisco Bay Area markets. Our assumed share is broadly consistent with Bay Area airport travelers' trip purposes that were reported in a 1995 survey conducted by the Oakland Metropolitan Transportation Commission and used by Pels, Nijkamp, and Rietveld (2001). It is also consistent with results contained in the 2001 National Travel Survey and national surveys periodically taken since the mid-1990s by the Gallup Organization. As a technical check, we found that the objective value of the moment function was smallest when we assumed 45% was the share of business travelers. Assuming smaller shares of business travelers, 35% and 25%, affected the deviation but not the weighted average of the price coefficients.

[4] Collinearity between the number of domestic and international destinations served prevented us from estimating separate coefficients for an airline's domestic and international presence at the origin and destination airports.

obtained from OLS estimation, which treats preferences as homogenous and assumes price and schedule delay are exogenous, and from instrumental variables (IV) estimation as in Berry (1994), which treats preferences as homogenous and assumes price and schedule delay are endogenous. The first column of the table shows that OLS estimates that ignore price endogeneity produce implausibly small demand elasticities and an implausibly high willingness to pay for non-stop flights. The second and third columns indicate that the IV and GMM baseline estimates of the overall demand elasticity are similar as are their estimates of the overall values of the travel time components.

Table A5 presents the BLP GMM estimates of the unknown parameters in equation (11), which capture unobserved shifts in airlines' prices after controlling for the price mark-up, aircraft operating costs, and airport landing fees. The price residual is negatively related to the number of segments suggesting that airlines charge lower prices for products using connecting flights because travelers find those flights less desirable than non-stop flights. Because part of the impact of segment distance on the product marginal cost is already captured by aircraft operating costs, the price residual is negatively related to the segment distance. The estimates of the carrier dummies are plausible with UA and AA offering the most costly products and Southwest and JetBlue and other low-cost carriers offering the least costly products. Finally, products using OAK and SJC are less costly than products using SFO.

Two-stage estimation and the GMM standard errors

The supply side moment conditions in the BLP GMM estimation are derived from equation (11) of the text, which is computed by using the estimated parameters in equation (A6) of the appendix. Thus, the statistical uncertainty of the parameters in the first stage carries through to the second stage GMM estimation and requires the GMM standard errors to be corrected (the parameter estimates are still consistent).

One acceptable approach is the bootstrap technique. The reported standard errors in tables A3 and A5 are estimated by

$$Var\left(\hat{\Theta}\right) = \left(\Psi'\Sigma\Psi\right)^{-1}\left(\Psi'\Sigma V\Sigma\Psi\right)\left(\Psi'\Sigma\Psi\right)^{-1} \qquad \text{(A13)}$$

where Ψ is the Jacobian matrix of the moment function evaluated at the GMM estimates; the weighting matrix takes the form of

$$\Sigma = diag\left(\left(\left(Z^{D}\right)'\left(Z^{D}\right)\right)^{-1},\left(\left(Z^{C}\right)'\left(Z^{C}\right)\right)^{-1}\right)$$

and $V = \sum_{m=1}^{M}\sum_{j=1}^{N_m}\Gamma_C\left(Z_j^C\right)'\Gamma_D\left(Z_j^D\right)'\left(\xi_j\left(\hat{\Theta}\right),\eta_j\left(\hat{\Theta}\right)\right)'\left(\xi_j\left(\hat{\Theta}\right),\eta_j\left(\hat{\Theta}\right)\right)\Gamma_D\left(Z_j^D\right)\Gamma_C\left(Z_j^C\right)$. To implement the bootstrap: take a draw from the estimated asymptotic distribution of the parameter estimates in equation (A6); compute the residuals $\left(\varepsilon_{if}^{Z}\right)$ given the draw; evaluate the marginal aircraft operating costs by using equation (A7) given the draw and the resulting residuals; substitute the computed marginal aircraft operating costs into equation (11) of the text to obtain the supply-side equation in the BLP GMM estimation; and run the BLP GMM estimation in equation (A11). The preceding steps can be repeated and the variance-covariance matrix of the parameters in (A13) can computed for each repetition. The averaged variance-covariance matrix could then be used to construct the standard errors of the BLP GMM estimates to take account of the statistical uncertainty in estimating the marginal aircraft operating costs.

Unfortunately, although the bootstrap technique is a valid approach, it is not feasible here because BLP GMM estimation is so time consuming. However, we can comment on why our standard errors would not be affected much by this correction. First, the parameter estimates in the marginal aircraft operating cost equation are highly statistically significant. Second, as noted, dropping the cost-side moments in the BLP GMM estimation had little effect on the demand estimates. Third, most of the cost parameter estimates in table A5 are highly statistically significant. Finally, as a partial test, we conditioned on the mark-up estimates from the BLP GMM estimation, used OLS to re-estimate the supply-side parameters in equation (11) of the text, used the preceding bootstrap procedure to account for the statistical uncertainty associated with the marginal aircraft operating costs, and found that the standard errors of the cost parameter estimates changed very little.

Computing the SPE to the Three-Stage Game of Airport Privatization under Different Scenarios

Computing the SPE to the three-stage game of airport privatization under different scenarios requires an algorithm to compute the SPE to the airline service-price subgame given airport charges. Definition 1 of the text summarizes the necessary conditions of the SPE under Assumption 4. We develop an algorithm to locate points that satisfy the necessary conditions. The computation is done by iterating the fixed-point equation that is defined in equation (6) of the text. Details of the algorithm are as follows.

Algorithm 2: Fixed-point iteration to compute the SPE to the airlines' capacity-price competition

Step 1: *Initialization.* Initialize capacities on the spoke-routes that are connected to the three SF airports.

Step 2: *Updating flight frequencies and airport delays*. Taking the average aircraft size as given, we determine the frequencies of each product and the airport delays. The flight frequencies for products using connecting flights (d_i) are determined by the flight frequencies on both segments based on regressing d_i on the number of daily airline departures on each flight segment:

$$d_i = \begin{cases} 0.3482 \times x_1 + 0.6153 \times x_2 & if \quad x_1 \geq x_2 \\ 0.8199 \times x_1 + 0.0231 \times x_2 & if \quad x_1 < x_2 \end{cases} \tag{A14}$$

where x_1 and x_2 are the flight frequencies on the first and second segment respectively. Daily flights at the three SF airports are divided equally into 15 minute intervals; equation (A9) in the appendix is then used to calculate average airport delays during operating hours, which are calibrated to obtain the observed delays at equilibrium.[5]

Step 3: *Computing the equilibrium of price competition given flight frequencies*. Given the flight frequencies and airport delays, we solve for the competitive equilibrium prices in each of the 120

[5] The average departure and arrival delays (in minutes) in the third quarter of 2007 are 17 and 5 at SFO, 10 and 2 at OAK, and 8 and 3 at SJC.

markets. We compute market equilibrium prices iteratively by allowing each carrier in the market to optimize the prices of the air travel products it offers taking the other carriers' prices of their products as fixed. An iteration of this computational procedure then involves F optimization problems, where F is the number of carriers in the market, which are solved by using the first-order condition in equation (5) of the text. Marginal costs in the first-order condition are calculated by equation (3)[6] and the mark-ups are calculated by using the third term of the left hand side of equation (11)[7] in the text. Let $\mathbf{p}_{\mathbf{m}}^{\mathbf{t+1}}$ and $\mathbf{p}_{\mathbf{m}}^{\mathbf{t}}$ denote the price vectors of market m from two successive iterations, equilibrium is reached when $\left\|\mathbf{p}_{\mathbf{m}}^{\mathbf{t+1}} - \mathbf{p}_{\mathbf{m}}^{\mathbf{t}}\right\|_{\infty} \leq 0.01$.

Step 4: *Convergence check*. Given equilibrium prices from step 3, compute demand quantities for the 20830 products using equations (A2), (A3), and (A4) in the appendix and the estimated parameters. Given the realized demand, each carrier updates the capacity on its spoke routes that are connected to the three SF airports to achieve a load factor of 70%. Let $\mathbf{T}^{\mathbf{t}+1}$ and $\mathbf{T}^{\mathbf{t}}$ denote the vectors of spoke capacities from two successive iterations, we check for convergence as follows: if $\left\|\mathbf{T}^{\mathbf{t+1}} - \mathbf{T}^{\mathbf{t}}\right\|_{\infty} \leq 1$, stop; otherwise set $\mathbf{T}^{\mathbf{t}} = \mathbf{T}^{\mathbf{t}+1}$ and return to step 2.

The algorithm can locate an equilibrium only if Bertrand equilibrium exists for each market given spoke capacities and if a fixed point of the self-map $\mathbf{H}(\cdot)$ exists given the load factor of 70%. Because the capacity constraint in equation (1) of the text is not binding at the equilibrium, we confine our discussion of the equilibrium of the price subgame to a given market with multi-product firms facing discrete-choice demands. Caplin and Nalebuff (1991) and Mizuno (2003) have studied the existence and

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[6] We include the estimated random component $\hat{\eta}_{jm}$, which captures the shift in marginal costs caused by unobserved product attributes.

[7] We include the estimated random component $\hat{\xi}_{jm}$, which captures travelers' preferences for unobserved product attributes.

uniqueness of pure strategy equilibrium in a price game among single-product firms facing discrete-choice demands (including the nested-logit model used in this paper). In the case of multi-product firms, Allon, Federgruen, and Pierson (2010) have shown that when total product costs are linear, price competition among multi-product firms with multinomial logit demand functions and random coefficients is supermodular and has a unique Nash equilibrium when prices are bounded by $\tilde{\mathbf{p}}$, where each element in the upper bound is the sum of the product's marginal cost and the absolute value of the inverse of the marginal utility of price. Using a fixed-point approach, Morrow and Skerlos (2010) prove the existence of Bertrand-Nash equilibrium for multi-product firms that face a multinomial logit demand with an underlying utility function that can be nonlinear.

Starting from different initial guesses, we found that step 3 of algorithm 1 can always locate a unique equilibrium for each market given spoke capacities. This result suggests that within the price space that we are exploring, a unique equilibrium exists for airline price competition in each city-pair market. For the outer loop that iterates the fixed-point equation $\mathbf{H}(\cdot)$ given a 70% load factor, we checked the robustness of the results by varying the initial guesses of spoke capacities and found no significant changes to the results. This is plausible because $\mathbf{H}(\cdot)$ is expected to be monotonically increasing. Larger spoke capacities indicate more frequent flights and higher service quality; in equilibrium, greater demand for air travel products exists when spoke capacities are larger. And when $\mathbf{H}(\cdot)$ is monotonically increasing, there is at most one fixed point for $\mathbf{H}(\cdot)$. The algorithm can also locate a unique solution if we increase the target load factor to 80% and 90%. However, we were unable to find a solution if we reduced the target load factor to 60%.[8]

[8] This finding is plausible because as shown in equation (6) of the text, the inverse of the load factor is the multiplier that maps a set of product demands to a set of spoke capacities. A smaller load factor implies a larger multiplier, such that a small disturbance can cause the dynamic system $\mathbf{H}(\cdot)$ to move

With Algorithm 1, we can compute the SPE to the three-stage game of private airport competition under different scenarios. We considered a scenario not shown in the text where only SFO is privatized; we use the grid search to determine the SPE to the three-stage game. Specifically, we first consider a wide range of airport charges at SFO [2, 200]. We then take 50 equally spaced points from the interval and set the airport charge at SFO at each of the 50 points and in an iteration of the loop; airport charges at OAK and SJC are set as the current weight-based landing charges. Algorithm 1 is used to compute the equilibrium outcomes of the airlines' capacity-price subgame given airport charges at each of the iterations. The data set from the loop is used to fit curves by spline interpolation, which represent the objective values (airport profits, social welfare, and airline profits under the equilibrium outcomes of the capacity-price subgame) as functions of the SFO charge. For the scenario of the SFO profit-maximizing charge subject to a non-negative change in consumer surplus (the last column of Table A8), the grid search is done over a much smaller interval [2, 20] because the solution to the problem is expected to result in a small charge.

When the three airports are privatized and purchased by the same firm, the private owner charges landing and takeoff fees at the three airports to maximize certain objectives. Again, we use the grid search to solve for the optimal charges at the three airports to maximize a certain objective. The grid search is on a three-dimensional space and we take 6 equally spaced points from the interval [2, 150] from each dimension. In total, we have 6^3 different airport charges and we use Algorithm 1 to compute the equilibrium outcomes of the capacity-price subgame of the airlines given each of those airport charges. We then use our data to approximate a surface by 3-dimension spline interpolation, which represents the objective value as a function of the charges at the three airports.

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away from the fixed-point when the load factor is small. Hence, the fixed-point is likely to be unstable when the load factor is small and the numerical algorithm cannot locate the fixed-point.

When the three airports are sold to different owners, the three airports engage in Bertrand competition. We develop an algorithm to compute the SPE to the three-stage oligopoly airport pricing game and the SPE is defined in Definition 2 of the text. An allocation of travelers across products under $(P(\varsigma), T(\varsigma)) \equiv \Lambda(\varsigma) \in \mathrm{O}(\varsigma)$ (an equilibrium of the service-price subgame of airlines given a set of airport charges ς) is denoted by the set $\{q_{jm}(\Lambda(\varsigma))\}_{j,m}$. We can define the demand (number of passengers) for airport n as

$$Q_n\left(\varsigma_n^A, \varsigma_{-n}^A\right) = \sum_{s \in \Xi_n} \left\{ \sum_m \sum_f \left(\sum_{j \in \Psi_{sf}} q_{jm}\left(\Lambda\left(\varsigma_n^A, \varsigma_{-n}^A\right)\right) \right) \right\}. \tag{A15}$$

Properties of the demand function, such as own-price and cross-price elasticities, cannot be characterized analytically because a change in airport charges causes a change in $\Lambda(\varsigma)$, which cannot be characterized analytically. Travelers respond to the change in equilibrium by adjusting their choices of air travel products to maximize utility.

As shown in Topkis (1979), the sufficient conditions for such a game to be a supermodular game are:

C1: $Q_n\left(\varsigma_n^A, \varsigma_{-n}^A\right)$ is an isotone function of $\varsigma_{n'}^A$ for each $n' \neq n$; and

C2: $-Q_n\left(\varsigma_n^A, \varsigma_{-n}^A\right)$ has antitone differences in $\left(\varsigma_n^A, \varsigma_{n'}^A\right)$ for each $n' \neq n$.

The first condition says that increasing the landing and takeoff charge at airport n' will increase the demand for airport n. The second condition says that the demand for airport n is more sensitive to its own landing and takeoff charge when the charge at airport n' is lower (and thus airport n' is more competitive with airport n).

Although we cannot verify analytically whether the demand function in (A15) satisfies those two conditions, it is reasonable to assume that it does. When an airport increases its landing and takeoff charges, the marginal aircraft operating costs of products that originate or terminate at the airport will increase, reducing the attractiveness of those products compared with substitutes using the other two airports (at the equilibrium of airline capacity-price competition given the airport charges) because those products will be relatively more expensive and less convenient (less flight frequency). The discrete choice demand model implies that travelers will respond to those changes by shifting to substitute products that use the other two airports; shifts to substitute products that use another airport are more likely when the charge at that airport decreases and charges at alternative airports are fixed.

Another assumption that we make to simplify the computation is that airport charges take discrete values when they are expressed in dollars. Under this assumption the incremental change of the landing and takeoff charges at an airport is $1.

The preceding assumptions ensure a nonempty set of the SPE (defined in Definition A2) exists that has the least and largest element. By definition, the three airports' charges at the least equilibrium point are the lower bound of airport charges at all equilibrium points of the set. At the least equilibrium point, travelers' surplus is the largest among all equilibrium points. The algorithm that computes the least point of the set of SPE is defined as follows.

Algorithm 2: Computing the SPE to the three-stage oligopoly airport price competition

Step 1: *Initialization*. Set $\boldsymbol{\varsigma}^0 \equiv \left({\varsigma_{SFO}^{A}}^{0}, {\varsigma_{SJC}^{A}}^{0}, {\varsigma_{OAK}^{A}}^{0} \right) = (0,0,0)$;

Step 2: *Updating*. Given airport charges from the last iteration $\boldsymbol{\varsigma}^t \equiv \left({\varsigma_{SFO}^{A}}^{t}, {\varsigma_{SJC}^{A}}^{t}, {\varsigma_{OAK}^{A}}^{t} \right)$

i) Solve the equilibrium of the capacity-price competition of airlines when airport charges are $\boldsymbol{\varsigma}^{try} \equiv \left({\varsigma_{SFO}^{A}}^{t} + 1, {\varsigma_{SJC}^{A}}^{t}, {\varsigma_{OAK}^{A}}^{t} \right)$ using Algorithm 1 and evaluate airport profits at the equilibrium. If $\pi_{SFO}^{A}\left(\boldsymbol{\varsigma}^t\right) < \pi_{SFO}^{A}\left(\boldsymbol{\varsigma}^{try}\right)$, set ${\varsigma_{SFO}^{A}}^{t+1} = {\varsigma_{SFO}^{A}}^{t} + 1$; otherwise, set ${\varsigma_{SFO}^{A}}^{t+1} = {\varsigma_{SFO}^{A}}^{t}$. Finally, set $\boldsymbol{\varsigma}^t = \left({\varsigma_{SFO}^{A}}^{t+1}, {\varsigma_{SJC}^{A}}^{t}, {\varsigma_{OAK}^{A}}^{t} \right)$.

ii) Solve the equilibrium of the capacity-price competition of airlines when airport charges are $\boldsymbol{\varsigma}^{try} \equiv \left({\varsigma_{SFO}^{A}}^{t+1}, {\varsigma_{SJC}^{A}}^{t} + 1, {\varsigma_{OAK}^{A}}^{t} \right)$ using Algorithm 1 in the appendix and evaluate airport profits at the equilibrium. If $\pi_{SJC}^{A}\left(\boldsymbol{\varsigma}^{t}\right) < \pi_{SJC}^{A}\left(\boldsymbol{\varsigma}^{try}\right)$, set ${\varsigma_{SJC}^{A}}^{t+1} = {\varsigma_{SJC}^{A}}^{t} + 1$; otherwise, set ${\varsigma_{SJC}^{A}}^{t+1} = {\varsigma_{SJC}^{A}}^{t}$. Finally, set $\boldsymbol{\varsigma}^{t} = \left({\varsigma_{SFO}^{A}}^{t+1}, {\varsigma_{SJC}^{A}}^{t+1}, {\varsigma_{OAK}^{A}}^{t} \right)$.

iii) Solve the equilibrium of the capacity-price competition of airlines when airport charges are $\boldsymbol{\varsigma}^{try} \equiv \left({\varsigma_{SFO}^{A}}^{t+1}, {\varsigma_{SJC}^{A}}^{t+1}, {\varsigma_{OAK}^{A}}^{t} + 1 \right)$ using Algorithm 1 in the appendix and evaluate airport profits at the equilibrium. If $\pi_{OAK}^{A}\left(\boldsymbol{\varsigma}^{t}\right) < \pi_{OAK}^{A}\left(\boldsymbol{\varsigma}^{try}\right)$, set ${\varsigma_{OAK}^{A}}^{t+1} = {\varsigma_{OAK}^{A}}^{t} + 1$; otherwise, set ${\varsigma_{OAK}^{A}}^{t+1} = {\varsigma_{OAK}^{A}}^{t}$.

iv) Set $\boldsymbol{\varsigma}^{t+1} = \left({\varsigma_{SFO}^{A}}^{t+1}, {\varsigma_{SJC}^{A}}^{t+1}, {\varsigma_{OAK}^{A}}^{t+1} \right)$.

Step 3: *Convergence check*. If $\boldsymbol{\varsigma}^{t+1} = \boldsymbol{\varsigma}^{t}$, stop; otherwise, return to step 2.

The algorithm generates three monotone sequences $\varsigma_n^{A^0} \le \varsigma_n^{A^1} \le \cdots \le \varsigma_n^{A^t} \le \varsigma_n^{A^{t+1}} \le \cdots$, $\forall n \in \{SFO, SJC, OAK\}$. When the oligopoly airport pricing game is supermodular, the sequences converge to $\boldsymbol{\varsigma}^{*} \equiv \left({\varsigma_{SFO}^{A}}^{*}, {\varsigma_{SJC}^{A}}^{*}, {\varsigma_{OAK}^{A}}^{*} \right)$, which is the lowest point of the equilibrium set.

We also consider negotiation scenarios between airports and airlines, where airlines that operate at an airport form a bargaining unit. One extreme case of those scenarios is that the landing and takeoff charges at each airport seek to maximize an airport's profits, but they are subject to the constraint of a nonnegative change (compared with the base case under the current weight-based landing fees) in the aggregate profits of the airlines that operate at the airport. Thus the constraint set faced by an airport is $\Phi_n \equiv \left\{ \varsigma_n^A : \pi_n^F\left(\Lambda\left(\varsigma_n^A, \boldsymbol{\varsigma}_{-n}^A\right)\right) - \pi_n^F\left(\Lambda\left(\hat{\varsigma}_n^A, \hat{\boldsymbol{\varsigma}}_{-n}^A\right)\right) \ge 0 \right\}, \forall n \in \{SFO, SJC, OAK\}$, where $\pi_n^F\left(\Lambda\left(\varsigma_n^A, \boldsymbol{\varsigma}_{-n}^A\right)\right)$ and $\pi_n^F\left(\Lambda\left(\hat{\varsigma}_n^A, \hat{\boldsymbol{\varsigma}}_{-n}^A\right)\right)$ are the aggregate profits of the airlines operating at airport n evaluated at the equilibria $\Lambda\left(\varsigma_n^A, \boldsymbol{\varsigma}_{-n}^A\right)$ and $\Lambda\left(\hat{\varsigma}_n^A, \hat{\boldsymbol{\varsigma}}_{-n}^A\right)$, which in turn are the equilibria of the capacity-price competition of airlines given airport charges $\varsigma \equiv \left(\varsigma_n^A, \varsigma_{-n}^A\right)$ and given current weight-based landing fees $\hat{\varsigma} \equiv \left(\hat{\varsigma}_n^A, \hat{\varsigma}_{-n}^A\right)$. We claim that the constraint set satisfies the following condition:

C3: Let $\varsigma^0 \equiv \left(\varsigma_n^A, \varsigma_{n'}^{A^0}, \varsigma_{-n,-n'}^A\right)$ and $\varsigma^1 \equiv \left(\varsigma_n^A, \varsigma_{n'}^{A^1}, \varsigma_{-n,-n'}^A\right)$, where $\varsigma_{-n,-n'}^A$ is the set of airport charges excluding airport n and n'. If $\varsigma_{n'}^{A^1} > \varsigma_{n'}^{A^0}$, we have

$$\Phi_n^0 \equiv \left\{\varsigma_n^A : \pi_n^F\left(\Lambda\left(\varsigma^0\right)\right) - \pi_n^F\left(\Lambda\left(\hat{\varsigma}\right)\right) \geq 0\right\} \subset \Phi_n^1 \equiv \left\{\varsigma_n^A : \pi_n^F\left(\Lambda\left(\varsigma^1\right)\right) - \pi_n^F\left(\Lambda\left(\hat{\varsigma}\right)\right) \geq 0\right\}$$

The condition says that the constraint set faced by an airport expands when another airport increases its landing and takeoff charges. Under the assumption that the demand function in (A15) satisfies condition C1, the constraint set faced by each airport satisfies C3 such that Algorithm 3 discussed below can be easily modified by incorporating the check for the constraint in step 2. The modified algorithm finds the lowest point of the equilibrium set.

Another extreme case of the negotiation scenarios is that the landing and takeoff charges at each airport seek to maximize the aggregate profits of airlines operating at the airport, but they are subject to the constraint that the airport's profits are nonnegative. Conditions C1-C3 are satisfied in this bargaining game and therefore the analysis of the equilibrium to this game is the same as in the previous analysis.

Model Validation

To validate our empirical models, we compute the SPE of the airlines' service-price subgame given airport charges by simulating the baseline equilibrium (2007:3) under the current policy that the SF airports are publicly owned. Commercial carriers pay the 2007 weight-based landing fee, but they are not charged for taking off from an airport, and travelers pay passenger facility charges that are included in the fare. We show in table A6 that based on a comparison of simulated with actual outcomes, that our model generates credible predictions of air travel activity at the SF airports as indicated by its close replication of the level of airport passengers and the distribution of product prices, demands, and spoke passengers. Our model tends to underestimate flight frequencies, but that is not surprising because we do not include connecting passengers whose flights do not originate or terminate at an SF airport.

Calibrations Accounting for General Aviation Operations

We assume distinct GA demand functions for the SF airports take a simple constant-elasticity demand form

$$Q_n^{GA} = A_n \cdot \left(FP_n\right)^{-e} \quad , \tag{A16}$$

where FP_n is the full-price of using airport n, which includes aircraft operating costs, airport charges, and passengers' time costs**,** e is the demand elasticity, and A_n is a scale parameter. Because the full prices of landing and taking off are different, equation (A16) implies that total GA demand for each of the SF airports is given by

$$Q_n^{GA} = A_n \cdot \left[\left(FP_n^T\right)^{-e} + \left(FP_n^L\right)^{-e}\right] \quad , \tag{A17}$$

where the superscripts T and L denote taking off and landing.

Consistent with the much larger percentage of GA operations at San Francisco airport (SFO) that are air taxi operations (table 1), GA aircraft that use Oakland (OAK) and San Jose (SJC) airports are assumed to have four seats and an average load factor of 60 percent and GA aircraft that use SFO are assumed to have eight seats and an average load factor of 60 percent. The GA aircraft operating cost function (in dollars per block hour) is assumed to be a linear function of total seats and we use the unit aircraft operating costs (dollars per block hour per seat) of small commercial aircraft as the basis for our estimate—that is, \$35 per seat for a 50 seat aircraft. Currently, GA aircraft using OAK and SJC are not charged landing fees and GA aircraft using SFO are charged a minimum of \$140 per landing.[9]

Turning to passengers' time costs, we assume that the predominantly business GA travelers who use SFO are airborne for two hours, on average, and that GA travelers who use OAK and SJC are airborne for one hour. We assume that GA travelers who use OAK and SJC have the values of airborne time and airport delay, \$40/hour and \$160/hour, which we obtained from our nested-logit model for business travelers using commercial aircraft, and we assume somewhat higher values, \$60/hour and \$200/hour, for GA travelers who use SFO. The full price elasticity of demand for GA travelers is assumed to be the same demand elasticity, -1.8, which we obtained for business travelers on commercial

[9] http://www.flysfo.com/investor/SummaryFY0910.pdf .

aircraft.[10] Finally, we set the values of A_n such that GA's predicted shares of total traffic at SFO, OAK, and SJC are consistent with their actual shares.[11]

Given the GA demand functions, we accounted for GA's effect on air travel delays by inflating the traffic volume in each of the 15-minute segments at the SF airports to include GA's traffic in accordance with its actual traffic shares and by re-estimating the translog delay function given in equation (A9). Unfortunately, data are not available that indicate how GA's traffic shares vary throughout the day. Estimation results for the new arrival and departure delay functions presented in table A7 show that including GA operations mainly affects the constant in those functions. Figure A2 plots the previous estimated departure and arrival delay functions and the estimated delay functions that account for general aviation. The vertical distance between the two delay functions for a given airport indicates that GA does contribute to delays at all the SF airports.

Additional Simulation Results

Besides the baseline simulation results presented in Table 4 and 5 in the text, we ran several other simulations. Table A8 presents the case where one of the airports in a metropolitan area participates in a privatization pilot program, in this case SFO, but the other airports are still owned and operated by the local government. The results show that privatizing SFO airport produces roughly an $85 million (quarterly) social welfare gain because SFO sets takeoff and landing charges that increase its profits and that greatly reduce departure and arrival delays. Airlines' profits decrease because their operating costs increase and because they cannot sufficiently raise their fares to offset the higher airport charges. Despite the increase in fares, travelers experience only a small loss in consumer surplus because they no longer pay passenger facility charges, benefit from much shorter delays, in some cases avoid the higher fares at SFO by switching to OAK and SJC airports and incurring only a modest increase in departure delays, and in some cases avoid both the higher fares at SFO and increase in departure delays at OAK and SJC by switching to the outside option of using an alternative mode or not traveling. As shown in the third and fourth columns of the table, SFO charges that maximize social welfare and airlines' total profit transfer some airport profits to airlines while having a modest effect on

[10] We calculated the elasticity from the demand estimates in table A3 by increasing both price and travel times (airborne time and airport delay) by 1%.

[11] GA airport shares, obtained from http://aspm.faa.gov/opsnet/sys/Airport.asp, are 30% for SFO and 35% for SJC and OAK.

the social welfare gain and the loss to travelers. That loss is eliminated only if SFO sets no charge (fifth column), which produces a social welfare loss, or a small charge (sixth column), which produces a much smaller welfare gain. Thus airport privatization has the potential to improve social welfare but distributional concerns arise because travelers do not stand to gain from the policy.

Table A9 presents two cases of privatizing all three airports. Under the monopoly case (second column), if the airports' profit-maximizing charge is subject to a nonnegative change in travelers' surplus, the charge generates a very small welfare gain. If airports engage in Bertrand competition to maximize their own profits, the charges would generate quarterly social welfare gains that are close to the social-welfare maximizing case. However, both airlines and travelers are worse-off.

We have assumed aircraft sizes are fixed (Assumption 3) when it is possible that airlines could respond to higher airport charges by increasing aircraft sizes and reducing flights, which would increase charges but reduce delays. As shown in the appendix table A10, we find that if, for example, airlines increase their aircraft sizes 50%, then the potential gains from airport privatization are increased because the airlines' gain from less delay exceeds their loss from higher charges, airports' profits increase, and the quarterly social welfare gains are an additional $130 million.

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Table A1. Delay functions at the SF Airports

	SFO	SJC	OAK
Departure delay			
b_{0n}	-2.9886 (0.0312)	-2.2606 (0.0388)	-0.7956 (0.0314)
b_{1n}	4.2989 (0.0405)	3.8172 (0.0523)	3.0890 (0.0286)
b_{2n}	-0.7852 (0.0193)	-0.6731 (0.0446)	-0.5159 (0.0326)
Adj. R^2	0.45	0.22	0.27
Arrival delay			
b_{0n}	-2.4557 (0.0269)	-1.7537 (0.0343)	-0.4314 (0.0269)
b_{1n}	3.0804 (0.0349)	1.9147 (0.0463)	2.4513 (0.0245)
b_{2n}	-0.5915 (0.0167)	-0.1824 (0.0395)	-0.9372 (0.0279)
Adj. R^2	0.36	0.10	0.25
# of observations	31754	25961	32435

Note: The dependent variable is the log of average aircraft delay (minutes per aircraft) in a 15-minute interval on a representative travel day in 2007 and the explanatory variables include a constant and the log of the volume-to-capacity ratio and its square in the 15-minute interval.

Table A2. Summary Statistics for the Demand Variables

Variable	Definition	Mean (std. dev.) or fraction in the sample
Fare ($100)	Fare paid by passengers for an itinerary. Source: DB1B	2.79 (1.60)
Airborne time (hour)	Total airborne time on a route. It is constructed by summing total airborne time for all segments. Source: T-100 Domestic Segment Data.	4.83 (1.29)
Airport delay (hour)	Total delays at airports on an itinerary. It is constructed by summing delays at origin and destination airports as well as departure and arrival delays at the connecting airport for connecting flights. Source: ASPM database.	0.58 (0.14)
Transfer time (hour)	Layover time at the connecting airport on an itinerary; zero for non-stop flights. Source: Back Aviation Solutions database.	1.34 (0.71)
Schedule delay (hour)	The difference between travelers' desired departure times and the closest available departure times. The expression to measure this difference is in footnote 1. Source: Back Aviation Solutions database.	3.98 (3.16)
Low cost carriers [a]	1 if the product is offered by a low cost carrier; 0 otherwise. Source DB1B	20%
Connecting flight	1 if the product is served by a connecting flight; 0 otherwise. Source: DB1B.	88%
Origin airport presence	Number of domestic and international destinations served by the carrier from the origin airport (100s of cities). Source: Back Aviation Solutions database.	0.18 (0.32)
Destination airport presence	Number of domestic and international destinations served by the carrier from the destination airport (100s of cities). Source: Back Aviation Solutions database.	0.19 (0.33)
OD Distance	Distance between the origin and destination airports (1000 miles)	2.04 (0.59)
Tourist city	1 if the city connecting to SF airports is located in Florida or Nevada; 0 otherwise	17%
Slot control	1 if the airport connecting to SF airports is under slot control; 0 otherwise. Airports under slot control are Chicago O'Hare, LaGuardia and Kennedy in New York, and National Reagan in Washington D. C.	18%
Hub route [b]	1 if the origin or destination airport is the carrier's hub airport (including the connecting airport for connecting flights); 0 otherwise.	66%
LCC route presence [a]	1 if the route connecting the origin and destination airports of a product is served by a low cost carrier (LCC); 0 otherwise	90%

Southwest route presence	1 if the route connecting the origin and destination airports of a product is served by Southwest; 0 otherwise	34%
Potential Southwest entry	1 if Southwest operates at the origin and destination airports but does not serve the route connecting the two airports; 0 otherwise.	0.01%
Market size (millions)	Geometric mean of the population of the end cities	4.36 (2.10)
Mean Income ($1000)	Geometric mean of income per capita of end cities	47.75 (3.16)
Number of observations	Number of products	20830

[a] Following Ito and Lee (2003), we classify the following carriers as low cost carriers: Air South, Access Air, Air Tran (FL), ATA (TZ), Eastwind, Frontier (F9), JetBlue (B6), Kiwi, Morris Air, National, Pro Air, Reno, Southwest (WN), Spirit, Sun Country (SY), ValuJet, Vanguard and Western Pacific.

[b]We include the following hubs in U.S. markets: Chicago-O'Hare (American. United), Cleveland (Continental), Newark (Continental), Atlanta (Delta), San Francisco (United), Dallas-Ft. Worth (American), Philadelphia (US Airways), Phoenix (US Airways), Detroit (Northwest), St. Louis (American), Houston (Continental), Washington-Dulles (United), Minneapolis-St. Paul (Northwest), Cincinnati (Delta), Salt Lake City (Delta), Denver (United), and Miami (American).

Table A3. BLP Demand estimation results

Variables	Model with preference heterogeneity: BLP GMM Estimates (standard errors)
Constant	-5.32 (0.42)
Price (hundred $):	
Leisure travelers	-1.29 (0.48)
Business travelers	-0.63 (0.21)
Connecting route dummy	-1.86 (0.16)
Airborne time (Hour)	-0.21 (0.03)
Airport delay (Hour)	-0.92 (0.24)
Long Transfer time dummy (> 1.5Hour)	-0.15 (0.04)
Schedule delay (Hour)	-0.07 (0.02)
Origin airport presence [a]	0.18 (0.05)
Destination airport presence [a]	0.13 (0.06)
Carrier dummy (United as the base)	
American	0.09 (0.04)
Delta	-0.28 (0.09)
Continental	-0.25 (0.09)
US Airways	-0.24 (0.07)
Northwest	-0.31 (0.09)
Alaska	0.11 (0.14)
Southwest	-0.40 (0.20)
Jet Blue	0.05 (0.17)
Other non-low-cost carriers	0.94 (0.20)
Other low-cost carriers	0.02 (0.15)
Airport dummy	
OAK dummy (SFO as the base)	-0.16 (0.06)
SJC dummy (SFO as the base)	-0.05 (0.03)
MDW dummy (ORD as the base)	-0.56 (0.13)
EWR dummy (JFK as the base)	-0.36 (0.11)
LGA dummy (JFK as the base)	-0.39 (0.14)
HOU dummy (IAH as the base)	-0.37 (0.10)
DAL dummy (DFW as the base)	-0.38 (0.21)
DCA dummy (IAD as the base)	0.25 (0.10)
LGB dummy (LAX as the base)	-0.10 (0.63)
BUR dummy (LAX as the base)	0.28 (0.28)
Market characteristics	
OD distance (thousand miles)	0.79 (0.25)
Square of OD distance	-0.06 (0.04)
Tourist city dummy	-0.07 (0.05)
Slot controlled airport dummy	-0.21 (0.05)
Other parameters	
Lamda(λ)	0.74 (0.03)
Number of observations	20830

Note: [a] An airline's airport presence is measured as the number of domestic and international destinations that it serves.

Table A4. Robustness Check to BLP Demand Estimation Results: Demand Elasticities and Value of Time Components Based on Demand Coefficients from Alternative Demand Estimations

Variables	Homogeneous preference: OLS estimates [a]	Homogeneous preference: IV estimates [a]	Heterogeneous preference: BLP GMM estimates
Aggregate price elasticity of demand for air travel			
Overall	-0.22	-1.23	-1.54
Business travelers	--	--	-1.35
Leisure travelers	--	--	-2.10
Value of Airborne time ($/hour)			
Overall	70	31	24
Business travelers	--	--	33
Leisure travelers	--	--	16
Value of Airport delay ($/hour)			
Overall	170	113	104
Business travelers	--	--	144
Leisure travelers	--	--	71
Value of flight frequency ($/flight)			
Overall	79	18	16
Business travelers	--	--	22
Leisure travelers	--	--	11
Willingness to pay for non-stop flights ($)			
Overall	1033	276	212
Business travelers	--	--	295
Leisure travelers	--	--	144
Willingness to pay for connecting flights with a connection that is less than 1.5 hours ($)			
Overall	100	23	17
Business travelers	--	--	24
Leisure travelers	--	--	12

[a] When preferences are homogenous, the analytical solution of unobserved product attributes can be derived and the following regression equation can be estimated (Berry (1994)):

$$\ln(S_{jm}) - \ln(S_{0m}) = X_{jm}B + \alpha \cdot p_j + \phi \cdot d_j + \gamma^f \cdot t_j^f + \gamma^a \cdot t_j^a + \gamma^l \cdot t_j^l + (1-\lambda)\ln S_{jm|A} + \xi_{jm}$$

In this regression model, price, schedule delay, and the market share within travel products ($S_{jm|A}$) are endogenous. We report results from OLS estimation of this regression, which ignores endogeneity, in the first column, and report results for instrumental variables estimation of this regression in the second column. The IVs for price and schedule delay were presented in the text and the IV for the market share within travel products is the average airport presence of airline competitors.

Table A5. Marginal Cost Parameter Estimates

Variable	Model with heterogeneous preferences: BLP GMM estimates (standard errors)
Constant	2.19 (0.52)
Number of segments	-0.77 (0.12)
Segment distance (thousand miles)	-0.67 (0.06)
Carrier dummy (United as the base)	
American	0.56 (0.16)
Delta	-0.20 (0.11)
Continental	0.19 (0.09)
US airways	0.23 (0.10)
Northwest	-0.09 (0.21)
Alaska	-0.04 (0.22)
Southwest	-0.17 (0.08)
Jet Blue	-0.03 (0.13)
Other non-low-cost carriers	0.82 (0.21)
Other low-cost carriers	-0.06 (0.10)
Airport dummy	
OAK (SFO as the base)	-0.24 (0.05)
SJC (SFO as the base)	-0.03 (0.05)
Non-SF airport dummies included	YES
Interactions of airline and airport dummies	
United × SFO	0.04 (0.10)
United × United hub airports [a]	0.55 (0.21)
American × American hub airports [a]	0.03 (0.11)
Delta × Delta hub airports [a]	0.38 (0.12)
Northwest × Northwest hub airports [a]	0.41 (0.19)
US airways × US airways hub airports [a]	0.01 (0.07)
Southwest × OAK	0.18 (0.11)
Airline presence at airports	
Origin airport presence [b]	0.24 (0.12)
Destination airport presence [b]	0.33 (0.13)
International presence at end-point airports [c]	0.15 (0.05)
Number of observations	20830

Note:
[a] The definition of hub airports of airlines is in footnote (b) of Table A2.
[b] An airline's airport presence is measured as the number of domestic and international destinations that it serves.
[c] The value of this variables takes three values: 0 if an airline has no international presence at end-point airports of a route; 1 if an airline has international presence at one of the end-point airports of a route; and 2 if an airline has international presence at both the end-point airports of a route;

Table A6. Comparison between Simulated and Observed Market Outcomes for 2007: 3

Market outcomes	Observed	Simulated outcome with 70% load factor
Product price ($)		
Mean	279	280
Median	242	245
Standard deviation	160	162
75%-ile	347	351
25%-ile	168	166
Product demand (number of passengers)		
Mean	311	340
Median	30	26
Standard deviation	1818	1999
75%-ile	70	71
25%-ile	10	11
Product frequency		
Mean	4.84	3.13
Median	4	2.69
Standard deviation	3.65	2.00
75%-ile	6	4.25
25%-ile	2	1.53
SF spoke route passengers[a]		
Mean	22,187	24,286
Median	16,095	17,953
Standard deviation	19,903	20,962
75%-ile	29,295	32,210
25%-ile	7,785	9,145
Airport passengers		
SFO	2,554,390	3,021,687
SJC	1,600,820	1,779,986
OAK	2,323,340	2,289,887
Number of Products	20830	20830
Number of SF spoke routes	292	292

[a] A SF spoke route is defined by a carrier and an airport pair, where the origin or destination is one of the three SF airports.

Table A7. Delay Functions at the SF Airports Accounting for GA Operations

	SFO	SJC	OAK
Departure delay			
b_{0n}	-4.6218 (0.0385)	-4.0299 (0.0508)	-2.2220 (0.0335)
b_{1n}	4.8590 (0.0532)	4.3971 (0.0833)	3.5335 (0.0407)
b_{2n}	-0.7852 (0.0193)	-0.6731 (0.0446)	-0.5159 (0.0326)
Adj. R^2	0.45	0.22	0.27
Arrival delay			
b_{0n}	-3.6297 (0.0332)	-2.6124 (0.0494)	-1.6613 (0.0287)
b_{1n}	3.5023 (0.0459)	2.0719 (0.0738)	3.2587 (0.0349)
b_{2n}	-0.5915 (0.0167)	-0.1824 (0.0395)	-0.9372 (0.0279)
Adj. R^2	0.36	0.10	0.25
# of observations	31754	25961	32435

Note: The dependent variable is the log of average aircraft delay (minutes per aircraft) in a 15-minute interval on a representative travel day in 2007; explanatory variables are the log of the volume-to-capacity ratio and its square in the 15-minute interval.

Table A8. Welfare Effects of Privatizing SFO

	Base case	SFO profit maximizing charge	SFO social welfare maximizing charge	SFO charge that maximizes airlines' total profit	SFO charge that maximizes airlines' profit at SFO	SFO profit maximizing charge subject to non-negative consumer surplus change
Airport charge ($/seat)[a]						
SFO	2.00	69	48	17	0	4
SJC	2.00	2	2	2	2	2
OAK	2.00	2	2	2	2	2
Airport Delay (min.)						
SFO						
Departure delay	15	4	7	13	16	16
Arrival delay	5	2	3	4	5	5
SJC						
Departure delay	9	10	10	10	9	9
Arrival delay	3	3	3	3	3	3
OAK						
Departure delay	10	11	11	10	10	10
Arrival delay	3	3	3	3	3	3
Change in Airport Profits (million $/quarter)						
SFO	0	105.46	97.23	44.25	-18.19	1.55
SJC	0	0.54	0.40	0.13	-0.06	0.00
OAK	0	0.91	0.70	0.24	-0.10	0.00
Total	0	106.91	98.33	44.62	-18.35	1.55
Change in Airline Profits by airport (million $ / quarter)						
SFO	0	-57.72	-24.23	8.81	13.87	10.03
SJC	0	17.27	12.55	4.03	-1.68	0.09
OAK	0	20.04	14.77	4.92	-1.88	0.12
Total	0	-20.41	6.09	17.76	10.31	10.24
Consumer surplus change (million $/quarter)[b]						
Business travelers	0	-1.52	-1.12	-0.38	0.15	0.00
Leisure travelers	0	-0.55	-0.44	-0.17	0.07	0.00
Total	0	-2.07	-1.56	-0.55	0.22	0.00
Change in social welfare (million $/quarter)[b]	0	84.43	102.86	61.83	-7.82	11.79

[a] The airport charge in the base case is the 2007 weight-based landing fee that is charged when a commercial carrier lands at an airport. The carrier is not charged when it takes off from an airport. Travelers pay passenger facility charges that are included in the fare. In the privatization scenarios, the weight-based landing charge and the passenger facility charges are replaced with the following charges. When an aircraft takes off from a San Francisco Bay Area airport, it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) as well as the weight-based landing charge at the non-San Francisco Bay Area airport. When an aircraft takes off from a non-San Francisco Bay Area airport it is not assessed a charge by that airport but it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) for its landing at a San Francisco Bay Area airport.
[b] Measured as the change from the base case.

Table A9. Welfare Effects of Privatizing All the Three SF Airports

	Base case	Monopoly: Airports' profit maximizing charges subject to non-negative consumer surplus change	Bertrand competition: charges maximize airports' profits
Airport charge ($/seat) [a]			
SFO	2.00	0	75
SJC	2.00	8	63
OAK	2.00	9	69
Airport Delay (min.)			
SFO			
Departure delay	15	16	5
Arrival delay	5	5	2
SJC			
Departure delay	9	9	2
Arrival delay	3	2	1
OAK			
Departure delay	10	9	2
Arrival delay	3	3	2
Change in Airport Profits (million $/quarter)			
SFO	0.00	-18.11	127.18
SJC	0.00	9.24	75.55
OAK	0.00	14.92	98.21
Total	0.00	6.04	300.94
Change in Airlines' Profits by airport (million $/quarter)			
SFO	0.00	16.50	27.33
SJC	0.00	6.30	13.31
OAK	0.00	8.84	19.70
Total	0.00	31.64	60.34
Consumer surplus change (million $/quarter)[b]			
Business travelers	0.00	0.01	-3.54
Leisure travelers	0.00	-0.01	-1.43
Total	0.00	0.00	-4.97
Change in social welfare (million $/quarter)[b]	0.00	37.68	235.63

[a] The airport charge in the base case is the 2007 weight-based landing fee that is charged when a commercial carrier lands at an airport. The carrier is not charged when it takes off from an airport. Travelers pay passenger facility charges that are included in the fare. In the privatization scenarios, the weight-based landing charge and the passenger facility charges are replaced with the following charges. When an aircraft takes off from a San Francisco Bay Area airport, it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) as well as the weight-based landing charge at the non-San Francisco Bay Area airport. When an aircraft takes off from a non-San Francisco Bay Area airport it is not assessed a charge by that airport but it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) for its landing at a San Francisco Bay Area airport.

[b] Measured as the change from the base case.

Table A10. Sensitivity analysis to changes in aircraft size after privatization

	No change in aircraft size after privatization **Bertrand competition: charges for commercial flights maximize the weighted sum of airlines and airport profits at each airport subject to a non-negative change in commercial travelers' surplus and a $280 price-cap on the GA charge[d]**	*Increase aircraft size 50% after privatization* **Bertrand competition: charges for commercial flights maximize the weighted sum of airlines and airport profits at each airport subject to a non-negative change in commercial travelers' surplus and a $280 price-cap on the GA charge[d]**
Airport charge for commercial airlines($/seat) [a]		
SFO	11	23
SJC	4	12
OAK	3	10
Airport charge for general aviation ($/flight) [b]		
SFO	280	280
SJC	280	280
OAK	280	280
Airport Delay (min.)		
SFO		
Departure delay	14	12
Arrival delay	4	3
SJC		
Departure delay	7	4
Arrival delay	2	2
OAK		
Departure delay	7	5
Arrival delay	3	2
Change in Airport Profits (million $/quarter)		
SFO	113.72	159.67
SJC	51.21	88.22
OAK	120.13	147.94
Total	285.06	395.83
Change in Airlines' Profits by airport (million $/quarter)		
By airports		
SFO	10.38	15.02
SJC	20.00	26.14
OAK	26.22	33.65
Total	56.60	74.81
Consumer surplus change (million $/quarter)[c]		
Business travelers	0.01	0.01
Leisure travelers	-0.01	-0.01
General aviation travelers	-6.53	-6.11
Total	-6.53	-6.11
Change in social welfare (million $/quarter)[c]	335.13	464.53

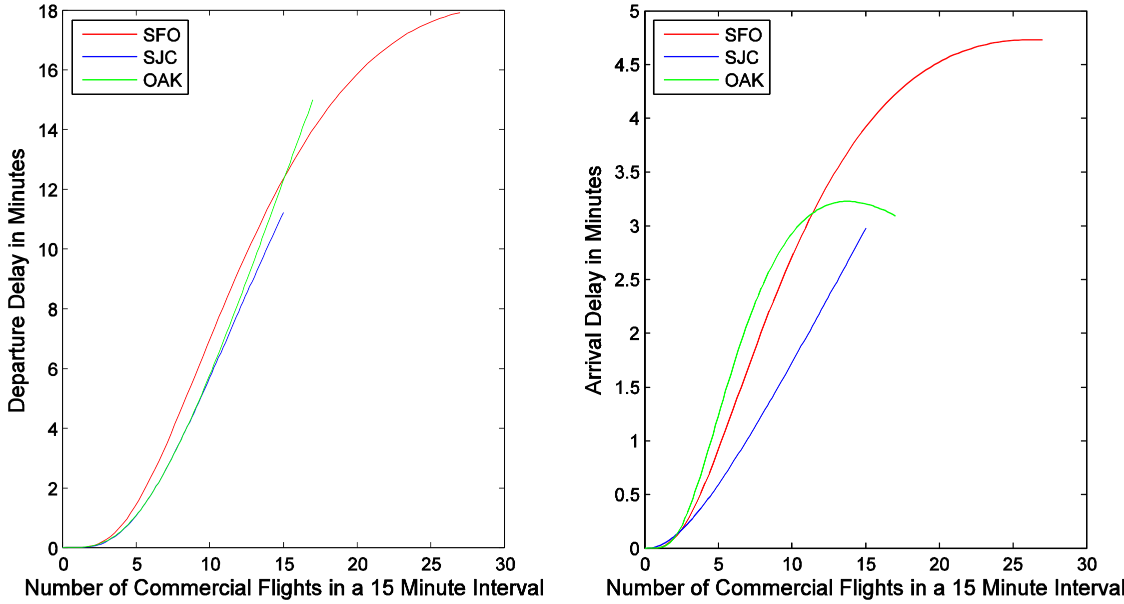
[a] The airport charge in the base case is the 2007 weight-based landing fee that is charged when a commercial carrier lands at an airport. The carrier is not charged when it takes off from an airport. Travelers pay passenger facility charges that are included in the fare. In the privatization scenarios, the weight-based landing charge and the passenger facility charges are replaced with the following charges. When an aircraft takes off from a San Francisco Bay Area airport, it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) as well as the weight-based landing charge at the non-San Francisco Bay Area airport. When an aircraft takes off from a non-San Francisco Bay Area airport it is not assessed a charge by that airport but it is assessed the charge indicated in the column heading (e.g., airport profit maximizing charge) for its landing at a San Francisco Bay Area airport.

[b] The airport charge at SFO for general aviation in the base case is the current minimal charge when a general aviation aircraft lands at the airport. A general aviation aircraft is not charged when it takes off from SFO. In the privatization scenarios, the current charge is replaced by a charge that is applied to both take-off and landing.

[c] Measured as the change from the base case.

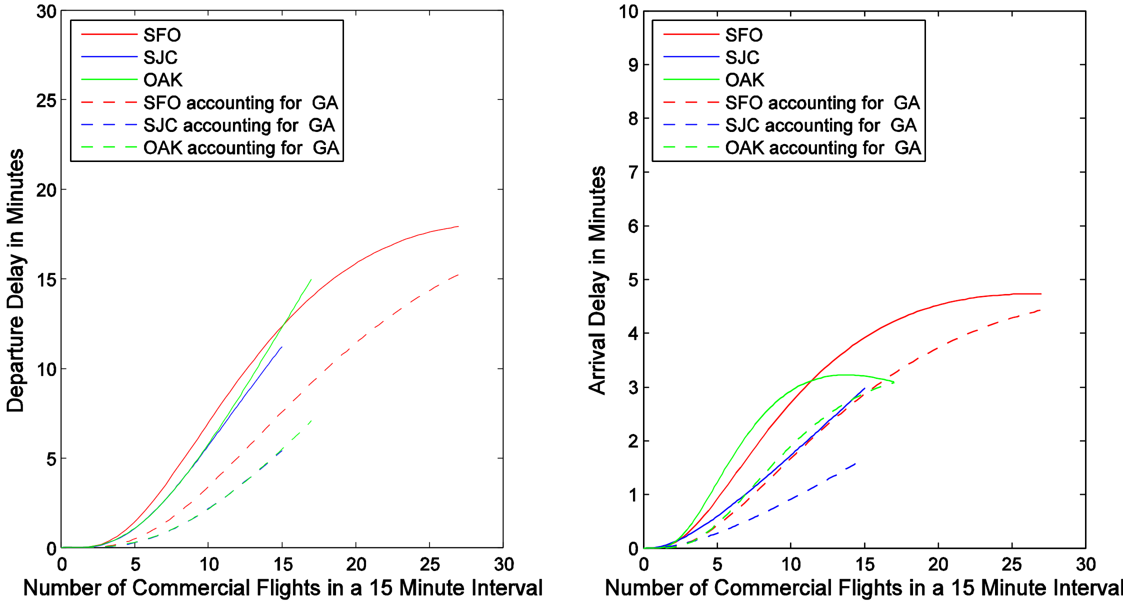
[d] In this scenario, each airport charges commercial flights to maximize: $\varpi \cdot \text{Airport Profits} + (1-\varpi) \cdot \text{Airlines'Profits}$, where $\varpi \in [0,1]$ represents the bargaining power of an airport when it negotiates charges with the airlines. When can find a threshold ϖ^*, when $\varpi \le \varpi^*$, under the bargaining equilibrium of oligopoly airport competition, the airports and airlines are better off and the commercial travelers are not worse off from privatization. Results presented in the column are bargaining outcomes when $\varpi = \varpi^*$.

Figure A1. Delay functions of the three SF airports



Note: Figure A1 plots the estimated delay functions presented in table 3. For each airport, we plot the departure and arrival delay functions within the range of the observed number of commercial flights in a 15 minute interval in the 3rd quarter of 2007. The maximum flights in this interval were 26 at SFO, 15 at SJC, and 17 at OAK.

Figure A2. Delay functions of the three SF airports including GA



Note: Figure 3 plots the previously estimated delay functions presented in table 3 and the delay functions in table 12 that account for GA operations.