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Pricing the major hub airports

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Implementing congestion pricing at twenty-seven major US airports would reduce delays by thirteen passenger-years and one thousand aircraft-hours every day, saving three to five million dollars. Chicago and Atlanta would save about one thousand dollars per aircraft. Airport revenues would increase about eleven million dollars daily. A bottleneck model with stochastic queues estimates substantial welfare gains whether or not airlines internalize self-imposed delays. Erroneously imposing fees from the non-internalizing specification on internalizing airlines, however, would be a costly mistake. The model calculates equilibrium traffic rates, queuing delays, layover times, connection times, and congestion fee schedules by minute of the day.
Keywords: airport congestion pricing, stochastic queuing, bottleneck model.
(JEL R4, H2, L5, L9)

Renewed academic interest in airport congestion pricing over the last several years mainly focuses on whether dominant hub-and-spoke airlines internalize their self-imposed congestion delays. As a theoretical matter, it is reasonable to believe that either Nash-dominant airlines already internalize this congestion or Stackelberg-dominant airlines ignore it (see, Brueckner [4]).[1] While the theoretical literature debates the implications of internalization for congestion pricing, the empirical literature has not previously compared actual congestion prices and welfare effects for these alternative specifications. This article uses detailed traffic data from twenty-seven major US airports to calculate the stochastic bottleneck equilibria assuming airlines do or do not internalize their self-imposed delays. Our results show that there are substantial welfare gains from congestion pricing under either hypothesis, but that incorrectly imposing pricing from the non-internalizing specification on an internalizing dominant airline is much worse than no pricing at all.

We use the same stochastic bottleneck model and data that Daniel and Harback [7] use to test the hypothesis that airlines internalize self-imposed congestion against the alternative that they ignore it.

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Daniel and Harback find that dominant airlines do not internalize self-imposed delays at most airports, but that they may internalize delays at some airports. That article uses the observed traffic patterns in its specification tests, but it does not calculate the stochastic bottleneck equilibrium. In this article, we remain neutral about whether dominant airlines internalize self-imposed delay by using both specifications of the model to calculate equilibrium traffic rates, delays, marginal congestion levels, price schedules, and welfare effects of congestion pricing at all twenty-seven major hub airports.

Most empirical models of congestion pricing specify traffic rates as functions of contemporaneous prices and travel times, without allowing traffic to shift between periods. The purpose of congestion pricing in such models is to reduce delay by "tolling off" traffic that exceeds socially efficient levels. In standard bottleneck models, total demand is fixed while traffic shifts between periods to establish equilibrium. The purpose of congestion pricing in bottleneck models is to reduce delays by smoothing the flow of traffic so that it does not greatly exceed capacity during peak periods. Welfare gains in these models result from more efficient scheduling of existing aircraft to reduce delays, not from tolling off traffic. We suspect that much opposition to congestion pricing arises from the belief that it would necessarily restrict access to airports, but our results show that significant savings are possible without eliminating any traffic.

While our model allows for changes in traffic levels caused by congestion pricing, we maintain the assumption of fixed demand throughout. This assumption is justified because we advocate implementing congestion pricing, whenever possible, in a way that leaves full costs (fees and time costs) of aircraft landings and takeoffs approximately unchanged. At optimally-sized airports that currently use weight-based landing fees to cover all airside operating costs, substituting congestion fees would generate at least as much revenue (assuming constant returns). At airports that currently subsidize air-side operations from ground-side revenues—by maximizing all other airport revenues before setting fees to cover the remaining deficit—we assume that the airport authority would continue to subsidize aircraft operations under congestion pricing. If necessary, the airport could achieve aircraft cost neutrality by rolling back the congestion fee schedule by a constant amount, or reducing other aircraft charges that are independent of their time of operation.

Clearly, cost-neutral implementation of congestion pricing is inconsistent with tolling off demand, but careful and detailed modeling of traffic patterns, random shocks to operating times, and stochastic queuing systems demonstrates that many, if not all, congested airports have enough unused capacity to benefit from smoother traffic rates. Traffic data at most major hub airports exhibit rapid periodic peaking associated with banks of arriving and departing flights that cluster around passenger interchange periods. This pattern is significantly different from the gradual morning and afternoon peaking that was common before widespread adoption of hub-and-spoke networks. When airport traffic peaks gradually, the fee schedules also vary gradually over time. When airports have rapid traffic fluctuations associated with hub-and-spoke operations, fee schedules must fluctuate rapidly to encourage some aircraft to use the capacity available during off-peak periods. Unlike most congestion pricing studies, our bottleneck model explicitly accounts for the tradeoff between queuing delay and layover time or missed connections. This article demonstrates that there are significant welfare gains from optimizing aircraft scheduling at most major airports irrespective of whether or not dominant airlines internalize their self-imposed delays.

The literature

There is a substantial literature on airport congestion pricing, but relatively few articles that attempt to calculate equilibrium fee schedules for real airports. Most of the literature concerns theoretical models, pricing of hypothetical networks, and (most recently) the internalization debate. Carlin and Park [5] estimate external congestion levels for New York's LaGuardia airport. Their model assumes that each arrival imposes delays equal to its service time (the time elapsed between consecutive aircraft touchdowns) on every subsequent arrival until the landing queue clears. This approach implicitly assumes a deterministic queuing system similar to the deterministic bottleneck model. When there is randomness in aircraft operating times, however, the effect of an operation on delays of subsequent aircraft diminishes over time even while the expected queue is positive. Koopman [10] develops a stochastic queuing model to calculate delays at New York's Kennedy and LaGuardia airports. Neither Carlin and Park [5] nor Koopman [10] models the endogenous adjustment of traffic patterns in response to imposition of congestion fees, so they only estimate the congestion that aircraft impose or experience in the weight-based-fee cases, not the equilibrium congestion-pricing cases.

Morrison [12] and Winston and Morrison [13] calculate airport delays, congestion prices, optimal capacities, and welfare effects from hypothetical congestion pricing at ten major airports. They estimate delay times by hour as functions of the hourly number and type of aircraft landing and taking off, the number of runways, and the air-traffic control expenditures at each airport. They model airport demand as functions of congestion prices and delay costs. Welfare gains accrue largely from tolling off aircraft that are unwilling to pay the full social costs of their operations. Their model does not include increased layover delay or reduced connection time that results when flights shift to less preferred periods. The airline industry has changed significantly since these studies in ways that make the models less applicable today. The quality, quantity, and availability of airport data have also improved dramatically. Our data show that hub-and-spoke operations produce traffic patterns that typically fluctuate greatly during any given hour. Consequently, regression models of hourly delays as functions of hourly volume-to-capacity ratios no longer capture airport delay patterns adequately (see Daniel and Pahwa, [8]). Modeling current airport delay patterns requires structural models with state-dependant queuing systems and endogenous traffic rates that adjust continuously.

Vickrey [16] and Arnott, et al., [1, 2] develop bottleneck models in which the timing of traffic adjusts endogenously to minimize the sum of travelers' schedule and congestion delay costs. They apply their models to rush-hour commuting, but the models also apply to hub airports where many aircraft arrive and depart through runway bottlenecks that prevent all aircraft from operating at precisely the beginning or end of the hub airlines' passenger interchange periods. These standard bottleneck models, however, have deterministic queues that are more appropriate for highway congestion where each vehicle is an infinitesimal part of traffic rather than airport congestion where each vehicle is non-negligible.

Earlier queuing models like Koopman's [10] have simple models of exogenous airport demand, while providing sophisticated probabilistic models of delays. Morrison [12] and Winston and Morrison [13] have credible models of endogenous airport demand, but their delay models are more suited to gradual traffic fluctuations experienced by airports before the proliferation of hub-and-spoke airline networks. This paper extends the model of Daniel [6] that combines stochastic queuing theory (Koopman, [10], Omosigho and Worthington, [14], and Oum, et al., [15]) with a bottleneck model (Vickrey, [16] and Arnott, et al., [1, 2]). The queuing model captures the stochastic nature of arrivals, departures, and queues, that is an essential element of airport capacity problems missing from deterministic bottleneck models. The bottleneck model provides endogenous adjustment of time-dependent traffic rates. Our model is similar to Henderson's [9] highway bottleneck model with flow-congestion in that pricing lengthens peak periods and does not eliminate all congestion, whereas in Vickrey [16] and Arnott, et al., [1, 2] pricing does not change the duration of peak periods and it completely eliminates congestion. Our model is more applicable to airports than Henderson's model because we use stochastic queuing rather than flow congestion.

This article also contributes to the literature by comparing the bottleneck equilibria when dominant airlines either internalize or ignore their self-imposed delays. Daniel [6] originally notes that dominant airlines might internalize their self-imposed delays and performs a series of empirical tests using tower log data from Minneapolis (MSP) airport that largely rejects the internalization hypothesis. In spite of this, subsequent researchers find the theoretical argument that dominant airlines should internalize their self-imposed delays to be compelling. Brueckner [3] and Mayer and Sinai [11] both find statistically significant—although weak—evidence that airport delays decrease as airport concentration increases. They argue that this relationship is due to internalization by dominant airlines and that congestion fees should reflect internalization of self-imposed delays. Brueckner proposes that dominant airline fees should be inversely proportional to their share of aircraft operations at the airport. Daniel and Harback [7] conduct specification tests similar to Daniel [6], for twenty-seven major hub airports and find that dominant airlines do not appear to internalize self-imposed delays at most major airports, but they do appear to internalize such delays at some airports. Brueckner [4] shows that conventional congestion models can generate internalizing or non-internalizing behavior, depending on whether dominant airlines follow Nash or Stackelberg strategies. This article remains neutral about the internalization issue by calculating congestion fees and welfare effects for both specifications. The results illustrate how traffic patterns and price schedules differ depending on these behavioral assumptions.

The model

We extend the stochastic bottleneck model described in Daniel and Harback [7] to calculate equilibria with weight-based fees and congestion prices at twenty-seven major airports. Interested readers can find a detailed mathematical description of the model in that article; we will describe the model here without restating the complete mathematical specification.

The standard deterministic bottleneck model describes how the timing of trips responds to delays or fees as vehicles flow through a bottleneck with limited capacity that prevents travelers from all arriving at their destinations at their preferred times. For simplicity, the trips usually originate at the entrance and terminate at the exit of the bottleneck, so the only travel time is the time required to traverse it. Travelers prefer to complete their trips at rates that exceed the bottleneck capacity. Consequently, some travelers complete their trips early and others complete their trips late. A deterministic queue develops at the bottleneck whenever the traffic rate exceeds the bottleneck capacity. Travelers have time values associated with queuing time, early completion time, and late completion time. The equilibrium requires that traffic rates at the bottleneck adjust so that the rates of change in queuing-, early-, and late-time costs sum to zero throughout the busy period. Increasing queuing-time costs just offset decreasing early-time costs for early travelers, and decreasing queuing-time costs just offset increasing late-time costs for late travelers. The standard application of this model is to commuting to work. Some commuters travel early to avoid traffic congestion, but have long boring waits at work before their shifts begins. Some travelers leave later and are caught in traffic, but get to work close to when their shifts begin. Some travelers wait until traffic is breaking up, get to work late, and suffer their bosses' wrath. A similar story applies to hub airports. Airlines want their aircraft to arrive at their hub airports to exchange passengers with one another. Runway capacity prevents all aircraft from landing at the same time. Some aircraft have longer layovers waiting for the other aircraft to arrive, some have shorter layovers but longer queuing delays, and some arrive late and risk missing connections. In any case, travelers or aircraft adjust their schedules so that in equilibrium no one can reduce costs by changing the intended time of operation. It follows that travelers with the same time values and operating-time preferences must have the same total cost in equilibrium.

There are several modifications to the standard model that are necessary for it to realistically describe hub-and-spoke airport traffic. First, actual arrival times of aircraft at the landing or takeoff queues are subject to significant random shocks. Travel time is affected, for example, by headwinds and tailwinds, other weather conditions, and directness of the flight path. Aircraft schedulers should account for uncertainty about the time at which aircraft operate by using the probability distribution on random operating time shocks to calculate their expected time costs, rather than acting as though aircraft always operate at their intended times as assumed in the standard deterministic model. We model the distribution of these random shocks by using observations on the distribution of the differences between actual aircraft-operating times and the mean operating time of aircraft with the same flight number over the sample period at each airport.

The queuing system also needs to account for randomness in aircraft operating times, particularly since each aircraft is a non-negligible unit of traffic (unlike automobiles). Stochastic queuing theory treats traffic rates and queue lengths probabilistically. In this model, arrivals at the queue are Poisson distributed with time-varying traffic rates. The state of the queuing system consists of a discrete probability distribution on the length of the queue. The Poisson assumption implies that the queuing system is Markovian, so that the rate of change in the state of the queuing system depends on the current traffic rate *and* the current state (probabilistic length) of the queue. The rate of change of a deterministic queuing system depends only on the traffic rate, *not* the length of the queue. Deterministic and stochastic queuing systems behave very differently when traffic rates are below the service rate. Daniel and Pahwa [8] show that stochastic queuing systems are more successful than deterministic queuing systems at modeling the evolution of airport queues over time. The specific queuing model used here is classified as *M(t)/s/k/d*; indicating that it has time-dependent Poisson traffic rates, a deterministic service rate, a maximum queue size, and multiple servers (runways). This specification is chosen for its realism and computational simplicity.

Daniel [6] wedded the stochastic queuing system to the bottleneck model to endogenize traffic rates, thereby modeling behavioral reactions of aircraft to delay times and congestion fees. The stochastic bottleneck model has the same basic structure as the deterministic version, but its equilibrium requires that the sum of *expected* rates of change in layover, connection, and queuing time costs is zero so that there is no incentive for airlines to change the intended operating time of any aircraft. In reality and in the model, when an airline schedules an aircraft it does not know what random shock the aircraft will experience or the precise state of the queue when the aircraft arrives for service. The airline can calculate expected layover, connection, and queuing times by using the distribution of random shocks and the distribution of queues lengths. The primary difference between deterministic and stochastic models is that stochastic queues have positive expected lengths whenever the traffic rate is positive, whereas deterministic queues do not develop as long as the traffic rate is at or below the service rate. The priced deterministic equilibrium has traffic operating at exactly the service rate throughout the entire busy period with no queue developing. Congestion pricing has no effect on the length of the busy period in the deterministic model. In the stochastic bottleneck model, however, airlines always face tradeoffs between layover, connection, and queuing times. Consequently, there is always some queuing delay in the stochastic equilibrium. In the subtitle of their article, Mayer and Sinai [11] refer to this delay by saying, "… not all airport delays are evil." Congestion pricing in the stochastic bottleneck model distinguishes between good (efficient) queuing delays that are required to optimize layover and connection times and evil (inefficient) queuing delays caused by externalities. Pricing only eliminates the evil external delays.

Congestion pricing in the stochastic bottleneck model eliminates inefficiencies from purely external delays by spreading out traffic and reducing peak traffic rates. One specification presented here (Nash dominant airline(s) with other non-dominant aircraft) has fees of dominant airlines equal to the additional delays that they impose on aircraft of other airlines, and fees of non-dominant aircraft equal to the additional delays that they impose on one another and on dominant aircraft. This specification assumes that dominant airlines already internalize the additional delays their aircraft impose on each other. Welfare gains result primarily from shifting non-dominant aircraft out of the dominant airlines' peak-traffic periods during which banks of flights interchange passengers. The other specification, (Stackleberg dominant airline(s) with other non-dominant aircraft) has fees of dominant airlines equal to the additional delays their aircraft impose on aircraft of other airlines *and* on one another, and the fees of non-dominant aircraft as before. Dominant airlines ignore self-imposed congestion in unpriced equilibria because they realize that any bottleneck equilibrium among the aircraft must have the same aggregate traffic patterns and congestion levels regardless of when dominant airlines schedule their own aircraft. Any attempt by dominant airlines to internalize delays by spreading out their traffic simply results in trading places with non-dominant aircraft.

Both these specifications would have the same priced-equilibrium traffic patterns *if they used the same time values*, but then the unpriced equilibria would have different equilibrium traffic patterns. Since we observe the same initial unpriced traffic pattern, the specifications *must have different time values* to be consistent with their respective assumptions about internalization. In both specifications, there are welfare gains from shifting non-dominant traffic out of the dominant airlines' flight banks. The non-internalizing specification, additionally, has excessive delays that dominant aircraft impose on each other in the unpriced equilibria. Congestion prices reduce these self-imposed delays by enabling dominant airlines to spread out their traffic while discouraging offsetting responses of non-dominant aircraft shifting back into the peak periods. The Nash specification treats dominant airlines' self-imposed delays as part of the optimal tradeoff between layover, connection, and queuing times. The Stackelberg specification treats these delays as though they are external and should be priced.

Our *M(t)/s/d/k* queuing system has Poisson arrivals with time varying rates (λ_t), multiple servers (s runways), a deterministic service interval (d), and a maximum queue size (k). The state vector ($\boldsymbol{q_t}$) has elements $[p_{0t}, p_{1t}, p_{2t}, \ldots, p_{kt}]$, representing the probabilities of the queue having lengths $0, 1, 2, \ldots, k$ at time t. The queuing system parameters (s, d, and k) and the time-varying traffic rates (λ_t) fully determine the transition matrices ($\boldsymbol{T}_t$) for all service periods. Multiplying the state vector by the period's transition matrix gives the next period's state vector ($\boldsymbol{q}_{t+1} = \boldsymbol{T}_t\, \boldsymbol{q_t}$). Iteratively multiplying the state vector by the transition matrices determines state of the queue in every subsequent period ($\boldsymbol{q}_{t+n} = \boldsymbol{T}_{t+n}\, \boldsymbol{T}_{t+n-1} \ldots \boldsymbol{T}_t\, \boldsymbol{q_t}$). The marginal effect of a current arrival on traffic in the next period is determined by differentiating the current transition matrix element by element with respect to the current arrival rate and multiplying the resulting matrix by the state vector ($\boldsymbol{\delta}_{t,t+1} = \boldsymbol{D_t}\, \boldsymbol{q_t}$). The vector ($\boldsymbol{\delta}_{t,t+\iota}$) gives the rate of change in probabilities that the queue is of lengths 0 to k in the next period with respect to the current arrival rate. Iteratively multiplying this vector by the transition matrices ($\boldsymbol{T}_{t+n}$) determines the vectors that specify the marginal changes in the probability distributions on queue lengths for all subsequent periods n ($\boldsymbol{\delta}_{t,t+n} = \boldsymbol{T}_{t+n}\, \boldsymbol{T}_{t+n-1} \ldots \boldsymbol{T}_{t+1}\boldsymbol{D_t}\, \boldsymbol{q_t}$). The inner product of these vectors ($\boldsymbol{\delta}_{t,t+n}$) with the vector $[0, 1, 2, \ldots, k]$ is the expected change in queue lengths in period n with respect to an arrival at time t. Multiplying each period's change in expected queue lengths by the probability that a given aircraft arrives during that period (from the distribution of actual about intended operating times $\boldsymbol{s}_{n,i}$) and summing over all the periods in which it potentially operates determines the expected marginal queuing delay that an actual arrival at period t imposes on an aircraft intended to arrive at period n ($\Delta_{t,n} = \Sigma_i\, \boldsymbol{s}_{n,i} \boldsymbol{\delta}_{t\,t+n+i} \cdot [0, 1, 2, \ldots, k]$). The expected marginal external queuing delay of a non-internalizing arrival in period t is the sum of these expected marginal delays ($\Delta_{t,n}$) over the set (A) that contains the intended operating times n of all aircraft (i.e., $\Sigma_{n\epsilon A}\,\Delta_{t,n}$). The expected marginal external queuing delay of internalizing dominant aircraft is the sum of marginal queuing delays ($\Delta_{t,n}$) over the set (N) that only contains the intended operating times n of other airlines' aircraft (i.e., $\Sigma_{n\epsilon N}\,\Delta_{t,n}$). Finally, the expected marginal external queuing delays for an aircraft intended to operate at time t is the sum of the probabilities of actually arriving in period $t+i$ times these expected marginal queuing delays at time $t+i$ (i.e., $\Sigma_{n\epsilon A}\,\Sigma_i\, s_{t,i}\,\Delta_{t+i,n}$ and $\Sigma_{n\epsilon N}\,\Sigma_i\, s_{t,i}\,\Delta_{t+i,n}$). An analogous process determines the changes in layover and connection times resulting from changes in queue lengths. Note that all these calculations are exact, have analytical expressions, and their derivations are independently verifiable under the assumptions of the model.

While the model determines the complete probability distributions of traffic and queue lengths and the exact expected marginal delaysfor given traffic rates, it is necessary to use computational methods to find the equilibrium traffic rates. For any initial schedule of operations, we can calculate the full cost (layover-, connection-, and queuing-time costs plus whatever fee is imposed) of scheduling aircraft of a particular type during any service interval. Different aircraft types allow for different costs of layover, connection, and queuing times and different distributions of preferred arrival times. Dominant hub airlines and their code affiliates have a single preferred operating time for each arrival or departure bank that is the start or end of the passenger interchange period. All non-dominant aircraft have uniformly distributed operating time preferences. We iteratively reschedule dominant aircraft from periods with above average and increasing expected costs to periods with below average and decreasing expected costs until all aircraft of a given type have the same (minimum) cost. Non-dominant aircraft are rescheduled similarly using the first differences of their expected costs that must sum to zero for all aircraft. Aircraft are categorized as: major dominant, regional (code sharing) dominant, major non-dominant, regional non-dominant, and other (mostly general aviation). Each of these types has its own time values that are scaled to adjust for different aircraft sizes.

Although the stochastic model is more complex computationally than the deterministic model, the models have essentially the same structure with the substitution of *expected* layover, connection, and queuing times for their corresponding deterministic values. The stochastic queuing system takes two additional parameters: namely the number of servers (runways) and a maximal queue size. The number of runways is easily determined empirically. The maximal queue size is necessary purely for computational purposes but is assumed to be large enough that it is reached with infinitesimal probability. Both the deterministic and stochastic models require parameters for the length of service intervals. The stochastic queuing system has continuously-varying traffic rates, while the deterministic system has only two traffic rates; early and late. Both cases, however, determine arrival rates endogenously so the stochastic model does not have more free parameters than the deterministic model. The additional complexity of the stochastic model is confined to the queuing system.

The Data

We use the Federal Aviation Administration's (FAA) data on Airline Service Quality Performance (ASQP) and the Enhanced Traffic Management System (ETMS) covering all arriving and departing flights at twenty-seven major airports from July 28th through August 3rd, 2003.[2] The airport data include scheduled and actual arrival and departure times, expected and actual flight distances, airborne time, taxi time, and aircraft type. This is the same data used by Daniel and Harback [7].

We isolate aircraft travel times that are due to queuing delay on landing at each airport by regressing aircraft flight time (from wheels liftoff to touchdown) on a vector of dichotomous variables for minute of operation while controlling for flight distance and speed. The common component of travel time experienced by flights with different originations that arrive at a particular airport during same minute is the airport-specific queuing delay at that time. Traffic patterns and queuing delays have regular diurnal patterns because airline flight schedules are highly similar from day to day. Using data from multiple days largely eliminates effects of weather and other airport-specific random effects that are not time dependent. This estimated delay as a function of operating time is precisely the delay that is susceptible to peak-load congestion pricing. Most empirical studies calculate delays as excess flight times over either average or minimum observed flight time of aircraft with the same origin and destination. Estimates based on average flight times understate delays because average flight time includes some queuing time. Estimates based on minimum observed flight times overstate delays by using the best realization of random shocks (such as favorable tail winds or more direct flight paths) as the normal flight time. The regression equation for arrivals is:

$$(1) \qquad \textit{Airborne time} = \boldsymbol{\beta_1} * \textbf{\textit{minute}} + \boldsymbol{\beta_2} * \textbf{\textit{spoke city}} + \boldsymbol{\beta_3} * \textit{distance} * \textbf{\textit{plane type}} + \varepsilon ,$$

where ***minute***, ***spoke city***, and ***plane type*** are vectors of dichotomous variables. The coefficients $\boldsymbol{\beta_1}$ are the estimates of queuing times by minute of operation. For departures, the dependent variable is the elapsed time between push back from the gate and wheels off the runway. This includes the taxi time to get from the gate into position at the runway to take off (which does not vary systematically with operating time), and the time spent waiting in the departure queue (which does vary systematically with operating time). The regression equations used to estimate the departure queues at each airport is:

$$(2) \qquad \textit{Taxi time} = \gamma_0 + \boldsymbol{\gamma_1} * \textbf{\textit{minute}} + \varepsilon .$$

The coefficients $\boldsymbol{\gamma_1}$ are estimates of the takeoff queues for each minute of the day. This process produces estimates of queuing times for each airport for every minute during which aircraft operations occurred, excluding overnight hours (usually between midnight and six AM) when there are few operations and expected queuing delay is very close to zero.

Daniel and Harback [7] report the observed traffic patterns and estimated queues from Equations (1) and (2) and compare them with the expected queues calculated by the stochastic queuing model for the observed traffic rates. The similarity of the estimated and calculated queues demonstrates the validity of the stochastic queuing model for the variety of traffic patterns observed at the twenty-seven airports. We additionally compare the estimated queues with those calculated from the stochastic bottleneck equilibrium traffic patterns, and find them highly similar (see Figures 3 and 4 below).

Daniel and Harback [7] categorized the airports based on the characteristics of their traffic and queuing patterns. The largest category includes hub-and-spoke airports with strongly dominant airlines that have obvious, periodic, and distinct traffic peaks. These include Atlanta (ATL), Charlotte (CLT), Chicago (ORD), Cincinnati (CVG), Denver (DEN), Detroit (DTW), Houston (IAH), Memphis (MEM), Miami (MIA), Minneapolis-St. Paul (MSP), Newark (EWR), Philadelphia (PHL), Phoenix (PHX), Pittsburgh (PIT), St. Louis (STL), Salt Lake City (SLC), San Francisco (SFO), and Washington-Dulles (IHD). All these airports have traffic that is highly consistent with the bottleneck model. In addition, Dallas-Ft. Worth (DFW) is also a strongly hub-dominated airport with significant traffic peaking, but it has minimal queuing during our sample period due to excess capacity and looser hub-and-spoke scheduling. Washington National (DCA), New York-LaGuardia (LGA), and New York-Kennedy (JFK) operated with slot constraints under high-density airport rules during the sample period. Washington National is a strongly hub-dominated airport that exhibits significant peaking of arrival traffic and delays in spite of slot constraints. LaGuardia and Kennedy do not have strongly dominant hub airlines and their traffic is clearly constrained by the slot reservation system. Their traffic does not exhibit periodic peaking associated with banks of interchanging arrivals and departures. Both airports have periods of heavy traffic in the morning and evening that generate significant queuing but not the sharp peaking characteristic of interchanging flight banks. Boston (BOS), Baltimore-Washington (BWI), Las Vegas (LAS), Los Angeles (LAX), and Seattle (SEA) lack clearly dominant airlines or are not strong hub airports. While some of these airports exhibit significant fluctuation in traffic rates, they do not have clearly coordinated peaking as those above.

Daniel and Harback [7] also used the data to calculate the relative values of layover, connection, and queuing times under alternative hypotheses of internalizing or non-internalizing behavior. These values are determined by the rate at which similar aircraft trade off queuing delay for layover or connection time. The bottleneck equilibrium condition requires that similar aircraft have offsetting costs of layover, connection, and queuing times. As aircraft choose their intended operating times, the queue adjusts endogenously to assure that the rates of change in these time costs sum to zero for all aircraft in equilibrium. Only when this condition holds for each group of homogeneous aircraft will there be no incentive for further adjustment of their scheduled operating times. Rearranging the bottleneck equilibrium condition to express the queue length as an endogenous function of the equilibrium time cost, layover time, and connection time gives:

(3) $$Q_t = \hat{C}/\hat{c}_q - \hat{c}_e/\hat{c}_q\, E_t - \hat{c}_l/\hat{c}_q\, L_t \;\forall \text{ scheduled operating times } t.$$

Equation (3) must hold for dominant aircraft that have the same preferred operating time. For non-dominant aircraft with homogeneous time values but different preferred operating times, the first difference of Equation (3) must hold:

(4) $Q_{t+1} - Q_t = -\hat{c}_e/\hat{c}_q\,(E_{t+1} - E_t) - \hat{c}_l/\hat{c}_q\,(L_{t+1} - L_t)$ ∀ scheduled operating times *t*.

Daniel and Harback [7] estimate the constants and coefficients in Equation (3) or (4) by regressing the appropriate measure of each aircraft's queuing delay on its early and late time and (for Equation 3) a bank-specific constant term. Depending on the specification, Q_t, E_t, and L_t are either the expected values of an aircraft's directly experienced delay times or the expected value of an aircraft's directly experienced delay times plus its indirect effect on delay times of other aircraft operated by its airline. The regression coefficients, - $\hat{c}_e/\hat{c}_q$ and - $\hat{c}_l/\hat{c}_q$, are (the negatives of) the values of layover and connection time relative to queuing time. Separate regressions by carrier type estimate different time values for each category of aircraft. Separate estimates are also obtained for landing and takeoff data. We use the same estimates as reported by Daniel and Harback [7], in Table 1.

While Daniel and Harback [7] use the resulting coefficients to conduct specification tests of the model for the *observed* traffic pattern, we use the coefficients as parameters to calculate *equilibrium* traffic patterns for cases with and without congestion pricing and assuming non-internalizing or internalizing behavior. In principle, the unpriced case with the correct behavioral assumption about internalization should fit the observed traffic pattern better than the incorrect specification, but our purpose here is to report the alternative price schedules and welfare effects without conducting additional specification tests. We note, however, that Daniel and Harback [7] found consistent support for the non-internalizing assumption at Atlanta, Charlotte, Washington National, Denver, Dallas, Detroit, Newark, Houston, Minneapolis, Chicago, San Francisco, and St. Louis, while there is some support for the internalizing assumption at Boston, New York-Kennedy, Los Angeles, and New York-LaGuardia.

The regression coefficients from the bottleneck equilibrium conditions in Equations (3) and (4) give the values of layover and connection time relative to time spent in the landing or takeoff queues. To assign dollar values to each type of delay, we use aircraft operating cost data from the FAA publication, *Economic Values for FAA Investment and Regulatory Decisions, a Guide,* Table 3-4, p 3-7 (2005) (aka, *Critical Values*). *Critical Values* specifies the methodology and economic values to be used in investment and regulatory decisions of the FAA. It compiles the operating costs of aircraft by seating capacity, narrow or wide body type, and number and type of engine as reported by the airlines on FAA Form 41. The data include number of aircraft of each type, passenger capacity, load factor, crew size, and fuel consumption. *Critical Values* also specifies the variable costs of aircraft operation based on this data. We modify these values to account for different rates of fuel consumption in the air versus on the ground. Passenger time costs are specified as $28.5 per passenger hour. Given FAA methodology, the variable costs of aircraft waiting in a landing queue or in a takeoff queue vary nearly proportionately with aircraft size. We calculate the in-air and on-ground queuing costs of the average sized aircraft and scale the costs proportionately to the average aircraft size of each airline group at each airport as given in our data. The average aircraft and crew, according to *Critical Values*, have variable cost per block hour of $1245 on the ground and $2096 in the air. Its passenger capacity is 157 and it is 72% full, giving a passenger cost per block hour of $3233. Different airports attract different fleet sizes of dominant airlines, code-affiliated dominant airlines, other major airlines, and other regional airlines so we calculate the average aircraft size from our data for each airline group and airport and scale the in-air and on-ground queuing costs accordingly. Finally, we use the regression coefficients for airline groups by airport to calculate the values of layover and connection times. We expect these values to vary by airline group and airport because of differences in the importance of coordinating flights at different hubs and of geographic relationships to the rest of airlines' networks. A few of the regression coefficients are incorrectly signed, particularly for the internalizing specification. To calculate equilibria in these cases, we assign time values within the range of similar airports while attempting to match the unpriced equilibiria traffic patterns. A table of the resulting time values for each airline group by specification and airport is available upon request. {Referees, please see Table A.1.}

The Results

Figures 1 and 2 compare the observed and calculated arrival rates at Atlanta, Chicago, Denver, Dallas, Los Angeles, and Minneapolis for the internalizing and non-internalizing specifications. We illustrate equilibrium arrival patterns at these airports because they are among the busiest and their traffic is representative of patterns at the remaining airports. The departure patterns are essentially similar to the arrivals patterns.[3] The observed traffic rates, plotted in dark black, illustrate the rapid periodic peaking caused by hub-and-spoke flight banks. Obviously, the hourly traffic rates commonly used in earlier pricing studies cannot adequately represent the traffic data shown here. The bottleneck model's unpriced equilibria, plotted in medium grey, should match the observed traffic patterns for the correct specification. The non-internalizing specifications in Figure 1 generally produce more rapidly peaking traffic, while the internalizing specification in Figure 2 produces more gradual fluctuations. The priced equilibria, plotted in light grey, have lower and broader traffic peaks. Pricing causes relatively more peak spreading in the non-internalizing specification because it regards more of the queuing delay as inefficient and subject to pricing.

Atlanta and Chicago are the busiest airports. Both exhibit regularly-shaped traffic peaks that repeat at regular intervals throughout the day. Chicago has two dominant airlines so it has more peaks that occur more frequently. The unpriced traffic patterns for the non-internalizing specification match the observed traffic patterns well at these airports, while the internalizing specification does not match the traffic fluctuations as well.[4] Minneapolis and Denver have the clearest hub-and-spoke traffic patterns. Their traffic is very similar to Charlotte, Cincinnati, Detroit, Houston, Newark, Philadelphia, Pittsburgh and Washington-Dulles. The non-internalizing specification reproduces the traffic patterns at these airports particularly well. Los Angeles and Dallas are also among the busiest airports and have several dominant airlines but they exhibit less rapid traffic fluctuations than the strongest hubs. Their traffic is reasonably similar to Boston, Baltimore, Miami, San Francisco, and Seattle. Both specifications of the model reproduce the traffic patterns at these airports reasonably well. Traffic at Washington National, New York-LaGuardia, and New York-Kennedy is atypical because they were subject to slot constraints under the high density airport rule. Consequently, their traffic is unusually spread out. Their unconstrained traffic patterns are unknown.

Figures 3 and 4 compare the estimated queues with equilibrium queues from the alternative specifications and show the predicted changes in queuing resulting from congestion pricing. The model's unpriced queues reproduce the observed patterns very well in most cases, even though the airports exhibit a variety of traffic patterns. As with the traffic rates, the non-internalizing model replicates rapidly fluctuating queues associated with strong hub airports. The internalizing model is relatively better at replicating the queues of airports with gradually adjusting traffic. The illustrations show the reduction in queuing that is possible by imposing congestion pricing. The non-internalizing specification shows the largest decreases. Note that queuing is not completely eliminated in the stochastic bottleneck equilibrium because positive traffic rates always cause some expected queuing. This is different from the deterministic bottleneck model where traffic rates at or below the service rates cause no congestion. The internalizing specification has less opportunity to reduce queues because there is less uninternalized delay before imposing pricing. The changes in time costs and queues are quantified below.

The unpriced non-internalizing equilibrium for Minneapolis matches its estimated queues almost perfectly. Equilibrium queues at Cincinnati, Detroit, and Houston also match the peaks and valleys, rates of increases and decreases, and timing of the estimated queues as well as Minneapolis does. Denver and Dallas have minor discrepancies between their calculated and estimated queues—as do Charlotte, Las Vegas, Philadelphia, Phoenix, and Washington-Dulles. Equilibrium queues at Atlanta and Chicago do not peak as sharply as their estimated queues, but they are still reasonably similar. All the previous airports have queues with distinct peaks in their unpriced non-internalizing equilibria. Pricing significantly smoothes and decreases the peaking of their queues. In their unpriced internalizing equilibria, however, equilibrium queues are much less peaked than the estimated queues. The timing of internalized delays prevents layover and connection times from taking sufficiently large values to generate queues as high as those estimated. At Los Angeles, queues do not have as distinct peaks as the previous airports. Baltimore, Boston, Miami, Newark, Salt Lake City, San Francisco, and Washington-National have similar queuing patterns. Their unpriced non-internalizing equilibria match their estimated queues reasonably well, in spite of their very different traffic patterns. In addition, the unpriced internalizing equilibria at Los Angeles, Baltimore, Miami, Newark, and San Francisco match their estimated queues similarly well. The similarity of the queues produced by the stochastic bottleneck model and those estimated from the data strongly supports the validity of the model.

Figures 5 and 6 illustrate the unpriced external congestion levels and the congestion fee schedules that we propose for the two specifications. In both figures, the unpriced external congestion schedule indicates the additional cost of delays that an operation in each period imposes on all other aircraft under the unpriced traffic pattern. For the non-internalizing specification in Figure 5, the graphs also depict the common fee structures that should be imposed on all aircraft in the priced equilibria. For the internalizing specification in Figure 6, the graphs depict the ideal (internalizing) fee structures for each dominant and non-dominant aircraft type. In addition, Figure 6 depicts the fee structure obtained by erroneously assuming the dominant airlines do not internalize when in fact they do.

For the non-internalizing case, the unpriced external congestion levels are typically many times higher than the equilibrium congestion fees because traffic has not adjusted to internalize congestion. Some early papers on airport congestion calculate queues or external congestion for existing unpriced traffic rates, but not the priced equilibrium congestion levels (Carlin and Park [5], Koopmans [10]). Their results may have led readers to incorrectly believe that equilibrium queues or congestion fees are similarly large. Treating traffic rates endogenously demonstrates how dramatically congestion pricing decreases congestion levels in the non-internalizing case. For the internalizing specification, the difference between unpriced and priced external congestion is much smaller. Dominant airlines already internalize their self-imposed congestion, so there is less external congestion for pricing to internalize. Assuming internalization of self-imposed delays by dominant airlines, the ideal congestion prices charge non-dominant aircraft for congestion imposed on all other aircraft, while they charge dominant airlines only for congestion imposed on other airlines' aircraft. Depending on market shares, dominant airline fees can be much lower than non-dominant fees. Imposing inappropriate non-internalizing fees on internalizing airlines cause them to double internalize self-imposed congestion. Dominant airlines spread their traffic out too much relative to the optimum. The incorrect fees are therefore lower in the center and higher at the edges of the peaks relative to the correct fee schedule.

All the fee structures have generally similar characteristics, but there are some variations among airports. Minneapolis' congestion fee structures are similar to Atlanta, Charlotte, Cincinnati, Detroit, Dulles, Houston, Las Vegas, Memphis, Miami, Philadelphia, Phoenix, Pittsburgh, and Seattle. Fees at these airports increase and decrease almost linearly over time, reaching their peaks just before the beginning of each interchange period. The fees fall to zero between peaks that are sufficiently separated from one another (e.g., Dallas), otherwise the periodic peaks rest on top of lower-frequency peaks that trend up and down with the diurnal variation in demand (e.g., Minneapolis). The dominant airlines' ideal fees in the internalizing case are lower than the non-internalizing fees and appear out of phase with their traffic peaks. These fees are lowest in the center and relatively higher at the edges of the peaks because external congestion is highest where the non-dominant aircraft operate.

The nearly linear rate of increase and decrease of the fee structures is due to the assumption that layover-, connection-, and queuing-time costs vary proportionately with the lengths of the delays. Several factors, however, can introduce non-linearities in the fee structures. Distributions of actual operating times around intended operating times are bell shaped, which can round off the peaks and bases of traffic rates and consequently round the fee structures. Regional aircraft affiliated with dominant airlines have lower time values and shift off peak at different rates than larger aircraft, causing the peaks to taper off at their edges. Non-dominant aircraft have uniformly-distributed operating time preferences and lower layover and connection time values. Congestion pricing shifts these regional and non-dominant aircraft towards the edge of the peaks and can flatten out the fee structures at the edges.[5]

Some airports have two or three dominant airlines that schedule their interchange periods at different times, resulting in many smaller peaks that crowd against each other, making the fee schedule appear more erratic. Boston, Chicago, Dallas, Los Angeles, San Francisco, and Washington National all have multiple dominant airlines with many peaks. Of these, Chicago and Dallas (at least) have discernable periodic peaking of the fee structure associated with their dominant airlines' flight banks. The other airports with multiple dominant airlines have weaker hub operations and are discussed below.

The importance of hub traffic varies among airports, causing weaker hubs to have lower layover and connection time values and less peaked traffic rates. Such airports include Boston, Los Angeles, Newark, and San Francisco. At these airports, the fee structures change gradually with daily demand, but lack the rapid peaking of stronger hubs. The bottleneck model still applies, because aircraft do have layover and connection times that they trade off against queuing delays, but the fees do not exhibit multiple periodic peaks so much as gradual daily demand fluctuation. The model acts as though there are one or two large peaks, with traffic shifting towards the early morning, mid day, and late evening. This comment also applies to New York's Kennedy and LaGuardia and Washington National, but these airports also were subject to slot constraints that may prevent stronger peaking. As we will see below, these airports benefit less from congestion pricing that optimizes aircraft schedules and may benefit more from congestion pricing that tolls off demand.

The highest congestion fees at most airports are higher than current weight-based landing fees, but as shown below, the average full costs (including time costs) of aircraft operations under congestion pricing are generally comparable to those under weight-based fees. Higher peak fees are offset by lower layover or more connection time, leading to constant costs over the busy periods. The fees must vary over time to reduce inefficient peaking of the queues. Many "congestion pricing" proposals attempt to "simplify" the fee structures by assigning flat fee surcharges over the morning and evening peak periods. These approaches may succeed in reducing peak traffic levels by tolling off traffic, but they cannot eliminate queuing of the remaining traffic, because it will follow an unpriced bottleneck equilibrium pattern. Flat fees, while simple, do not address the causes of inefficient demand peaking and queuing. The fee schedules we propose, as shown in Figures 5 and 6, vary nearly linearly over time as a function of when an aircraft joins the landing or takeoff queues. These linear fee schedules are not so complex as to unduly tax the comprehension of the airlines or result in high administrative costs for airports.

Tables 1, 2, and 3 summarize the costs and welfare effects of congestion pricing at all twenty-seven airports for the specifications with non-internalizing airlines, internalizing dominant airlines, and internalizing airlines with fees that erroneously assume non-internalizing behavior. The tables categorize aircraft by airline types that combine each dominant airline with its code-affiliated aircraft, and group all non-dominant aircraft together. The first column of Table 1 shows the number of aircraft that land at the airport during the busy periods. The ten largest airports by number of operations in 2003 are Atlanta, Chicago, Dallas, Los Angeles, Denver, Houston, Phoenix, Minneapolis, Charlotte, and Philadelphia.[6] Congestion at Newark, Washington National and New York's LaGuardia and Kennedy, receives much attention, but these airports have significantly less traffic and congestion than the largest airports.

The second column of Table 1 shows the approximate weight-based landing fee for each airline group.[7] Airports have two basic methods of calculating their prices per unit weight. The cost-center approach sums annual costs associated with all airside operations of the airport and divides by the total landed weight of aircraft operating during the year. The residual cost approach takes all airside and groundside costs per annum, subtracts all revenues from other sources, and divides the shortfall by total landed weight of aircraft during the year. These different approaches lead to large differences in fees. Atlanta, for example, has a low fee of $0.95 per thousand pounds, while Denver has by far the highest fee of $17.00. Newark assesses a flat surcharge of $100 for landing between 8 and 10 AM or between 5 and 10 PM in addition to a weight based fee of $5.65. Most fees are between $1.00 and $4.00 per thousand pounds landed weight.

The third column of Table 1 shows the average congestion fee for each airline group. Comparing "out of pocket" costs of weight-based and congestion fees ignores differences in layover, connection, and queuing costs. The sums of fees and time costs are shown in columns six and seven. Although congestion fees are often much higher than weight-based fees, differences in full landing and takeoff costs are generally smaller, often nearly zero because of reductions in delays. Landing and takeoff costs are only small parts of total flight costs, so the airports' demand elasticities with respect to landing and takeoff cost alone should be small. Cross-price elasticities of airport demand are unknown, but should not be significantly greater than the own-price elasticities. It is appropriate to treat airport demand as fixed, because these elasticities are small and airports can offset changes in full cost by adjusting other airport fees, such as aircraft fueling, parking and gate fees.

Columns four and five show the expected queuing times under weight-based pricing and congestion pricing. Again, this excludes changes in layover and connection times, but focuses on the most directly-perceived delays. Airports with the highest queuing delays under weight-based pricing experience dramatic reductions in queuing times. Average queuing delay at Atlanta drops from about twenty minutes to just over seven. At Chicago, it drops from about twenty-five to about seven-and-one-half minutes. Dallas, Boston, Houston, Washington-Dulles, Minneapolis, and Philadelphia cut queuing delays by about half. On the other hand, Washington National, Los Angeles, LaGuardia, and Kennedy experience negligible decreases.

The remaining columns of Table 1 summarize the welfare gains per aircraft, airline group, and airport. Absent compensating reductions in other airport charges, congestion pricing modestly increases airline costs at most airports, but not by the full amount of the congestion fee—thus producing a net social gain. Deadweight loss from delay is converted into airport revenues. Congestion pricing recovers over

$1000 of delays per aircraft at Chicago, and nearly that much at Atlanta. Dallas saves about $500 per aircraft. Houston and Philadelphia save around $400. Boston, Cincinnati, Charlotte, Dulles, Minneapolis, Memphis, St. Louis all recover in the range of $200-$300 per aircraft. Denver is an unusual case because its weight-based fees are higher than its congestion fees. Airlines have lower costs under congestion pricing and Denver loses revenue. Reductions in delays still produce social gains of over $100 per aircraft. This is less than other airports of similar size because Denver is overbuilt and underutilized due to its high weight-based landing fee.

Table 2 presents results analogous to Table 1 for the alternative specification in which dominant airlines do internalize their self-imposed delays. Notice that either specification can result in larger welfare gains from congestion pricing, even though there is less uninternalized delay in the unpriced internalizing specification. There are several explanations for this. The queuing time values are based on aircraft operating costs that are the same across specifications, but layover delay and connection time values differ depending on the tradeoffs between of layover, connection, and queuing times. The internalizing specification usually has higher estimates of layover and connection time values and therefore higher cost levels, *ceteris paribus*. Moreover, at least one set of estimates uses an incorrect specification to estimate the time values and generate the equilibrium traffic patterns. Both the unpriced baselines and priced equilibria traffic patterns are wrong for the incorrect specification, and which specification is incorrect may vary by airport. The amount of uninternalized congestion varies with the dominant airlines' market shares and the number of dominant airlines. Airports with several dominant airlines have both higher values of layover and connection time and higher levels of uninternalized delay. These airports appear to gain more from pricing than otherwise similar airports with either a single internalizing airline or non-internalizing airlines. When comparing the dollar values across the two specifications in Tables 1 and 2, keep in mind that they do not use identical time values.

Columns one and two of Table 2 show the weight-based and congestion fees for the specification with internalizing dominant airlines. The main role of congestion pricing in these cases is to price non-dominant aircraft out of the dominant airlines flight banks that interchange passengers at hub airports. Most commonly, therefore, the congestion fees are lower for dominant airlines than for the others. Strongly dominated hubs like Atlanta, Charlotte, Chicago, Cincinnati, Dulles, Detroit, Houston, Newark, Minneapolis, Philadelphia, Pittsburgh, and St. Louis all have substantially lower dominant than non-dominant fees. The busiest airports have very large differences in fees. The average congestion fees at Atlanta are $864 for dominant aircraft and $4,175 for others; and at Chicago, $3,353 for dominant aircraft and $6,131 for others. More typically, dominant aircraft at Dallas pay $412 and other aircraft pay $1,222 on average. Some airports with multiple dominant airlines have little difference in fee levels for example Boston, Washington National, Kennedy, Los Angeles, and LaGuardia. The average congestion fees at Boston are about $500 for dominant aircraft and $610 for others; and at Los Angeles about $400 for dominant aircraft and $570 for others. The latter airports have high estimates of layover and connection time values and multiple dominant airlines that impose uninternalized delays on one another.

Columns three and four of Table 2 show the expected queue lengths for the unpriced and priced equilibria. With some exceptions, this specification has expected queues that are lower in the unpriced case and higher in the priced case than the non-internalizing specification, so there is less reduction in queuing time as a result of pricing. Internalization of unpriced queuing delay flattens the peaks relative to non-internalizing equilibria, while the priced queues are more peaked because queuing is relatively less costly. Atlanta's average queues decrease from about 11 to 8 minutes and Chicago from about 15 to about 10 minutes. These differences are much less than in the non-internalizing case. Again, the notable exceptions to this pattern are the airports with multiple dominant airlines that impose external delays on each other while internalizing self-imposed delays. In particular, congestion pricing reduces queues at Boston, Denver, Kennedy, LaGuardia, Los Angeles, and Phoenix at least as much as the non-internalizing specification. Boston's average queues decrease from about 5 to 3 minutes and Los Angeles from about 3.8 to about 3.4 minutes. These differences are about the same as in the non-internalizing case. Comparison of unpriced queuing levels with those estimated from actual traffic data, however, show that the non-internalizing equilibria are usually closer to the actual queuing levels.

Columns five and six of Table 2 show the changes in time costs and fees per aircraft for the internalizing specification. The time costs exclude the indirect costs that dominant aircraft impose on each other because these costs are included as direct cost of other dominant aircraft. In this specification, gains from congestion pricing accrue largely from shifting non-dominant aircraft out of the dominant airlines' peaks. Dominant aircraft already bear self-imposed delay costs so their fees reflect only the delays they impose on other airlines. There is relatively little effect on net time costs and fees of dominant aircraft, while non-dominant aircraft experience large increases in fees and more layover and connection costs. At Atlanta for example, the full landing and takeoff costs increase from $2,157 to $2,456 for dominant aircraft, and from $1,610 to $5,257 for others; at Chicago from $2,467 to $4762 for dominant aircraft, and from $2,602 to $6,694 for others; and at Dallas from $1,565 to $1,372 for dominant aircraft, and from $1,514 to $2,095 for others. The airports with multiple dominant airlines have small differences in full costs, at Boston and Los Angeles for example, they increase by about $100 and $200 for all airline types. An important policy concern is that the internalizing specification often leads to low fees and high benefits for the dominant airline, and high fees and losses for the non-dominant airlines. While congestion pricing produces unequal fees, the full costs of time and fees are usually more equal. Congestion pricing in the internalizing specification imposes disproportionate costs on non-dominant airlines relative to weight-based fees, but it makes access to airports available on a more economically neutral basis. The current system subsidizes non-dominant operations from dominant operations.

Columns seven, eight, and nine of Table 2 report the welfare and revenue changes as a result of congestion pricing in the internalizing specification. Social savings per aircraft and airport as shown in columns seven and nine at are about one third lower than in the non-internalizing specification because there is less reduction in queuing delay. The total social savings at all airports is about three million dollars, two-thirds as much as the non-internalizing case. Airports with a single strongly dominant airline usually have less social savings from congestion pricing under the internalizing specification, while those with multiple dominant airlines often have larger social savings. Airport revenues shown in column eight total about eleven million dollars and are about ninety percent as high as the non-internalizing specification. Congestion pricing recovers over $800 of delays per aircraft at Chicago, and nearly $500 at Atlanta. Philadelphia, Dulles, and Memphis save about $250, and Houston, Boston, Denver, Minneapolis, Cincinnati, and Charlotte all recover in the range of $100-$200 per aircraft. St. Louis and Dallas save only $75. While the gains are generally lower in the internalizing specification, we can unequivocally conclude that there are substantial welfare gains from congestion pricing under either specification.

Table 3 shows what happens if we incorrectly impose fees meant for non-internalizing airlines on internalizing airlines. Because the results describe what not to do, we focus on the general outcome rather than on specific airports. The problem with imposing the wrong fee is that dominant airlines double internalize self-imposed congestion causing them to spread their traffic out too much. As they shift traffic away from their interchange periods, other airlines find peak periods cheaper and shift traffic towards the peaks. This results in perverse equilibria in which dominant airlines that prefer operating closest to their interchange periods have the longest layover delays or the shortest connection times, while other aircraft that have dispersed operating-time preferences operate closest to the interchange periods. Dominant aircraft have relatively low congestion delays and fees, but long layover delays or short connection times. Non-dominant aircraft have relatively high congestion delays and fees. Exactly how bad this situation is for social welfare depends on aircraft time values, operating time preferences, the number of dominant airlines, the number of aircraft of each type, and airport capacity. Table 3 shows that imposing the wrong fee on an internalizing airline is almost always worse than no congestion pricing at all. A few airports have positive welfare changes, but well below their optimal levels. While erroneous pricing has very bad welfare implications, the dominant airlines' double internalizing behavior is easily detected and the pricing rule is easily corrected.

A final case involves incorrectly imposing fees meant for internalizing airlines on (non-internalizing) Stackelberg-dominant airlines. The Stackelberg equilibrium is more fault tolerant than the Nash equilibrium. If the tolling authority correctly estimates the time values of non-dominant airlines, they face the correct fee schedule while dominant Stackelberg airlines are underpriced. The Stackelberg dominant airlines are now free to internalize the difference between their self-imposed delays and congestion fees, while relying on the correct non-dominant fees to keep other aircraft from shifting back into their peaks. In the best case, internalizing fees with Stackelberg dominant behavior would result in the same traffic pattern as non-internalizing fees. This case is just like Table 1, except Stackelberg dominant airlines would keep the self-imposed portion of their non-internalizing fees. Another way of looking at this case is that, with Stackelberg-dominant airlines, the tolling authority can maximize social welfare by imposing either internalizing or non-internalizing fees, provided it determines the correct time values. There are, however, other reasons to charge non-internalizing fees. Confronting all airlines with an identical fee structure is more equitable (i.e., politically acceptable), does not risk anti-competitive effects, and generates sufficient revenues to pay for the optimal runway capacity.

Policy Implications and Conclusions

The bottleneck model and particularly its stochastic version have been slow to gain adherents among transportation economists. This is unfortunate and difficult to understand. It is true that the stochastic queuing model is more complex than other airport congestion models and that it does not have a closed-form solution for equilibrium traffic rates. Similar complexities, however, are often present in models of other transportation modes. The bottleneck model includes important features of airport delays that are largely absent from other airport congestion models but commonly included in models of surface transportation, most notably the tradeoff between schedule and congestion delays. This tradeoff is essential to endogenously generating demand peaking caused by hub-and-spoke airlines. Accounting for changes in layover delays and connection times is necessary to accurately quantify the effects of congestion pricing and is of considerable importance to airlines and policymakers. The bottleneck model has state-contingent delays, unlike most other airport models in which delays are functions only of contemporaneous traffic rates. State contingency is an important issue in modeling airports because rapid fluctuations in traffic make the current queue length highly dependent on the previous period's queue length as well as the traffic rate. The bottleneck model allows continuous-time variation in traffic rates, whereas most other airport congestion models aggregate traffic by hour. The stochastic queuing system is more complex than some congestion functions, but hardly more opaque than algorithms used to load traffic on highway networks. Stochastic queuing models are widely used and understood in other disciplines. The stochastic and deterministic bottleneck models are similar except for the substitution of *expected* layover, connection, and queuing times for their deterministic values. The additional complexity is confined to the queuing system. The stochastic version is a precise mathematical model that, for given traffic patterns, determines the complete probability distributions on queues and the exact marginal changes in delays imposed on other aircraft. These have analytic expressions that are mathematically verifiable. Computational methods are only required to determine the equilibrium traffic rates as the fixed point (functional) of a mapping from the set of continuously varying traffic rates back into itself.

Nothing in the stochastic bottleneck model itself determines whether or not dominant airlines internalize self-imposed delays. This issue depends on what behavioral assumptions are made about the dominant and non-dominant airlines. As this paper demonstrates, the stochastic bottleneck model can estimate congestion prices under internalizing or non-internalizing specifications. The reader is free to adopt either set of results. Many researchers apparently believe that it is incorrect to model dominant airlines as "naively" ignoring their self-imposed congestion. On the other hand, assuming dominant airlines do internalize self-imposed congestion ignores other airlines' behavioral responses to their attempts to internalize congestion. Empirical evidence on this point is mixed, suggesting that dominant airlines behave differently at different airports. Their behavior may be influenced by the number of other dominant airlines, the strength of their hub operations, the amount of airport capacity, the presence of slot constraints, and the proportion of dominant to non-dominant aircraft.

Our results show that under either specification, there are substantial benefits from congestion pricing. For a given set of time values, the non-internalizing specification produces larger time savings because it assumes that much of the self-imposed congestion is inefficient: i.e., it is not part of the optimal tradeoff between layover delay, connection time, and queuing delay. Imposition of congestion pricing enables the airport to recover the value of these inefficient internal delays in addition to the external delays. The internalizing specification has smaller time savings, for a given set of time values, because it assumes that the initial self-imposed congestion is efficient; i.e., the dominant airline has already internalized its inefficient self-imposed delays leaving an optimal balance of queuing delays against layover delays and connection times. Congestion pricing only enables the airport to recover the value of the external delays. For the values of layover and connection time to be consistent with the observed traffic patterns they must be different in the non-internalizing and internalizing specifications. Consequently, either specification can generate more welfare gains under congestion pricing—depending on whether increases in time values offset decreases in time savings.

This paper focuses on airport delays that are endemic to the airline scheduling practices, not those due to unusual weather events. Passengers ordinarily experience the delays measured here as unnecessarily long travel times. The FAA's "on time" arrival statistics defines aircraft as delayed only when they operate more than fifteen minutes after their scheduled times as published in the *Official Airline Guide*. Bad weather increases service times required at runway bottlenecks, causing even longer queues than normal. The additional weather delay may cause aircraft to fail to operate on time, so airlines attribute these *additional* delays to bad weather. Published airline schedules, however, include extra travel time to allow for expected congestion delays and improve their on-time arrival and departure statistics. FAA's on-time arrival statistics, therefore, are at best tenuously related to actual increases travel times due to airport congestion. Using on-time arrival statistics that ignore congestion built into airline schedules, the FAA and the airlines often maintain that delays are overwhelmingly due to bad weather. This model demonstrates that even for ordinary weather conditions much airport delay is built into airline schedules and it is possible to significantly reduce these delays by optimizing the intended operating times of aircraft. Our model can be extended to include the effects of weather on the service rates of airport bottlenecks, but this is beyond the scope of the present paper. While bad weather contributes to airport delays, the effect is compounded by airlines that ignore external delays and over schedule aircraft during the most desirable periods. Smoother traffic rates would also help airlines recover from weather events, so our welfare results underestimate the benefits of congestion pricing with weather induced delays.

The Department of Justice (DOJ) recently floated a proposal for an airport slot auction system. While this issue is beyond the scope of this paper, we derive the optimal price, quantity, and timing of airport operations that presumably also solve a dual problem for slot auctions. Proponents argue that setting quantity (and timing) of operating slots and letting the market determine price is simpler than congestion pricing which sets price and lets the market determine quantity (and timing) of operations. The quantity and timing of slots, it is claimed, are purely matters of capacity: simply auctioning one slot for each service interval avoids the need to model demand. This works in a deterministic world. Every aircraft arrives exactly on time for its slot and there is no queuing. In a world with random deviations from intended operating times, aircraft that miss their service intervals cause queuing when they finally arrive. Queues persist until future aircraft that are late allow queues to clear temporarily, but then even longer queues develop when those aircraft arrive. Since the airport can never recover unused service intervals, average arrival rates must be held below the service rates to allow the airport to catch up, and even then expected queues will be positive. Offering fewer slots than service intervals does not resolve the problem, however, because there are also some highly desirable periods (say 8:00AM) that should be oversold to reduce the probability that they go unused (just as overbooking passengers on aircraft is optimal). These oversold high-demand periods should be followed by undersold low-value periods to allow the queue to diminish. In other words, the optimal length of slot intervals varies over time depending on demand peaking. A stochastic queuing model with endogenous traffic rates is needed to determine the optimal time-varying slot intervals. Auctioning fixed slot intervals substantially reduces the welfare gains from congestion pricing at strong hub airports. Fixed slot rates could be effective at simply tolling off demand and might be appropriate at busy airports with weak hubs and relatively constant traffic rates like Kennedy, La Guardia, Boston, and Los Angeles.

Based on the specification tests in Daniel and Harback [7] and the welfare results presented in Table 1, the authors argue that there is a strong case for imposing the non-internalizing fee structures as shown in Figure 5 on aircraft at Atlanta, Chicago, Charlotte, Cincinnati, Dallas, Denver, Detroit, Houston, Minneapolis, Newark, Philadelphia, Pittsburgh, St. Louis, and Washington-Dulles. For readers who believe the internalizing specification, Table 2 makes a strong case for imposing the internalizing fee structures as shown in Figure 6 at these airports. Most welfare gains from congestion pricing are attributable to these airports. The specification tests are more ambiguous for airports with less peaked traffic and the benefits of either form of pricing are usually smaller. These airports include: Boston, Baltimore, Las Vegas, Los Angeles, Memphis, Miami, Phoenix, Seattle, San Francisco, and Salt Lake City. Firm conclusions about Washington National, New York-LaGuardia, and New York-Kennedy are difficult to make because they were subject to slot constraints when the data were collected, but these airports would likely have traffic patterns similar to those at Washington-Dulles and Newark in the absence of slot constraints, making them candidates for congestion pricing.

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[1] The Nash outcome depends on dominant airlines assuming that other aircraft will not respond to their attempts to reduce congestion. The best responses of other aircraft, however, will maintain the congestion levels of a non-internalizing equilibrium. Stackelberg-dominant airlines anticipate the best responses of other aircraft and ignore their self-imposed congestion knowing they cannot effectively internalize it. The Dominant airline prefers the Stackelberg outcome because excessive traffic spreading increases its cost in Nash equilibrium. The Nash equilibrium has dominant aircraft spread out on either side of a bottleneck equilibrium among other aircraft. Non-dominant aircraft must have weakly lower direct costs in or they would not be in equilibrium. Joining them in a non-internalizing equilibrium is less costly than remaining on the edges of the peak (by the properties of bottleneck equilibria). Dominant aircraft remain on the edges in a Nash Equilibrium only because they do not realize that other aircraft would accommodate their joining the peak and thereby reduce their costs.

[2] Thanks also to Stephen Welman of MITRE for providing information about the air traffic control process. The analysis in this article is solely that of the authors and does not represent the position of Metron Aviation or MITRE or its employees.

[3] Illustrations of departure patterns and traffic at other airports are available upon request.

[4] The calculated equilibria have traffic peaks at the end of the day instead of the observed pattern of low traffic because the model treats this traffic like other flight banks, while in reality these passengers do not have to arrive in time to connect with other flights. If we used bank-specific time values, the model could reproduce these late-night traffic tails.

[5] The saw-toothed nature of fees apparent at Denver and Los Angeles results from a technical simplifying assumption in the queuing calculation—the "true" fee schedules smooth out the saw teeth but retain the larger peaks.

[6] Our traffic counts have a slightly different ordering due to weekly and seasonal variations in demand.

[7] We calculate these fees by taking an airline's average aircraft capacity as a fraction of the average aircraft capacity by airport and multiplying by the price per unit weight times the average aircraft weight at each airport.

Figure 1--Comparison of Observed, Simulated, and Priced Arrival Rates (non-internalizing)

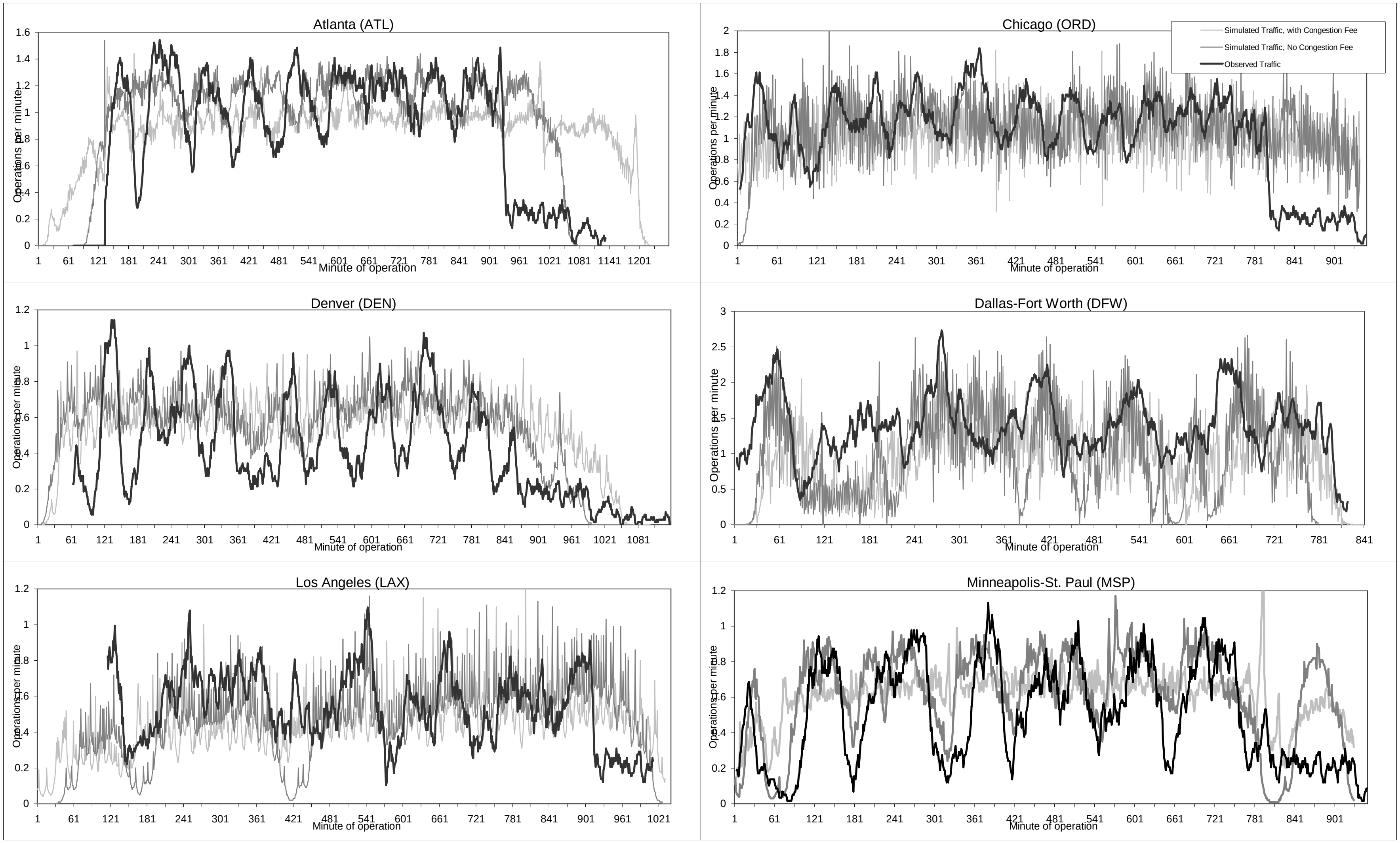

Figure 2--Comparison of Observed, Simulated, and Priced Arrival Rates (internalizing)

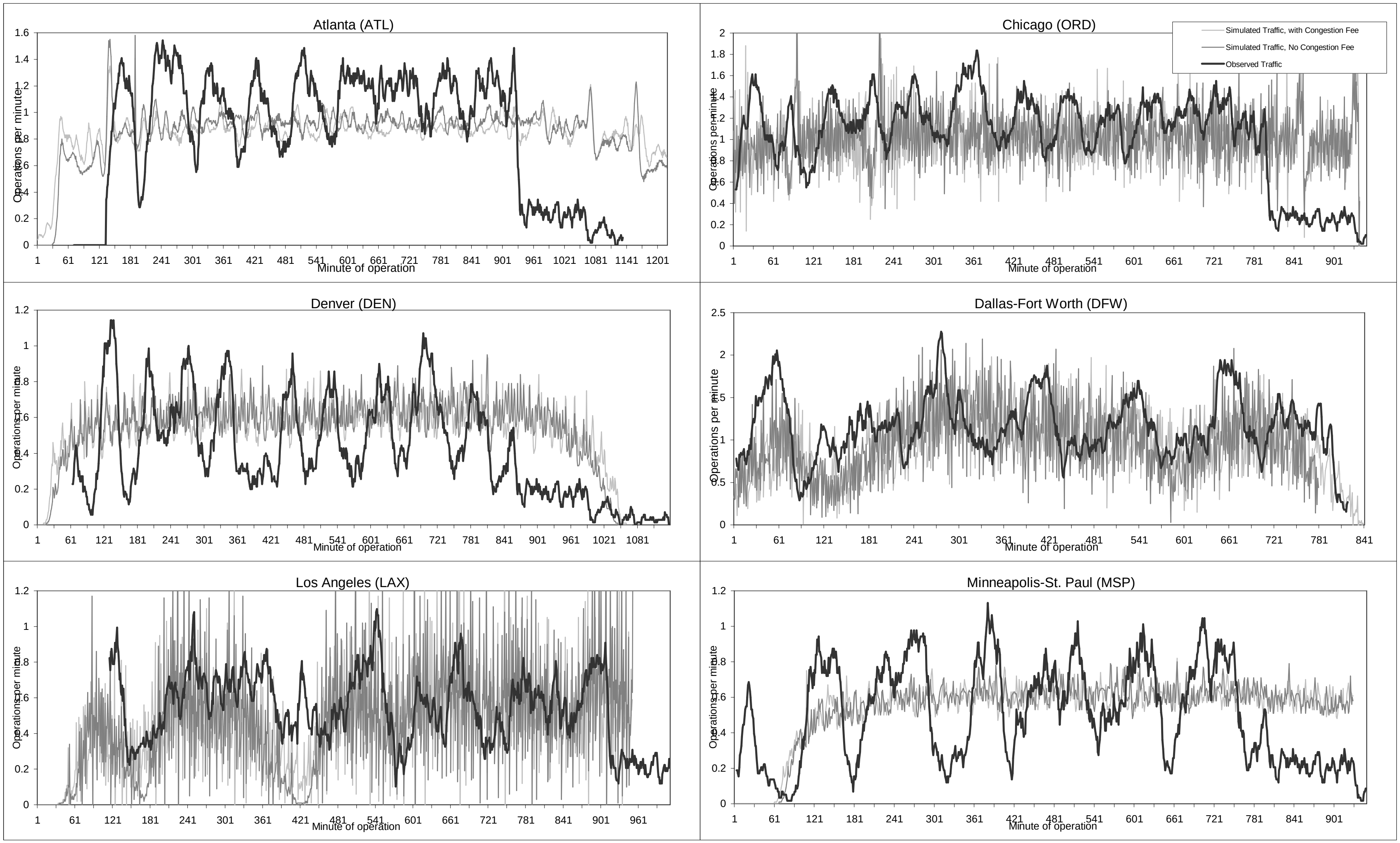

Figure 3--Comparison of Observed, Simulated, and Priced Arrival Delays (non-internalizing)

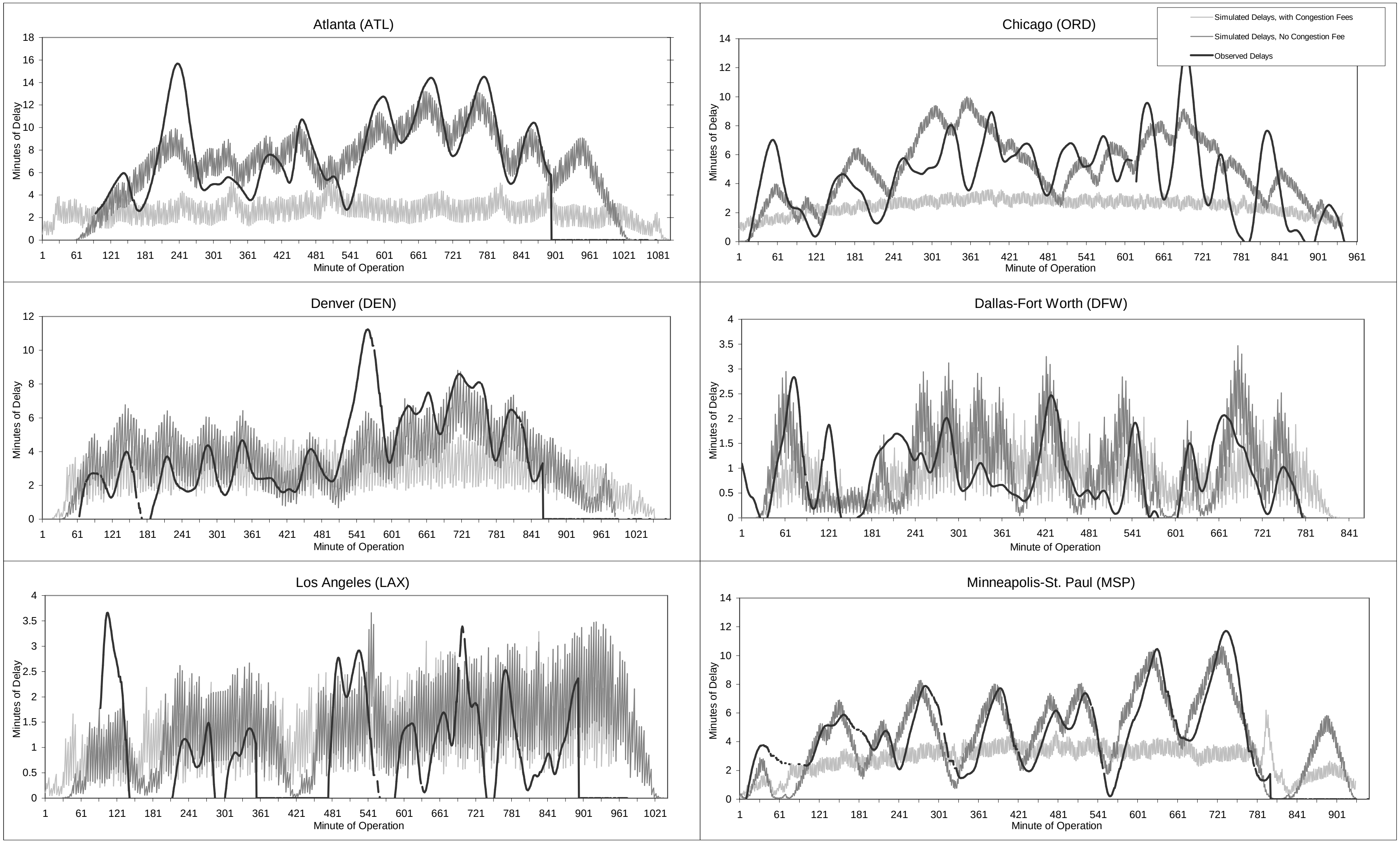

Figure 4--Comparison of Observed, Simulated, and Priced Arrival Delays (internalizing)

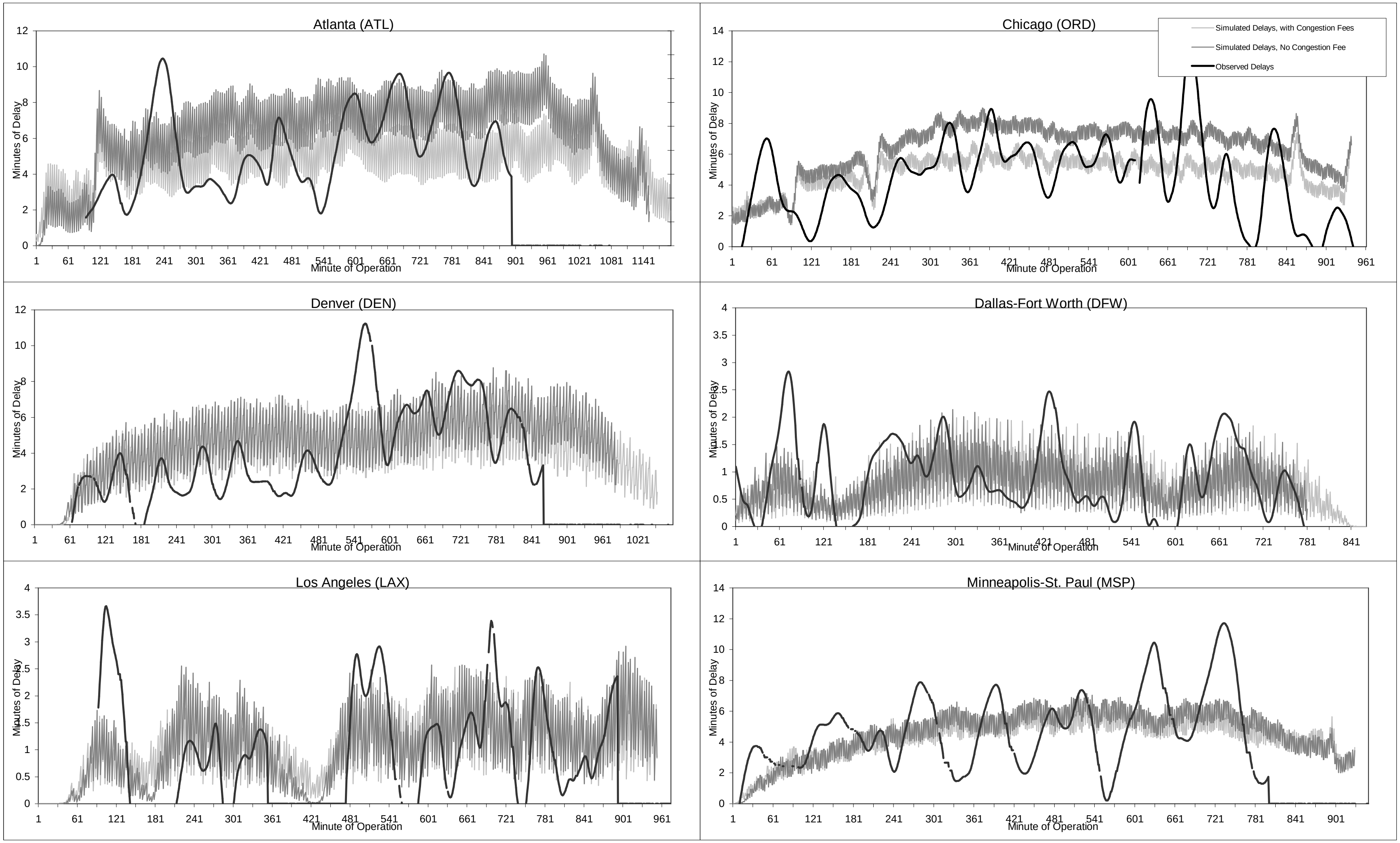

Figure 5--Congestion Fees, External Congestion (non-internalizing)

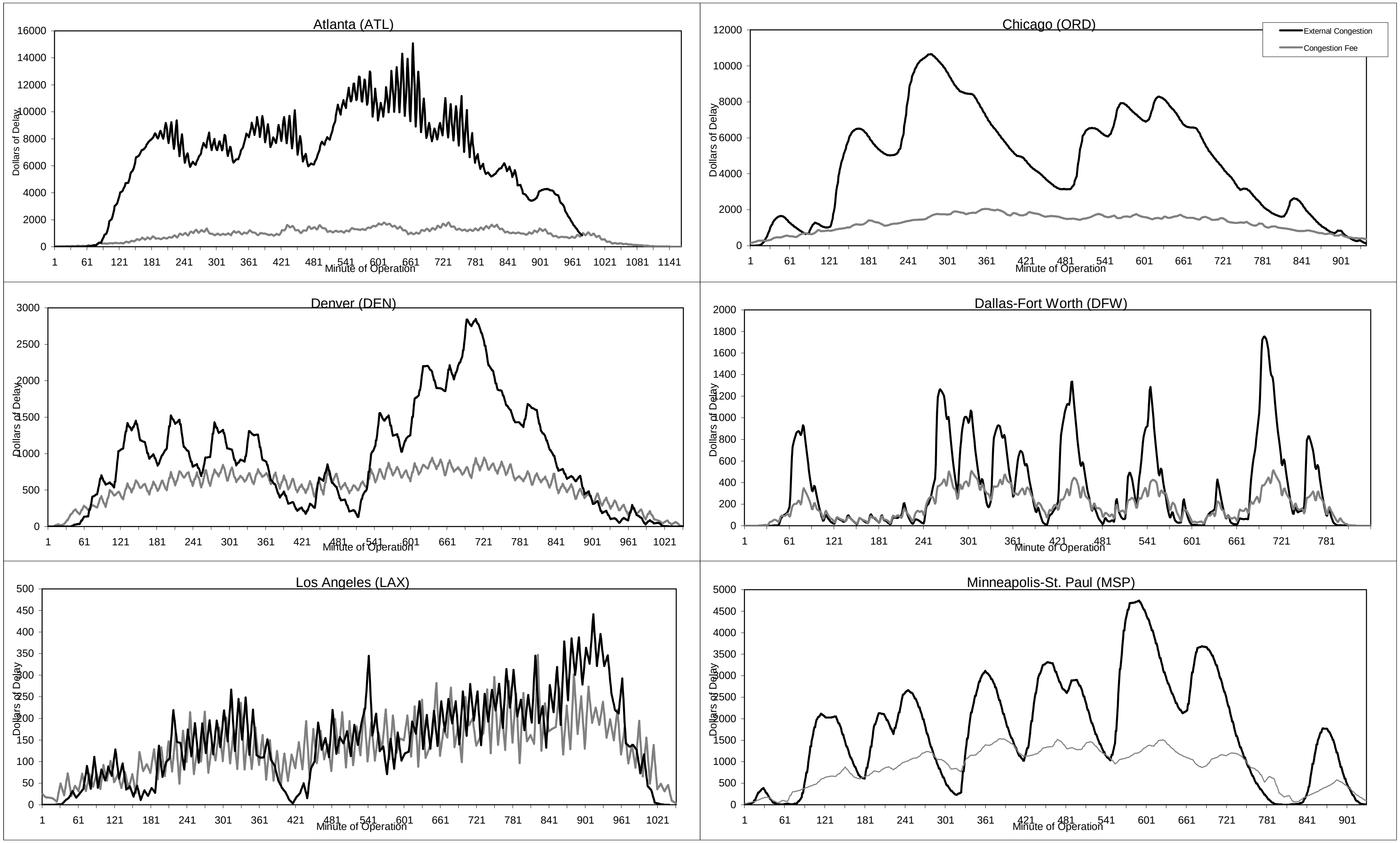

Figure 6--Congestion Fees, External Congestion (internalizing)

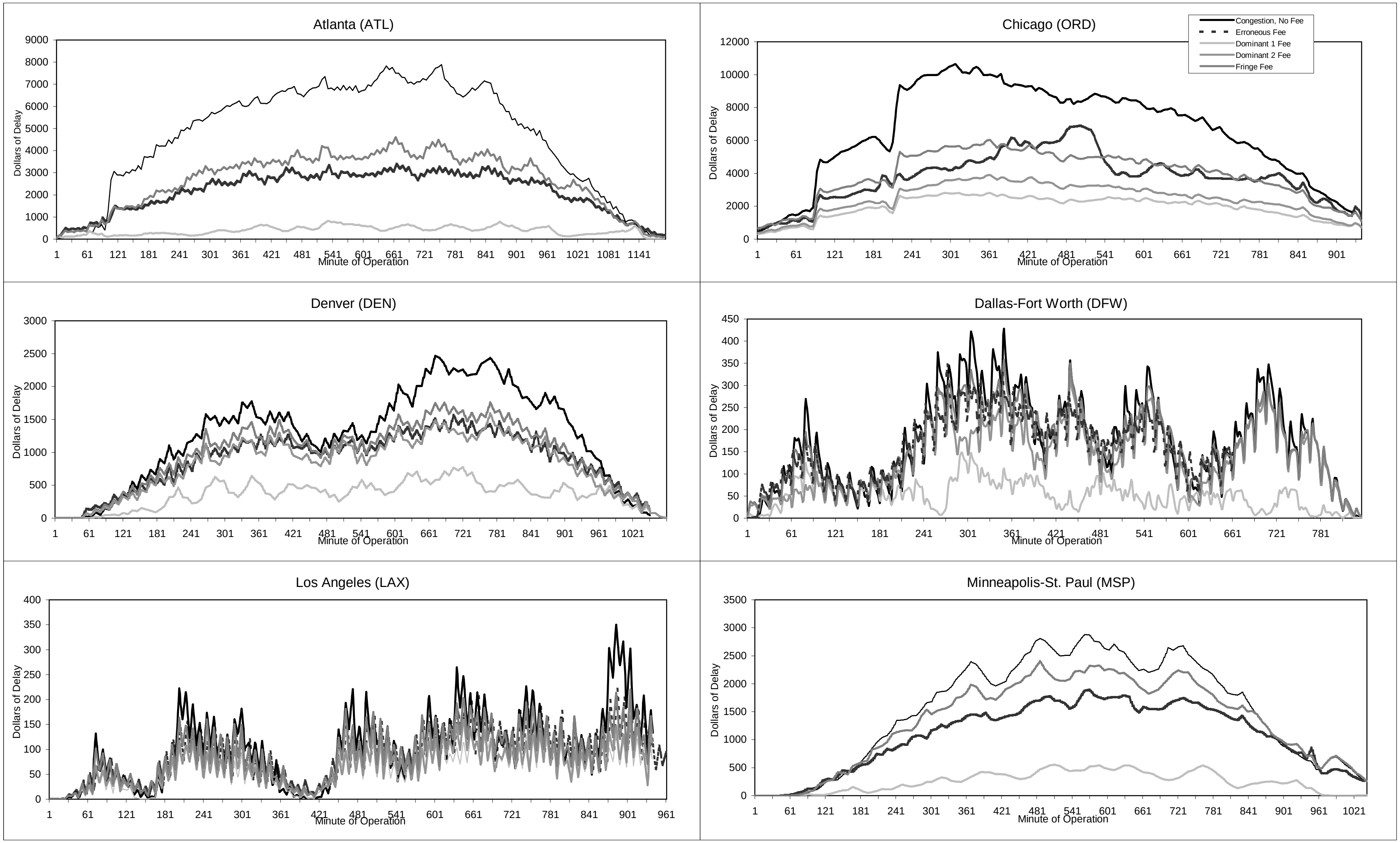

Table 1--Welfare Effects of Correct Identical Pricing of Non-Internalizing Dominant and Other Aircraft

	Number of Arrivals	Average Weight-Based Fee	Average Congestion Fee	Average Delay, Weight-Based Fee	Average Delay, Congestion Pricing	Time & Fee Costs per Aircraft, Weight-Based Fee	Time & Fee Costs per Aircraft, Congestion Pricing	Social Savings per Aircraft	Change in Daily Cost per Operator	Change in Daily Revenues	Net Gain per Airport
Atlanta (ATL) $0.95											$1,038,090
	769	$71	$2,753	20.68	7.27	$2,403	$3,951	$1,134	$1,190,232	$2,062,491	
	285	$35	$2,323	19.19	7.28	$1,488	$3,194	$582	$486,137	$651,968	
Boston (BOS) $3.89											$76,261
	93	$272	$564	6.83	3.00	$854	$894	$252	$3,658	$27,111	
	94	$242	$546	6.40	2.95	$745	$852	$197	$10,085	$28,592	
	67	$244	$551	7.01	2.98	$764	$846	$225	$5,498	$20,577	
	205	$265	$560	5.83	3.00	$563	$765	$94	$41,427	$60,649	
Baltimore-Washington (BWI) $1.63											$24,432
	112	$126	$656	4.90	4.78	$515	$988	$57	$52,928	$59,298	
	128	$111	$261	2.74	2.04	$352	$361	$141	$1,148	$19,210	
Charlotte (CLT) $0.45											$149,629
	400	$52	$659	7.42	2.77	$986	$1,253	$340	$106,837	$242,838	
	85	$31	$394	6.85	2.25	$476	$679	$160	$17,245	$30,874	
Cincinnatti (CVG) $2.09											$215,550
	453	$193	$1,469	7.34	3.91	$1,334	$2,232	$378	$406,726	$578,124	
	149	$142	$1,066	4.54	3.33	$652	$1,279	$296	$93,492	$137,644	
Washington National (DCA) $2.35											$20,993
	131	$129	$432	3.98	2.83	$460	$701	$63	$31,569	$39,788	
	60	$144	$428	3.83	2.68	$505	$710	$79	$12,305	$17,073	
	55	$141	$425	3.85	2.69	$494	$707	$70	$11,707	$15,569	
	68	$160	$328	2.54	2.42	$501	$608	$61	$7,244	$11,389	
Denver (DEN) $17.00											$78,565
	349	$2,070	$649	5.32	3.88	$2,653	$1,136	$96	-$529,232	-$495,889	
	99	$1,878	$789	4.93	3.86	$2,393	$1,064	$240	-$131,570	-$107,780	
	134	$1,853	$562	3.94	3.69	$2,299	$848	$160	-$194,479	-$173,046	
Dallas-Fort Worth (DFW) $4.94											$345,007
	511	$486	$853	12.77	5.08	$2,093	$1,912	$547	-$92,374	$187,383	
	137	$439	$599	12.56	4.59	$1,693	$1,609	$244	-$11,510	$21,941	
	121	$494	$419	5.16	3.53	$1,864	$1,526	$263	-$40,896	-$9,096	
Detroit (DTW) $3.39											$54,491
	360	$232	$438	5.65	3.20	$878	$949	$135	$25,550	$74,158	
	95	$231	$311	2.90	2.73	$748	$766	$62	$1,716	$7,599	
Newark (EWR) $5.65											$66,146
$100 fee 8 - 10 & 17 - 22	241	$356	$994	6.77	4.32	$1,029	$1,478	$189	$108,178	$153,626	
	119	$434	$860	6.79	4.15	$852	$1,104	$174	$29,952	$50,650	
Dulles (IAD) $2.13											$91,173
	196	$160	$714	6.64	3.20	$883	$1,160	$277	$54,212	$108,507	
	126	$145	$455	3.56	2.66	$515	$532	$293	$2,122	$39,002	
Houston (IAH) $2.93											$208,129
	395	$194	$1,594	11.61	4.95	$1,452	$2,382	$470	$367,353	$552,829	
	70	$199	$1,072	7.08	4.06	$1,140	$1,689	$324	$38,454	$61,107	
New York, Kennedy (JFK) $5.35											$40,027
	69	$499	$556	3.70	2.95	$787	$780	$65	-$513	$3,955	
	102	$613	$655	4.11	3.19	$1,005	$959	$88	-$4,662	$4,348	
	67	$590	$689	4.43	3.28	$994	$1,001	$91	$494	$6,607	
	101	$583	$595	3.83	3.00	$881	$691	$202	-$19,233	$1,203	
Las Vegas (LAS) $1.23											$61,358
	127	$136	$749	5.69	3.39	$718	$1,216	$116	$63,166	$77,850	
	86	$140	$703	5.61	3.26	$728	$1,152	$139	$36,444	$48,440	
	192	$134	$721	4.55	3.28	$589	$996	$181	$78,008	$112,687	
Los Angeles (LAX) $2.31											$3,868
	162	$169	$462	3.84	3.41	$421	$714	$0	$47,526	$47,600	
	111	$203	$451	3.78	3.47	$508	$763	-$7	$28,354	$27,622	
	68	$204	$467	3.61	3.42	$487	$762	-$12	$18,698	$17,887	
	118	$252	$499	2.74	3.46	$501	$703	$45	$23,823	$29,161	
New York, LaGuardia (LGA) $5.15											$14,977
	98	$524	$226	1.93	1.69	$673	$353	$22	-$31,378	-$29,173	
	97	$562	$226	1.92	1.69	$722	$362	$24	-$34,921	-$32,556	
	152	$394	$226	1.93	1.70	$509	$317	$24	-$29,194	-$25,567	
	112	$561	$201	1.61	1.52	$698	$277	$60	-$47,197	-$40,416	
Memphis (MEM)											$55,885
	161	$184	$528	5.49	2.87	$1,004	$1,086	$262	$13,205	$55,426	
	26	$131	$301	4.35	2.51	$570	$598	$142	$731	$4,412	
	47	$131	$380	3.74	2.49	$728	$765	$212	$1,706	$11,689	
Miami (MIA) $1.85											$37,622
	129	$145	$609	5.97	3.63	$880	$1,123	$222	$31,279	$59,896	
	48	$81	$428	5.99	3.29	$492	$786	$53	$14,103	$16,644	
	53	$126	$526	5.53	3.40	$549	$827	$122	$14,731	$21,195	
Minneapolis-St. Paul (MSP) $1.98											$178,903
	466	$219	$1,503	9.31	4.56	$1,356	$2,302	$338	$440,670	$598,360	
	104	$198	$1,303	6.42	4.39	$911	$1,812	$204	$93,694	$114,907	
Chicago (ORD) $2.99											$1,382,658
	512	$297	$3,622	25.02	7.60	$2,543	$4,806	$1,062	$1,158,590	$1,702,126	
	399	$289	$4,196	25.22	7.49	$2,475	$4,719	$1,663	$895,314	$1,558,685	
	124	$326	$3,466	21.63	7.33	$2,440	$4,163	$1,417	$213,678	$389,429	
Philadelphia (PHL) $1.93											$206,871
	274	$125	$1,364	10.33	5.12	$1,112	$1,981	$371	$237,992	$339,557	
	236	$131	$1,161	8.24	4.73	$920	$1,504	$446	$137,746	$243,051	
Pheonix (PHX) $1.11											$33,017
	171	$77	$534	4.74	3.13	$585	$967	$76	$65,253	$78,281	
	92	$87	$550	4.70	3.23	$647	$999	$111	$32,311	$42,570	
	218	$75	$393	2.52	2.26	$352	$624	$45	$59,358	$69,088	
Pittsburgh (PIT) $1.99											$28,661
	261	$132	$325	3.77	2.49	$483	$590	$85	$28,054	$50,336	
	64	$135	$277	3.19	2.34	$426	$468	$100	$2,667	$9,046	
Seattle (SEA) $3.24											$80,527
	287	$277	$762	6.16	3.48	$799	$1,190	$94	$112,174	$139,230	
	319	$353	$783	4.65	3.52	$944	$1,206	$168	$83,519	$136,990	
San Francisco (SFO) $3.93											$26,587
	208	$237	$580	4.64	3.10	$643	$925	$61	$58,787	$71,405	
	154	$267	$568	3.72	3.13	$591	$801	$91	$32,294	$46,262	
Salt Lake City (SLC) $1.25											$30,954
	319	$82	$305	4.15	2.86	$510	$664	$69	$49,005	$71,141	
	28	$114	$381	4.35	3.03	$678	$789	$157	$3,107	$7,501	
	63	$85	$316	3.80	3.03	$432	$593	$70	$10,160	$14,583	
St Louis (STL) $2.19											$112,357
	350	$270	$1,677	7.99	4.82	$1,171	$2,346	$232	$411,133	$492,493	
	49	$336	$1,764	8.25	4.87	$1,478	$2,568	$338	$53,403	$69,960	
	57	$239	$1,694	7.16	4.95	$943	$2,144	$253	$68,503	$82,943	

Table 2--Welfare Effects of Separate Pricing of Internalizing Dominant Aircraft and Non-internalizing Other Aircraft

	Average Weight-Based Fee	Average Congestion Fee	Average Delay, Weight-Based Fee	Average Delay, Congestion Pricing	Time & Fee Costs per Aircraft, Weight-Based Fee	Time & Fee Costs per Aircraft, Congestion Pricing	Social Savings per Aircraft	Change in Daily Cost per Operator	Change in Daily Revenues	Net Gain per Airport
Atlanta (ATL) $0.95										$516,766
	$71	$864	10.33	8.50	$2,157	$2,456	$495	$229,356	$609,834	
	$36	$4,175	11.82	8.86	$1,610	$5,257	$492	$1,010,754	$1,147,042	
Boston (BOS) $3.89										$94,346
	$272	$500	5.15	3.19	$1,086	$1,147	$166	$5,724	$21,176	
	$242	$495	5.35	3.12	$913	$1,071	$95	$14,845	$23,780	
	$244	$505	6.04	3.10	$946	$1,155	$52	$13,993	$17,470	
	$262	$610	4.94	3.03	$1,077	$1,103	$321	$5,428	$71,910	
Baltimore-Washington (BWI) $1.63										$84,178
	$140	$392	5.54	4.72	$2,049	$1,777	$524	-$30,440	$28,214	
	$108	$380	4.70	4.06	$1,194	$1,289	$176	$13,819	$39,343	
Charlotte (CLT) $0.45										$57,332
	$52	$206	4.58	4.46	$1,791	$1,792	$153	$293	$61,455	
	$31	$1,662	5.00	4.42	$1,237	$2,913	-$45	$142,477	$138,648	
Cincinnatti (CVG) $2.09										$78,131
	$193	$349	5.42	4.86	$1,181	$1,234	$103	$23,980	$70,719	
	$144	$1,857	5.65	4.59	$735	$2,235	$213	$221,312	$252,704	
Washington National (DCA) $2.35										$11,602
	$129	$266	3.34	2.92	$463	$572	$29	$14,246	$17,990	
	$144	$351	3.56	2.77	$478	$668	$18	$11,376	$12,457	
	$141	$364	3.62	2.83	$470	$680	$13	$11,529	$12,254	
	$159	$413	3.19	2.85	$568	$732	$89	$11,179	$17,231	
Denver (DEN) $17.00										$90,563
	$2,070	$558	6.41	5.76	$3,213	$1,561	$141	-$576,602	-$527,527	
	$1,879	$1,292	7.87	5.79	$2,744	$2,164	-$6	-$57,409	-$58,032	
	$1,853	$1,369	6.34	5.27	$3,138	$2,339	$314	-$106,982	-$64,871	
Dallas-Fort Worth (DFW) $4.94										$56,261
	$486	$412	6.42	5.97	$1,565	$1,372	$119	-$98,792	-$37,873	
	$439	$948	7.17	5.70	$1,178	$1,850	-$163	$91,956	$69,649	
	$494	$1,222	6.33	5.67	$1,514	$2,095	$146	$70,380	$88,029	
Detroit (DTW) $3.39										$17,809
	$232	$158	4.75	4.62	$872	$776	$22	-$34,667	-$26,770	
	$231	$716	4.94	4.55	$875	$1,257	$104	$36,255	$46,168	
Newark (EWR) $5.65										$116,822
$100 fee 8 - 10 & 17 - 22	$356	$838	8.07	6.22	$1,536	$1,844	$173	$74,172	$115,971	
	$434	$1,944	8.67	6.00	$1,919	$2,799	$630	$104,649	$179,672	
Dulles (IAD) $2.13										$86,448
	$160	$454	5.95	4.45	$913	$1,010	$196	$19,017	$57,478	
	$145	$1,005	5.27	4.06	$559	$1,039	$381	$60,443	$108,430	
Houston (IAH) $2.93										$86,427
	$194	$650	9.73	8.08	$1,498	$1,824	$130	$128,807	$180,054	
	$199	$2,840	8.74	7.43	$1,367	$3,505	$503	$149,652	$184,833	
New York, Kennedy (JFK) $5.35										$115,883
	$499	$1,155	6.92	4.54	$1,230	$1,853	$33	$43,001	$45,256	
	$613	$1,222	8.02	5.17	$1,730	$2,029	$310	$30,499	$62,091	
	$590	$1,689	10.33	5.83	$1,814	$2,533	$380	$48,157	$73,623	
	$561	$1,587	7.40	5.18	$1,362	$1,849	$539	$51,139	$107,709	
Las Vegas (LAS) $1.23										$50,460
	$85	$717	4.73	4.13	$507	$1,076	$64	$72,205	$80,280	
	$87	$746	4.10	3.58	$492	$1,089	$62	$51,340	$56,640	
	$84	$1,003	4.87	4.02	$451	$1,177	$193	$139,346	$176,431	
Los Angeles (LAX) $2.31										$21,105
	$169	$367	4.56	3.86	$521	$698	$22	$28,623	$32,118	
	$203	$411	4.84	4.03	$623	$797	$35	$19,319	$23,180	
	$204	$451	4.90	3.98	$587	$822	$11	$16,020	$16,759	
	$253	$570	5.02	4.06	$733	$939	$111	$24,058	$37,068	
New York, LaGuardia (LGA) $5.15										$48,714
	$327	$790	5.51	3.97	$939	$1,324	$78	$37,749	$45,412	
	$350	$800	5.51	4.01	$1,012	$1,363	$99	$34,065	$43,635	
	$246	$713	5.20	3.99	$757	$1,188	$37	$65,412	$71,049	
	$350	$954	5.09	3.91	$1,027	$1,401	$230	$41,828	$67,671	
Memphis (MEM)										$56,155
	$173	$189	4.51	4.12	$1,467	$1,232	$251	-$37,791	$2,560	
	$123	$838	6.08	4.09	$1,007	$1,498	$224	$12,760	$18,575	
	$124	$648	5.10	3.47	$907	$1,217	$215	$14,407	$24,396	
Miami (MIA) $1.85										$35,495
	$145	$446	5.53	4.86	$1,230	$1,302	$229	$9,286	$38,882	
	$81	$768	6.67	4.17	$574	$1,387	-$126	$39,012	$32,976	
	$126	$1,018	5.88	4.59	$979	$1,675	$196	$42,501	$54,436	
Minneapolis-St. Paul (MSP) $1.98										$81,248
	$219	$733	7.84	7.34	$1,841	$2,237	$118	$184,443	$239,571	
	$198	$3,645	8.60	7.50	$1,497	$4,693	$251	$332,338	$358,458	
Chicago (ORD) $2.99										$835,029
	$297	$3,353	15.47	10.29	$2,467	$4,726	$796	$1,156,737	$1,564,399	
	$289	$4,098	15.73	10.13	$2,283	$5,546	$547	$1,301,815	$1,519,923	
	$330	$6,131	15.96	9.82	$2,602	$6,694	$1,708	$501,320	$710,579	
Philadelphia (PHL) $1.93										$140,214
	$125	$481	7.33	5.67	$983	$1,190	$149	$56,700	$97,547	
	$0	$1,388	7.38	5.21	$762	$1,730	$421	$228,275	$327,641	
Pheonix (PHX) $1.11										$61,365
	$77	$1,248	7.70	6.29	$1,253	$2,263	$161	$172,775	$200,321	
	$87	$1,686	8.19	6.35	$1,209	$2,739	$69	$140,765	$147,123	
	$201	$2,104	7.74	5.86	$1,131	$2,698	$336	$128,200	$155,660	
Pittsburgh (PIT) $1.99										$16,871
	$132	$102	3.84	3.62	$787	$737	$20	-$13,089	-$7,935	
	$135	$415	3.95	3.61	$849	$946	$183	$6,204	$17,921	
Seattle (SEA) $3.24										$108,740
	$173	$734	5.25	4.96	$658	$1,172	$47	$147,668	$161,087	
	$233	$1,368	5.34	4.89	$945	$1,764	$316	$247,202	$342,523	
San Francisco (SFO) $3.93										$37,595
	$237	$336	3.99	3.61	$749	$801	$49	$10,622	$20,737	
	$264	$769	4.39	3.59	$827	$1,156	$176	$51,324	$78,803	
Salt Lake City (SLC) $1.25										$11,531
	$82	$111	3.52	3.36	$550	$558	$21	$2,501	$9,169	
	$114	$467	4.11	3.55	$618	$969	$3	$9,815	$9,886	
	$85	$436	3.84	3.40	$506	$781	$76	$17,345	$22,138	
St Louis (STL) $2.19										$31,274
	$168	$634	6.56	5.93	$1,441	$1,813	$93	$130,175	$162,865	
	$210	$2,308	7.33	6.09	$1,326	$3,576	-$151	$110,216	$102,838	
	$149	$2,377	6.94	6.29	$1,246	$3,369	$105	$121,030	$126,992	

Table 3--Welfare Effects of Erroneous Identical Pricing of Dominant and Other Aircraft

	Average Weight-Based Fee	Average Congestion Fee	Average Delay, Weight-Based Fee	Average Delay, Congestion Pricing	Time & Fee Costs per Aircraft, Weight-Based Fee	Time & Fee Costs per Aircraft, Congestion Pricing	Social Savings per Aircraft	Change in Daily Cost per Operator	Change in Daily Revenues	Net Gain per Airport
Atlanta (ATL) $0.95										-$1,770,664
	$71	$823	10.33	8.11	$2,157	$5,477	-$2,567	$2,552,617	$578,482	
	$36	$4,312	11.82	8.63	$1,610	$5,151	$734	$981,482	$1,184,952	
Boston (BOS) $3.89										$60,466
	$272	$459	5.15	3.06	$1,086	$1,283	-$10	$18,338	$17,378	
	$242	$464	5.35	2.99	$913	$1,169	-$35	$24,100	$20,845	
	$244	$487	6.04	3.00	$946	$1,221	-$32	$18,421	$16,292	
	$262	$608	4.94	3.02	$1,077	$1,100	$323	$4,769	$71,579	
Baltimore-Washington (BWI) $1.63										-$16,712
	$126	$377	5.54	4.27	$2,035	$2,421	-$135	$43,163	$28,072	
	$98	$383	4.70	3.90	$1,183	$1,480	-$11	$43,004	$41,383	
Charlotte (CLT) $0.45										-$541,232
	$52	$190	4.58	3.90	$1,791	$3,354	-$1,424	$625,043	$55,369	
	$31	$1,806	5.00	4.34	$1,237	$2,678	$335	$122,477	$150,919	
Cincinnatti (CVG) $2.09										-$648,626
	$193	$330	5.42	4.70	$1,181	$2,836	-$1,518	$749,799	$62,174	
	$144	$1,811	5.65	4.52	$735	$2,138	$264	$207,028	$246,027	
Washington National (DCA) $2.35										-$20,560
	$129	$248	3.34	2.78	$463	$730	-$148	$35,021	$15,611	
	$144	$327	3.56	2.70	$478	$722	-$60	$14,651	$11,022	
	$141	$341	3.62	2.78	$470	$732	-$63	$14,419	$10,968	
	$159	$401	3.19	2.78	$568	$723	$87	$10,545	$16,474	
Denver (DEN) $17.00										-$135,476
	$2,070	$500	6.41	5.28	$3,506	$2,414	-$478	-$380,998	-$547,756	
	$1,879	$1,201	7.87	5.54	$2,744	$2,207	-$141	-$53,101	-$67,024	
	$1,853	$1,325	6.34	5.19	$3,138	$2,272	$337	-$116,023	-$70,819	
Dallas-Fort Worth (DFW) $4.94										-$419,397
	$486	$355	6.42	5.53	$1,565	$2,232	-$798	$340,782	-$67,093	
	$439	$936	7.17	5.53	$1,178	$1,943	-$268	$104,788	$68,013	
	$494	$1,175	6.33	5.51	$1,514	$1,986	$209	$57,192	$82,445	
Detroit (DTW) $3.39										-$177,744
	$232	$150	4.75	4.34	$872	$1,314	-$524	$158,985	-$29,732	
	$231	$701	4.94	4.47	$875	$1,230	$115	$33,714	$44,686	
Newark (EWR) $5.65										-$170,426
$100 fee 8 - 10 & 17 - 22	$356	$737	8.07	5.78	$1,536	$2,924	-$1,007	$334,459	$91,804	
	$434	$1,910	8.67	5.85	$1,919	$2,788	$607	$103,345	$175,574	
Dulles (IAD) $2.13										-$66,305
	$160	$404	5.95	4.13	$913	$1,768	-$612	$167,672	$47,732	
	$145	$1,016	5.27	3.95	$559	$1,004	$426	$56,094	$109,730	
Houston (IAH) $2.93										-$865,853
	$194	$568	9.73	7.69	$1,498	$4,142	-$2,271	$1,044,425	$147,534	
	$199	$2,569	8.74	7.05	$1,367	$3,294	$443	$134,869	$165,908	
New York, Kennedy (JFK) $5.35										$2,262
	$499	$1,089	6.92	4.28	$1,230	$1,966	-$147	$50,818	$40,665	
	$613	$1,079	8.02	4.97	$1,730	$2,536	-$339	$82,206	$47,590	
	$590	$1,490	10.33	5.77	$1,814	$2,861	-$146	$70,125	$60,315	
	$561	$1,523	7.40	5.12	$1,362	$1,782	$541	$44,138	$100,979	
Las Vegas (LAS) $1.23										-$6,395
	$85	$706	4.73	4.13	$507	$1,426	-$297	$116,683	$78,909	
	$87	$727	4.10	3.46	$492	$1,227	-$96	$63,214	$54,982	
	$84	$990	4.87	4.03	$451	$1,151	$206	$134,433	$174,043	
Los Angeles (LAX) $2.31										-$33,667
	$169	$349	4.56	3.73	$521	$809	-$107	$46,566	$29,243	
	$203	$386	4.84	3.88	$623	$906	-$100	$31,494	$20,393	
	$204	$430	4.90	3.89	$587	$871	-$59	$19,350	$15,316	
	$253	$430	5.02	4.06	$733	$920	-$10	$21,848	$20,639	
New York, LaGuardia (LGA) $5.15										-$35,194
	$327	$739	5.51	3.84	$939	$1,509	-$158	$55,855	$40,407	
	$350	$753	5.51	3.91	$1,012	$1,567	-$153	$53,922	$39,060	
	$246	$693	5.20	3.88	$757	$1,408	-$204	$98,886	$67,871	
	$350	$933	5.09	3.84	$1,027	$1,377	$233	$39,170	$65,302	
Memphis (MEM)										-$49,449
	$269	$229	4.51	3.54	$1,562	$2,038	-$515	$76,528	-$6,311	
	$191	$1,045	6.08	4.26	$1,075	$1,444	$486	$9,574	$22,210	
	$193	$812	5.10	3.72	$976	$1,149	$446	$8,044	$28,798	
Miami (MIA) $1.85										-$46,648
	$145	$389	5.53	4.37	$1,230	$1,919	-$445	$88,894	$31,449	
	$81	$727	6.67	4.06	$574	$1,371	-$151	$38,251	$31,024	
	$126	$997	5.88	4.51	$979	$1,554	$295	$35,130	$53,154	
Minneapolis-St. Paul (MSP) $1.98										-$991,066
	$219	$580	7.84	6.42	$1,841	$4,432	-$2,229	$1,207,015	$168,438	
	$198	$3,153	8.60	6.90	$1,497	$3,996	$457	$259,847	$307,358	
Chicago (ORD) $2.99										-$2,023,478
	$297	$3,204	15.47	10.10	$2,467	$8,157	-$2,783	$2,913,277	$1,488,279	
	$289	$3,924	15.73	9.95	$2,283	$7,990	-$2,073	$2,277,340	$1,450,137	
	$330	$6,171	15.96	9.94	$2,602	$6,575	$1,867	$486,684	$715,406	
Philadelphia (PHL) $1.93										-$153,161
	$125	$471	7.33	5.66	$983	$2,227	-$898	$340,859	$94,804	
	$0	$1,397	7.38	5.21	$762	$1,766	$394	$236,806	$329,699	
Pheonix (PHX) $1.11										-$184,961
	$77	$1,111	7.70	5.93	$1,253	$3,241	-$953	$339,921	$176,916	
	$87	$1,500	8.19	5.97	$1,209	$3,216	-$594	$184,633	$130,022	
	$201	$2,034	7.74	5.77	$1,131	$2,565	$399	$117,332	$149,987	
Pittsburgh (PIT) $1.99										-$68,296
	$132	$83	3.84	3.27	$787	$1,036	-$297	$64,960	-$12,683	
	$135	$395	3.95	3.46	$849	$963	$146	$7,300	$16,646	
Seattle (SEA) $3.24										-$63,789
	$173	$714	5.25	4.72	$658	$1,758	-$560	$315,883	$155,187	
	$233	$1,334	5.34	4.82	$945	$1,725	$321	$235,341	$332,249	
San Francisco (SFO) $3.93										-$40,299
	$237	$313	3.99	3.36	$749	$1,163	-$338	$86,035	$15,814	
	$264	$741	4.39	3.54	$827	$1,112	$192	$44,465	$74,387	
Salt Lake City (SLC) $1.25										-$80,875
	$82	$99	3.52	3.17	$550	$837	-$269	$91,487	$5,517	
	$114	$413	4.11	3.28	$618	$939	-$22	$8,989	$8,383	
	$85	$429	3.84	3.36	$506	$760	$91	$15,962	$21,663	
St Louis (STL) $2.19										-$519,990
	$168	$530	6.56	5.33	$1,441	$3,278	-$1,475	$642,753	$126,555	
	$210	$2,035	7.33	5.55	$1,326	$3,469	-$318	$105,011	$89,419	
	$149	$2,187	6.94	5.74	$1,246	$3,076	$207	$104,334	$116,135	

Table A1--Cost Coefficients

	Arrivals					Departures				
	Non Internalizing			Internalizing		Non Internalizing			Internalizing	
	Early Arrival	Late Arrival	Arrival Queue	Early Arrival	Late Arrival	Early Departure	Late Departure	Arrival Queue	Early Departure	Late Departure
Atlanta (ATL)										
Delta	7.42	16.35	138.84	14.52	22.50	9.28	9.96	112.32	*33.70*	*33.70*
Code Sharers	1.38	3.04	25.81	2.70	4.18	1.72	1.85	20.88	*6.26*	*6.26*
Others	4.76	10.48	89.00	9.31	14.43	5.95	6.38	72.00	*21.60*	*21.60*
Regional	3.33	7.34	62.30	6.52	10.10	4.16	4.47	50.40	*15.12*	*15.12*
Boston (BOS)										
	5.32	3.18	132.43	8.50	3.56	3.15	*2.14*	107.14	*25.71*	*25.71*
	2.43	1.45	60.52	3.89	1.63	1.44	*0.98*	48.96	*11.75*	*11.75*
	4.39	2.62	109.29	7.02	2.94	2.60	*1.77*	88.42	*21.22*	*21.22*
	2.40	1.43	59.81	3.84	1.61	1.42	*0.97*	48.38	*11.61*	*11.61*
	5.12	3.06	127.45	8.18	3.43	3.04	*2.06*	103.10	*24.74*	*24.74*
	2.21	1.32	55.00	3.53	1.48	1.31	*0.89*	44.50	*10.68*	*10.68*
Baltimore (BWI)										
	7.66	*2.03*	101.46	*20.29*	*20.29*	*3.28*	4.17	82.08	*16.42*	*16.42*
	6.72	*1.78*	89.00	*17.80*	*17.80*	*2.88*	3.66	72.00	*14.40*	*14.40*
Charlotte (CLT)										
	13.97	22.88	190.26	25.65	40.43	*61.57*	*36.94*	153.92	*43.10*	42.30
	8.18	13.41	111.50	15.03	23.69	*36.08*	*21.65*	90.21	*25.26*	24.79
	6.53	10.70	89.00	12.00	18.91	*28.80*	*17.28*	72.00	*20.16*	19.79
Cincinnatti (CVG)										
	11.93	25.24	183.25	12.44	17.78	12.59	10.31	148.25	*7.41*	7.58
	5.98	12.66	91.94	6.24	8.92	6.31	5.17	74.38	*3.72*	3.80
	5.79	12.26	89.00	6.04	8.64	6.11	5.01	72.00	*3.60*	3.68
Washington (DCA)										
	3.97	2.37	98.79	*3.16*	3.18	5.33	31.76	79.92	5.33	31.76
	2.08	1.24	51.89	*1.66*	1.67	2.80	16.68	41.98	2.80	16.68
	3.99	2.38	99.43	*3.18*	3.20	5.36	31.97	80.44	5.36	31.97
	2.30	1.38	57.41	*1.84*	1.85	3.10	18.46	46.44	3.10	18.46
	4.24	2.53	105.64	*3.38*	3.40	5.70	33.96	85.46	5.70	33.96
	1.96	1.17	48.86	*1.56*	1.57	2.63	15.71	39.53	2.63	15.71
Denver (DEN)										
	7.71	5.26	118.37	13.86	12.69	9.38	2.09	95.76	20.13	22.24
	4.06	2.77	62.30	7.30	6.68	4.94	1.10	50.40	10.60	11.70
	6.67	4.55	102.35	11.99	10.97	8.11	1.81	82.80	17.41	19.23
	3.65	2.49	56.07	6.57	6.01	4.44	0.99	45.36	9.54	10.53
	5.80	3.96	89.00	10.42	9.54	7.05	1.57	72.00	15.14	16.72
Dallas (DFW)										
	6.40	*6.40*	106.62	1.94	2.75	*20.70*	*20.70*	86.26	*17.25*	*17.25*
	3.12	*3.12*	51.98	0.95	1.34	*10.09*	*10.09*	42.05	*8.41*	*8.41*
	6.35	*6.35*	105.82	1.93	2.73	*20.55*	*20.55*	85.61	*17.12*	*17.12*
	3.33	*3.33*	55.54	1.01	1.43	*10.78*	*10.78*	44.93	*8.99*	*8.99*
	5.34	*5.34*	89.00	1.62	2.30	*17.28*	*17.28*	72.00	*14.40*	*14.40*
Detroit (DTW)										
	9.20	7.20	108.85	15.60	8.62	7.48	6.13	88.06	*4.58*	4.50
	5.04	3.95	59.63	8.54	4.72	4.10	3.36	48.24	*2.51*	2.47
	7.52	5.89	89.00	12.75	7.05	6.11	5.01	72.00	*3.74*	3.68
Newark (EWR)										
	8.99	7.14	93.09	55.50	10.42	*18.07*	*30.12*	75.31	*22.59*	*22.59*
	4.59	3.64	47.53	28.34	5.32	*9.23*	*15.38*	38.45	*11.53*	*11.53*
	8.59	6.82	89.00	53.06	9.96	*17.28*	*28.80*	72.00	*21.60*	*21.60*
Dulles (IAD)										
	17.36	17.43	172.30	16.89	9.94	1.73	19.98	139.39	*0.28*	41.30
	7.32	7.35	72.62	7.12	4.19	0.73	8.42	58.75	*0.12*	17.41
	8.97	9.01	89.00	8.72	5.14	0.89	10.32	72.00	*0.14*	21.33
Houston (IAH)										
	19.76	11.21	111.34	19.10	*17.81*	11.79	27.73	90.07	*21.62*	22.86
	10.35	5.87	58.30	10.00	*9.33*	6.18	14.52	47.16	*11.32*	11.97
	15.80	8.96	89.00	15.27	*14.24*	9.43	22.17	72.00	*17.28*	18.28
New York (JFK)										
	5.37	0.69	75.65	18.84	*18.16*	4.00	*3.67*	61.20	3.95	6.33
	7.25	0.94	102.08	25.42	*24.50*	5.40	*4.96*	82.58	5.34	8.54
	5.48	0.71	77.16	19.22	*18.52*	4.09	*3.75*	62.42	4.03	6.46
	6.95	0.90	97.81	24.36	*23.47*	5.18	*4.75*	79.13	5.11	8.19
	5.40	0.70	76.10	18.95	*18.26*	4.03	*3.69*	61.56	3.98	6.37
	6.32	0.82	89.00	22.17	*21.36*	4.71	*4.32*	72.00	4.65	7.45

Las Vegas (LAS)										
	7.25	*7.25*	90.60	2.08	1.99	*5.86*	6.51	73.30	*1.76*	1.76
	7.85	*7.85*	98.08	2.25	2.16	*6.35*	7.05	79.34	*1.90*	1.91
	5.97	*5.97*	74.67	1.71	1.64	*4.83*	5.37	60.41	*1.45*	1.45
	7.12	*7.12*	89.00	2.04	1.96	*5.76*	6.40	72.00	*1.73*	1.73
Los Angeles (LAX)										
	0.64	2.29	90.78	4.56	1.60	3.08	2.84	73.44	3.78	*3.67*
	0.27	0.96	38.18	1.92	0.67	1.30	1.20	30.89	1.59	*1.54*
	0.68	2.41	95.76	4.81	1.69	3.25	3.00	77.47	3.99	*3.87*
	0.41	1.47	58.38	2.93	1.03	1.98	1.83	47.23	2.43	*2.36*
	0.51	1.82	72.27	3.63	1.27	2.45	2.26	58.46	3.01	*2.92*
	0.63	2.24	89.00	4.47	1.57	3.02	2.79	72.00	3.70	*3.60*
New York (LGA)										
	0.44	0.61	106.53	2.80	*2.77*	4.09	*1.72*	86.18	*17.24*	*17.24*
	0.19	0.26	45.92	1.21	*1.19*	1.76	*0.74*	37.15	*7.43*	*7.43*
	0.47	0.65	113.03	2.97	*2.94*	4.33	*1.83*	91.44	*18.29*	*18.29*
	0.22	0.31	53.40	1.40	*1.39*	2.05	*0.86*	43.20	*8.64*	*8.64*
	0.41	0.56	98.08	2.58	*2.55*	3.76	*1.59*	79.34	*15.87*	*15.87*
	0.21	0.29	49.84	1.31	*1.30*	1.91	*0.81*	40.32	*8.06*	*8.06*
	0.37	0.51	89.00	2.34	*2.31*	3.41	*1.44*	72.00	*14.40*	*14.40*
Memphis (MEM)										
	35.71	13.35	168.12	41.33	14.55	8.21	*8.16*	136.01	*20.95*	20.96
	21.15	7.91	99.59	24.48	8.62	4.86	*4.83*	80.57	*12.41*	12.42
	18.90	7.06	89.00	21.88	7.70	4.35	*4.32*	72.00	*11.09*	11.10
	18.90	7.06	89.00	21.88	7.70	4.35	*4.32*	72.00	*11.09*	11.10
Miami (MIA)										
	8.30	9.27	114.37	23.84	10.59	3.39	*3.39*	92.52	18.27	16.29
	5.06	5.65	69.69	14.53	6.45	2.06	*2.06*	56.38	11.13	9.93
	2.07	2.31	28.48	5.94	2.64	0.84	*0.84*	23.04	4.55	4.06
	7.10	7.93	97.90	20.41	9.07	2.90	*2.90*	79.20	15.64	13.95
	6.46	7.21	89.00	18.55	8.24	2.64	*2.64*	72.00	14.22	12.68
Minneapolis (MSP)										
	11.73	18.89	116.15	14.92	14.88	8.68	10.59	93.96	*30.07*	29.99
	6.31	10.16	62.47	8.02	8.00	4.67	5.70	50.54	*16.17*	16.13
	8.99	14.48	89.00	11.43	11.40	6.65	8.11	72.00	*23.04*	22.98
Chicago (ORD)										
	8.10	5.66	99.24	11.29	*11.31*	*14.45*	14.45	80.28	16.19	23.60
	4.50	3.14	55.06	6.26	*6.28*	*8.02*	8.02	44.55	8.99	13.09
	7.89	5.51	96.65	11.00	*11.02*	*14.07*	14.07	78.19	15.77	22.98
	4.35	3.04	53.31	6.06	*6.08*	*7.76*	7.76	43.13	8.70	12.68
	7.27	5.08	89.00	10.12	*10.15*	*12.96*	12.96	72.00	14.52	21.16
Philadelphia (PHL)										
	9.36	11.21	117.48	9.94	12.82	5.34	8.53	95.04	8.60	10.37
	4.21	5.03	52.78	4.47	5.76	2.40	3.83	42.70	3.86	4.66
	7.09	8.49	89.00	7.53	9.71	4.04	6.47	72.00	6.51	7.86
Pheonix (PHX)										
	3.85	4.93	109.74	8.24	9.53	4.59	6.90	88.78	22.51	24.08
	2.24	2.87	63.81	4.79	5.54	2.67	4.02	51.62	13.09	14.00
	3.60	4.61	102.62	7.70	8.92	4.30	6.46	83.02	21.05	22.52
	3.12	4.00	89.00	6.68	7.73	3.73	5.60	72.00	18.26	19.53
Pittsburgh (PIT)										
	4.73	2.41	140.62	10.16	9.60	2.89	*2.28*	113.76	8.22	7.76
	2.02	1.03	59.90	4.33	4.09	1.23	*0.97*	48.46	3.50	3.31
	3.00	1.53	89.00	6.43	6.07	1.83	*1.44*	72.00	5.20	4.91
Seattle (SEA)										
	8.85	*8.85*	88.55	0.80	0.23	*7.16*	*7.16*	71.63	*14.33*	*14.33*
	5.29	*5.29*	52.95	0.48	0.14	*4.28*	*4.28*	42.83	*8.57*	*8.57*
	8.90	*8.90*	89.00	0.80	0.23	*7.20*	*7.20*	72.00	*14.40*	*14.40*
San Francisco (SFO)										
	3.62	4.62	102.35	18.19	4.08	4.28	3.98	82.80	4.93	16.10
	1.61	2.06	45.57	8.10	1.82	1.90	1.77	36.86	2.19	7.17
	3.15	4.02	89.00	15.82	3.55	3.72	3.46	72.00	4.29	14.00
Salt Lake City (SLC)										
	4.57	4.78	145.07	7.81	5.86	2.90	8.07	117.36	5.80	16.58
	1.99	2.08	63.19	3.40	2.55	1.26	3.51	51.12	2.53	7.22
	3.76	3.93	119.26	6.42	4.82	2.39	6.63	96.48	4.77	13.63
	2.80	2.93	89.00	4.79	3.60	1.78	4.95	72.00	3.56	10.17
St Louis (STL)										
	3.43	10.28	138.84	8.06	17.18	9.30	19.79	112.32	51.49	47.14
	1.52	4.56	61.59	3.58	7.62	4.13	8.78	49.82	22.84	20.91
	3.10	9.29	125.49	7.29	15.53	8.41	17.88	101.52	46.54	42.61
	2.20	6.59	89.00	5.17	11.01	5.96	12.68	72.00	33.01	30.22