

# The Role of Airline Frequency Competition in Airport Congestion Pricing

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**Abstract:** Airport congestion pricing has often been advocated as a means of controlling demand for airport operations and for achieving efficient resource allocation. Competition between airlines affects the extent to which an airline would be willing to pay for airport slots. Accurate modeling of competition is critical in order to determine the effectiveness of a congestion pricing mechanism. We develop an equilibrium model of airline frequency competition in the presence of delay costs and congestion prices. Using a small hypothetical network, we evaluate the impacts of congestion prices on the various stakeholders and investigate the dependence of effectiveness of congestion pricing on the characteristics of frequency competition in individual markets. We find that the effectiveness of congestion pricing critically depends on three essential parameters of frequency competition. Our results show that variation in the number of passengers per flight plays a vital role in determining the degree of attractiveness of congestion pricing to the airlines. A significant part of the impact of congestion pricing cannot be accounted for using the models in prior literature, which are based on the assumptions of constant load factors and constant aircraft sizes. Further, we find that, in comparison to flat pricing, marginal cost pricing is more effective in reducing congestion without penalizing the airlines with exceedingly high congestion prices.

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## 1. BACKGROUND

With airport capacity being a scarce resource, market-based mechanisms such as congestion pricing and slot auctions are expected to bring demand and supply in balance by placing monetary prices on the airport capacity. These market-based mechanisms rely on the ability of the airlines to assess the economical value of airport slots, while bidding for slots in the case of auctions and for determining the demand for slots at a given level of prices in the case of congestion pricing. Airlines are typically assumed to be rational decision makers, each driven by its own profit-maximization objective. However, an airline needs to account for competition from other airlines operating in the same markets as it does, while ascertaining its own valuation of an airport slot. In this paper, we model the airline frequency decisions under congestion pricing through explicit modeling of competition and assess the dependence of the effectiveness, or lack thereof, of congestion pricing on the characteristics of airline markets. Many prior studies have accounted for airline competition using conventional micro-economic models of firm

competition. However, these generalized models fail to capture the essential characteristics of competition which are peculiar to the airline industry and consequently, as we show in this paper, tend to underestimate congestion pricing benefits to the airlines. We capture these characteristics through an industry-specific competition model and generate insights that were not possible with the previous models.

Section 2 summarizes the existing literature on airport congestion pricing. Section 3 provides details of our equilibrium model of frequency competition. Section 4 describes our delay model that captures the dependence of flight delays on airline frequency decisions. Section 5 outlines the data sources and experimental setup for the computational experiments. Section 6 provides results of delay function fitting. Section 7 presents computational results for a small hypothetical network. Section 8 concludes with a summary of the practical implications of this research and a description of directions for future research.

## **2. LITERATURE REVIEW**

A user (such as an airline) of a public resource (such as an airport) generates value for itself through the utilization of the resource. Such utilization might sometimes result in detrimental effects to the other users of the public resource. In particular, an airline operating at a congested airport imposes additional delay costs on the other airlines operating at the same airport. Economists have long been advocating the use of pricing of public resources in the presence of negative externalities such as congestion, wherein each user of the public resource is required to pay a price equal to the marginal cost imposed by that user on all the other users of the resource (1). Such prices based on marginal costs have been claimed to achieve efficient allocation of resources. Not surprisingly, early studies on airport congestion pricing have advocated marginal cost pricing of airport resources (2, 3). Levine (2) proposed to implement a system in which each airport user is charged fully for the marginal cost of an additional operation, while Carlin and Park (3) recommended a hybrid system involving pricing and administrative controls due to various practicality issues associated with a full marginal cost pricing scheme.

Airport congestion pricing, however, is fundamentally different from pricing of resources such as highway infrastructure which involve a large number of users, each using a very small portion of the capacity of the resource, otherwise known as atomistic users. Airlines, on the other hand, are considered to be non-atomistic users of airport resources because each airline typically operates more than one flight at an airport, and the number of users of an airport resource is comparatively smaller. So each additional operation by an airline delays the flights of other airlines as well as the other flights of the same airline at that airport. More recent studies recognize the fact that airlines automatically internalize a part of the congestion costs they impose (4, 5, 6, 7, 8). A recent study by Morrison and Winston compared the

atomistic (or flat) and non-atomistic pricing policies across 74 commercial US airports in 2005 (9). They found the difference between the net benefits generated by the two congestion pricing policies to be small because the bulk of airport delays are not internalized. In this paper, we analyze the impacts of various levels of flat pricing (also known as atomistic pricing) as well as the marginal cost pricing (also known as non-atomistic pricing) equilibrium for non-atomistic users.

Daniel modeled the interaction between airport demand, slot prices and delays using detailed queuing theoretic models, but did not capture frequency-based competition for passenger share in a market, even though such competition between airlines is intricately related to the congestion problem at major airports (4, 5). Several other studies have tackled this problem from a microeconomic perspective and have mathematically derived Nash equilibrium outcomes under congestion pricing (6, 7, 8, 10). These studies model airline decisions using general micro-economic models of firm competition, which typically assume quantity-based (Cournot) competition. By assuming constant load factors and constant aircraft seating capacities, they fail to recognize the important distinguishing features of the airline industry for which the quantity produced can be captured by three different entities: number of flights, number of seats and number of passengers carried.

The incremental profitability of having an extra flight in a particular market largely depends on the number of additional passengers that the airline will be able to carry because of the additional flight, which in turn depends on the schedule of flights offered by the competitor airlines in the same market. So, given a set of congestion prices, the total demand for slots should reflect these competitive interactions. However, Cournot models of firm competition do not incorporate the inverse dependence of one airline's market share on competitor airlines' frequencies, which is a critical component of such competitive interactions.

Furthermore, the assumption of constant load factors and constant aircraft seating capacities means that studies such as Brueckner (6, 7), Pels and Verhoef (8), and Perakis and Sun (10), cannot account for the possibility of increases in average number of passengers per flights (through increased load factors, or increased number of seats per aircraft, or both) as the slots become expensive under congestion pricing. Consequently, delay cost reductions have often been considered as the only type of benefit from congestion pricing. Most of the prior studies evaluate congestion pricing benefits in terms of overall societal welfare gain, rather than in terms of the benefits to airlines and passengers. Perakis and Sun (10) conclude that, while congestion pricing leads to the welfare maximization solution, both airlines and passengers are worse off than without congestion pricing because the welfare gain from congestion pricing is in the form of the revenue generated from pricing. Many of the prior congestion pricing studies

propose some form of direct or indirect mechanisms for re-distribution of this revenue gain if the congestion pricing scheme is to be attractive to the airlines.

Our models are able to capture the phenomenon of varying number of passenger per flight explicitly. In fact, as we show in Section 7, a reduction in operating costs is an important driver of the benefits of congestion pricing to the airlines, which has not been considered in any of the prior studies.

Schorr provided a model of airline frequency competition under flat pricing of airport slots and produced interesting results on the benefits of flat pricing, albeit focusing on symmetric equilibria for the somewhat restrictive case of identical airlines (11). We model airline frequency competition under congestion pricing using a popular market share model of frequency competition, which is similar to Schorr's model. We consider the general case of non-identical airlines and do not restrict our analysis to symmetric equilibria.

The main objective of this research is to investigate the role of airline frequency competition under congestion pricing. The major contributions of this paper are threefold. First, we develop a model for airline frequency competition that explicitly accounts for the relationship between the number of flights operated, number of seats flown and the number of passengers carried by an airline under slot pricing. To the best of author's knowledge, this is the first computational study that accounts for this relationship. Second, using a small hypothetical network, we evaluate the impacts of congestion prices on the various stakeholders and investigate the dependence of effectiveness of congestion pricing mechanisms on the different characteristics of airline competition. Third, we provide computational results under flat as well as marginal cost pricing. Our results show that the variation in number of passengers per flight plays a vital role in determining the degree of attractiveness of congestion pricing to the airlines.

### **3. MODEL**

By providing more frequency on a route, an airline attracts more passengers. Given an estimate of total demand on a route, the market share of each airline depends on its own frequency as well as on the competitor frequency. Market share can be modeled according to the so-called *S-curve* or *sigmoidal* relationship between the market share and frequency share, which is a well-accepted notion in the airline industry (12, 13). Empirical evidence of the relationship was documented in some early studies and regression analysis was used to estimate the model parameters (14, 15, 16). Over the years, there have been several references to the S-curve (17, 18). In a recent study, Wei and Hansen provide further statistical support for the S-curve, based on a nested Logit model for non-stop duopoly markets (19). The most commonly used mathematical expression for the S-curve relationship (16, 13) is given by,

$$MS_i = \frac{FS_i^\alpha}{\sum_{j=1}^n FS_j^\alpha}. \quad (1)$$

$MS_i$  is the market share of airline  $i$ ,  $FS_i$  is the frequency share of airline  $i$ , and  $n$  is the number of competing airlines.  $\alpha \geq 1$  is a model parameter.

Our model of airline decision-making explicitly incorporates the relationship between market share and frequency share as described by equation (1). In our computational experiments, we assume that congestion pricing is being considered at a single airport. This airport under consideration for implementation of congestion pricing will be simply denoted as *the airport*. First, we describe the relevant notation.

$A$ : Set of airlines operating at the airport

$A_s$ : Set of airlines whose set of potential segments includes  $s$

$M_s$ : Total passenger demand on segment  $s$

$\alpha_s$ : Exponent of the S-curve relationship between market share and frequency share on segment  $s$

$p_{as}$ : Average fare charged by airline  $a$  on segment  $s$

$Q_{as}$ : Number of passengers carried by airline  $a$  on segment  $s$

$C_{as}$ : Operating cost per flight for airline  $a$  on segment  $s$

$f_{as}$ : Daily frequency of flights for airline  $a$  on segment  $s$  (the decision variables)

$S_a$ : Set of potential segments for airline  $a$  with destination at the airport

$U_a$ : Upper bound on the number of slots available for airline  $a$

$L_a$ : Lower bound on the number of slots available for airline  $a$

$c_a$ : Unit cost of flight delays to airline  $a$  (e.g. \$/aircraft-minute)

$LF_{max}$ : Maximum average segment load factor

$\mathbb{O}$ : Total number of operations at the airport

$D(\cdot)$ : Average flight delay as a function of the total number of operations at the airport

$T(\cdot, \cdot)$ : Toll (in \$) charged to an airline as a function of that airline's demand for operations and total number of operations at the airport.

Our model of airline decision making is an extension of the *basic model* developed by Vaze and Barnhart (20). Expressions (2) through (7) describe the problem of deciding the flight frequencies as an optimization formulation from the perspective of a single airline. The objective function, (2), consists of three parts: 1) the difference between the total revenue and operating costs summed across all markets, 2) flight delay cost incurred by the airline, and 3) the congestion prices paid by the airline. The operating cost inside the first summation excludes the cost due to flight delays. Flight delay cost is the product of unit cost of flight delay ( $c_a$ ) to that airline, the total number of operations of that airline at the airport ( $\sum_{s \in \mathbb{S}_a} f_{as}$ ), and the average flight delay ( $D$ ) which is a function of total number of operations from all airlines at the airport ( $\sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's}$ ). The congestion price ( $T$ ) paid by the airline is decided by the airport administrator. It is reasonable to expect that  $T$  will be a non-decreasing function of total number of operations of that airline at the airport ( $\sum_{s \in \mathbb{S}_a} f_{as}$ ). Furthermore, for the same number of operations of airline  $a$  at the airport, we can expect  $T$  to also be a non-decreasing function of the total number of operations ( $\mathbb{O}$ ) by all airlines at the airport. Greater the total number of operations of all airlines at the airport, the greater is the additional delay cost imposed by airline  $a$  on other users, and consequently, the higher is the total congestion price paid by airline  $a$ . So we consider  $T$  to be a function of  $\sum_{s \in \mathbb{S}_a} f_{as}$  and  $\sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's}$ . Note that this framework is general enough and it still accounts for the possibility that  $T$  is a constant (a constant function).

$$\text{maximize } \sum_{s \in \mathbb{S}_a} (p_{as} Q_{as} - c_{as} f_{as}) - c_a \left( \sum_{s \in \mathbb{S}_a} f_{as} \right) * D \left( \sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's} \right) - T \left( \sum_{s \in \mathbb{S}_a} f_{as}, \sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's} \right) \quad (2)$$

$$\text{subject to: } Q_{as} \leq \frac{f_{as}^{\alpha_s}}{\sum_{a' \in \mathbb{A}_s} f_{a's}} M_s \quad \forall s \in \mathbb{S}_a \quad (3)$$

$$Q_{as} \leq LF_{max} S_{as} f_{as} \quad \forall s \in \mathbb{S}_a \quad (4)$$

$$\sum_{\forall s \in \mathbb{S}_a} f_{as} \leq U_a \quad (5)$$

$$\sum_{\forall s \in \mathbb{S}_a} f_{as} \geq L_a \quad (6)$$

$$f_{as} \in \mathbb{Z}^+ \quad \forall s \in \mathbb{S}_a \quad (7)$$

In this paper, we present two types of experiments. First, we compute the impacts of continuously varying slot prices. Here, we assume flat prices, that is, an equal (flat) price per slot ( $c_F$ ) charged to each airline

regardless of the total number of operations of that airline. Under flat pricing, the total congestion price paid by airline  $a$  is,

$$T\left(\sum_{s \in \mathbb{S}_a} f_{as}, \sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's}\right) = c_F \sum_{s \in \mathbb{S}_a} f_{as}. \quad (8)$$

In such experiments, we compute the airlines' frequency decisions such that the frequencies of each airline are optimal with respect to the frequencies of other airlines at the airport. We compute one such competitive equilibrium for each  $c_F$  value. Let's denote these experiments as *Type I Experiments*.

In the second type of experiments, we compute an equilibrium between prices and demand. The total congestion price paid by an airline equals the marginal delay cost imposed by that airline on remaining airlines. Mathematically, at an equilibrium,

$$\begin{aligned} & T\left(\sum_{s \in \mathbb{S}_a} f_{as}, \sum_{a' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a'}} f_{a's}\right) \\ &= \sum_{a' \in \mathbb{A}, a' \neq a} \left( c_{a'} * \left( \sum_{s \in \mathbb{S}_{a'}} f_{a's} \right) \left( D\left( \sum_{a'' \in \mathbb{A}} \sum_{s \in \mathbb{S}_{a''}} f_{a''s} \right) - D\left( \sum_{a'' \in \mathbb{A}, a'' \neq a} \sum_{s \in \mathbb{S}_{a''}} f_{a''s} \right) \right) \right). \end{aligned} \quad (9)$$

In such experiments, we compute the airlines' frequency decisions such that the frequencies of each airline are optimal with respect to the frequencies of other airlines at the airport, as well as the corresponding prices, that satisfy equation (9). Thus the demand-price equilibrium involves equilibrium decisions by all the airlines and by the airport administrator. Let us denote such experiments as *Type II Experiments*.

Inequality (3) ensures that the number of passengers carried by an airline cannot be more than that given by the S-curve relationship. Inequality (4) ensures that the number of passengers cannot exceed the number of seats on each segment, subject to a maximum load factor. Inequalities (5) and (6) are the upper and lower bound constraints on the number of slots available to each airline, the same as those in Vaze and Barnhart (20).

In all of our computational experiments, we assumed that the aircraft sizes in terms of the numbers of seats per aircraft do not change with a change in congestion prices. This assumption can be considered to be reasonable in short term, because (a) it takes a considerable amount of time for an airline's fleet to undergo changes, and (b) given a fixed fleet, airlines typically do not have a great deal of flexibility to change aircraft sizes significantly. Furthermore, it is very difficult to predict the actual flexibility

available to each airline to change the aircraft sizes on individual segments. But in the long term, an airline can be expected to increase its aircraft sizes for flights subjected to congestion pricing. Therefore, the actual increases in the number of passengers per aircraft can be expected to be even higher than those predicted by our models. Thus our analysis is somewhat conservative in predicting the cost reduction impacts of congestion pricing.

In the next section, we describe our choice of delay model  $D(\cdot)$ .

#### 4. FLIGHT DELAY MODEL

Flight delays at a congested airport are dependent largely on the utilization ratio (the ratio of flight demand to airport capacity). However, some part of flight delay is independent of congestion at that airport. Such delays are due to other effects such as propagated delays, delays due to mechanical failures, absence of crews etc. Some prior studies have developed detailed queuing-theoretic models of delays as a function of operations and solved them through simulation or numerical methods (4, 5). Such detailed simulation models are beyond the scope of this research. We are interested in a simple delay function that captures the critical queuing-theoretic insights. Many existing studies have used simplified assumptions for modeling delay as a function of utilization. Carlin and Park (3) as well as Pels and Verhoef (8) assumed delays to be an increasing linear function of the number of operations. A linear delay function is not very realistic given that it is well known that delays increase with utilization and the rate of increase itself increases very fast as the utilization ratio approaches 1.0. Brueckner (6, 7) assumed the delay cost to be a general non-decreasing and convex function of the number of airport operations. Zhang and Zhang suggested four standard conditions that a delay function must satisfy (21). Morrison, and Zhang and Zhang used delay functions derived from steady-state queuing theory (22, 21). The expression that we chose for the delay function is given in equation (10), with  $\rho$  being the utilization ratio, that is, the ratio of the total number of scheduled operations to the airport capacity.

$$D = a \frac{1}{1 - \rho} + b. \tag{10}$$

Here,  $a$  and  $b$  are parameters of the model that have to be estimated. This expression has a number of favorable properties. It is non-decreasing and convex in the number of operations as assumed by Brueckner (6, 7). Also it satisfies all the four conditions specified by Zhang and Zhang (21). The functional form is somewhat different from the one used by Morrison, and Zhang and Zhang. We considered using the exact functional form used by these two studies, but decided in favor of the chosen form because it gave a much better fit to the empirical delay data, as shown in Section 6.



## 5. EXPERIMENTAL SETUP AND DATA SOURCES

In order to allow extensive analysis of the relationships between congestion pricing and the market characteristics, we opt for a simple experimental setup consisting of 3 airports and up to 5 airlines. AP0 is the used to denote the airport under congestion pricing. In order to have balanced operations, on average, an airline operates approximately the same number of flights per day in both directions on a segment. Therefore, we focus on only the flights arriving at AP0 and not on those departing from AP0. Our model assumes segment-based demand. We assume that passengers demand non-stop service from airport AP1 to AP0 and from airport AP2 to AP0. We assume two airlines, denoted as AL1 and AL2, operating in each of these two markets. In order to generate broader insights into the effectiveness of congestion pricing mechanisms, we varied important characteristics of our markets (viz. sensitivity of the passengers to frequency, average fares, number of competitors in the markets) and tested their impacts on the effectiveness of the congestion pricing mechanism.

Our experiments are loosely based on data from two important markets into LaGuardia (LGA) airport at New York, namely, Logan (BOS) airport to LGA and Reagan (DCA) airport to LGA. The data is loosely based on two major airlines, namely, Delta Airlines (DL) and US Airways (US) operating in each of these two markets. We obtained data on average fares, seating capacities, aircraft operating costs and passenger flows through the Bureau of Transportation Statistics (BTS) website. We obtained the average fares from the DB1B Market database (23). We retrieved the operating cost values from the Form 41 financial data reported by the airlines in Schedules P-5.2, and Schedule P-7 (24, 25). Aircraft seating capacities and passenger flows were obtained from the T100 Segment database (26). Actual flight frequencies were obtained from the ASQP database (27). All the data used in our computational experiments corresponds to the 1<sup>st</sup> quarter of 2008.

## 6. DELAY FUNCTION FITTING

As mentioned in Section 4, the delay function represents the relationship between airport utilization and average delays to flights. To model this relationship, we used data including average flight delays, number of operations and the expected values of airport capacities from 34 major airports in the continental US. The expected values of airport capacities were obtained from the FAA's airport capacity benchmark report (28). The number of airport operations is obtained from the Aviation System Performance Metrics (ASPM) database maintained by the FAA (29). The average utilization rate for each airport is calculated as the ratio of the average number of operations (takeoffs and landings) that took place at that airport in the 18-hour time period from 6:00 am to midnight across all days of the 1<sup>st</sup> quarter of 2008, to the product of the expected value of hourly capacity of that airport and 18. The average flight delay is computed as the average of delays to all the flights of the ASQP-reporting airlines landing and

taking off from that airport during the 18-hour time period, from 6:00 am to midnight across all days of the 1<sup>st</sup> quarter of 2008.

Parameters  $a$  and  $b$  are estimated by using simple linear regression with average flight delays as the dependent variable and  $\frac{1}{1-\rho}$  as the independent variable. The resultant parameter estimates are:  $a = 1.905$  and  $b = 9.9369$ . The regression analysis gave a strong goodness-of-fit, with an  $R^2$  value of 53.37%. We use this delay function in our computational experiments described in Section 8 for calculating: 1) average flight delays; and 2) the marginal delay cost imposed by any one airline on others at the airport.

## 7. CONGESTION PRICING RESULTS

The equilibrium model described in Section 3 is solved using an iterative algorithm. The reader is referred to Vaze (30) for a detailed description of the solution algorithm. In all the analysis we assume that there are neither upper nor lower bounds on the number of slots, that is,  $U_a = \infty, L_a = 0, \forall a \in A$ . In Sub-section 7.1, we present the flat pricing results and in Sub-section 7.2, we present the marginal cost pricing equilibrium results.

### 7.1 Flat Pricing Results

#### *Experiment 1: Zero Slot Prices*

In this experiment, we assume that the slot prices are zero. The model predictions from this experiment are represented in Table 1. We refer to these results as the *base case* and use it as a reference point for our remaining experiments, all of which involve congestion prices.

**TABLE 1 Base Case Results**

Market	Carrier	Avg. Fare	Model Freq.	Seats/Flight	Passengers	Operating Cost (\$)	Revenue (\$)	Profit (\$)
AP1	AL1	161	15	134	726	110,813	116,886	6,073
AP1	AL2	163	16	124	797	110,984	129,911	18,927
AP2	AL1	152	15	134	741	110,269	112,632	2,363
AP2	AL2	160	16	124	813	108,747	130,080	21,333

Vaze and Barnhart proved that the level of congestion introduced by airline competition is an increasing function of three factors, namely, 1) the S-curve parameter  $\alpha$  (i.e. the sensitivity of passenger demand to frequency), 2) a measure of the gross profit margin in a market (i.e. the ratio of average fare to operating cost per seat), 3) the number of competitors (31). The higher the value of any of these three factors, the greater is the incentive for the airlines to schedule more frequent flights, and hence the greater is the

adverse impact of competition on congestion. In the absence of congestion prices, airline competition leads to congestion. Thus, it is reasonable to expect that the success of a congestion pricing mechanism depends directly on the extent to which the congestion prices can discourage the airlines from scheduling frequent flights. Therefore, each of these three factors is expected to play a critical role in determining the success of a congestion pricing mechanism. In each of the next three experiments, we analyze the impact of one of these three factors. Note that, in order to analyze the impact of gross profit margin (which is the ratio of average fare to operating cost per seat), we will vary the average fares.

In the next three experiments, we evaluate the impacts of varying the slot prices assuming a flat prices. Obviously, an exceedingly high value of congestion price per slot would result in airlines no longer being able to operate flights profitably. So in each case, we make sure that we do not reach such high levels of congestion prices per slot. In each of these three experiments, we vary the congestion price per slot and evaluate the impacts on total delay costs to passengers and total operating profits of the airlines. The results are shown in Figure 1. In each of the 6 charts in Figure 1, the flat slot price, in \$/slot, is on the x-axis. The y-axis of charts in parts (a), (c), and (e) show the normalized value of the total delay cost to passengers. The normalization of delay costs is performed such that the value for zero slot prices equals 100. The y-axes of the charts in parts (b), (d), and (f) show the change in combined operating profit margin percentage for the airlines. The combined operating profit margin percentage is defined as the ratio of total operating profit earned by both airlines in both markets to total fare revenue generated by both airlines in both markets.

### *Experiment 2: Effect of Sensitivity of Passenger Demand to Frequency*

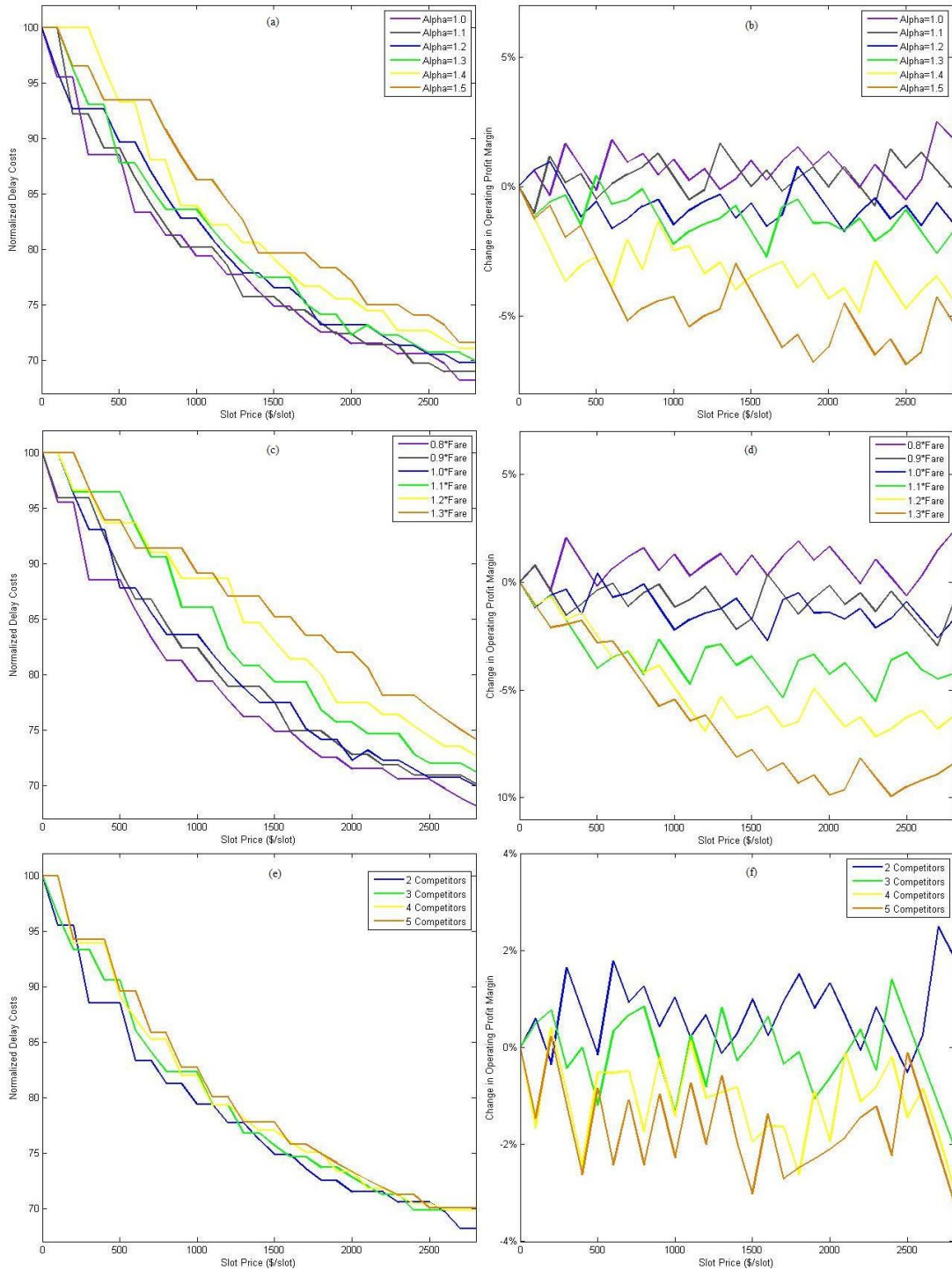
The extent to which the distribution of market share is affected by frequencies is called the sensitivity of passenger demand to frequency. In the S-curve model, as shown in equation (1), sensitivity of passengers to frequency is represented by parameter  $\alpha$ . In the *base case*, we assumed  $\alpha = 1.5$ .

Each line in Figures 2(a) (and 2(b)) corresponds to a different value of  $\alpha$ . The plots are not smooth because of the integrality constraints on the number of flights in each market. Each time the slot price exceeds a certain threshold value, it abruptly becomes unprofitable to operate the last flight being operated by an airline. So the demand drops in a lumpy fashion, resulting in non-smooth trends in the performance metrics. Therefore, rather than looking at any single slot price for comparison across different  $\alpha$  values, we base our conclusions on the overall trends that can be observed from these charts.

As expected, with an increase in slot price, the total demand for airport operations falls and consequently, the total passenger delay cost decreases. The impact on operating profit margin percentage is more complicated. Due to increasing slot prices, the airlines are incentivized to reduce their flight frequency,

thus increasing load factors. Therefore, the airlines benefit from lower aircraft operating costs, as well as from a reduction in flight delay costs. Depending on whether these benefits partially or fully offset the total congestion price paid by the airlines, the airline profits increase or decrease.

At higher  $\alpha$ , passengers are more sensitive to frequency, which means that for a given level of slot price, airlines' demand larger numbers of slots and therefore the total delay costs are higher. Also, because airlines are comparatively more reluctant to reduce flight frequency at a higher  $\alpha$  value, airline profits are lower. Thus  $\alpha$  plays a crucial role in determining the effectiveness of flat pricing. At high  $\alpha$ , slot prices result in very little reduction in delays and a significant reduction in airline profits. However, at lower  $\alpha$  values, slot prices result in larger reduction in delays and a less decrease (or increase) in airline profits. Also, a reduction in passenger delays can possibly result in some increase in average fares. The airlines could potentially monetize a part of the passengers' gains through increased fares, which might result in further increases in airline profits.



**FIGURE 1** Delay costs and changes in operating profit margin for different slot prices, (a) delay costs for different  $\alpha$  values, (b) changes in operating profit margin for different  $\alpha$  values, (c) delay costs for different fares, (d) changes in operating profit margin for different fares, (e) delay costs for different number of competitors, (f) changes in operating profit margin for different number of competitors

As shown in Figure 1(b), in the absence of average fare increases, operating profits are decreasing with increasing slot prices for  $\alpha$  values of 1.5, 1.4, 1.3, and 1.2. For  $\alpha$  values of 1.1 and 1.0, there is a slight increase in operating profits in some cases, but not more than 1% or 2% across different values of  $\alpha$  and slot prices. In Sub-section 7.2, we note somewhat different results under marginal cost pricing and discuss the reasons in details.

### *Experiment 3: Effect of Average Fare*

The ratio of average fare to operating cost per seat (which we term as *gross profit margin* or GPM) also affects the effectiveness of congestion pricing. Markets with higher GPM are the markets where fares are relatively high compared to the aircraft operating cost, which indicates that the passengers are willing to pay more for a given travel distance. So the passengers in such markets are more valuable to the airlines. So the airlines have an even greater incentive to acquire more market share and hence, are more reluctant to give up market share by decreasing the number of flights under congestion pricing. In this experiment, we vary the average fare (thus varying the GPM) on each segment in increments of 10% each assuming  $\alpha = 1.3$ , and hold the aircraft operating cost and flight seating capacities equal to those in the *base case*.

For a high  $\alpha$  value (such as 1.4 or 1.5) and for a low average fare value, (such as 0.8 times the *base case* fare), the combination of low fares and extreme sensitivity of passenger demand to frequency, makes it impossible for the airlines to continue operating profitably even at moderately high congestion price per slot, resulting in discontinuation of service. So the range of slot prices under consideration gets reduced. Therefore, in order to improve the expository power of our analysis, we decided in favor of using an  $\alpha$  value of 1.3 instead of 1.5 for this particular experiment.

As shown in Figure 1(c), at a given slot price, there is a smaller decrease in passenger delay costs for a higher value of GPM. Also, at a higher value of GPM, a given slot price yields a smaller reduction in flight frequencies, thus leading to a smaller increase (or greater decrease) in operating profits. Airline profits could be even higher if airlines are able to monetize a part of the passengers' delay reduction gains through increased fares. In the absence of such fare increases, Figure 1(d) shows that the airline profits decrease (or increase by less than 2%) across all slot price levels and across all the 6 levels of GPM considered here.

### *Experiment 4: Effect of the Number of Players*

The number of competing airlines in a market also affects the extent of congestion introduced by competition. However, the effect of the number of competitors on the extent of congestion is not as strong

as that of  $\alpha$  or GPM. Figures 2(e) and 2(f) show the impact of variation of the congestion price per slot for different numbers of competitors.

Vaze and Barnhart (31) proved that for a symmetric game, the maximum number of competitors which can have a non-zero frequency at a Nash equilibrium, cannot exceed  $\frac{\alpha}{\alpha-1}$ . Extending the same intuition to unsymmetric games, we conclude that at higher values of  $\alpha$ , the maximum number of competitors with non-zero frequencies at a Nash equilibrium will be low. This was also confirmed by our computational experiments. So we decided in favor of using  $\alpha = 1.0$  for this experiment. The operating cost, average fare and the seating capacities used for this experiment are the same as those for the *base case*.

We vary the number of competitors from 2 to 5. For the 3-, 4-, and 5-competitor cases, we assume that respectively 1, 2, and 3 additional competitors compete with AL1 and AL2 in each market. All additional competing airlines are assumed to have average fares, seating capacities and operating costs equal to the average values for DL and US on that respective segment. Vaze and Barnhart proved that the level of congestion introduced by competition increases 1) linearly with  $\alpha$ , 2) linearly with GPM, and 3) slower than linearly with the number of competitors (31). This is found to be consistent with the trends in Figure 1(e) and 1(f). The effect of the number of competitors on the passenger delay costs is not as high as that of  $\alpha$  or GPM. But the reduction in passenger delay costs does decrease with an increase in number of competitors for the same slot prices. The effect of number of competitors on airline profit is more obvious. As the number of competing airlines increases, the operating profit margin decreases, for the same slot prices.

Partial monetization of passenger delay reduction gains through increases in average fares can increase airline profits beyond the values shown in Figure 1(f). However, assuming constant average fares, we observe that the airlines' operating profits decrease with increasing flat slot prices.

## 7.2 Marginal Cost Pricing Results

### *Experiment 5: Marginal Cost Pricing*

We conduct three Sub-experiments, for understanding the impacts of variation in  $\alpha$ , GPM, and the number of competitors on the effectiveness of marginal cost congestion pricing. Table 2 summarizes the results.

In sub-experiment 5a, as  $\alpha$  decreases, a greater percentage reduction is achieved in passenger delay costs. Also, the percentage improvement in airline profits at equilibrium is greater at lower values of  $\alpha$ . Thus,

congestion pricing can be more beneficial in markets with lower sensitivity of demand to frequency. These results are consistent with the results from Experiment 2.

In Sub-experiment 5b, we assumed  $\alpha = 1.3$  and used the operating costs and seating capacities equal to those in the *base case* experiment. In markets with a higher GPM, airlines continue to find it profitable to operate high frequency even if it means paying congestion prices. Loosely speaking, in such markets, airlines benefit more from an additional flight than the marginal delay cost they impose on other users. Comparatively, congestion pricing has a more positive impact for lower GPM. These results are consistent with our flat pricing results in Experiment 3.

In Sub-experiment 5c, we assumed  $\alpha = 1.0$ . The average fares, operating costs and seating capacities are assumed to be those in the *base case* experiment. The extent of congestion introduced by competition increases slower than linearly with an increase in the number of competitors (31). Consequently, as shown in Experiment 4, the reduction in passenger delays and the increase in airline profits is greater for a smaller number of competitors. But the effect is not as strong as the effect of  $\alpha$  or GPM. As shown in Table 2, with increases in the number of competitors, the percentage reduction in delays increases while the increase in operating profit margin shows no clear trend.

On the face of it, the results in Sub-experiment 5c appear to be inconsistent with those in Experiment 4, but the disparity can be easily explained by noting that these results are for marginal cost pricing, while those in Experiment 4 are for a given level of flat prices. As the number of competitors increases, the marginal delay cost imposed by each airline on all other airlines also increases, which in turn increases the slot prices under marginal cost pricing, leading to a greater reduction in operations and delays. Thus, for greater number of competitors, the airlines benefit more from reduction in operating costs and delays, but at the same time have to pay more slot prices. Thus the net effect of increase in number of competitors on the operating profit margin is complicated and no clear trend is observed. This phenomenon cannot be observed under the flat pricing regime (in Experiment 4), leading to the apparent inconsistency between results in Experiment 4 and in Sub-experiment 5c.

Beyond these factors affecting the effectiveness of congestion prices, results presented in Table 2 show airline profit increases due to marginal cost pricing, while the results from the flat pricing experiments show the operating profits to be either decreasing (or increasing very modestly) with congestion prices in most cases. This is another interesting manifestation of the difference between flat prices and marginal cost prices. Under marginal cost pricing, an airline has to pay a congestion price equal to the cost of the increase in the delays to other airlines because of the operations of that airline. Therefore, the additional congestion price of a marginal slot to an airline is often substantially greater than the average cost being



paid by each airline. So under marginal cost pricing, the additional cost of an extra operation becomes prohibitively high at a level of demand where the actual average congestion price per slot being paid by the airlines is still relatively low. Consequently, airlines are discouraged from adding extra frequency even though they pay a relatively small congestion price per slot for the flights they operate. Thus marginal cost pricing can discourage airlines from increasing airport operations without penalizing them with an exceedingly high congestion price per slot, leading to a lower level of congestion and higher profits for the airlines. This is a ramification of the fact that some of the delay is internalized by the airlines.

**TABLE 2 Marginal Cost Pricing Results (Experiment 5)**

Sub-experiment	Quantity Varied	% Change in Passenger Delay Costs	Change in Operating Profit Margin			
			Due to Tolls	Due to Delays	Due to Operating Costs	Overall
5a Impact of Variation in $\alpha$	$\alpha = 1.0$	-16.67%	-2.58%	2.25%	4.69%	4.35%
	$\alpha = 1.1$	-15.90%	-2.97%	2.36%	4.69%	4.08%
	$\alpha = 1.2$	-15.22%	-3.23%	2.40%	4.86%	4.02%
	$\alpha = 1.3$	-14.44%	-3.61%	2.45%	4.86%	3.70%
	$\alpha = 1.4$	-14.14%	-3.81%	2.50%	4.89%	3.58%
	$\alpha = 1.5$	-11.61%	-4.42%	2.15%	4.09%	1.82%
5b Impact of Variation in Profit margin (i.e. Fare Variation) for $\alpha = 1.3$	0.8*Fare	-16.67%	-3.23%	2.81%	5.86%	5.44%
	0.9*Fare	-15.56%	-3.37%	2.61%	5.43%	4.67%
	1.0*Fare	-14.44%	-3.61%	2.45%	4.86%	3.70%
	1.1*Fare	-11.84%	-3.94%	1.97%	3.68%	1.71%
	1.2*Fare	-11.37%	-3.87%	1.82%	3.40%	1.35%
	1.3*Fare	-10.93%	-3.46%	1.69%	2.78%	1.01%
5c Impact of Number of Players under $\alpha = 1.0$	2 Competitors	-16.67%	-2.58%	2.25%	4.69%	4.35%
	3 Competitors	-17.67%	-5.26%	3.08%	6.59%	4.41%
	4 Competitors	-18.01%	-7.30%	3.50%	7.34%	3.53%
	5 Competitors	-18.70%	-8.42%	3.82%	8.36%	3.76%

Consider a concrete example of the phenomenon described above. Specifically, consider the case in the sixth row below the header row of Table 2. Under marginal cost pricing, the passenger delay costs are reduced by 11.61% and the price of each additional slot is approximately \$1046. However, the average congestion price being paid by the airlines is approximately \$367. As a result, the combined operating profit margin increases by 1.82% compared to the base case. Under flat pricing case, in order to achieve the same 11.61% delay cost reduction, the marginal as well as the average congestion price paid by the

airlines equals \$900 per slot. As a result, the total operating profit margin decreases by 4.43%. Alternatively, at a flat congestion price of \$367 per slot, airline operations are reduced to a lesser extent, resulting in passenger delay cost reductions of just 6.54%, and a 1.12% decrease in total operating profit margin of the airlines.

It is important to note that these results are for a relatively small number of airlines at the airport; 2 in most experiments and 3, 4, or 5 in the remaining experiments. Thus the large differences between flat pricing and marginal cost pricing results obtained in our experiments, are partly owing to the small number of airlines, which internalize a large part of the delays. It should be noted that for airports with many airlines each contributing a smaller part of the operations at that airport, the difference between the flat and marginal cost pricing results is expected to be lower.

Finally, and very importantly, it must be noted that a large proportion of the congestion pricing benefits to the airlines come from a reduction in operating costs due to operating a smaller number of flights. In fact, in many cases in the Table 2, the benefits due to delay reduction are more than compensated by the congestion tolls. Hence operating cost reduction due to a smaller number of flights is a prime reason behind the profit increases.

## **8. SUMMARY**

In this paper, we model airline frequency competition under congestion prices and investigate the differences between the atomistic and non-atomistic pricing. We identify a variety of characteristics of airline markets that critically determine the effectiveness of airport congestion pricing mechanisms. Our model of frequency competition under slot pricing is consistent with a popular form of relationship between market share and frequency share.

Our results showed that the frequency sensitivity of passenger demand (or the S-curve parameter), a measure of the gross profit margin (or the ratio of average fare to operating cost per seat), and the number of competitors in a market, critically affect the effectiveness of a congestion pricing mechanism. As expected, slot prices reduce the congestion by reducing the number of operations at the airport. But the impact of slot prices on airlines' operating profit margin is not that straightforward. Airlines benefit from reduction in operating costs because of fewer flights and higher load factors, and also benefit from the delay cost reduction. The net impact of airline profit margin depends on whether these benefits are sufficient to offset the slot prices paid by the airlines.

While flat pricing has the advantage of being comparatively easier to understand and implement, we found that the marginal cost pricing (non-atomistic pricing) is more effective in reducing congestion

without penalizing the airlines with exceedingly high congestion prices. Marginal cost pricing discourages the airlines from scheduling additional operations through high incremental price for an additional slot, while keeping the average price for the purchased slots relatively low. On the other hand, for flat pricing, the incremental and average congestion prices are equal by definition. As a result, compared to flat pricing, marginal cost pricing results in greater operating profit margins for the airlines for the same level of congestion reduction. It must be noted that these differences between flat and marginal cost pricing paradigms were amplified because our example network involved a small number of airlines.

The main aim of this research was to develop a model of congestion pricing under airline frequency competition and to generate insights into the critical factors that affect the effectiveness of a congestion pricing mechanism. Our research in this chapter was conducted for a small hypothetical network, consisting of 2 markets and 2, 3, 4 or 5 airlines. In order to fully quantify the effects of congestion pricing, it is necessary to develop a full-scale case study of a congested airport. Furthermore, we made a number of assumptions including a segment-based demand, constant average fares and constant aircraft sizes. In order to conduct a full investigation of the impacts of congestion pricing, the extent of validity of these assumptions needs to be assessed and the effects of relaxing these assumptions need to be quantified.

Although, this evidence based on a small hypothetical network is insufficient to conclude whether the net effect of congestion pricing on airline profits will be positive or negative, the results clearly show that appropriately capturing the variation in number of passengers per flight could have a decisive impact on the answer to this important question. Therefore, an interesting follow-up study would be a more detailed experiment with a much larger real dataset. Our results and insights based on a small network provide sufficient motivation for a full-fledged analysis of airline frequency competition under congestion pricing, and the models and algorithms developed by us in this research will serve as useful tools for this follow-up analysis.

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