Price Dispersion under Costly Capacity and Demand Uncertainty[1]

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Abstract

This paper tests the empirical importance of the price dispersion predictions of the Prescott-Eden-Dana (PED) models. Equilibrium price dispersion is derived in a setting with costly capacity and demand uncertainty where different fares can be explained by the different selling probabilities. The *PED* models predict that a lower selling probability leads to a higher price. Moreover, this effect is larger in more competitive markets. Mostly because of the difficulty of coming up with an appropriate measure of the selling probabilities, little empirical evidence exists for the *PED* models, despite their applications to several important market phenomena. Using a unique panel of U.S. airline fares and seat inventories, we find evidence that strongly supports both predictions of the models. After controlling for the effect of aggregate demand uncertainty on fares, we also obtain evidence of second degree price discrimination in the form of advance-purchase discounts.

Key Words: Costly Capacity, Demand Uncertainty, Market Structure, Airline Industry
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I. Introduction

It is widely observed that prices of homogeneous goods within the same market exhibit price dispersion. Some of the most recent evidence includes retail prices for prescription drugs in Sorensen (2000), and internet electronic equipment markets in Baye and Morgan (2004). Various models, including search frictions, information asymmetries, and bounded rationality, have been proposed to explain this phenomenon. Here we seek to establish the empirical importance of the price dispersion predictions in the Prescott (1975), Eden (1990) and Dana's (1999b) models.

Prescott (1975) considers an example of hotel rooms where sellers set prices before they know the number of buyers, then the equilibrium prices will be dispersed; lower-priced units will sell with higher probability, while higher-priced units will sell with lower probability. Hence, sellers face a tradeoff between price and the probability of making a sell. This same tradeoff is observed in Eden (1990), who formalizes Prescott's model in a setting where consumers arrive sequentially, observe all offers and after buying the cheapest available offer they leave the market. He derives an equilibrium that exhibits price dispersion even when sellers are allowed to change their prices during trade and have no monopoly power. This flexible price version of the Prescott model, developed in Eden (1990, 2005a) and Lucas and Woodford (1993), is known as the Uncertain and Sequential Trade (*UST*) model. Dana (1999b) extends the Prescott model with price commitments for perfect competition, monopoly, and oligopoly and shows that firms offer output at multiple prices. In the oligopoly equilibrium, the market distribution of prices converges to the Prescott's distribution as the number of firms approaches to infinity. Moreover, as competition is greater, average price level falls and price dispersion increases. As explained in Eden (2005b), from the positive economics point of view it does not matter whether prices in the Prescott's model flexible of rigid. From the point of view of the seller and this paper, both will have the same resulting allocation. In this paper, both the flexible and the rigid version of the model are commonly referred as Prescott-Eden-Dana (*PED* hereafter) models.

Versions of the *PED* model have been applied to solve a variety of economic phenomena, such as wage dispersion and market segmentation (Weitzman, 1989), procyclical productivity (Rotemberg and Summers 1990), the role of inventories (Bental and Eden 1993), real effect of monetary shocks (Lucas and Woodford, 1993; Eden, 1994), destructive competition in retail markets (Deneckere, Marvel, and Peck 1997), advance purchase discounts (Dana 1998), stochastic peak-load pricing (Dana 1999a), gains from trade (Eden 2005) and seigniorage payments (Eden 2007). Despite its wide applications, few papers test the empirical predictions of the *PED* model.

This paper provides a formal test of the *PED* models while helping to explaining price dispersion in the airline industry that is considered to have one of the most complex pricing systems. We take advantage of a unique U.S. airlines' panel disaggregated at passenger level that contains the evolution of fares and inventories of seats over a period of 103 days for 228 domestic flights departing on June 22nd, 2006. This represents the perfect environment to test the price dispersion under demand uncertainty and costly capacity. First, the air tickets expires at a point in time; once the plane departs carriers can no longer sell tickets. Second, capacity is fixed and can only be augmented at a relatively high marginal cost. Moreover, as in the *PED* models, after we control for ticket restrictions that screen costumers, all airplane seats are the same and buyers have unit demands. In order to explain price dispersion we enlarge the definition of airplane seats by an additional 'selling probability' dimension. Once this is achieved, although prices themselves may be dispersed, this dispersion can be explained by appropriately rescaling the price of each unit by its selling probability.

At the risk of over-making this point, let us consider the following example in a perfectly competitive market with zero profits. Each time a carrier sells a seat, the expected marginal revenue is set to be equal to the marginal cost. Because of demand uncertainty, airlines hold inventories of seats that are sold only some of the times. For those seats that are sold only when demand is high, fares must be set higher to compensate for the lower probability of sale. In this paper we develop a measure of this selling probability and adjust the marginal cost of capacity, or ex-ante shadow cost, by this selling probability.

By dividing the constant unit cost of capacity by the probability of sales, we can obtain the Effective Cost of Capacity (*ECC*), then we can measure the impact of *ECC* on fares. As predicted by Prescott (1975) and Eden (1990), *ECC* should have a positive effect on fares. Moreover, as predicted in Dana (1999b), this effect should be greater in more competitive market. In this paper we provide evidence supporting both predictions. On average, a 1 percent decrease in the probability of sale would lead to .13 percent increase in prices. Moreover, this effect was found to be larger in more competitive markets. The reason is straight forward, in a perfectly competitive marker where firms have no markups; every dollar increase in the *ECC* will be transferred to prices. On the other hand, in less competitive markets, part of the increase in the *ECC* will be absorbed by the markup.

The findings in this paper can be additionally motivated as an example of a spot market subject to demand uncertainty and opened to advance purchases. The standard formulation of a spot markets subject to uncertain excess demand, assumes either implicitly or explicitly, a tatonnement process that restricts trade until the market-clearing price is found. As pointed out in

Dana (1999b), a spot market subject to price commitments should be opened to advance purchases. As we approach the departure date, the dynamics of fares and inventories in a flight is an example of how the market clearing price is achieved *without* having to restrict trade in the resolution of uncertainty in the demand. Along the paper we discuss how the analysis carried out resembles a spot market with price commitments.

Furthermore, our paper empirically offers an additional source to the price dispersion of the airline industry of Borenstein and Rose (1994), who calculate that the expected absolute difference in fares between two passengers on a route is 36 percent of the airline's average ticket price. One important source of this price dispersion is the existence of intrafirm price dispersion due to advance-purchase discounts (APD). Substantial discounts are generally available to travelers who are willing to purchase tickets in advance. This kind of pricing practices can promote efficiency by expansions in output when demand is elastic or may be the only way for a firm to cover large fixed costs. Gale and Holmes (1993) justify the existence of APD in a monopoly model with capacity constraints and perfectly predictable demand. They show that firms using APD can divert demand from peak period to off-peak period and achieve a profit-maximizing method of selling tickets. In a similar setting, but with demand uncertainty, Gale and Holmes (1992) show that APD can promote efficiency by spreading consumers evenly across flights before timing of the peak period is known. In competitive markets, Dana (1998) finds that firms may offer APD when individual and aggregate consumer demand is uncertain and firms set prices before demand in known. The Eden's (1990) version of the Prescott's (1975) model that we test, where passengers arrive sequentially, explains why carriers offer lower priced seats to 'earlier' purchasers.[2] Our results show that one source of price variation found by Borenstein and Rose (1994) comes from the fact that carriers face capacity constraints and have to deal with uncertainty in the demand. Moreover, we find that this source of price dispersion is greater in more competitive markets, result that has also been found in Borenstein and Rose (1994). Our results represent a refinement of Borenstein and Rose (1994) findings. They attribute this result to price discrimination using a model of monopolistic-competition with certain demand. We argue that if demand uncertainty is considered, this price dispersion can be explained by carriers dealing with capacity costs.

Despite a number of applications of the *PED* models, few papers test the empirical predictions of the model. Eden (2001) provides a test and finds a negative relationship between

[2] Note that the term 'earlier' used refers to the case when passengers who buy before other passengers, rather than a temporal dimension. Travelers purchasing seats even long before departure may not benefit from APD if most of the seats in the airplane have already been sold.

inventories and output. However, as pointed in the same article, this negative relationship is not necessarily an outcome of the *PED* models. In fact, other models, such as the model of inventory control, would generate the same prediction. Wan (2007) tests the models using data from online book industry. She tests the effect of stock-out probability and search cost on price dispersion and finds evidence that higher stock-out probabilities are associated with higher prices. The *PED* models requires capacity (how many books to store or how many seats on an airplane) to be fixed in the short run. This is less likely to be true for the online book industry than for the airline industry. In addition, Wan (2007) does not test the effect of competition on the prices.[3]

The organization of this paper is as follows. Section II describes the data and its characteristics. The theoretical motivation and the empirical specification are presented in Section III; first explaining the theoretical motivation, then showing how we model demand uncertainty with an application. Section IV explains the empirical results. Finally, Section V concludes the paper.

II. The Data and Its Main Characteristics

The main data source in this paper comes from data collected on the online travel agency Expedia.com® for flights that departed on June 22nd, 2006. It is a panel with 228 cross section observations during 35 periods making a total of 7980 observations. Each cross section observation corresponds to a specific carrier's non-stop flight between a pair of departing and destination cities. The data across time has one observation every three days. The first was gathered 103 days prior departure, the second 100 days and so on until 7, 4, and 1 day(s) prior departure, making the 35 observations in time per flight. As in Stavins (2001), the date of the flight is a Thursday to avoid the effect that weekend travel could have. The carriers considered are American, Alaska, Continental, Delta, United and US Airways. The number of flights per carrier was chosen to make sure the share of each of these carriers on the dataset is close to its share on the US airlines' market. For each flight at each time period, this dataset gives us the cheapest available economy class fare and the number of seats that have been sold up to that period.

To calculate the sold out probabilities, the analysis uses a second dataset collected also from Expedia.com®. Most airlines and online travel agencies do not display sold-out flights on their websites. The reason, according to Roman Blahoski, spokesman of Northwestern, is that

[3] Bilotkach (2006) mentions the potential role of the *PED* models in explaining price airline dispersions, but his dataset does not allow him to formally test the model.

they do not want to disappoint travelers. Keeping the online display simple may also be a motive, and according to Dan Toporek, spokesman of Travelocity.com®, "showing sold-out flights alongside available flights could be confusing."[4] Regardless of the reason, this fact allows us to get the information about the sold out probability in each of the routes. We initially make a census of all the available nonstop flights in each of the 81 routes used in the first dataset for seven days from February 2nd to February 8th in 2007. The total number of flights is 5,881. The collection is done couple of weeks before the beginning of February when we expect that no flights have yet been sold out, hence Expedia.com® should show them all. Then, for each of these seven days of the week we check Expedia.com® once again late at night the day before departure to see whether each of the flights has still tickets available. If the flight is no longer there, we assume that it has already sold all its tickets. This procedure permits us to calculate the sold out probabilities for each of the routes. We interpret this sold out probability as a lower bound because i) February is not necessarily a high demand period, and ii) because there may still be some tickets sold the day of the flight that did not enter the computation.

A second important source of data is the *T-100* data from the *Bureau of Transportation Statistics*. From the *T-100* we obtain a panel containing the yearly average load factors at departure for the same routes as in the main dataset over the period 1990 to 2005. This helped us to calculate the expected number of tickets sold in each route. Moreover, this T-100 gave us the number of enplanements at each endpoint airport to construct some of the instruments.

2.1 Fares, Inventories and Ticket Characteristics

A typical flight in the sample looks like the American Airlines Flight 323 from Atlanta, GA (ATL) to Dallas-Forth Worth, TX (DFW) depicted in Figure 1. The best way to look at the evolution of seat inventories, in a way that is comparable between flights, is to look at the load factor, defined as the ratio of available seats to total seats in the aircraft at each point in time prior departure.[5] Load factor will go from zero when the plane is empty to one when it is full. In Figure 1, the load factor for this flight increases from 0.2, 103 days prior departure to 0.88 with one day left to depart. The increase is not necessarily monotonic as can be observed when moving from 34 to 31 days prior departure. This is because some tickets may have been reserved

[4] Both quotes are from David Grossman, "Gone today, here tomorrow," *USA Today*, August 2006.
[5] Airline's literature defines load factor only once the plane has departed and as the percentage of seats filled with paying passengers. It is calculated by dividing revenue-passenger miles by available seat miles. Here the load factor is defined at each point in time as the flight date approaches.

and never bought or maybe bought and cancelled later. In this flight fares initially look fairly stable between $114 and $144, but they have a sharp increase during the last two weeks before departure and peak its maximum at $279 the last day.

FIGURE 1 [somewhere here]

Figure 2 depicts the average fares for the 228 flights in the sample for each of the days prior to departure. The most important characteristic is how fares trend upwards from an average of $258, 103 days prior departure to an average of $473, the last day prior departure. This means that average fares almost doubled during the period of study.

FIGURE 2 [somewhere here]

Figure 3 shows the change in average load factors for the 228 flights at each point in time prior departure. The figure suggests that as the flight date approaches, more seats get sold. The majority of the seats are being sold during the last month and there seems to be a drop in sales during the last few days close to departure.

FIGURE 3 [somewhere here]

It is important to know that inventories evolve not just as a result of sales at the one-way, non-stop flight we are considering. Seats for each city pairs in the sample can be sold as part of a larger trip or as part of a round trip with an extremely large amount of possible options. Along this paper we will be looking at the carriers' optimal pricing decision for the one-way, non-stop flight of June 22nd and this will have its own dynamics. This detail is implicit in these types of datasets that look at non transaction data like Stavins (2001), McAfee and Velde (2006), Chen (2006).

The fares used in this paper are the cheapest fare available at each point in time for a seat in economy class. The cheapest economy class fare at each point in time prior departure is just the search results found by Expedia.com® for any other online travel agency or carrier's website when searching for the fare of a given flight.[6] It is worth pointing out that every time a carrier

[6] Different types of fares sometimes available are the ones travel agencies directly negotiate with airline partners. One example is Clearance Fares and FlexSaver offered by hotwire.com. These fares come with substantial discounts but impose additional restrictions and involve higher uncertainty. They do not allow changes or refunds and do not allow the traveler to pick the flight times or airline at the moment of

changes its prices, it also changes some characteristics associated with this fare.[7] The key point here is that these ticket characteristics that change along with fares are irrelevant for the travelers, and if buying online, it is sometimes impossible for the buyer to change these characteristics. Carriers change these irrelevant tickets characteristics to justify the changes in fares. They do not want to charge two different fares for exactly the same product just because the transactions occurred at different points in time, even if these differences in the product do not have any impact on the purchase decision. In the empirical test we control for the ticket restrictions that do have an impact on the quality of the ticket. Again, a similar assumption has been implicitly made in McAfee and Velde (2006) and Chen (2006) and just look at the variations in fares without keeping track of the corresponding variation in irrelevant ticket characteristics. Stavins (2001) omits most of these irrelevant ticket characteristics but includes dummy variables for some advance purchase restrictions. These dummy variables may explain changes in fare, but they do not reflect the underlying force behind why carriers offer advance purchase discounts in the first place. As we argue in this paper, once the relevant ticket characteristics are controlled for, the key underlying force is seats inventories.

2.2 Representative Fare

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booking. Additionally, the traveler cannot earn frequent flyer miles and the fare paid does not guarantee a specific arrival time. Delays can be greater than a day.

[7] To show how fares can be explained with irrelevant ticket characteristics, let's look again at the fares of American Airlines Flight 323 depicted in Figure 1. In this example, when the price decreased from $134 to $114 between 103 (March 11th) and 100 (March 14th) days prior to departure, the ticket characteristics changed from a 10- to a 14-days-in-advance-purchase-requirement, it changed the first-day-of-travel-requirement from February 11th to March 14th, and some blackout dates where included along with changes in day-and-time-of-the-flight restrictions. None of these restrictions have a real impact on the purchase decision or the effective quality of the ticket unless the traveler knows these characteristics and carries out a detailed analysis evaluating the possibility of canceling the flight later on. If the ticket is bought either 103 or 100 days prior the flight day, having a 10- or a 14-days-in-advance-purchase-requirement is irrelevant. If the passenger has already decided to fly on June 22nd and is buying the ticket either on March 11th or March 14th, the first-day of-travel-requirement of February 11th or March 14th are irrelevant as well. Blackouts and day-and-time-of-the-flight restrictions are only important if the traveler decides to change the day of the flight and the new date happens to be exactly in one of the blackout dates. Changing dates will be anyway subject to further restrictions on the tickets available in the new date, and a penalty of 50 plus the differences in fares. The fact is that really few passengers actually know these restrictions even exist since you cannot modify them online and are not printed out in the ticket or the e-ticket. This example also shows that even if the ticket is bought with more that 21 days in advance, it does not necessarily mean it gets the discount of a 21-days-in-advance-purchase-requirement. The same goes along with other restrictions; even if the traveler is willing to accept any blackout or purchase a non-refundable ticket, if only refundable tickets are available, she may well end up buying it, sometimes without knowing the extra benefits. Stavins (2001), McAfee and te Velde (2006), and Chen (2006) also look at these type of fare changes, but do not mention this point.

A typical concern among people who search to buy tickets online is to know whether or not the fare paid in one place is effectively “the cheapest.” The concern for us is to know if the fares found in Expedia.com® represent the actual fares offered by the carrier. We want to make sure that the fact that we collected the fare online does not restrict the analysis to just online fares.

The fares reported on different sites are sometimes different. One source of discrepancy comes from the fact that different online travel agencies have different algorithms to report the fares found in the Computer Reservation Systems (CRS). This plays a roll when searching complex itineraries that may involve international flights. In our dataset this discrepancy does not arise since we are already restricting the search for a specific flight number on a specific departure date. A second important source of differences comes from variation across purchasing time and seat availability at purchase, the subject matter of this paper. The third important source of variation arises because different fees and commissions differ across travel agencies. Expedia.com® charges a lump sum booking fee of $5 for every one-way ticket, Travelocity.com® charges $5 as well, while *Hotwire.com*® charges $6. Other websites like Priceline.com®, CheapTickets.com® or Orbitz.com® allow fees to be a function of the base airfare, the carrier or the destination. For example, fees at Orbitz.com®' range from $4.99 to $11.99. “Brick-and-mortar” travel agencies charge even higher fees that can go up to $50. Buying on the phone also imposes additional different fees i.e. CheapTickets.com® charges $25 while Travelocity.com® charges $15.95 for over the phone bookings. Requesting a printed ticket will also impose additional variation. Even the carriers themselves charge different prices for exactly the same ticket. For example US Airways charges no fees if purchased through its website, but charges a $5 fee for tickets purchased through the airline's reservation centers and $10 for tickets issued at the airport or at the city ticket offices. Moreover, the baseline fare may still be different depending on which Computer Reservation System (CRS) the travel agency uses to book its tickets.[8]

Currently, there are four Computer Reservation Systems which store and retrieve travel information used by all travel agents. These are Amadeus, Galileo, Sabre and Worldspan. Airlines pay an average booking fee per segment of $4.25 when using a CRS, while travel agencies usually obtain CRS at no cost or receive certain payments in exchange for agreeing to use the system. According to the 2005 Report from American Society of Travel Agents (ASTA), the “brick-and-mortar” travel agencies have responded by booking part of their sales using the

[8] Additional fees common to all include taxes, special surcharges, segment fees and September 11 security fees.

carriers' websites and not the CRS. The main source of information of Expedia.com® is the Worldspan, but as well as Orbitz.com®, they have established direct connection with airlines' internal reservation systems to bypass Worldspan and avoid the CRS fees.

While it is difficult to evaluate price differences for exactly the same ticket offered offline, for online markets the information is readily comparable. Chen (2006) using a dataset gathered online in 2002 obtained that for quotes found in multiple online sites the differences in prices are on the order of 0.3 to 2.2 percent. Even though not mentioned in her paper, these price differences can be tracked down just by comparing the different fees charged at each site. Currently, carriers like American, Alaska and United offer a promise that travelers will always find the cheapest fare in its own websites. If the traveler finds a cheaper fare (with more that a $5 difference), they offer paying back the difference plus additional bonus frequent flyer miles. This shows the carriers' interest on selling through its own websites. In response, Orbitz and Expedia adopted similar policies.

Based on all the multiple ways in which fares can potentially differ for exactly the same ticket, we have to come up with a clean measure of a "ticket's fare". The best candidate is each carrier website fare which is directly under the carrier's control and is free of any additional fees imposed by CRS, travel agencies or the same carrier if sold offline. For all the carriers in our sample, the fare found in Expedia.com® is $5 more than each carrier's website fare, thus obtaining the carriers' website fare is straight forward. Moreover, it is interesting to know ASTA reported that in 2002 the biggest on-line travel agency was Expedia, with a market share of 28.7 percent, followed by Travelocity (28.5 percent) and Orbitz (21.3 percent).

Regarding online sales, we know that they have been growing significantly during the last couple of years. The ASTA's report in 2005 citing PhoCusWright Inc. as the source, state that for leisure and unmanaged air sales, the overall online sales as a percentage of total sales went up from 30.8 percent in 2001 to 56.2 percent in 2004. Of these sales, 38.3 percent correspond to online travel agencies and 61.7 percent to sales through the airlines web sites.

III. The Empirical Model

3.1. A Oligopoly Model of Costly Capacity and Demand Uncertainty

In this section we derive a simple oligopoly model under capacity constraints and demand uncertainty. The predictions of this basic model were already obtained in a more formal environment in Dana (1999b). The current derivation extends naturally to our formulation of demand uncertainty and testing procedure in the empirical section.

Let the total number of demand states be $H + 1$. The uncertainty in the demand comes from the fact that each carrier does not know *ex ante* which demand state may occur. Let N_h be the number of consumers who will arrive at the demand state h, where $h = 0, \ldots, H$ and $N_h \leq N_{h+1}$. This ordering implies that all the travelers who arrive at demand state h will also arrive at a higher-numbered demand state $h+1$. Now, define a batch as the additional number of travelers that arrive at each demand state when compared to the immediate lower demand state, so batch h will be given by $N_h - N_{h-1}$ and the first batch is just N_0.

Consider the case where consumers' reservation values for homogeneous airplane seats are uniformly distributed $[0, \theta]$, then the demand at state h is given by:

$$D_h(p) = \left(1 - \frac{p}{\theta}\right) N_h \tag{1}$$

Each demand state h occurs with probability ρ_h. Given that all demand states have at least N_0 potential travelers, the probability of having N_0 potential travelers arriving is $\Pr_0 = \sum_{\kappa=0}^{H} \rho_\kappa = 1$. In general, the probability that at least N_h potential travelers arrive is the summation of the probabilities of demand states that have at least N_h customers, $\Pr_h = \sum_{\kappa=h}^{H} \rho_\kappa$. This implies that the probability that N_h potential consumers arrive is always as high as the one that N_{h-1} potential consumers arrive, $Pr_h \geq Pr_{h+1}$. Following Prescott (1975), the only cost for the carriers is a strictly positive cost λ incurred on *all* units, regardless whether these units are sold or not. This cost can be interpreted as the unit cost of capacity (or shadow cost), or the cost of adding an additional seat in the aircraft. Unlike Dana (1999b), we assume that the unit marginal cost of production incurred only on the units that are sold is zero.[9] Define the *effective cost of capacity* (*ECC*) as $ECC_h = \lambda/Pr_h$. This *ECC* adjusts the unit cost of capacity by the probability that this unit is sold. Since some of the seats will be sold only at higher-numbered demand states, if these units are sold, the effective cost of capacity reflects the costs that should be covered whether or not they are sold. If the unit cost of capacity is \$100, but this unit is sold only half of the times, if it gets sold, the cost that should be covered is \$200.

[9] In our setting this basically means that the only relevant cost for the carriers is the one incurred when deciding whether or not to hold inventories for an additional seat. The cost that is assumed to be zero is peanuts (or pretzels and soft drinks plus any other marginal cost, i.e. baggage transportation). In the hotel example these marginal costs may include cleaning the room, changing towels, sheets and in many cases the breakfast.

The number of identical carriers in the market is M. When the demand state is $h=0$ with the corresponding firm's effective cost of capacity ECC_0, the standard symmetric Nash equilibrium solution of a Cournot oligopoly competition is:

$$
\begin{aligned}
p_0 &= \frac{\theta + M \cdot ECC_0}{M+1} \\
\delta_0 &= D_0(p_0) = \frac{N_0(\theta - ECC_0)M}{\theta(M+1)}
\end{aligned}
\tag{2}
$$

where p_0 is the equilibrium price, and δ_0 is the total amount of seats sold. Note each firm would allocate δ_0/M number of seats at price p_0. From the second part of (2) we obtain that the potential number of passengers that arrive at demand state $h=0$ is:

$$
N_0 = \frac{\theta(1+M)}{M} \cdot \delta_0 \cdot [\theta - ECC_0]^{-1} \tag{3}
$$

When the demand state is $h = 1$, according to (1), the total demand at price p_0 is given by:

$$
D_1(p_0) = \left(1 - \frac{p_0}{\theta}\right) N_1 \tag{4}
$$

Note that $D_1(p_0) \geq D_0(p_0)$ since $N_1 \geq N_0$, i.e., the total amount of seats demanded at price p_0 when $h = 1$ is at least as large as the pre-allocated number of seats δ_0. Dana (1999b) uses proportioning rationing to assign seats at p_0. This means that everybody has a equal chance $\delta_0/D_1(p_0) = N_0/N_1$ to get a seat at p_0. The residual demand, therefore, is:

$$
\begin{aligned}
R_1(p \mid p_0) &= D_1(p)\left(1 - \frac{\delta_0}{D_1(p_0)}\right) \\
&= \left(1 - \frac{p}{\theta}\right)(N_1 - N_0)
\end{aligned}
\tag{5}
$$

Again, the symmetric Nash equilibrium solutions if the demand function is $R_1(p|p_0)$ in (5) will be:

$$
\begin{aligned}
p_1 &= \frac{\theta + M \cdot ECC_1}{M+1} \\
\delta_1 &= M(N_1 - N_0)\frac{(\theta - ECC_1)}{\theta(M+1)}
\end{aligned}
\tag{6}
$$

Compare (2) and (6), we can see that $p_1 \geq p_0$ given that $Pr_1 \leq Pr_0$.

In this case, from the second part of (6) we obtain that the potential number of passengers that arrive at demand state $h = 1$ is given by:

$$
N_1 = \frac{\theta(1+M)}{M} \cdot \delta_1 \cdot [\theta - ECC_1]^{-1} + N_0 \tag{7}
$$

If the demand state is $h = 2$, we are interested in the residual demand after those travelers who have bought tickets at price p_0 and p_1, denoted as $R_2(p|p_0, p_1)$. To find out $R_2(p|p_0, p_1)$, we start with the residual demand after those who bought tickets at p_0, denoted as $R_2(p|p_0)$, which can be obtained from (6):

$$R_2(p \mid p_0) = \left(1 - \frac{p}{\theta}\right)(N_2 - N_0) \tag{8}$$

Travelers who are still in the market after the tickets at p_0 have been sold out will now have the chance to purchase tickets at p_1. The number of potential consumers who will demand tickets at p_1 is $R_2(p_1|p_0)$, given by (8), and the number of tickets available at price p_1 is $R_1(p_1|p_0)$, given by (5), $R_2(p_1|p_0) \geq R_1(p_1|p_0)$. We apply the proportional rationing again to get the residual demand $R_2(p|p_0, p_1)$:

$$\begin{aligned} R_2(p \mid p_0, p_1) &= R_2(p \mid p_0)\left(1 - \frac{R_1(p_1 \mid p_0)}{R_2(p_1 \mid p_0)}\right) \\ &= \left(1 - \frac{p}{\theta}\right)(N_2 - N_0)\left(1 - \frac{\left(1 - \frac{p_1}{\theta}\right)(N_1 - N_0)}{\left(1 - \frac{p_1}{\theta}\right)(N_2 - N_0)}\right) \\ &= \left(1 - \frac{p}{\theta}\right)(N_2 - N_1) \end{aligned} \tag{9}$$

The symmetric Nash equilibrium solution for the residual demand function $R_2(p|p_0, p_1)$ in (9) is given by:

$$p_2 = \frac{\theta + M \cdot ECC_2}{M + 1}, \qquad \delta_2 = M(N_2 - N_1)\frac{(\theta - ECC_2)}{\theta(M + 1)} \tag{10}$$

It is important to mention that here carriers are assumed to not observe the seat availability of their competitors. Once carriers sell their portion δ_0/M for the first batch N_0 of potential travelers they take the next step which is pricing the second batch $N_1 - N_0$ of consumers. This assumption guarantees that any given carrier does not try to allocate its entire capacity to the first batch at the expense of their competitors. At the end of the derivation once we generalize the findings for a continuum of demand states, this assumption will be no longer needed.

This Cournot pricing strategy at each of the batches may allow the possibility that competitors behave strategically as in a repeated Cournot game where in each subsequent stage of the game firms face each time higher costs given by *ECC*. Since this is a finitely repeated game, we just obtain the subgame perfect Nash equilibrium by backward induction. Firms will not be able to collude since each subgame is played as a static Cournot game.[10]

Proposition 1 generalizes previous discussions to any number of demand states.

Proposition 1: Let aggregate demand function be given in (1). $R_k(p \mid p_{k-1}, \cdots, p_1, p_0)$ is the residual demand when demand state is *k* and travelers who have bought tickets at lower prices $p_0, \ldots, p_{k-1}$ have left the market (as in Eden (1990)). We have:

$$R_k(p \mid p_{k-1}, \cdots, p_1, p_0) = \left(1 - \frac{p}{\theta}\right)(N_k - N_{k-1}) \qquad (11)$$

Proof:

When the demand state $k = 1$, according to (5), the proposition holds.[11] We will prove: if the proposition holds at demand state *k*, then it must hold at demand state *k*+1.

Suppose the proposition at demand state *k* holds. When demand state is *k*+1, according to (9), the residual demand after travelers who have bought tickets at lower prices of $p_0, \ldots, p_{k-1}$ have left the market is given by:

$$R_{k+1}(p \mid p_{k-1}, \cdots, p_1, p_0) = \left(1 - \frac{p}{\theta}\right)(N_{k+1} - N_{k-1}). \qquad (12)$$

Therefore, the residual demand after travelers who have bought tickets at lower prices of $p_0, \ldots, p_{k-1}, p_k$ have left the market is given by:

$$\begin{aligned} R_{k+1}(p \mid p_k, p_{k-1}, \cdots, p_0) &= R_{k+1}(p \mid p_{k-1}, \cdots, p_1, p_0)\left(1 - \frac{R_k(p_k \mid p_{k-1}, \cdots, p_0)}{R_{k+1}(p_k \mid p_{k-1}, \cdots, p_0)}\right) \\ &= \left(1 - \frac{p}{\theta}\right)(N_{k+1} - N_{k-1})\left(1 - \frac{\left(1 - \frac{p_k}{\theta}\right)(N_k - N_{k-1})}{\left(1 - \frac{p_k}{\theta}\right)(N_{k+1} - N_{k-1})}\right) \qquad (13) \\ &= \left(1 - \frac{p}{\theta}\right)(N_{k+1} - N_k) \end{aligned}$$

Note $R_k(p_k \mid p_{k-1}, \cdots, p_0)$ in (13) is from (11) and $R_{k+1}(p_k \mid p_{k-1}, \cdots, p_0)$ is from (13). Equation (13) proves *Proposition 1*.

From the residual demand equation of (12), it is easy to get that:

[10] The continuum of demand states is like an infinitely repeated game. If collusion is achieved in this scenario, we just require collusion payoffs in each stage game to be a function only of the same stage payoffs for the results in this section to hold. Again, for a stricter derivation of the same results see Dana (1999b).

[11] According to (9), the proposition also holds for $k = 2$.

$$p_k = \frac{\theta + M \cdot ECC_k}{M+1}, \qquad \delta_k = M\left(N_k - N_{k-1}\right)\frac{\left(\theta - ECC_k\right)}{\theta(M+1)} \tag{14}$$

For the general case, using the second part of (14) we obtain that the potential number of passengers that arrive at demand state h=k is given by:

$$N_k = \frac{\theta(1+M)}{M} \cdot \delta_k \cdot \left[\theta - ECC_k\right]^{-1} + N_{k-1} \tag{15}$$

By recursive substitution, considering the construction of the *ECC* for each batch of travelers, and for a continuum and infinite number demand states we can obtain that the number of potential travelers that arrive at demand state h is given by:

$$N_h = \frac{\theta(1+M)}{M} \int_0^h \delta_\omega \left[\theta - \lambda \cdot \left(\int_\omega^\infty \rho_\kappa d\kappa\right)^{-1}\right]^{-1} d\omega \tag{16}$$

From these N_h consumers that arrive at demand state h, only $\int_0^h \delta_\kappa d\kappa$ are able to buy a seat. Moreover, notice that the price paid by each group ω is different and given by:

$$P_\omega = \frac{1}{1+M}\left[\theta + M \cdot \lambda \left(\cdot \int_\omega^\infty \rho_\kappa d\kappa\right)^{-1}\right] \qquad \forall \omega \in [0,h] \tag{17}$$

This is just the continuum version of the first part of equation (14).

We now just use this last equation to derive two testable implications:

$$\frac{\partial p_\omega}{\partial ECC_\omega} = \frac{M}{M+1} > 0, \text{ and } \qquad \frac{\partial\left(\frac{\partial p_\omega}{\partial ECC_\omega}\right)}{\partial M} = \frac{1}{(M+1)^2} > 0. \tag{18}$$

The first part of equation (18) tells us that when the *ECC* increases (larger demand uncertainty combined with costly capacity, or lower probability of selling this ticket), price also increases. The second part implies that as the market becomes more competitive (larger M), the marginal effect of *ECC* on fares is greater. Therefore, for a given distribution of demand uncertainty more competitive markets will show greater price dispersion. The expressions in equations (18) reduce to a monopoly when $M = 1$ and to a perfectly competitive market when $M \rightarrow \infty$. Note that in a perfectly competitive market, (18) predicts that every dollar increase in the *ECC* is transferred to prices as no markups exist to absorb part this increase.

3.2 Modeling Demand Uncertainty

Let's initially assume that carriers commit to an optimal distribution of prices for each flight before demand is known.[12] By price commitment we mean that when demand is low, a traveler who arrives early or arrives late will face the same price as long as the carrier has not sold tickets in the meantime. Prices increase only if carriers have been selling tickets. Therefore, the information in the price schedule can be implicitly included in the functional form specified for the selling probability. This basically means that the probabilities are predetermined for each price schedule and the specification of demand uncertainty. The price schedule will be optimal and firms will not want to depart from it as long as they do not start learning about the state of the demand. As mentioned by Dana, useful information about the demand may only be available close to departure or once it is too late for carriers to change fares. Furthermore, as long as carriers do not learn any useful information about the state of the demand during the trading process, we can relax the price rigidity assumption (Eden (1990)).

Starting with the simplest scenario where each demand state is equally likely with probability given by $\rho_h = \alpha/m$. This just means that demand states are uniformly distributed [0, m/α] with m being the total number of seats in the aircraft and $\alpha \geq 1$. The last inequality assures that there is a positive probability that the last seat gets sold. Following the intuition from Section 3.1, having m/α demand states is the same as having $m/\alpha = H + 1$ batches $(N_k - N_{k-1})$of travelers with the first batch N_0 showing up with the highest probability and the subsequent ones showing up each time with a lower probability than the previous one. Assume that the lowest demand state has one consumer buying a ticket ($\delta_0 = 1$) and for subsequent demand states we have one additional buyer each time we move to the next higher demand state ($\delta_k=1$ for all k). Because in every demand state there is at least one consumer buying a ticket, the probability of selling the first seat is equal to one. In all but the lowest demand state there are at least two travelers, so the probability of selling the second ticket is given by one minus the probability of the having the lowest demand state, that is $1 - \alpha/m$. In general, the probability that seat h gets sold is given by:

$$\Pr_h = \left[1 - h\frac{\alpha}{m}\middle| q(p)\right], \qquad h \in \{1,2,...,m\}, \tag{19}$$

which is just one minus the probability of having any demand state with lower demand than state h given the carrier's price distribution $q(p)$. In this equally likely demand states case, α is a constant that determines the rate at which the probability that the next seat gets sold diminishes.

[12] Later in the empirical section we will allow for some deviations from price commitment. In particular, we allow the possibility of current shocks affecting future prices by estimating a dynamic model of Arellano and Bond (1991).

Assuming that each demand state is equally likely seems too restrictive. Given our construction of demand uncertainty, this would imply that having only one passenger flying is as likely as having the plane at half capacity and that the probability of selling one additional seat decreases linearly. To allow for more flexibility in the characterization of demand uncertainty we consider the case where $\rho_h = \varphi_h$, with φ being the *pdf* of a normal density that has mean μ and standard deviation σ. From the discussion so far we know that the probability of selling seat h is the summation of the probabilities of all demand states that have at least h travelers. For a continuum of demand states, this is given by $\Pr_h = \int_h^{\infty} \rho_\kappa d\kappa$. Therefore, the probability of selling seat h for the normal density will be:

$$\Pr_h = \int_h^{\infty} \phi_\kappa d\kappa \mid q(p) = 1 - \Phi_h \mid q(p), \quad (20)$$

with Φ being the *cdf* of a normal distribution.

3.3 Calibrating the Probability Density of Demand Uncertainty

To obtain Pr_h used in calculating the *ECC*, it is necessary to get the values for the parameters α in the uniform distribution and the mean, μ, and standard deviation, σ, in the normal distribution. In this subsection we calibrate the values of these parameters to mimic the demand uncertainty conditions in each of the routes.

A key source of information for the calibration comes from the *T-100* data from the *Bureau of Transport Statistics*. We use this dataset to obtain yearly occupancy rates, or load factors at time of departure. This is done in three steps. First, for each of the routes in the sample, we calculate its load factor for the 81 routes in the sample for the period 1990 to 2005, based on the T-100 data. Second, each of these 81 series is used to estimate an ARMA model. Finally, the estimated ARMA model is applied to obtain the 2006 value using a one-step ahead forecast.[13] For routes where the ARMA model predicts a high load factor, meaning that most of the seats are expected to be sold, the calibration procedure will assign higher probabilities to higher demand states. In this case the *ECC* is going to be relatively low for a large majority of the tickets. When the forecasted load factor is low, the probability of selling the last couple of seats is going to fall fast, meaning that the cost of stocking inventories is higher.

[13] The details of the estimation are available upon request.

The problem with the information obtained from the *T-100*, however, is that we have a measure of the forecasted value of the average number of tickets sold rather than of the forecasted value of the average number of tickets demanded. This arises because the demand state is censored when transformed to the number of tickets sold. Once the aircraft is sold out the *T-100* no longer records higher demand states. To overcome this limitation let the underlying demand state h^*, be distributed $N(\mu, \sigma^2)$ with the observed number of seats sold $h = h^*$ if $h < m$ or else $h = m$. Recall here that m is the maximum number of seats available in the airplane. Then the expected number of tickets sold is given by the first moment of the censored normal:

$$E(h) = \Pr(h = m)E(h \mid h = m) + \Pr(h < m)E(h \mid h < m)$$
$$= \left(1 - \Phi\left(\frac{m-\mu}{\sigma}\right)\right)m + \Phi\left(\frac{m-\mu}{\sigma}\right)\left[1 - \sigma\frac{\phi((m-\mu)/\sigma)}{\Phi((m-\mu)/\sigma)}\right] \tag{21}$$

The expression for $E(h|h<m)$ is obtained from the mean of a truncated normal density. The *pdf* and the *cdf* of the normal density are evaluated at the moment the flight sells out. Hence, the value $\Phi((m-\mu)/\sigma)$ is interpreted as the sold out probability. Using information on the probability that a flight sells out, based on the second dataset obtained from Expedia.com®, and the expected number of tickets sold, obtained from the ARMA models, we can use (21) to obtain values for μ and σ.

Calibrating the value of α in the uniform distribution is simpler. We obtain the analog of equation (21), $E(h)=1- \alpha/2$, by using the truncated uniform distribution. This equation can be used directly to get α. In this case since we only have to calculate one parameter, the sold-out probabilities are no longer needed. The cost of requiring less information is to have less flexible characterization in which one single parameter α affects both the mean and the variance of the distribution of demand states.

3.4 Estimated Equation and Interpretation

Following a similar approach as Stavins (2001), we estimate a reduced-form model of log airfare on *ECC*, market concentration, carrier's market share and route-specific factors. The key new variable in our analysis is the *ECC* that measures the effect of costly capacity and demand uncertainty by adjusting the unit cost of capacity by the probability that the ticket gets sold. The construction of the dataset also allows us to control for all other relevant ticket-specific characteristics as explained in Section II. The equation to be estimated is given by:

$$\ln FARE_{ijt} = \beta_0 + (\delta_0 + \delta_1 HHI_j)\, ECC_{ijt} + \beta_1\, DAYADV_{ijt} + \beta_2\, DIST_j + \beta_3 DISTSQ_j$$

$$+ \beta_4 ROUSHARE_{ij} + \beta_5 HHI_j + \beta_6 DIFTEMP_j + \beta_7 DIFRAIN_j + \beta_8 DIFSUN_j + \beta_9 AVEHHINC_j + \beta_{10} AMEANPOP_j + \gamma_1 HUB_{ij} + \gamma_2 SLOT_j + u_i + v_{ijt} \quad (22)$$

where the subscript *i* refers to the flight, *j* to the route, and *t* is time. Dummy variables have estimated coefficients denoted by γ, otherwise *β*. u_i denotes the unobservable flight specific effect and v_{ijt} denotes the remainder disturbance. Different error structures will be assumed along the empirical section. Each observation in the sample represents a unique ticket for a carrier on a route. By route we mean a combination of departure and arrival airports on a one-directional trip. $FARE_{ijt}$ is price paid in *US* dollars. From Table 1, the sample mean fare is $291, with a minimum of $54 for an American Airlines flight from Dallas Fort Worth, TX to Houston International, TX when at least 80 percent of the plane was empty. The maximum is $1,224 in a United Airlines flight from Philadelphia International, PA to San Francisco International, CA when there are less than 9 percent of the seats available.

The key variable in the analysis is *ECC* which is obtained from $ECC = \lambda/Pr_h$. In particular, when the distribution is uniform as defined in (19), we should have:

$$ECC_{ijt} = \frac{\lambda}{\Pr_{h_{ijt}}} = \frac{\lambda}{1 - h_{ijt}\dfrac{\alpha_j}{m_{ij}}}, \quad (23)$$

where m_{ij} is the total number of seats in the aircraft and $h_{ijt} - 1$ is the number of seats that have already been sold at time *t*. α_j is the mean of the uniform distribution. *ECC* is measured in the same units as *FARE*, nevertheless to be able to interpret the magnitude of the coefficient; we initially normalize λ to be equal to one.

For the normal density case as presented in (20), *ECC* is given by:

$$ECC_{ijt} = \frac{\lambda}{\Pr_{h_{ijt}}} = \lambda \times \left[\int_{h_{ijt}/m_{ij}}^{\infty} \sqrt{2\pi\sigma_j^2} \times \exp\left(-(\kappa - \mu_j)^2 / 2\sigma^2\right) d\kappa \right]^{-1} \quad (24)$$

The values for μ_j and σ_j are allowed to change across routes, so they are indexed by route *j*. h_{ijt} and m_{ij} are directly observable from our dataset.

Now we take a look at three different cases where the *ECC* should play no role in the pricing decisions and analyze how our construction of this measure respond in each of these cases. In other words, these are the cases where the model of section 3.1 should predict no price dispersion due to costly capacity and demand uncertainty.

(i) For routes where we expect higher load factors, costly capacity will play a less important role. On the limit, when we expect to sell all the seats in the aircraft in every occasion

E(h) = 1. In the case for uniform density $\alpha_j = 0$, and from (19) we get that the probability of selling the next seat does not decrease with the cumulative number of seats sold, $\Pr_h = 1$. For the normal density case $\mu_j \rightarrow \infty$. In both situations, there will be no rising *ECC* as more seats are sold. Holding inventories of additional seats will have no cost since we know for sure that they will be sold. In summary, $\lim_{E(h)\rightarrow 1} ECC = \lambda$.

(ii) A similar phenomenon would happen if aircrafts had infinite capacity, i.e. no capacity constraints. This can be interpreted as carriers being able to adjust the size of the aircraft anytime before departure at no additional cost. An alternative interpretation could be that the good is not perishable; if the good is not sold today, it can be sold anytime in the future. Characteristic that does not hold for airline travel since once the plane departs; carriers can no longer sell tickets. Again, we have $\lim_{m\rightarrow\infty} ECC = \lambda$ for both the uniform and the normal.

(iii) Finally, in the case of no demand uncertainty, carriers would just set their capacity levels to match to the certain number of travelers, hence the *ECC* would play no role, i.e., $\lim_{\sigma\rightarrow 0} ECC = \lambda$ for the normal, but no demand uncertainty holds also for the uniform.

In all three scenarios the price that an airline charges would be same for every seat, and there will be no price dispersion. That is why models omitting demand uncertainty in their interpretations like Borenstein and Rose (1994) or Stavins (2001) would lead to interpret this variation in prices as price discrimination rather than the effect of the combination between costly capacity and demand uncertainty. Failing to adjust the unit cost of capacity by the probability that the seat gets sold would lead to predict that the shadow cost remains constant, when it doesn't.

In addition to *ECC*, the specification in (22) includes the *Herfindahl-Hirshman Index* (*HHI*) that measures the concentration on the route. *HHI* is calculated using *ROUSHARE*, which is the carrier's share of total number of *seats* in all the direct flights on that route. Even though similar estimation specifications like in Stavins (2001) assumes that *HHI* is exogenous to airfare estimation, here we provide instruments for both *ROUSHARE* and *HHI*. We use *GEOSHARE* for *ROUSHARE* and *XFLTHERF* for *HHI*, as constructed in Borenstein (1989) and Borenstein and Rose (1994). A short explanation of these instruments is given in the Appendix and the summary statistics of these two instrument variables are shown in Table 1.

TABLE 1 [somewhere here]

The rest of the regressors in the equation are control variables when the estimation is carried out using carrier fixed effects. *DAYADV* is the number of days prior departure, while *DIST* and *DISTSQ* are the distance and distance square between the two endpoint airports on a route. *DIFTEMP*, *DIFRAIN*, and *DIFSUN*, are the differences in the average end of October temperature, rain, and sunshine between the two endpoints. They are measured in Fahrenheit degrees, precipitation in inches, and in percentages respectively. Their role is to control for some of the travelers' heterogeneity (i.e. mix of business and tourists). *AVEHHINC* and *AVEPOP* are average median household income in *US* dollars and average population of the two cities respectively.[14] *HUB* is equal to one if the carrier has a hub in the origin or destination airport, zero otherwise. *SLOT* is a dummy variable equal to one when the number of landings and takeoffs is regulated in either origin or destination airport.[15] The summary statistics of all these variables are presented in Table 1.

To get an estimate of the unit cost of capacity $\hat{\lambda}$, let $\hat{\delta}_k$ for $k = \{0, 1\}$, denote the estimates of δ_k when the estimation of (22) is carried out assuming λ being one. As we have previously seen, one important implication from the perfectly competitive market is that every dollar increase in *ECC* is passed to prices (see equation (18), but assuming $M \rightarrow \infty$). This means that $\partial FARE/\partial ECC = \left(\hat{\delta}_0 + \hat{\delta}_1 HHI\right) FARE = 1$ when $HHI=0$. This condition leads to the estimate $\hat{\lambda} = \hat{\delta}_0 \times \overline{FARE}$, evaluated at the sample mean of *FARE* and with $\hat{\delta}_0$ being interpreted as the share of fares that corresponds to *ECC*. Since there is no reason to believe that λ changes across market structures, we fix it at this value, $\lambda = \hat{\lambda}$. Then, the marginal effect of *ECC* on fares for any market structure will be obtained from $\partial FARE/\partial ECC = 1 + \left(\hat{\delta}_1 / \hat{\delta}_0\right) HHI$.

Because of potential changes in costs, Stokey (1979) mentioned that the mere presence of price variation over time is not an adequate measure of intertemporal price discrimination. Here we are appropriately controlling for raising marginal costs due to aircraft's capacity constraints under demand uncertainty. Given the construction of the model, *DAYADV* is expected to capture the effect of a type of second degree price discrimination named advance purchase discounts.

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[14] For cities with more than one airport, the population is apportioned to each airport according to each airport's share of total enplanements. Source: Table 3, *Bureau of Transportation Statistics*, Airport Activity Statistics of Certified Air Carriers: Summary Tables 2000.

[15] In some airports like Kennedy (JFK), La Guardia (LGA), and Reagan National (DCA), the U.S. government has imposed limits on the number of takeoffs and landings that may take place each hour. To take into account the scarcity value of acquiring a slot, the variable *SLOT* equals to one if either endpoint of route *j* is one of these airports and zero otherwise.

IV. Results of the Empirical Analysis

The estimates for equation (22) using the censored normal construction of the *ECC* and carrier fixed effects are presented in Table 2. The numbers in parentheses are *t-statistics* calculated using robust standard errors. The first column shows the results when assuming that the effect of *ECC* on fares does not vary with market concentration. Consistent with the theoretical predictions, its effect is positive and significant, implying that higher unit costs of capacity increase fares. When this effect is allowed to vary with market concentration in Column (2), we find that greater market concentration, as measured by higher values of the *HHI*, decreases the positive marginal effect. The intuition, again, is that in competitive markets every dollar increase in unit cost of capacity is fully transferred to prices since there are zero markups. In non competitive markets when markups are positive, part of the increase in unit costs of capacity are absorbed by markups and the final effect on prices is lower. All the regression results reported are obtained using the instrument variable *GEOSHARE* for *ROUSHARE* and *XFLTHERF* for *HHI*, as suggested in Borenstein (1989) and Borenstein and Rose (1994).

TABLE 2 [somewhere here]

Most of the estimates are directly comparable to the ones obtained in Stavins (2001) who uses a similar dataset collected in 1995.[16] Even though it is useful to know our estimates are comparable to effects already documented in the literature, in this paper we are not directly interested in the coefficients of time invariant parameters. Taking advantage of the panel structure of the data, a more suitable specification that will be able to control for unobserved time invariant parameters, but will wipe out these estimates is a model with flight fixed effects. These estimates are presented in Table 3. Moving from carrier to flight fixed effects greatly improves the goodness-of-fit as measured by R^2. In all specifications that include flight fixed effect, R^2 are greater than 0.86.

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[16] The main difference is that Stavins did not have information about seat availability, thus was unable to control for probability of selling each ticket. Moreover, her dataset had less ticket observations over only twelve routes, while here we have eighty-one routes. Consequently we expect our *HHI* to be a very good approximation of the market structure. The signs for the estimated coefficients were found to be the same for number of days in advance purchase (*DAYADV*), distance and distance square, market share (*ROUSHARE*), hub, slot, difference in temperature and average household income. The only comparable coefficient sign that does not match is average population. We believe our estimate is a better approximation since she did not adjust average population by the number of airport enplanements as we did. More populated cities get lower airfares.

TABLE 3 [somewhere here]

Table 3 also runs some robustness checks on the construction of the *ECC*. Column (1) still uses the censored normal, while Column (2) constructs the *ECC* under the censored uniform assumption on the distribution of demand states. Both specifications predict that greater market concentration decreases the positive effect of *ECC* on fares. However, the magnitude of the effect is very sensitive to the choice of the demand state distribution. The reason why the censored uniform predicts greater marginal effects is simple: it puts excessive weight on lower demand states. The censored uniform predicts that low demand states are as likely as any other demand state. This causes that the *ECC* rises too fast when the first couple of seats are sold, over dimensioning the costs of capacity constraints and demand uncertainty. However, what it's important is to realize that the basic conclusion holds with different specifications of the uncertain demand.

Our measure of the selling probability which is used to construct the *ECC* is a function of the number of seats that have already been sold. However, the number of seats that were sold depends on past level of fares. This questions the strict exogeneity assumption about the *ECC*. To account for this potential endogeneity problem, in column (3) we consider a dynamic panel data model where we only have to assume that the explanatory variables are weakly exogenous, plus still instrumenting for the *HHI*. The idea is to difference the regression equation (22) to remove any omitted variable created by unobserved flight-specific effects, and then instrument the right and side variables using lag values of the original regression to eliminate potential parameter inconsistency arising from simultaneity bias. The estimates represent GMM in *first differences* as developed in Arellano and Bond (1991). Here the error term in the model (v_{ijt} in equation (22)) may affect future dependent and independent variables. For example, suppose the airline experiences a positive shock at time t that drives up the number of tickets sold. The Arellano and Bond (1991) estimate allows fares and number of tickets sold at t+1 to change in response to such a shock, hence the specification is robust to the fact that the amount of seats sold up to this period is a function of prices in the previous periods. The result measure how the exogenous component of *ECC* impacts fares. This specification is robust against deviations from the price commitment as suggested in Eden (1990). Estimates in Column (3) are close to the ones in Column (1), supporting the two basic predictions of the theory.

Another important result is the coefficient estimate for *DAYADV*, the number of days prior departure. As discussed in Section I, advanced-purchase discounts (*APD*) have been argued in the literature as a way to divert demand from peak periods to off peak periods (Gale and Holmes 1992, 1993; Dana 1999a). In Column (2), we include *DAYADV* as a control variable. The coefficient estimate is negative and significant, providing evidence that supports *APD*. Buying the ticket one day earlier reduces the fare by 87 cents. Having been controlled for the *ECC* and under the assumptions that carriers cannot learn about the state of the demand, this 87 cents is an appropriate measure of intertemporal price discrimination. The conditions for this to be considered intertemporal price discrimination are the same as the ones in Dana (1998).

TABLE 4 [somewhere here]

To ease the concern that *DAYADV* may enter into the model nonlinearly, in Table 4 we show the results for three additional specifications. The first one, presented in Column (1), includes a square term for days in advance (*DAYADVSQ*), while the second one, in Column (2), includes a cubic term (*DAYADVCU*). A completely flexible model where each time period is allowed to be different with no further restrictions is flight fixed-effects, reported in Column (3). Comparing the coefficients reported in Table 4 with the ones previously obtained, we conclude that that the positive coefficient for *ECC* (δ_0 in equation (22)) the negative coefficient for *ECC·HHI* (δ_1 in equation (22)) hold. However, magnitude of the estimates of the estimates is somewhat smaller.

FIGURE 4 [somewhere here]

To see how the different specifications assign different weights to different demand states, Figure 4 shows the probability of selling seat *h* for the uniform and the normal specifications. The schedules shown are calibrated to match the values for the route Orlando International in Orlando, FL (MCO) to La Guardia in New York, NY (LGA). The 2006 forecasted load factor for this route is 0.82, also higher than the average across routes of 0.74, while the sold out probability was 0.254, higher than the sample average of 0.225. The forecasted value for this route is shown in the figure as the expected number of seats sold $E(h)$ = 0.822. Because of the nature of the censored normal, this value is lower than the average of demand states $\mu_j = 0.855$. σ_j and α_j are 0.048 and 0.356 respectively. Note that Figure 4 has two different probabilities. The probability that seat *h* gets sold, ρ_h, measured on the vertical axis and the probability of demand state *h*, Pr_h, measured as the absolute value of the slope. In an $m = 100$ seat airplane, the censored normal predicts that the 40^{th} passenger will come with a probability

$\rho_{0.4}$ = 0.98 which obviously does not prevent the next passengers from arriving, whereas the probability that the plane actually departs with exactly 40 passengers is $\Pr_{0.4}$ = 0.21 percent. Moreover, the area below each of the curves is equal to the expected load factor *E*(*h*).

From the estimates under various specifications in Tables 2, 3 and 4 it is clear that the main conclusion is robust to various specifications: the effect of *ECC* is greater in more competitive markets. Now we can extend the analysis to study the magnitude of the effect. Under the assumption of zero markups in perfectly competitive markets, i.e., *HHI* = 0, we have a direct interpretation of the coefficient on *ECC*. In Column (1) of Table 3, the coefficient for *ECC* is 0.175, which means that the unit cost of capacity represents 17.5 percent of the average fare. Given the average fare of $291, we can calculate the shadow cost of a unit capacity, $\hat{\lambda} = \$50.85$. The marginal effect of *ECC* on fares is given by $\partial FARE/\partial ECC$=1+(-0.134/0.175)*HHI*. When it is evaluated at the sample mean of *HHI* (0.684), the marginal effect of *ECC* on *fares* is 0.476. This implies that for the average market structure one dollar increase in *ECC* leads to an increase in 48 cents in fares. When evaluating the effect of *ECC* on fares at values of *HHI* of 0.25, 0.50, and 0.75, we get this one is 0.809, 0.618 and 0.427 respectively. For a monopoly carrier from each dollar increase in *ECC*, 24 cents go to increase prices while 76 cents are absorbed by the markup.

TABLE 5 [somewhere here]

As noted in the construction of the sold out probability, this may be interpreted as a lower bound rather than an unbiased calculation of it. To see the response of the estimated coefficients to higher sold out probabilities, Table 5 provides the estimates when the sold out probability for each of the flights is increased by a lump sum 10, 20 and 30 percent in Columns (1), (2) and (3) respectively. Again, the main conclusion of the analysis still holds: greater effect of ECC on fares in more competitive markets. However, the magnitude of $\hat{\lambda} = \hat{\delta}_0 \times \overline{FARE}$ changes; as the sold out probability increases, the share of the unit cost of capacity on fares increases as well. This proportion, calculated in Table 3 as 17.5 percent, it is now 29.0, 43.0 and 61.1 percent for average sold out probabilities of 32.5 (22.5+10), 42.5 and 52.5 percent respectively. It would be reasonable to believe that this proportion is greater than our original estimate of 17.5 percent in Column (1) of Table 3. To get an idea of the magnitude, Figure 5 presents the same AA flight 323 from ATL to DFW shown in Figure 1. The *ECC* was calibrated with the censored normal with $\hat{\lambda}$ = .611 * 148.14. It would be difficult to argue about the exact size of the markup, but the ranges we are talking about here look quite reasonable. Moreover, the schedule of *ECC* on Figure 5 seems to explain quite well the path followed by fares with the sharp increase for the last couple of seats.

FIGURE 5 [somewhere here]

The estimates in Table 5 prove robustness in one additional dimension. As the marginal effect of *ECC* on fares is measured by $\partial FARE / \partial ECC = 1 + \left(\hat{\delta}_1 / \hat{\delta}_0\right) HHI$, we are interested in whether the ratio $\hat{\delta}_1 / \hat{\delta}_0$ changes with the sold out probability. In our estimates of Column (1) in Table 3, this one is -0.76 (-18.80) with the t-statistic in parentheses. For columns (1), (2), and (3) in Table 4 this one is -0.70 (-14.63), -0.70 (-13.81), and -0.74 (-13.71) respectively. This provides some evidence that our estimate of the marginal effect of *ECC* on fares is stable, and its magnitude can be obtained with just a lower bound estimate of the sold out probability.

When dropping the assumption of no markups under perfect competition and without any normalization or knowing the value of λ, we can come with an interpretation of the magnitude of the effect of costly capacity on fares. However, this one is not robust to the magnitude of the sold out probabilities.[17] For our estimates in Column (1) in Table 3, a one standard deviation increase in the *ECC*, evaluated at sample means of *HHI* and fares, increases prices by $23.77, which corresponds to an increase of 0.14 standard deviations.

TABLE 6 [somewhere here]

Finally, Table 6 presents the last set of estimates. These estimates take advantage of the fact that if we take logarithm of *ECC*, we break its components in two parts. The log of λ will become part of the constant in the regression, while the *negative* value of the logarithm of the probability that batch *h* arrives (Pr_h) will keep the same elasticity coefficient as the *ECC*. In these results the *negative* value of the logarithm of the probability takes the place of *ECC* to make the signs comparable to the previous results. Column (1) tells us that a one percent increase in the *ECC* (or same as one percent decrease in the selling probability), increases fares by .219 percent. Once more, as illustrated in Columns (2) and (3), the response to *ECC* is greater in more competitive markets.

[17] The results follow from the fact that the marginal effect of *ECC* on *FARE is homogeneous of degree zero in* λ. The marginal effect holds for any positive value of *a*:

$$\frac{\partial FARE}{\partial ECC} = \left(\frac{\delta_0}{\alpha\hat{\lambda}} + \frac{\delta_1}{\alpha\hat{\lambda}} HHI\right) FARE \times StdDev\left(\alpha\hat{\lambda}\right)$$

V. Conclusions

This paper sets to test the empirical importance of the price dispersion predictions presented in Prescott (1975), formalized in Eden (1990) and extended in Dana (1999b). The basic idea in these theoretical models is that the equilibrium price dispersion can be explained by the different selling probabilities associated with each of the units sold. These selling probabilities play an important role in industries that face capacity constraints and uncertainty about the number of arriving consumers. Although the ideas in Prescott (1975) have been extended to multiple areas in the economic literature, few papers attempt to directly test the basic predictions due to the difficultness of coming up with an appropriate measure of the selling probabilities.

In particular, the paper seeks to find evidence for the two main predictions. i) Lower selling probabilities characterized by higher effective costs of capacity will lead to higher prices. ii) This effect will be larger in more competitive markets. We start building a simple theoretical framework based on Prescott (1975), Eden (1990) and Dana (1999b) that contains these two main predictions. The richness of this simple model comes from the fact that it naturally extends to accommodate the calibration of the demand uncertainty and the empirical procedure developed later.

The airline industry landscapes the ideal scenario to test this theory. First, because capacity is set and can only be changed at a relatively large marginal cost. Second, the product expires at a point in time, and third, there is uncertainty about the demand. The empirical section takes advantage of a unique dataset that observes the evolution of prices and inventories of seats of 228 flights for over a period of 103 days prior departure. We control for ticket restrictions that screen travelers and isolate the effect of the selling probability on prices.

Using the information on seat inventories, plus calculations of the sold out probabilities (based on a second dataset), and the forecasted values of utilization rates (based on a third dataset), we are able to construct the distribution of demand uncertainty for each of the 81 routes in the sample. With this distribution we generate a measure of the selling probability and the effective cost of capacity (*ECC*) for each of the seats in an aircraft. This allows us to test the model by finding out if *ECC* has any effect on the prices, and if so, how this effect varies with market concentration.

Under various specifications, our empirical tests strongly support both predictions of the theory. We show that for the average market structure, when *ECC* increases by one dollar, fares increase by 48 cents, whereas the remaining 52 cents is absorbed by the markup. The elasticity specification tells us that one percent increase in the *ECC* (or same as one percent decrease in the selling probability), increases fares by .219 percent. Moreover, price dispersion due to costly capacity under demand uncertainty was found to be greater in more competitive markets. The idea is that more competitive markets have smaller markups, so an increase in marginal costs goes directly to prices. In more concentrated markets where markups are greater, higher costs are partially absorbed by the markup and the effect on fares is smaller. In addition, under the assumption that carriers do not learn about the state of the demand, our results support an intertemporal price discrimination effect that indicates that buying the ticket one day earlier reduces fares by 87 cents. During the estimation the paper takes care of various sources of potential endogeneity, building a set of instruments for the market structure and benefiting from the panel structure of the data by running a dynamic model.

Although the dataset collected enjoys some very nice features, it has some drawbacks that limit extending the results to the airline industry as a whole. The one-way non-stop ticket is only a portion of the tickets sold in each flight, and often it is a small portion. The price schedule posted by carriers as the flight date approaches and tickets are sold is a great example of the PED models, but in order for the results in this paper to hold for the entire industry, we require that the prices of other tickets vary accordingly with the one-way ticket fares.[18] One of the authors believed that this is true, but the other was skeptical. Showing this formally is beyond the scope of this paper and would require working with a dataset that encompasses more complex itineraries.

Appendix

The construction of the instruments follow Borenstein (1989) and Borenstein and Rose (1994). In particular, the instrument for *ROUSHARE* is called *GEOSHARE*, defined as:

$$GEOSHARE = \frac{\sqrt{ENP_{x1} \cdot ENP_{x2}}}{\sum_{y} \sqrt{ENP_{y1} \cdot ENP_{y2}}},$$

with y indexes all airlines and x indexes the observed airline. ENP_{y1} and ENP_{y2} are airline y's average daily enplanements at the two endpoint airports during the second quarter of 2006.

[18] Using data at transaction levels, Puller, Sengupta, and Wiggins (2007) estimate that about 20% of airline tickets are one-way tickets.

The instrument for *HHI* is called *XFLTHERF*:

$$XFLTHERF = ROU\hat{S}HARE^2 + \frac{HHI - ROUSHARE^2}{(1 - ROUSHARE)^2} \cdot (1 - ROU\hat{S}HARE)^2 .$$

This instrument assumes that the concentration of the flights on a route that is not performed by the observed airline is exogenous with respect to the price of the observed carrier. More on these instruments can be found in Borenstein (1989) and Borenstein and Rose (1994).

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Table 1: Summary Statistics

	Mean	Standard Deviation	Minimum	Maximum	Observations
FARE (US$)	291.087	171.879	54.000	1224.000	7933
DAYADV	52.289	30.154	1.000	103.000	7933
DIST	1104.380	620.720	91.000	2604.000	7933
ROUSHASEA	.665	.314	.119	1.000	7933
HHI	.684	.287	.259	1.000	7933
HUB	.737	.440	.000	1.000	7933
SLOT	.298	.458	.000	1.000	7933
DIFTEMP	6.210	4.137	.000	19.000	7933
DIFRAIN	2.010	1.484	.000	4.900	7933
DIFSUN	7.911	8.461	.000	45.000	7933
AVEHHINC (US$)	35580	4620	25198	53430	7933
AVEPOP	1044072	631862	187704	2897818	7933
GEOSHARE	.674	.324	.025	1.000	7933
XFLTHERF	.708	.285	.252	1.000	7933
ECC - Censored Normal	1.557	.940	1.000	11.668	7933
ECC - Censored Normal / Constant Sold Out Prob.	1.548	.787	1.000	4.442	7933
ECC - Censored Uniform	1.453	1.086	1.005	55.887	7931
Observed Load Factor at last obs. of each flight	.881	.153	.227	1.000	228
Observed Sold Out Probability	.227	.104	.037	.571	81
Forecasted Load Factor (ARMA)	.738	.083	.469	.890	81

Table 2: Estimation Results for the Censored Normal

	(1)		(2)	
Variables	Coefficient	t-statistic	Coefficient	t-statistic
ECC	.092	(13.470)	.163	(8.868)
ECC·HHI			-.091	(-4.388)
DAYADV	-.003	(-12.395)	-.003	(12.198)
DIST	.002	(37.285)	.002	(37.180)
DISTSQ	-3.4e-7	(-25.577)	-3.4e-7	(-25.435)
ROUSHARE	.252	(5.818)	.254	(5.866)
HHI	-.079	(-1.660)	.066	(1.119)
HUB	-.024	(-1.759)	-.026	(-1.868)
SLOT	-.246	(-14.445)	-.253	(-14.755)
DIFTEMP	.003	(2.322)	.003	(2.341)
DIFRAIN	-.0171	(-33.264)	-.174	(-33.305)
DIFSUN	.004	(5.149)	.004	(4.987)
AVEHHINC	1.7e-5	(12.562)	1.7e-5	(12.515)
AVEPOP	-1.2e-7	(-11.844)	-1.2e-7	(-11.554)
Carrier FE	Yes		Yes	
Flight FE	No		No	
Period FE	No		No	
R-square	.482		.484	

The results reported here are obtained using *GEOSHARE* as the excluded instrument variable for *ROUSHARE* and *XFLTHERF* as the excluded instrument variable for *HHI*.
The independent variable is log(*FARE*), $N = 7933$ with 228 routes. *t*-statistics (in parenthesis) are based on White robust standard errors. Carrier fixed effects not reported. The estimation was carried out with an unbalanced panel of 7933 observation because some fares were no longer available for flights that sold out a couple of days before departure. The missing observations account for less that 0.6 percent of the sample and we don't expect this to bias the estimates.

Table 3: Summary of Robustness Checks

	(1)		(2)		(3)	
	Censored normal		Censored uniform		Censored normal Arellano and Bond	
Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	z-statistics
LNFARE(-1)					.589	(43.103)
ECC	.175	(11.883)	.520	(11.512)	.185	(12.131)
ECC·HHI	-.134	(-8.058)	-.519	(-11.503)	-.122	(-6.403)
DAYADV	-.003	(-24.023)	-.003	(-25.687)	-4.3e-4	(-4.055)
Carrier FE	No		No		No	
Flight FE	Yes		Yes		Yes	
Period FE	No		No		No	
R-square	.865		.876		n.a.	

The independent variable is log(*FARE*), *N*=7933 for columns (1) and (2), and 7472 for column (3) with 228 cross sectional observations in all cases. t-statistics is based on White robust standard errors. The construction of the *ECC* is based on the censored normal in column (1) and (3) and is based on the censored uniform on Column (2).

Table 4: Nonlinearities in Time

	(1)		(2)		(3)	
	Censored normal		Censored normal		Censored normal	
Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	t-statistics
ECC	.121	(8.155)	.097	(6.634)	.096	(6.561)
ECC·HHI	-.113	(-6.960)	-.105	(-6.592)	-.106	(-6.699)
DAYADV	-.010	(-18.502)	-.024	(-18.802)		
DAYADVSQ	6.4e-5	(14.920)	3.8e-4	(15.800)		
DAYADVCU			-1.9e-6	(-14.318)		
Carrier FE	No		No		No	
Flight FE	Yes		Yes		Yes	
Period FE	No		No		Yes	
R-square	.870		.875		.880	

The independent variable is log(*FARE*), *N*=7933 with 228 cross sectional observations. t-statistics based on White robust standard errors. The construction of the *ECC* is based on the censored normal. *DAYADVSQ* and *DAYADVCU* are *DAYADV* square and cube respectively.

Table 5: Sensitivity to Sold-out Probabilities

	(1)		(2)		(3)	
	Censored normal sold-out prob +10 percent		Censored normal Sold-out prob +20 percent		Censored normal Sold-out prob +30 percent	
Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	t-statistics
ECC	.290	(11.784)	.430	(11.387)	.611	(10.553)
ECC·HHI	-.203	(-7.245)	-.301	(-7.037)	-.451	(-6.923)
DAYADV	-.003	(-20.133)	-.003	(-18.398)	-.003	(-17.989)
Carrier FE	No		No		No	
Flight FE	Yes		Yes		Yes	
Period FE	No		No		No	
R-square	.864		.863		.862	

The independent variable is log *FARE*, *N*=7933 with 228 cross sectional observations. t-statistics based on White robust standard errors. The construction of the *ECC* based on the censored normal with different sold out probabilities across routes. Columns (1), (2), and (3) increase the sold out probability in each or the routes by a lump sum 10, 20, and 30 percent respectively.

Table 6: Elasticities

	(1)		(2)		(3)	
	Censored normal		Censored normal		Censored normal Arellano and Bond	
Variables	Coefficient	t-statistics	Coefficient	t-statistics	Coefficient	z-statistics
LNFARE(-1)					.592	(43.385)
(-)LN(Pr)	.219	(15.644)	.398	(12.177)	.397	(10.331)
(-)LN(Pr)·HHI			-.252	(-6.722)	-.201	(-3.947)
DAYADV	-.002	(-17.985)	-.002	(-17.691)	1.1e-4	(.863)
Carrier FE	No		No		No	
Flight FE	Yes		Yes		Yes	
Period FE	No		No		No	
R-square	.850		.855		n.a.	

The independent variable is log(*FARE*), *N*=7933 for columns (1) and (2), and 7472 for column (3) with 228 cross sectional observations in all cases. t-statistics based on White robust standard errors. The construction of the *ECC* based on the censored normal.

Figure 1

Fares and Load Factors at Different days from Departure

(Flight AA 323 ATL-DFW)

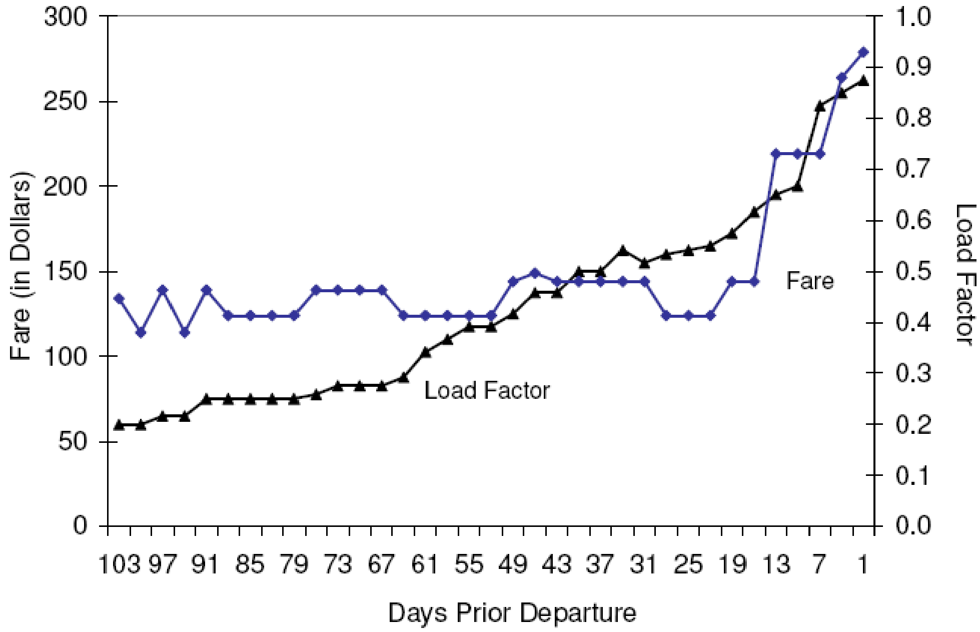

Figure 2

Average Fares at Different Days from Departure

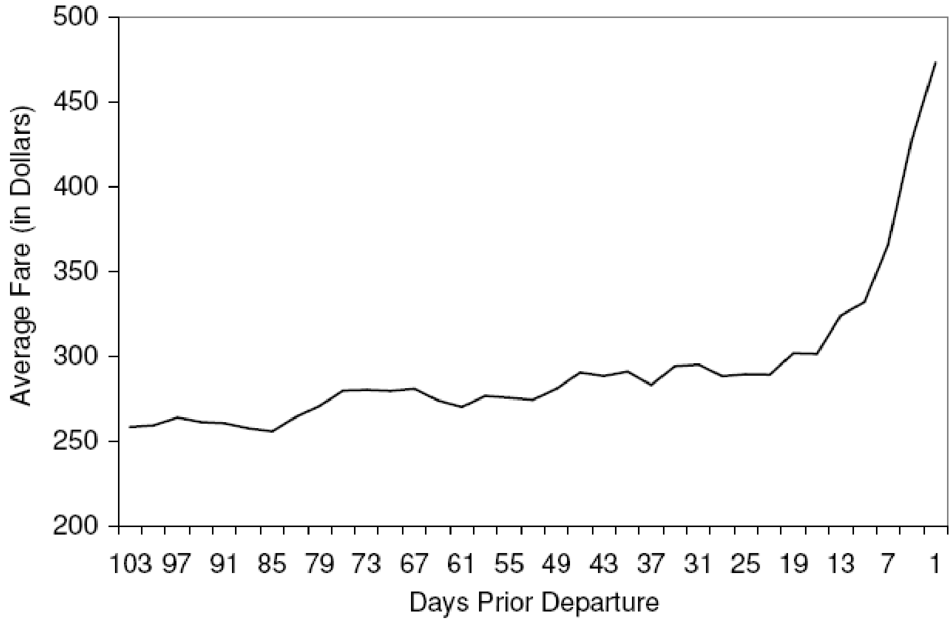

Figure 3

Average Sales (Δ Load Factors) at Different Days Prior Departure

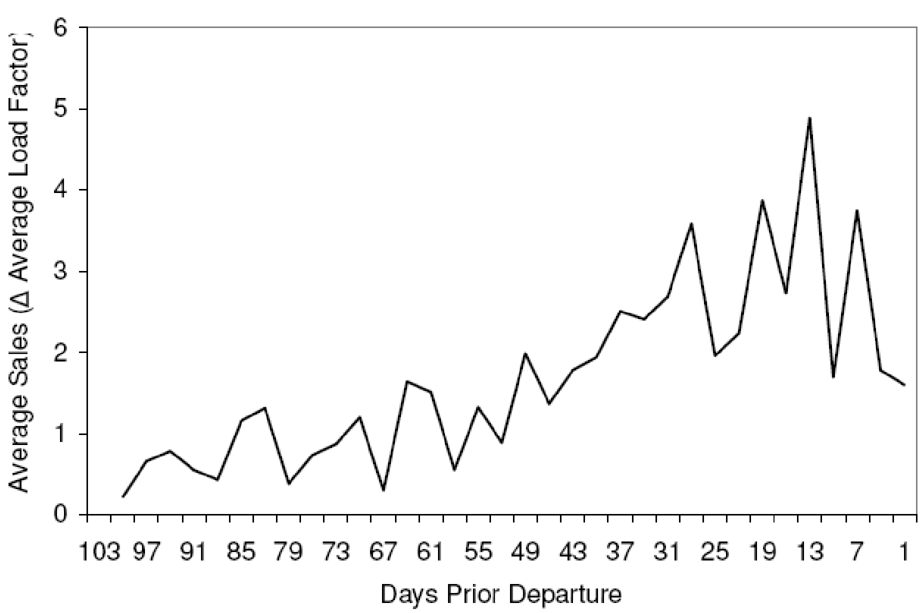

Figure 4

Probability that seat h gets Sold (MCO-LGA)

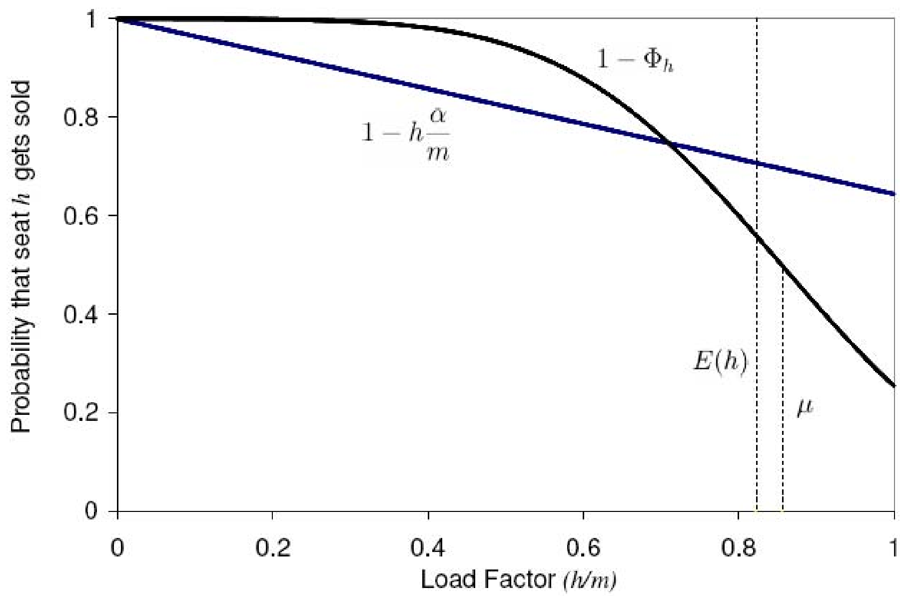

Figure 5

Fares and Effective Cost of Capacity at Different Days Prior Departure
(Flight AA 323 ATL-DFW)