Systematic peak-load pricing, congestion premia and demand diverting: Empirical evidence

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January 2009

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January 14, 2009

Abstract

This paper finds empirical support to *systematic* peak-load pricing in airlines—higher fares in *ex-ante* known congested periods. It estimates a congestion premia and supports the main empirical prediction in Gale and Holmes (1993)—less discount seats on peak fights.

Keywords: Airlines, Congestion Premia, Peak-load pricing

JEL Classifications: C23, L93

*The author thanks Li Gan, Paan Jindapon, and Carlos Oyarzun for their comments. Stephanie C. Reynolds provided excellent research assistance. Financial support from the Private Enterprise Research Center at Texas A&M and the Bradley Foundation is gratefully appreciated.

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1 Introduction

Peak-load pricing is the practice of charging higher prices during peak periods when capacity constraints cause marginal costs to be high.[1] For the airline industry, Borenstein and Rose (1994) explain that changes in capacity utilization over different days or flights generate differences in the opportunity cost of the seats in an aircraft. During peak periods most of the airline's aircrafts will be in the air and the expected shadow cost of aircraft capacity will be quite high. When airlines are operating near capacity, congestion is associated with higher marginal costs.

Borenstein and Rose (1994) make the distinction between two types of peak-load pricing. The first is *systematic* peak-load pricing which reflects variations in the expected shadow costs of capacity at the time the flight is scheduled. This is based on variations in shadow costs known when a flight is opened for booking. This implies that carriers know *ex-ante* (when they create their flight schedules) which periods are peak. Hence, flights departing for the Thanksgiving holiday, an *ex-ante* known peak period, should be assigned less discount tickets. The second is *stochastic* peak-load pricing and refers to aggregate demand uncertainty for individual flights once flight schedules have been made. This depends on the degree of price flexibility once carriers start selling tickets. As explained in Crew and Kleindorfer (1986), if carries can adjust price as demand is reveal over time the optimal peak-load pricing will depend on the probability at the time the ticket is sold that demand will exceed capacity and the expected shadow cost if this happens. Under price rigidity or if airlines are not able to learn about

[1]See Crew and Kleindorfer (1986) or Crew *et.al.* (1995) for a review of the literature on peak-load pricing.

the demand as they go selling tickets, there will be no *stochastic* peak-load pricing. Dana (1999b) mentions that useful information about the demand may only be available close to departure or once it is too late for carriers to change fares.

Because of capacity constraints during peak demand periods, if a firm wants to expand output it has to divert demand from the peak period to the off-peak period. Gale and Holmes (1993) demonstrated that the imposition of an advance-purchase requirement may be the profit-maximizing strategy for a monopoly airline facing capacity constraints during peak demand. They derive this in a setting where the carrier perfectly predicts the peak period and offers discounts in the off-peak period. Individuals with low time costs that originally wanted to fly in the peak period will shift to the off-peak period.

In their empirical study of price dispersion Borenstein and Rose (1994) control for *systematic* peak load pricing under the assumption that this one is correlated with the variability in airlines' fleet utilization rates and airports' operation rates.[2] However, they are not able to measure any congestion premia. In this paper I provide a measure of the congestion premia for an *ex-ante* known peak period − the 2005 Thanksgiving holiday − and provide empirical support for the main empirical prediction in Gale and Holmes (1993, p.144); airlines will limit the availability on discount seats on peak periods.

Gale and Holmes (1993) do *not* consider different marginal costs across peak and off-peak periods, but peak-load pricing models can achieve the

[2]Daniel (1995) addresses the importance of *airport* peak-load congestion pricing. Using simulations he finds that congestion pricing would reduce net social costs by about 24% by smoothing out demand of landings and takeoffs in the Minneapolis-St. Paul airport.

same efficient demand diverting. The findings in this paper, to my knowledge, are the first ones to provide empirical evidence of the existence of peak-load pricing in airlines along with evidence of demand diverting and an estimation of the congestion premia associated to a peak demand period.

The price rigidity in Dana (1999b) and Gale and Holmes (1993) is a strong assumption. The results in this paper are also relevant and consistent with the revenue management literature that allows dynamic pricing decisions. For the pricing of inventories over finite horizon, Gallego and van Ryzin (1994) find that under certain conditions two basic properties hold. (1) At a given time, the optimal price decreases in the number of seats left. (2) With any given number of seats left, the optimal price decreases over time. Here I find that the empirical results are consistent with the first, but not with the second. The lack of evidence for the second can be explained by the fact that Gallego and van Ryzin assume that the reservation price distribution is the same across consumers. For a given number of seats, price increases over time can be explained by consumers with higher reservation price arriving closer to the departure date. Zhao and Zheng (2000), who allow for reservation price distribution to change over time, also found (1), and explain that (2) is not likely to hold for travel services.

2 Empirical Results

2.1 Data

The dataset used in this paper was collected during the last week of September 2005 from the online travel agency *expedia.com* following a similar procedure as Stavins (2001). The uniqueness of this dataset is the information on seat availability at each price. The dataset is a panel with 103 cross-section observations during 20 periods. Each cross-section observation corresponds to a specific carrier's flight-number (e.g. American Airlines flight 936 from Miami (MIA) to Boston (BOS)) in one of the 47 routes considered. A route is a pair of departing and destination airports, where fares and seat availabilities correspond to economy class one-directional non-stop flights. Different observations in time for a given flight-number were collected all the same day for flights departing at various dates in the future and by keeping the same flight-number with the corresponding identical departure time. Specifically, the data across time covers ten weeks between October and December 2005 with two observations per week (Tuesday and Thursday). This strategy allowed keeping the same route and flight-number characteristics while changing demand intensities at different departing dates. The summary statistics of the variables is presented in table 1.[3]

Table 1. Summary Statistics (2060 Observations)

Variable	Mean	St. Deviation	Minimum	Maximum
FARE	253.56	172.43	49.00	1114.00
THKSGIV	0.05	0.22	0.00	1.00
LOAD	0.59	0.20	0.14	1.00
DAYADV	35.19	35.50	1.00	70.00
TUESDAY	0.50	0.50	0.00	1.00

FARE is the one reported by *expedia.com* and represents the least expensive available fare for a particular flight. *THKSGIV* is equal to one for flights departing on Tuesday, November 22^{nd}, zero otherwise. This *ex-ante* known peak period is actually before the Thanksgiving Day because travelers are expected to fly earlier to be home during the holiday. *LOAD* is the

[3]The carriers considered are American, Alaska, Continental, Delta, Northwestern, United, US Airways, and America West. Escobari and Gan (2007) have a detailed description of the characteristics of a similar dataset and an explanation why these fares from *expedia.com* are ideal for this analysis (see sections 2.1 and 2.2).

ratio of occupied seats to total seats in the aircraft, where the available preferred or prime seats reported by *expedia.com* are counted as available seats. Given that overbookings are usually a small fraction of the total number of tickets, *LOAD* is assumed to be proportional to bookings. *DAYADV* is the number of days between the departure date and the date the fare was recorded. *DAYADVSQ* and *DAYADVCU* are *DAYADV* squared and cubed respectively. *TUESDAY* is one if the flight departs on a Tuesday, else zero.

2.2 Results

Given the construction of the dataset I perfectly control for important sources of price dispersion observed in the industry (e.g. saturday-night-stayover, minimum and maximum stay, different connections/legs, fare class). Moreover, estimating the model using flight-number fixed effects allows controlling for unobservable time invariant characteristic, which include all the time invariant control variables included in Stavins (2001) (e.g. flight-number, carrier, and route characteristics).

The model is a reduced form equation of log*FARE* on Thanksgiving, capacity utilization, and controls for time trend or nonlinearities in time, i.e.,

$$\begin{aligned} logFARE_{it} &= \beta_0 + \beta_1 THKSGIV_{it} + \beta_2 LOAD_{it} \\ &\quad + \beta_3 DAYADV_{it} + \beta_4 TUESDAY_{it} + \mu_i + \nu_{it} \end{aligned} \tag{1}$$

where i refers to the flight-number, and t to time. The estimation results using flight-number fixed effects are presented in table 2.

Table 2. Model Estimates

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$THKSGIV$	0.291	0.359	0.285	0.174	0.282	0.219
	(8.056)	(9.818)	(7.640)	(4.712)	(7.440)	(5.689)
$LOAD$				0.548	0.322	0.285
				(8.259)	(4.759)	(4.366)
$DAYADV$	−0.005	−0.023	−0.052	−0.001	−0.019	−0.047
	(−13.548)	(−16.597)	(−14.664)	(−2.425)	(−11.775)	(−13.242)
$DAYADVSQ$		$2.0e^{-4}$	0.001		$2.3e^{-4}$	0.001
		(15.019)	(11.944)		(12.677)	(11.527)
$DAYADVCU$			$-9.7e^{-6}$			$-9.3e^{-6}$
			(−10.114)			(−9.904)
$TUESDAY$	−0.063	−0.069	−0.068	−0.034	−0.052	−0.052
	(−5.107)	(−6.104)	(−6.110)	(−2.425)	(−4.537)	(−4.719)
$R-squared$	0.835	0.856	0.863	0.844	0.858	0.866
F	94.35	109.13	115.37	99.67	110.48	116.34

Notes: The independent variable is $\log FARE$, N=2060 with 103 cross-sectional observations. t-Statistics in parentheses based on White robust standard errors. All regressions are estimated with flight-number fixed effects, not reported.

The positive and significant *THKSGIV* coefficient from the first three different specifications presented in columns (1), (2) and (3), show evidence that carriers are setting higher fares in this *ex-ante* known peak period. However, as suggested by various theoretical models (e.g., Eden (1990), Gale and Holmes (1992), Dana (1998), Dana (1999a), Dana (1999b)) and empirical evidence (e.g., Stavins (2001), Escobari and Gan (2007)) carriers have various reasons to set lower fares for earlier purchasers and higher fares for later purchasers.[4] Under this pricing strategy, higher fares in Thanksgiving may

[4]Lower fares for earlier purchasers is consistent with Gallego and van Ryzin (1994) and Zhao and Zheng (2000) if assuming that later purchasers have a higher reservation price. Moreover, consumers that arrive when inventories are high, typically early in the selling process, will benefit from lower prices as well.

be the result of an *ex-post* higher demand state and not necessarily because carriers are allocating *ex-ante* less discount seats. To present stronger evidence that carriers are effectively charging higher fares because they knew *ex-ante* this was a peak period it is necessary to control for the status of the demand state at each price level, i.e. availability of seats. Columns (4), (5) and (6) report the estimates when controlling for capacity utilization.[5] All specifications have a positive and significant coefficient, this time providing stronger evidence of higher fares during an *ex-ante* known peak period. Using the estimate from column (6) it is obtained that travelers of this peak-period have to pay 21.9% higher fares than off-peak travelers. This 21.9% is the congestion premia.[6]

3 Conclusions

Using a unique panel of U.S. airline fares and inventories at the ticket level, this paper shows that carriers charge higher fares in *ex-ante* known peak demand periods. This results provide empirical evidence supporting the demand diverting predictions of Gale and Holmes (1993) and the *system-*

[5]Previous fares in a flight may impact current availability of seats. Recall that the dataset has 2060 observations from different flights (across 103 flight-numbers). Hence, previous values of *FARE* for the same flight-number in the panel do not impact current values of *LOAD*, implying the strict exogeneity assumption of *LOAD* is not violated. The positive sign of *LOAD* is consistent with the theoretical predictions in Gallego and van Ryzin (1994) and Zhao and Zheng (2000), who obtain that at a given time the optimal price increases with lower inventories.

[6]Under an alternative pricing strategy, the same *LOAD* in two flights that have different booking forecasts will be associated with different fare responses by revenue management systems. Escobari (2008) considers this specific fare response by looking at the relation of cumulative bookings and the forecast booking curve, labeled expected load factor.

atic peak-load pricing argument for airlines in Borenstein and Rose (1994). Moreover it was calculated that travelers faced a congestion premia of 21.9% higher fares when flying in the *ex-ante* known peak period for the Thanksgiving holiday of 2005.

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