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COMPETITION AND PRICE DISPERSION IN THE U.S. AIRLINE INDUSTRY

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ABSTRACT

This paper analyzes dispersion in the prices that an airline charges to different customers on the same route. Such variation in airlines fares is substantial: the expected absolute difference in fares between two of an airline's passengers on a route averages thirty-six percent of the airline's average ticket price on the route.

The pattern of price dispersion that we find does not seem to be explained solely by cost differences. Dispersion is higher on more competitive routes, possibly reflecting a pattern of discrimination against customers who are less willing to switch to alternative flights or airlines. We argue that the data support an explanation based on theories of price discrimination in monopolistically competitive industries.

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I. Introduction

Explaining price differences among related products and among buyers of the same product is a popular pasttime for economists. Is a restaurant's markup on wine higher than on food because wine purchase signals a low demand elasticity for the whole meal or because it indicates a customer who is more costly to serve? Are grocery prices higher in poor neighborhoods than in wealthy ones because the cost of doing business is higher in poor areas or because buyers there are less mobile and less able to switch stores? Until recently, explanations that implied price discrimination often were discounted in markets with easy entry and firms earning normal returns in the long run. That response, however, has become less compelling with the presentation of numerous theoretical models in which price discrimination persists in the markets with multiple firms and even where firms earn zero economic profits.¹

This paper analyzes price dispersion in the U.S. airline industry in the context of the recent theoretical advances on competitive price discrimination. We focus on two objectives. First, we wish to quantify the extent of fare inequality in the airline industry and to describe patterns of price dispersion across markets.² Second, we attempt to distinguish price dispersion due to discriminatory pricing from dispersion that results from variations in costs.³ To meet this objective, we examine the degree to which dis-

¹ See Katz, 1984, Borenstein, 1985, and Holmes, 1989. For thorough treatments of price discrimination in monopoly and competitive markets, see Tirole, 1988, and Varian, 1989. While there has been little empirical work on price discrimination - see Pratt, Wise and Zeckhauser, 1979, and Dahlby and West, 1986, for example- recent analyses have begun to account for the effects of competition on the type and degree of discrimination. See Borenstein, 1989b, and Shepard, forthcoming.

² Throughout this study, we use the term "price dispersion" to refer to the variation in prices charged to different passengers on the same airline and route.

³ Following Stigler, 1987, and Varian, 1989, we think of discriminatory prices as

persion is affected by population, product, and market characteristics that should influence the amount of variation due to price discrimination, while attempting to control for the dispersion due to costs. We are especially interested in measuring the effects of market structure and the firm's relative market position on observed price variation.

We find considerable dispersion in airline prices. The expected difference in prices paid for two passengers selected at random on a route is more than 35 percent of the mean ticket price on the route. We find that dispersion is higher on more competitive routes and that increased market density and high concentrations of tourist traffic are associated with lower levels of price dispersion, consistent with models of competitive price discrimination (Borenstein, 1985, and Holmes, 1989).⁴ We also find that variations in airport congestion levels are associated with increased dispersion, as would be expected from peak-load pricing.

While we interpret the evidence as suggestive of price discrimination, it is important to recognize that our analysis is descriptive rather than normative. As we know from theoretical research, price discrimination may increase or decrease social welfare. Airline cost functions also may imply that some degree of price discrimination (in the form of Ramsey prices, for example) is necessary to enable carriers to break even.

We describe our measure of price dispersion in U.S. airline markets and the variations in dispersion across carriers and markets in section II. Section III discusses possible sources of price dispersion, including both discrimination-based and cost-based explanations. The empirical model

differing in markups of price over cost, while cost-based differences, such as peak-load pricing, hold markups constant.

⁴ Some of these findings could also be consistent with specific models of peak-load pricing. We discuss this at length below.

and methodology are described in section IV. Results are presented in section V and their implications are explored in the concluding section.

II. Summary Measures of Airline Price Dispersion

Little is known about the extent of actual price dispersion in the U.S. airline industry, despite evidence of substantial variation in published fares, as well as widespread recognition of the critical role of "yield management."⁵ To determine the magnitude of price dispersion and to describe its distribution across markets, we first develop measures of price dispersion based on actual prices paid for air travel.

The data set we use, based on the Department of Transportation's database DB1A, records the prices paid for a 10 percent random sample of all airline tickets used in the U.S. during the second quarter of 1986. Our analysis focuses on direct coach class travel in the largest direct service U.S. domestic air markets.⁶ Change-of-plane and first class travel are excluded because they entail significantly different qualities of service than direct coach travel and controlling for their associated cost differences would be very difficult.

We restrict the sample to routes in the top 1200 airline markets on which more than 80% of passengers traveled direct. For these markets, we calculate price dispersion measures for each of the 11 major U.S. domestic

⁵ "Yield management" refers to the industry's dynamic allocation of discount seats so as to maximize revenue on each flight. See Belobaba, 1989, for an extensive discussion of this practice.

⁶ Direct service means that a passenger does not change planes, i.e., it excludes connecting service. The data do not allow us to distinguish between nonstop service and other direct service, i.e., travel with on-plane stops. The chief disadvantages of the database are that it records neither the date of purchase nor the flight on which the ticket is used, nor any advanced-purchase, minimum-stay or other restrictions associated with the fare paid - limitations discussed in the following sections.

carriers at the time: American, Continental, Delta, Eastern, Northwest, Piedmont, Republic, TWA, United, Western, and USAir.⁷ The selection criteria leave us with a data set of 1021 carrier-route observations on 521 routes. The largest route in the sample is Boston - LaGuardia (New York), with 58,607 direct service passengers during the quarter. The smallest route is Seattle - Ketchikan (Alaska), with 235 direct service passengers during the quarter. The data appendix details the construction of the data set.

Measuring Price Dispersion

We measure price dispersion, or inequality, with a Gini coefficient (*GINI*) of fares paid.⁸ The Gini coefficient is twice the area between the 45 degree line (the line of absolute equality in prices) and the Lorenz curve, where the Lorenz curve is defined as the proportion of total revenues contributed by the bottom x proportion of customers, $x \in (0, 1.00)$, and

⁷ We include price observations only for carriers reporting fare information for more than 50 direct passengers on the route during the quarter. Prices are measured as one-way fares; these are computed as one-half the reported fare for round-trip tickets.

⁸ The results of our study are very similar when we instead measure dispersion by the coefficient of variation (*CV*), defined as the standard deviation of fares divided by the mean fare. This is not surprising, because the two measures have a correlation of 0.94 in our sample. Other empirical studies of price dispersion have used the variance or standard deviation of prices (Pratt, Wise and Zeckhauser, 1979; Dahlby and West, 1986) or the ratio of highest to lowest prices (Pratt, Wise and Zeckhauser, 1979; and Schwieterman, 1985). Unscaled variances or standard deviations, however, are likely to be functions not only of differences in dispersion across markets, but also of differences in mean price levels. We also have analyzed the degree of price dispersion using a measure of the relative interquintile range (*IQRANGE*), where $IQRANGE = (80\text{th percentile price} - 20\text{th percentile price})/\text{median price}$, and have found similar results. *IQRANGE* is in the spirit of a minimum-to-maximum price difference measure that has been used in some previous work, but it has two advantages over measures based on more extreme prices: (1) if few passengers pay the absolute minimum or maximum prices extreme price differences may look deceptively large for some markets, and (2) extreme price measures are likely to be much more sensitive to recording errors in price data. *IQRANGE* shares a significant drawback of other dispersion measures based on the price range, however, in that it does not reflect differences in the distribution of prices between the measured endpoint prices. Because of this, we focus on the Gini coefficient.

Table 1

Price Dispersion in Direct Airline Markets
1021 Observations

Mean Price Dispersion Measures

<u>Summary Measures</u>	<u>Mean</u>	<u>Standard Deviation</u>
Gini	.181	.063
CV	.362	.117
Mean Fare	\$104.81	\$ 41.06

Distribution of Price Dispersion Measures

<u>Observation</u>	<u>Gini</u>	<u>Mean Fare</u>	<u>Carrier</u>	<u>Route</u>
Minimum Gini	.018	\$ 65.10	Eastern	Boston-LaGuardia
10th Percentile Gini	.103	75.10	Delta	DFW-New Orleans
25th Percentile Gini	.131	192.10	United	LAX-Kona, Hawaii
50th Percentile Gini	.178	153.10	Delta	Atlanta-Tampa
75th Percentile Gini	.224	45.00	Piedmont	Charlotte-Charleston
90th Percentile Gini	.258	190.30	American	Chicago-Hartford
Maximum Gini	.416	91.60	TWA	Phoenix-Las Vegas

passengers ranked by fares paid. Multiplying the Gini coefficient by two gives the expected absolute difference in prices as a proportion of the mean price for two customers drawn at random from a population.⁹ A Gini coefficient of .10 therefore implies an expected absolute price difference of 20 percent of the mean fare.

Stylized Facts about Airline Price Dispersion

The data reveal substantial dispersion in the prices that an airline charges different customers in the same market. The average Gini coefficient for our sample is .181 (standard deviation, .063), which corresponds to an expected absolute fare difference of 36 percent of the mean fare for two passengers selected at random on a given carrier and route. In fact, average fare differences *across* carriers on a route are small relative to differences in prices among customers of each airline: on the 336 routes in our sample served by more than one major carrier, the ratio of within-carrier price variation to total (within and between) variation averages 97 percent.¹⁰

There also is considerable variation in price dispersion across different carrier-routes. Table 1 provides information on the distribution of price dispersion across markets by reporting selected observations ranked in order of their Gini coefficients. The Gini coefficient in our sample ranges from .018 (an expected price difference of 3.6 percent of mean fare) on Eastern's Boston-LaGuardia Shuttle route to .416 (an expected price difference of 83.2 percent) on TWA's Phoenix-Las Vegas route. In the market with

⁹ We are grateful to Lawrence Summers for pointing out this interpretation to us. The expectation is independent of distributional assumptions, but holds only asymptotically; the expected difference as a fraction of the mean price is 2.04 times the Gini with a sample of 50 and 2.02 with a sample of 100.

¹⁰ The conclusion is not very sensitive to the exclusion of small carriers from our data set. This ratio averages 94 percent for the 425 non-monopoly routes when all carriers, not just the 11 major carriers, are included in the calculation.

the 10th percentile Gini, the bottom half of the passengers contribute 37 percent of total revenues, while in the market with the 90th percentile Gini, the bottom half of passengers contribute only 27 percent of total revenues – and this contribution drops to 20 percent in the maximum Gini market. The Lorenz curves associated with the minimum, 10th, 50th, 90th, and maximum percentile Gini observations are illustrated in figure 1.

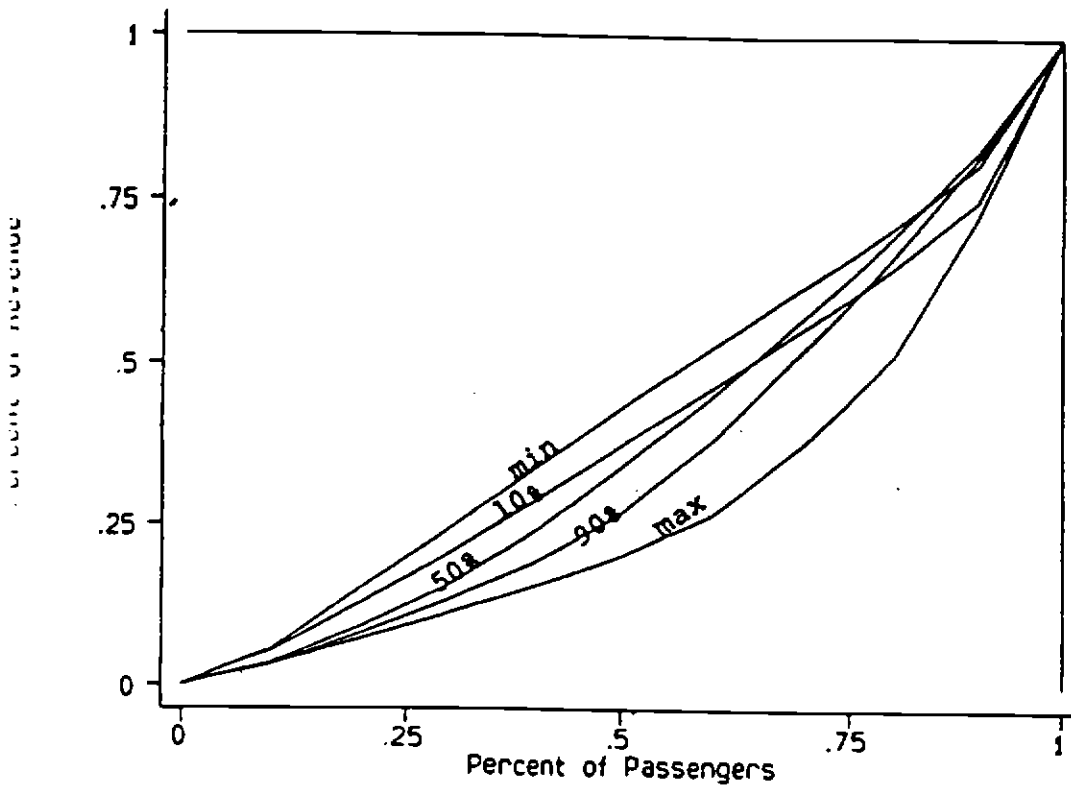
Before attempting to model the determinants of this range of dispersion across carrier-routes, we characterize some of the patterns of dispersion that appear in the data. First, price dispersion is inversely correlated with concentration on the route. The correlation between the Gini coefficient and the passenger Herfindahl index on the route is -0.153 .¹¹ This result may be consistent with both models of price discrimination under imperfect competition and certain forms of peak-load pricing behavior in airline markets. We explore these explanations in the following sections.

Second, the dispersion of fares for a carrier-route is larger when the average fare is itself large; the correlation coefficient between *GINI* and average fare is 0.354. This may suggest that airlines with more sophisticated yield management techniques are able to raise average fares through more precise market segmentation. Yield management is also often credited with allowing airlines to fill more seats on each flight without sacrificing revenues, an assertion that is supported by a positive correlation of 0.130 between *GINI* and the carrier's average load factor on its nonstop flights on the route.

Finally, for routes on which two or more major carriers compete,

¹¹ If these two variables are assumed to be distributed bivariate normal, this correlation is significantly different from zero at the 1% level. Under the bivariate normal assumption all of the correlations discussed in the remainder of this section are significant at the 1% level.

Figure 1: Lorenz Curves, Selected Observations



higher within-carrier price dispersion is associated with higher between-carrier dispersion of mean fares, with a correlation of .361 between the two coefficients of variation. This also may reflect differences in the effectiveness of yield management across carriers. When fare spreads are high, small differences in carriers' yield management abilities may translate into significant differences in average fares.

III. Sources of Airline Price Dispersion

The dispersion we observe in airline prices may arise both from variations in the costs of serving different passengers and from discriminatory pricing, *i.e.*, variations in the mark-up of price over marginal cost. Disentangling these sources of price dispersion is difficult because product heterogeneities that may affect the airline's costs – for example, the time and day of the week that travel occurs, ticketing restrictions, and the number of stops or plane changes that a passenger must make – also may provide a basis for self-selective price discrimination. Indeed, self-selective discrimination relies upon product heterogeneity, since it is carried out by offering consumers a set of alternatives and allowing their choices to reveal information about their characteristics.¹² Many restrictions associated with discount tickets seem intended to foster self-selection, separating business passengers from discretionary passengers (*e.g.*, those traveling on vacation or to visit friends or relatives).

Ideally, one would distinguish cost-based dispersion from price discrimination by calculating marginal cost and the markup over marginal cost. Unfortunately, data limitations combined with the nature of airline

¹² This is in contrast to what Spence, 1973, calls index sorting, in which consumers are classified by the seller and have no ability to change classes.

cost functions preclude direct calculation of marginal cost for each ticket.¹³ We therefore study the relationship between price dispersion and factors that might indicate a basis either for cost variations or price discrimination. This approach permits us to distinguish among competing explanations of price dispersion if we can identify variables that affect price dispersion only through cost variation or only through price discrimination but not both, or if the expected signs of the variables differ depending on whether cost differences or discrimination drive the price variation. We describe below both discriminatory and cost-based sources of price dispersion and sketch the factors that may contribute to each.

Price Discrimination

Price discrimination conventionally has been studied in the context of monopoly markets. In those markets, discrimination is limited only by the diversity of the demand elasticities in the customer population and by the firm's ability to segment demand. At the opposite extreme of market structure – perfect competition – price discrimination cannot be sustained. Traditionally, these polar cases have been used as a guide to the likely outcomes from market structures that lie between the two extremes. Under this view, the degree of observed price dispersion would be expected to decrease as a market became less concentrated.

Recent theoretical works by Borenstein (1985) and Holmes (1989) indicate, however, that price discrimination may increase as a market moves from monopolistic to imperfectly competitive. Under monopoly, the firm's profit-maximizing price for each customer group will depend on the group's elasticity of demand for the product. When there are competitors in the

¹³ Marginal cost is particularly difficult to quantify given fixed capacity in the short-run and a shadow capacity cost for each flight that varies over time.

market, a firm's price may depend on both a group's elasticity of demand for the product, which we will refer to as the group's "industry elasticity" of demand, and its "cross-elasticity" of demand among brands or firms.¹⁴ The expected effect of competition on price discrimination is ambiguous in these models.

For example, consider a market in which all buyers have identical industry elasticities (or reservation prices) for the product, but some have strong preference among brands of the product while others have much higher cross-elasticities across brands. The profit-maximizing monopoly prices would depend only on a buyer's industry elasticity, because the monopolist would control all brands (or outlets) of the product, and thus would be indifferent as to which brand of the product a person bought. If industry elasticities are identical, the monopolist will charge a single price.¹⁵ If the differentiated brands were owned by competing firms, however, the demand elasticity faced by each firm would depend both on the industry elasticity of the buyers and on their cross-elasticities among brands. Even if all buyers have identical industry elasticities, differences in cross-elasticities could induce the firms to charge different consumers different prices.

In the more competitive case, in which every buyer gets positive net consumer surplus from at least two brands (owned by different firms),

¹⁴ This terminology is from Holmes. Analogously, Borenstein presents a spatial model of competition in which consumers differ in their reservation prices for the product and in their cost (per unit distance) of buying brands that are away from their preferred points in characteristic space. Both models consider only firms that sell one brand each. If we think of brands as flights located around a clock, then this is not an accurate description of an airline's service in most markets. The theory of price discrimination under multi-product monopolistic competition unfortunately has not, to our knowledge, been formalized.

¹⁵ In the case of perfect first-degree price discrimination, the firm would want each buyer to choose the brand that maximizes her surplus and would then want to extract all of that surplus with a price equal to her reservation price for the product, which is the same for buyers in this example.

industry elasticities become irrelevant to each firm's optimal prices, because each potential customer's best alternative to buying one brand is to buy a competing brand. In this case, competitive firms could discriminate only on cross-elasticities. If all buyers had identical cross-elasticities, but differed in their industry elasticities (or reservation prices), then competitive firms would be unable to price discriminate, while a monopolist controlling all brands of a product would be able to use the differences in industry elasticities to price discriminate.

To develop an intuition for how price discrimination may increase with competition, consider an airline market in which the single incumbent charges "full fare" to business travellers (who are likely to have low industry and cross- elasticities) and a discount fare to discretionary travellers (who are likely to have higher industry and cross- elasticities). If entry induces the incumbent to lower both prices, but to lower the discount price by relatively more, then price dispersion will increase as concentration declines in the market. This pattern appears quite common in airline markets. Borenstein (1989a) finds that more competitive routes have lower average fares, other things equal, and that lower end fares are even more responsive to competition than are higher end fares.

We will refer to the case in which price discrimination is based primarily on industry elasticities as "monopoly price discrimination," and the case in which discrimination is based primarily on cross-elasticities as "competitive price discrimination." Whether sorting of customers is related primarily to their industry elasticities or primarily to their cross- elasticities, the factors that determine the amount of price dispersion that results from the discrimination tend to fall into three categories: market structure, consumer population attributes, and product characteristics.

Market Structure: Market structure could exert a strong effect on the level of price discrimination, although the direction of the effect on price dispersion will depend upon whether monopoly or competitive price discrimination dominates. Cross-elasticities of demand become a relatively more important determinant of price discrimination and industry elasticities become relatively less important as a higher proportion of a firm's marginal customers are deciding which of the available firms to buy from rather than deciding whether or not to buy the product at all. This will occur if, holding constant the number of flights on a route, those "brands" (flights) are operated by a large number of firms. Assuming that industry- and cross-elasticities of demand are positively correlated in the population, discrimination is likely to increase with concentration if industry elasticities are the more prevalent basis for segmentation (monopoly discrimination), and to decrease with concentration if heterogeneities in cross-elasticity are the more common source of discrimination (competitive discrimination). To measure market concentration, we construct *FLTHERF*, a Herfindahl Index based on the share of total flights performed by each airline on the route, defined over the range 0, 1.¹⁶

Population Attributes: Price discrimination is likely to increase with the variance of attributes in the population that reflect buyers' industry elasticities or cross-elasticities among brands.¹⁷ In most air travel markets,

¹⁶ Potential endogeneity of right-hand side variables is discussed in the next section. For *FLTHERF* as well as *FLTTOT* and *FLTSHARE*, described below, we also constructed analogous variables using passenger totals and shares, even though the theory suggests that flight-based variables are more appropriate measures, at least for the market density and share variables. The results using passenger-based variables are broadly consistent with those presented but the estimates are much less precise.

¹⁷ An exception to this can occur if the dispersion of some characteristic within the population implies a higher price for a group that would pay a lower price in the absence of that dispersion, or vice versa.

these consumer characteristics are likely to be strongly positively correlated. Business travelers seem to have lower industry demand elasticities and to have higher time valuations, making them less willing to switch flights to get a lower fare and implying a lower cross-elasticity of demand across firms or flights. Discretionary or "tourist" travelers are more likely to have high industry demand elasticities and to view competing flights or firms as close substitutes, implying high cross-elasticities. This suggests that under both monopoly and competitive price discrimination, price dispersion will be lower in markets where either business or tourist customers dominate the population than in markets where both types of passengers are prevalent.

Our control for variations in customer distribution is a somewhat crude measure of the tourist/business mix on a route. This variable, *TOURIST*, is based on a tourism index for each endpoint city weighted by the share of the carrier's traffic originating at the other endpoint city. *TOURIST* does well in identifying high tourism markets, but is not very powerful in distinguishing among markets with low or moderate amounts of tourist traffic.¹⁸ We therefore expect price dispersion to decrease as *TOURIST* rises even though a more precise measure of the tourist/business mix might show a quadratic effect.

The size of the consumer population and the resulting demand for air travel on a route is likely to affect the degree of price discrimination in a market. Greater population density is likely to generate greater equi-

¹⁸ Our tourism index is quite skewed, with only 10% of the observations falling more than one standard deviation above the mean. A few high tourism cities (such as Las Vegas and Reno and some of the Florida cities) account for a substantial share of the variation in *TOURIST*. Preliminary work with nonlinear functions of *TOURIST* suggested a limited ability of the data to pick up any but the high tourist market effects.

librium product variety, as measured by flight frequency, which may affect both monopoly and competitive price discrimination, although in opposite ways. More frequent service increases the convenience of traveling on the route and thus raises consumers' reservation prices generally (lowering industry elasticities). The increased value of the product probably is greater for business travelers, who tend to place a higher value on their time. Under monopoly price discrimination, improvements in service would imply increased price dispersion.

A high density of flights on a route also decreases the time between competing flights, thereby increasing the substitutability across flights. If these flights are offered by competing firms, the cross-elasticity across firms will tend to increase. This may lessen firms' abilities to discriminate on the basis of differences among consumers in their costs of switching flights. If heterogeneity in cross-elasticities is the basis for segmentation of demand – *i.e.*, competitive price discrimination – price dispersion is likely to decline as density increases.¹⁹

The effect of density highlights a possible asymmetry in price dispersion across firms that may depend on firms' relative positions in the market. If a carrier has a large share of the flights on a route, it may be less likely to respond to differences in cross-elasticities when setting its prices. For example, if an airline offers 10 of the 11 daily flights on a route, then a customer's willingness to switch from his most preferred departure time may have little effect on the carrier's pricing strategy, since the customer's second most preferred flight is likely to be with the same airline. The airline that offers only 1 of the 11 daily flights would be quite concerned

¹⁹ In the context of a spatial model of competition where each firm has only one outlet, this is analogous to a decrease in the "size" of the market holding constant the number of firms.

with distinguishing which of its potential passengers can most easily switch flights, however. In a sense, this is a continuity result from the position of a monopolist, who receives the business of a customer regardless of which flight is chosen.²⁰ This analysis suggests that price dispersion may decrease with market share under competitive price discrimination.

Market density is measured by the total number of flights on the route (*FLTTOT*). Its predicted effect is positive under monopoly price discrimination and negative under competitive price discrimination. We measure a carrier's market share by its share of total flights on a route (*FLTSHARE*). Under competitive price discrimination, price dispersion seems likely to fall as *FLTSHARE* rises.

Product Attributes: Differences between two markets in product attributes could induce differences in the level of price dispersion even if distributions of consumer types across the two markets are identical. This could occur when changes in some attribute of the product have a nonuniform effect on the elasticities of different customers. In the airline industry, frequent flyer plans (FFPs) seem to be the attribute most likely to increase the variance in customer elasticities.²¹ These programs offer bonuses, usually free trips, after passengers have purchased specified amounts of air travel from the carrier. Typically these schemes are highly nonlinear, with an increasing marginal value of bonuses as total miles flown with the carrier increases.

²⁰ Neither Borenstein, 1985, nor Holmes, 1989, address multiproduct firms and we have found no other theoretical work that sheds light on these hypotheses. Our intuition is that the asymmetry in price discrimination is likely to occur in a spatial model in which each brand competes more directly with some set of "neighbors" than with the remainder of the brands. It is less likely to occur in a model in which each brand competes symmetrically with all other brands.

²¹ Given that we have eliminated first-class and connecting service passengers from consideration.

FFPs tend to reduce both industry and cross-elasticities, by increasing the value of the total product delivered with a ticket (raising a customer's reservation price) and by giving a customer an incentive to concentrate his business with a single firm. These effects are likely to be much stronger for business travelers than for discretionary travelers, since infrequent travelers are much less likely to be active FFP participants.²² Since business travelers generally pay higher prices even in the absence of FFPs, these programs probably raise the dispersion of prices charged by an airline.²³

Unfortunately, the ticket data do not record whether the purchaser is a member of the airline's FFP, nor do we have direct data on the importance of FFP participation by airline and route. We use as a proxy for the potential significance of FFPs a measure of the airline's dominance of traffic at the endpoint airports on a route. FFPs are likely to be most attractive when an airline offers many flights from a customer's "home" airport, both because this offers opportunities for faster accumulation of mileage (and therefore more valuable bonus trips) and because it offers broader choices of destinations for bonus travel.²⁴ We try to capture this effect by *ENDDOMO*, a measure of the carrier's share of all originating

²² Given the nonlinear bonus schedules, customers who fly only a few times a year typically would take a number of years to qualify for bonus travel. This, combined with uncertainty about changes in the terms of free travel under the plans and the continued existence of FFPs over time, reduces their value to infrequent travelers.

²³ This tendency probably is exacerbated by the principal/agent problem that arises between the business traveler and his employer. Because the employee does not fully internalize marginal payments for airline tickets, while he receives the FFP bonuses directly, he is more likely to be willing to pay higher air fares in exchange for the FFP bonus.

²⁴ As Levine (1987) and Borenstein (1989a) argue, the frequent traveler may tend to concentrate his business with the airline that he is most likely to fly on in the future, which will probably be one of the airlines that offers the most flights from his home airport.

passengers at each endpoint airport on a route, weighted by the fraction of passengers on the route originating at that endpoint.²⁵ As a proxy for FFP effectiveness, we expect *ENDDOMO* to be positively associated with price dispersion under either monopoly or competitive price discrimination.²⁶

Table 2 summarizes the predicted signs of each variable discussed above under the alternative models of monopoly and competitive price discrimination.

Cost – based Sources of Price Dispersion

Price dispersion may be generated by cost variations as well as by price discrimination. We consider two sources of cost variations across passengers that may generate significant variation in observed ticket prices in our data set.²⁷ Both are types of peak-load or congestion pricing, which we distinguish as either “systematic” or “stochastic.” Systematic peak-load pricing reflects variations in the expected shadow costs of capacity at the time a flight is scheduled, while stochastic peak-load pricing refers to demand uncertainty for individual flights that is resolved only after equipment scheduling decisions are made. Though somewhat *ad hoc*, this distinction proves useful because the data allow us to control directly for the former effect, but not for the latter.

²⁵ We also have experimented with a measure of endpoint dominance based on the carrier's share of enplanements at each endpoint airport, *ENDDOME*. Differences between these two variables reflect the extent of hubbing at an airport. Both *ENDDOMO* and *ENDDOME* yield similar results in models that include carrier-specific fixed effects.

²⁶ This effect may be somewhat offset under competitive price discrimination to the extent that airport dominance lessens the threat of potential entry on a route from the airport and allows a carrier to behave more like a monopolist.

²⁷ As noted above, first-class and change-of-plane tickets are excluded, so these sources of cost-based dispersion are not considered explicitly.

Table 2

Predicted Coefficient Signs Under Alternative Models
of Price Dispersion

	<u>Price Discrimination</u>		<u>Peak-load Pricing</u>	
	<u>Monopoly</u>	<u>Competitive</u>	<u>Systematic</u>	<u>Stochastic</u>
Concentration (FLTHERF)	+	-	?	?
Density (FLTTOT)	0/+	-	0	0/+
Market Share (FLTSHARE)	+	-	?	?
Endpoint Dominance (ENDDOMO)	+	+	0	0
TOURIST	-	-	0	-
Variation in Flight Capacity (SDCAPFLT)	0	0	+	0
Variation in Airport Capacity (SDCAPAPT)	0	0	+	0
Uncongested Airport (DUMAPT)	0	0	-	0

Systematic Peak-load Pricing: Variations in capacity utilization over the time of day or day of week may generate differences in the opportunity cost of providing airline service, leading to prices that depend on when a particular customer travels.²⁸ During daily or weekly peak periods (*e.g.*, weekdays, especially Fridays, from 4:00 p.m. to 7:00 p.m.), most of an airline's aircraft will be in the air, so the expected shadow cost of aircraft capacity will be quite high. At other times, airlines may be operating 60 percent or less of their equipment, and the shadow cost of additional seats will be near zero. Similarly, when airport runways or air traffic control are operating near capacity, congestion is likely to lead to slowdowns and associated cost increases. Airlines may be unable to add additional flights, raising the shadow cost of a seat. Peak-load pricing, reflecting variations in these shadow costs, will result in higher prices during congested periods and lower during off-peak periods.

This type of price variation can be systematic in the sense that it is based on variations in shadow costs that are known at the time a flight is opened for booking (typically 11 months prior to its departure date). Airlines know their own utilization rates (and presumably expected airport congestion levels) at the time their flight schedule for a route is set. Flight schedules are rarely changed in response to demand patterns once a flight is opened for booking. Flights scheduled for peak periods will be allocated fewer discount seats, thus raising their average fares. Off-peak flights will tend to be allocated a larger number of discount seats, with lower average fares.

²⁸ Holidays, *e.g.*, Thanksgiving, and seasonal variations in demand also may generate predictable peak-load pricing patterns over the year. The period we examine, April-June, is a "shoulder" demand period (*i.e.*, neither the summer peak nor the winter trough) and does not have significant holiday spikes in traffic.

The Department of Transportation's airline ticket database does not provide information on the travel times or flight numbers corresponding to recorded fares. While this precludes a direct estimate of time-of-day or day-of-week congestion premia, price dispersion due to systematic peak-load pricing should be correlated with the variability in airlines' fleet utilization rates and airports' operations rates. For example, if all flights on American between two (uncongested) airports take place at off-peak periods, when less than, say, 60 percent of American's fleet is in use, there should be almost no price variation due to peak-load pricing. On the other hand, if one of American's flights on this route occurs at 8 a.m. on weekdays, when nearly all of the carrier's planes are in use, and its other flights on the route are at off-peak times, then variation in the shadow price of aircraft capacity for American's flights on this route will imply variation in observed ticket prices. Similarly, if some of a carrier's flight on a route occur when the endpoint airports are congested and others do not, variation in the shadow cost of runway usage should be reflected in price variation. Information on airlines' fleet utilization rates and the endpoint airports' operations rates for flights on each route may enable us to identify dispersion due to congestion pricing.

Using this information requires us to identify the constraints at peak periods and to decide how to quantify variations in these constraints so as to reflect variations in costs on the route. We assume that airline fleet capacity and airport congestion are the two most important constraints on providing peak service.²⁹ Congestion costs and shadow capacity costs

²⁹ Neither of these measures controls explicitly for a third congestion cost that occurs when most or all of the airline's gates at an airport are in use at the same time. Scarce gate capacity will add an additional cost, but we believe that this cost will be highly correlated with the two measures of congestion that we examine.

are probably highly nonlinear functions of capacity utilization. The effect of a marginal change in utilization is likely to be greatest at high levels of capacity utilization and to be relatively small over a wide range of low utilization rates. *Variations* in congestion costs and shadow costs of aircraft capacity are therefore likely to be low when most flights take place on a route during periods of low or moderate fleet or airport utilization, to rise as more flights are scheduled during high (peak) utilization rate periods, and to fall when most flights are scheduled during peak utilization rate periods.³⁰ To capture the notion that congestion and shadow costs are convex in capacity utilization, we use higher order powers of the utilization rate to represent the cost variables and measure variations in such costs by the standard deviation of these variables over the periods that flights on the route are scheduled.³¹

The results reported below use the standard deviation of the cubed airline fleet utilization rate, *SDCAPFLT*, and the standard deviation of the cubed airport operations utilization rate, *SDCAPAPT*, to reflect variations in peak usage. Qualitatively similar results were obtained with measures based on squared rates or higher order terms. Because traffic never reaches capacity levels at most smaller U.S. airports, even during peak travel periods, we construct airport capacity utilization rates only for the 22 airports that as of 1986 were designated by the Federal Aviation Administration as congested and two additional airports that have strict use restrictions imposed by local authorities. For routes between the remain-

³⁰ This last possibility – most or all flights on a route scheduled during high utilization rate periods – is rarely observed in our data.

³¹ The actual construction of these variables is detailed in the data appendix. In the analysis reported below, fleet utilization rates are measured by aircraft utilization rates. The results are substantially the same when utilization rates are based on seats.

ing airports, we assume that variations in airport operations rates do not contribute to variations in congestion or shadow costs of providing service. We therefore set *SDCAPAPT* equal to zero and include a dummy variable, *DUMAPT*, for these routes. To the extent that price dispersion is related to cost-based peak-load pricing variations, the coefficients on *SDCAPFLT* and *SDCAPAPT* should be positive and the coefficient on *DUMAPT* should be negative.

Systematic peak-load pricing also could affect coefficient estimates for some of the variables used to distinguish between monopoly and competitive price discrimination. Since this may influence the interpretation of our results, we describe the coefficient patterns that may be suggested by peak-load pricing and summarize these predictions in table 2, column 3. The extent of price dispersion due to variations in the shadow cost of fixed inputs may be affected by market structure, suggesting that effects from peak-load pricing may influence the coefficient estimates for *FLTHERF* and *FLTSHARE*. Unfortunately, these effects cannot be signed *a priori*. Depending on the shape and location of the demand curves, the differences between peak and off-peak prices may be larger or smaller for competitive firms than for a monopolist.³² Of course, to the extent that that price variation departs from shadow cost variation, we could accurately refer to such departures as price discrimination under the definitions suggested by Stigler (1987) and Varian (1989). We do not expect dispersion due to sys-

³² This statement is clearly true when the peak and off-peak demand curves have very different elasticities. Simulations revealed, however, that it is also true when the elasticities do not change as the strength of demand varies. We assumed a demand function $Q = L/P^e$, where L is a uniformly distributed random variable, marginal cost is constant, and per-unit capacity rental costs are constant. The monopolist that chooses capacity optimally in such a market and then charges the profit-maximizing price in each period (after demand is revealed) may have a greater or lesser coefficient of variation in its prices than would obtain when capacity and prices are set in a competitive market.

tematic peak-load pricing to be correlated with the number of flights in a market, endpoint dominance, or tourism, once we control for the variation in flight times through the capacity utilization variables.

Stochastic Peak-load Pricing: Models of peak-load pricing under demand uncertainty suggest that optimal prices should reflect marginal operating costs plus a charge based on both the probability that demand will exceed capacity and the expected shadow cost of capacity if it does.³³ If uncertainty about demand is resolved over time, changing the perceived probability that demand will exceed capacity, then observed prices may depend on when a ticket is purchased. For example, if demand is revealed over time to be higher than expected for an April 15, 4 p.m. flight, tickets purchased close to April 15 may carry higher prices than tickets purchased long before the departure date.³⁴ This stochastic component may induce price variation among the passengers on a single flight or the same flight number on different days (with identical expected demands *ex ante*), as compared to systematic effects that can induce variation in the prices paid by passengers on different flights with differing expected demands *ex ante*.

Diagnosis of the effects of stochastic peak-load pricing on price dispersion requires at least information on the variability of demand across individual departures on a route. Average price, demand, or load factor by scheduled flight number, *e.g.*, the average demand for the Friday 4 p.m. flight on a route, is not sufficient information to determine the effects of possible stochastic peak-load pricing. Since historical data on these aver-

³³ See, Crew and Kleindorfer (1986).

³⁴ It is the uncertainty about the probability of reaching capacity that generates such cost-based price differences. If a flight is almost certain to be less than full, prices should not change as the flight date approaches, even if there is some variation in expected demand, as long as the probability of a full flight does not change significantly.

ages would be available to the airline at the time that flights are scheduled, predictable variations of this sort should be addressed in aircraft scheduling. The stochastic component of demand for a flight, in the sense that we are discussing it here, is orthogonal to all information that a carrier has at the time that it opens a flight for booking. Absent information on each flight departure, we cannot directly control for price dispersion due to stochastic peak-load pricing.

This raises the question of how omission of direct controls for stochastic peak-load pricing affects the interpretation of the parameter estimates that we use to detect price discrimination. First, as with systematic peak-load pricing, the price dispersion that results from stochastic peak-load pricing may be larger for monopolists or for competitive firms, depending on the characteristics of demand, affecting coefficient estimates for *FLTHERF* and *FLTSHARE*. Stochastic peak-load pricing is likely to have a non-negative effect on the coefficient estimate for *FLTTOT*, since the variance of passenger demand for each specific flight will tend to be constant or increasing in number of flights.³⁵ An effect on the *TOURIST* coefficient also is possible, a positive influence if tourists as a whole generate more demand variance for specific flights and a negative influence if tourist demand for specific flights is less variable. We do not expect *ENDDOMO* to be affected by stochastic peak-load pricing, and the capacity variables, which reflect systematic peak-load variations, should be orthogonal to stochastic variations in demand by definition. These pre-

³⁵ Assuming that average load factors are not affected. For example, consider two markets, one with N passengers and F flights and a second with $2N$ passengers and $2F$ flights. If each passenger has some probability p , $p = 1/FLTTOT$, of choosing flight i , and flight choices follow a binomial distribution, then the variance of the number of passengers choosing flight i , is equal to $Np(1-p)$. For the smaller market, this variance is equal to $N(1-1/F)/F$. For the larger market, the variance is equal to $N(1-0.5/F)/F$.

dicted signs are summarized in column 4 of table 2.

While we cannot directly control for stochastic peak-load pricing, it is important to recognize that airline pricing patterns deviate from the predictions of peak-load pricing models in a number of ways. Perhaps most significant are the restrictions that accompany discount tickets – advance-purchase and minimum-stay requirements rather than just time-of-use or time-of-purchase differentials. These cannot be justified solely on the basis on shadow capacity costs. Discounts for tickets that require Saturday night stays but do not restrict departure or return dates cannot be explained by either systematic or stochastic peak-load cost differences. One airline pricing manager has described these as “the single best restriction of them all [for] separating business from pleasure travel.”³⁶ Substantial advance purchase discounts are too large to be explained solely by cost differences, although two cost-based arguments frequently are offered. The first is that bookings made far in advance allow the airline to more accurately forecast demand and, in response, to reschedule equipment. As mentioned above, airlines almost never alter flight schedules in response to advance bookings. The second is that the type of people who meet these restrictions have more firm travel plans and are therefore less likely to be “no-shows.” This certainly is true, particularly with the large cancellation penalties now attached to many discount tickets, but Borenstein, 1983, demonstrates that the difference in the no-show rates of discount versus full-fare passengers can justify at most a 6% price differential under the most extreme assumptions. Under realistic assumptions, and recognizing that the practice of overbooking allows airlines to lessen the cost of no-shows, the cost-based

³⁶ Elkins (1986)

price difference would probably be 2% or less.³⁷

IV. Specification of the Empirical Model

An observation in our empirical work is the price dispersion of a single carrier, k , among all "local" passengers that it carries between two airports, i, j .³⁸ We measure price dispersion by the *GINI* coefficient of fares, as defined in section II. Because theory provides little guidance on the functional form of the empirical model, we present results from log-log (constant elasticity) and linear functions.³⁹ The basic specification we estimate is the constant elasticity log-log model:⁴⁰

³⁷ Gale & Holmes, 1990, argue that advance-purchase restrictions could be used to efficiently allocate seats on peak-demand flights to those who value them most, but they then conclude that such restrictions dominate explicit peak-load pricing for a (monopoly) firm because they allow greater extraction of consumer surplus. This result suggests to us price discrimination, not cost-based price variation.

³⁸ The term "local" here means that passengers who travel between these two airports, but are connecting to other flights, are excluded. We treat individual airports within a city (such as O'Hare and Midway in Chicago) as separate markets.

³⁹ We also estimated the equation in log-linear form (constant proportionality). Because the log-log results generally fit the data better than do the log-linear results, we present results only the log-log and linear specifications. The results are, however, qualitatively similar across all three functional forms.

⁴⁰ This implicitly assumes that the error term ϵ_{ijk} is distributed log-normal. While the limited range of the *GINI* could pose difficulties with this assumption, there are no observations at the lower boundary of zero dispersion and none close to (within twice the estimated standard deviation of the error term) the theoretical upper boundary of the *GINI*, 1.00

$$\begin{aligned}
\ln GINI_{ijk} = & \beta_0 + \beta_1 \ln FLTHERF_{ij} \\
& + \beta_2 \ln FLTTOT_{ij} + \beta_3 \ln FLTSHARE_{ijk} \\
& + \beta_4 \ln ENDDOMO_{ijk} + \beta_5 \ln TOURIST_{ijk} \quad (2) \\
& + \beta_6 \ln SDCAPFLT_{ijk} + \beta_7 \ln SDCAPAPT_{ijk} \\
& + \beta_8 DUMAPT + \ln \epsilon_{ijk},
\end{aligned}$$

where \ln denotes the natural log and ϵ_{ijk} is the error term.⁴¹ Descriptive statistics for all variables used in the analysis are contained in table 3.

The regressions reported are estimated by two-stage least squares, which addresses the likely endogeneity of several of the right-hand side variables, as we discuss below. Carrier-specific fixed effects are included to allow for the possibility that carrier effects are correlated with the other right-hand side variables. If common route-specific effects induce a correlation of the errors ϵ_{ijk} across carriers on the same route, ordinary (or two-stage) least squares would be unbiased, but inefficient. Tests for within route correlation of errors were highly significant, so we have estimated the regressions by feasible generalized least squares with route-specific random effects.⁴²

If price discrimination enables a carrier to increase its number and share of passengers (and therefore of flights), the variables *FLTTOT* and *FLTSHARE* may be correlated with the error in our price dispersion equation. To treat this potential endogeneity, we instrument for *FLTTOT*

⁴¹ In the log-log regressions, the log of *SDCAPAPT* is set equal to zero for observations in which *DUMAPT* is equal to one.

⁴² Estimation with route-specific fixed effects would require elimination of 185 routes on which we have only one carrier observation and would not permit us to estimate the effect of variables common to all observations on a route, i.e., *FLTHERF* and *FLTTOT*.

Table 3

Summary Statistics for Observations Used in Regression Analysis

<u>Variable</u>	<u>Mean</u>	<u>Standard Deviation</u>	<u>Minimum</u>	<u>Maximum</u>
GINI	0.181	0.063	0.018	0.416
FLTHERF	0.437	0.190	0.163	1.000
FLTTOT	0.177	0.126	0.014	0.930
FLTSHARE	0.394	0.244	0.002	1.000
ENDDOMO	0.207	0.117	0.009	0.715
TOURIST	0.013	0.013	0.003	0.070
TOURISTD	0.148	---	0.000	1.000
SDCAPFLT	0.197	0.063	0.000	0.358
SDCAPAPT	0.092	0.058	0.000	0.288
DUMAPT	0.089	---	0.000	1.000
GEOSHARE	0.269	0.171	0.011	1.000
AMEANPOP	2.891	1.574	0.376	8.921
GMEANPOP	2.292	1.378	0.197	8.909
PAX1975	1336.0	1596.7	0.100	13058.0
DISTANCE	624.32	468.60	77.00	2677.00

with a pre-deregulation measure of total passenger volume on the route (*PAX1975*), the geometric and arithmetic averages of the 1986 populations at the two endpoints of the route (*GMEANPOP* and *AMEANPOP*), and the distance between the two airports (*DISTANCE*). The instrument for *FLTSHARE* is a measure of the carrier's share of enplanements at both of the endpoint airports (*GEOSHARE*).⁴³ If *FLTSHARE* is endogenous, the measure of overall concentration, *FLTHERF*, also will be contaminated. We therefore include as an instrument *XFLTHERF*, which uses a predicted route share rather than the actual route share of the observed carrier in constructing the Herfindahl Index.⁴⁴

V. Results of Empirical Analysis

Table 4 reports estimates for the basic model specified in equation (1) and for a linear version of the same model. The first 2 columns report coefficients from random-effects, 2SLS estimation; the last 2 columns report corresponding coefficients from 2SLS estimation without correction for correlation of the residuals. The general robustness of the results across these two weighting schemes suggests that omitted variables, including potential route fixed effects, do not substantially bias the results.⁴⁵ For the two linear specifications, the point estimates within about one standard error of one another for all variables. In the log-log specification, the coefficient

⁴³ See the data appendix for the construction of this instrument and see Borenstein, 1989a, for a discussion of its use as an instrument for route share.

⁴⁴ Specification tests for the endogeneity of *FLTTOT*, *FLTSHARE*, and *FLTHERF* provided evidence of some bias if the first two were treated as exogenous. No bias was indicated in treating *FLTHERF* as exogenous, but since these tests have low power and *FLTHERF* is in part a function of *FLTSHARE*, we present results treating all three flight variables as endogenous.

⁴⁵ Hausman and Taylor, 1981.

Table 4

Price Dispersion Regression Results

Dependent Variable: GINI
(n = 1021)

<u>Variable</u>	<u>2SLS -- RANDOM EFFECTS</u>		<u>2SLS</u>	
	<u>Log-log</u>	<u>Linear</u>	<u>Log-log</u>	<u>Linear</u>
FLTHERF	-.421 ^a (.079)	-.121 ^a (.028)	-.270 ^a (.067)	-.094 ^a (.033)
FLTTOT	-.279 ^a (.058)	-.106 ^a (.039)	-.246 ^a (.057)	-.066 ^a (.025)
FLTSHARE	.020 (.064)	.043 (.030)	-.103 (.086)	.020 (.040)
ENDDOMO	.076 ^b (.030)	.054 ^b (.026)	.127 ^a (.038)	.072 ^b (.030)
TOURIST	-.082 ^a (.023)	-.596 ^a (.177)	-.082 ^a (.020)	-.589 ^a (.148)
SDCAPFLT	.056 ^c (.031)	-.018 (.034)	.089 ^b (.043)	-.008 (.039)
SDCAPAPT	.040 ^c (.024)	.068 ^c (.040)	.078 ^a (.027)	.080 ^c (.044)
DUMAPT	-.353 ^a (.086)	-.022 ^b (.008)	-.470 ^a (.089)	-.022 ^b (.008)

All regressions include carrier specific fixed effects.
Asymptotic standard errors reported in parentheses.

a - significant at 1% level
b - significant at 5% level
c - significant at 10% level

estimates are slightly less stable, but are within two times the standard errors of one another for all variables except *FLTHERF*. The qualitative results generally are insensitive to other changes in the specification of the model, although the precision of the parameter estimates varies. We focus our discussion on the results from the constant-elasticity, random-effects specification.

The strongest result is the significant negative effect of increases in route concentration on price dispersion. In the log-log model, holding constant the carrier's route share, an increase of one standard deviation in *FLTHERF* from its mean reduces *GINI* by about 18%. This result is consistent with the predictions of competitive price discrimination models, suggesting that price dispersion due to discriminatory pricing may increase as airline markets become more competitive. While the negative *FLTHERF* coefficient estimates reject the model of monopoly price discrimination as the sole or dominant source of airline price dispersion, the estimates could reflect peak-load pricing, as explained earlier.

Further support for the competitive price discrimination interpretation of the *FLTHERF* coefficient is provided by the coefficient on the route density variable, *FLTTOT*. Higher route density appears to lower a carrier's price dispersion, holding constant market concentration and the carrier's route share. In the log-log model, increasing *FLTTOT* by one standard deviation from its mean reduces the Gini coefficient by 20%. This is consistent with price discrimination that is based on differences in customers' willingness to switch firms, which become less important as the number of flights increases and the differences among firms decrease (as measured by differences in departure times).⁴⁶ The sign of this coefficient

⁴⁶ Competitive price discrimination implies that the effect of density should depend

is inconsistent with the predictions generated by models of monopoly price discrimination, systematic peak-load pricing, and stochastic peak-load pricing, as noted in table 2.⁴⁷ This does not imply that price dispersion is due solely to competitive price discrimination, rather that observed patterns of dispersion across markets and carriers appear at least in part attributable to competitive price discrimination.

The estimated effects of a carrier's relative market position on price dispersion are mixed. The estimated impact of larger route shares, measured by *FLTSHARE* is positive in both specifications when estimated with random effects, but is not statistically significant and it is negative in the log-log model when the GLS correction is not carried out. Airport dominance, measured by *ENDDOMO*, tends to raise dispersion. In the log-log specification, a one-standard deviation increase in *ENDDOMO* from its mean raises dispersion by 4%. Though our analysis does not enable us to diagnose the mechanism through which endpoint dominance induces higher price dispersion, the results are consistent with a greater effectiveness of frequent flyer programs in raising high-end or business class fares at airports that the carrier dominates.

Higher concentrations of tourist traffic are consistently associated with lower levels of price dispersion, as expected. When the value of *TOURIST* is one standard deviation above its mean value, the Gini coefficient is 8% smaller than it is at the mean of *TOURIST*. This effect

on market concentration levels. While the coefficient on *FLTTOT* is more negative when *FLTHERF* is low, consistent with this implication, the data do not allow us to statistically distinguish between *FLTTOT* coefficients in low and high concentration markets.

⁴⁷ There is a possible caveat to this conclusion. If higher *FLTTOT* lowers the stochastic component of demand for a flight at peak demand time, which would probably lower the expected shadow value of capacity at peak demand time, then this result could be consistent with stochastic peak-load pricing.

may reflect variation in both industry and cross-elasticities, since tourist travelers are likely to have higher absolute values of both. We expected this attribute of the consumer population to act nonlinearly on price dispersion, causing less dispersion when it is at either its high or its low end. In exploratory analysis, however, *TOURIST* appeared to capture only the decrease in dispersion on routes with the highest tourist values, primarily those routes including cities in Hawaii, Florida, and Nevada. This may result from the rather crude nature of our tourism proxy: the variable does best at distinguishing high tourism markets and is less effective at distinguishing primarily business markets from more balanced markets.⁴⁸

The results for our controls for airline and airport capacity utilization measures are roughly as expected. *SDCAPFLT*, which measures variation in airline fleet utilization rates, is statistically insignificant in the linear model, but is significant at the 10% level in the log-log model, where a one-standard deviation increase in *SDCAPFLT* from its mean raises dispersion by 2%. Increased variation in airport operations rates, reflected in *SDCAPAPT* and *DUMAPT*, is consistently associated with increased price dispersion, as would be expected if airlines engage in peak-load or congestion pricing over time-of-day and time-of-week. In the log-log specification, a one standard deviation increase in *SDCAPAPT* from its mean raises the Gini coefficient by 3%. Routes on which neither endpoint airport is congested (*DUMAPT* equal to 1) average 26% less price dispersion than do routes on which at least one endpoint airport is congested, other things

⁴⁸ We also have replaced *TOURIST* with a dummy variable (*TOURISTD*) for high tourism routes. In these models, the estimated Gini coefficient for high tourism routes is roughly 25% below that for all other routes. The data do not distinguish further differences in price dispersion among the high tourism markets.

equal.⁴⁹

The results of this statistical analysis suggest the existence of price discrimination based on heterogeneity in cross-elasticities of demand, as well as dispersion due to peak-load pricing. This does not imply that either discrimination based on industry elasticities or dispersion attributable to other cost variations is absent. The regressions have significant nonzero constant terms and predict price dispersion even on monopoly routes. Moreover, since the regressions account for less than 20% of the variation, there is considerable price dispersion that may be explained by factors related to sorting on industry elasticities or by factors related to unobserved variations in the cost of service.

The results also suggest that price dispersion may be affected by differences in carriers' abilities to execute sophisticated pricing policies. The data reveal substantial differences in the average level of price dispersion across carriers, even after controlling for the specified population, product, and market characteristics. Table 5 reports the estimated carrier fixed effects from the constant elasticity Gini regressions estimated with random effects. These coefficients measure each carrier's average price dispersion relative to American Airlines' average dispersion. Notably, airlines that operated a computer reservation system (CRS) in 1986 – American, Delta, Eastern, TWA, and United – generally exhibit a greater degree of price dispersion than carriers that did not operate CRSs. In fact, the difference between the average fixed effect for carriers that operate CRSs and the average for those that do not is statistically quite significant. The result is

⁴⁹ This figure comes from calculating the effect of $\ln SDCAPAPT$ on price dispersion at its average non-zero value and comparing it to the estimated decrease in dispersion when $DUMAPT$ is equal to one (and, by construction, $\ln SDCAPAPT$ is set equal to zero).

Table 5

Estimated Carrier-Specific Effects from 2SLS Random Effects Estimation
(n = 1021)

	<u>Log-log Model</u>	<u>Linear Model</u>
<u>Owners of Computer Reservation Systems:</u> (relative to American Airlines)		
DELTA	-.015 (.038)	-.011c (.006)
EASTERN	-.077c (.040)	-.016b (.006)
TRANS WORLD	.243a (.050)	.042a (.008)
UNITED	-.128a (.037)	-.023a (.006)
 <u>Non-Owners of Computer Reservation Systems:</u> (relative to American Airlines)		
USAIR	-.171a (.047)	-.033a (.008)
CONTINENTAL	-.153a (.046)	-.030a (.007)
NORTHWEST	-.156a (.048)	-.033a (.007)
PIEDMONT	.025 (.051)	-.007 (.008)
REPUBLIC	-.118b (.048)	-.026a (.008)
WESTERN	-.154b (.069)	-.030a (.010)

Fixed effect for American Airlines omitted from estimation.
Asymptotic standard errors reported in parentheses.

a - significant at 1% level
b - significant at 5% level
c - significant at 10% level

consistent with the claim that a CRS assists in utilization of sophisticated "yield management" techniques, *i.e.*, methods for allocating discount seats in a way that maximizes revenue on each flight.

VI. Conclusion

This study documents the existence of significant dispersion in the prices charged by a given airline in a given airline market. It provides clear evidence that the level of a carrier's price dispersion within a market is related to the structure of the market. As the number of competitors in a market grows, holding constant the total number of flights, price dispersion increases. This and other empirical results of the analysis imply that traditional monopoly theories of price discrimination may give neither complete explanations nor accurate predictions of pricing patterns in monopolistically competitive markets.

In addition to providing a description of pricing behavior in the airline industry, this study points out a need for additional theoretical work on price discrimination. Price discrimination in markets with many multi-product firms seems to respond to additional factors and to behave in substantially different ways than does price discrimination in markets characterized either by multi-product monopoly or by many single-product monopolistically competitive firms. The theoretical literature has been relatively quiet on this subject, though some of the extensions from literature on monopolistically competitive price discrimination may be straightforward.⁵⁰ A careful, thorough model of such a market, possibly along the line of Holmes' (1989) duopoly model, may provide a useful guide for fu-

⁵⁰ The literature on price discrimination with search costs or imperfect information may also shed light on the topic. See, for instance, Salop, 1977, and Salop & Stiglitz, 1977.

ture empirical work.

Our exploration of airline price dispersion is not exhaustive and some of the cost-based explanations for price dispersion are not fully testable with these data. The basic relationships appear to be quite robust, however, and seem unlikely to be explained solely on cost bases. Our findings invite further research to determine whether the relationships we find between price dispersion and market structure variables extend to other industries.

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Appendix: Data Description and Construction of Variables

Each observation in the sample is a unique carrier-route pair. A route is a pair of airports between which passengers in this sample travel without changing planes. A round-trip ticket is considered to be two directional trips on the route and the fare paid on each directional trip is taken to be half of the round-trip fare. A one-way ticket is one directional trip on the route.

PRICE DATA :

The source of the ticket and price data is Databank 1A (DB1A) of the Department of Transportation's Origin and Destination Survey for the second quarter of 1986. The DB1A is a random 10% sample of all tickets that originate in the U.S. on U.S. air carriers. We use a version of the database that has been processed by Boeing Computer Services. The Boeing processing eliminates all tickets that are not either one-way or round-trip travel, such as open-jaw (e.g., LAX-BOS-SEA) and circle trips (LAX-MIA-BOS-LAX). It also removes tickets that involve more than one change of plane on any directional trip.

After intensive examination of the DB1A data and discussions with Boeing and Department of Transportation officials, a number of further adjustments to the database were made:

1. Exclusion of tickets that:
 - a. Included one or more segments of first-class travel.
 - b. Included travel on more than one airline on a directional trip (known as interline tickets).
 - c. Included an origin or destination at an airport outside the U.S. or at an airport that is not one of the 200 largest U.S. airports. This latter criterion is not unduly restrictive, as the 200th largest U.S. airport is in Deadhorse, Alaska, where an average of 138 passengers were enplaned each day.
2. Exclusion of tickets that indicated probable fare keypunch error or frequent flyer bonus trips. These were selected as follows:
 - a. All tickets with fares of \$10.00 or less. These are presumed to be frequent flyer bonus trips, which are not reported in any consistent way by different carriers.
 - b. Tickets with fares in excess of specified multiples of the calculated Standard Industry Fare Level (SIFL) for the route. This criteria is similar to one used by Boeing Computer Services in their internal processing of the DB1A. The SIFL for a route is based on a non-linear function of distance similar to the formula that was used by

the Civil Aeronautics Board (CAB) to determine permissible regulated airfares. To calculate the SIFL we computed the nonstop DISTANCE in miles (described below) between the two endpoint airports and applied a formula used by Boeing Computer Services to calculate 1986, 2nd quarter fares. The formula is:

$$SIFL = 26.02 + .1423 * (\text{MILES } 0 - 500) + .1085 * (\text{MILES } 501 - 1500) \\ + .1043 * (\text{MILES } 1501 - \text{END})$$

For routes of 500 miles or less, we excluded tickets reporting fares of 4.0 or more times the SIFL. For routes above 500 miles, we excluded tickets reporting fares of 3.5 or more times the SIFL.

3. Exclusion of all Alaskan Airlines tickets. This decision was dictated by the unreliability of data reported by this airline, including an exceptionally high frequency of fare errors (e.g. very high percentages of one-way coach fares in excess of \$5,000).

4. Exclusion of all routes served by United Airlines that included LaGuardia or JFK International Airports as an endpoint. This was required by United's tendency to combine most tickets with a LGA or JFK endpoint under a single generic New York City Airport #7 code.

5. Assignment of New York Air's tickets with a reported endpoint of Washington, D.C. Airport #3 (which does not exist) to Dulles International Airport (Washington, D.C. airport #1), based on advice from officials at Boeing Computer Services.

From the DB1A, we calculated the total reported passengers for all carriers on each route and selected the 1200 largest routes (there were 1201 routes due to a tie for position 1200). The analysis in this study is conducted for the routes in this set for which 80 percent or more of the passengers travelled direct (i.e., without a change of plane on the directional trip). To maximize comparability of service quality across passengers, tickets indicating a change of plane were excluded from the analysis. The DB1A does not permit us to distinguish nonstop service from direct service that includes on-flight stops.

VARIABLE DESCRIPTIONS :

GINI: Geometrically, the Gini coefficient is defined as twice the area between the 45 degree line in a plot of percent-of-passengers on percent-of-revenue and the Lorenz curve, which is the line that plots the percent of revenue contributed by the bottom $x\%$ of passengers ($0 \leq x \leq 1$). We computed *GINI* by the formula:

$$GINI = 1 - 2 * \left(\sum_{i=1, N} Fare_i * PAX_i / Total Revenues \right) \\ * \left(PAX_i / Total PAX + \left(1 - \sum_{j=1, i} PAX_j / Total PAX \right) \right)$$

where N is the number of different fare level tickets reported by a carrier on a route, $Fare_i$ is the reported fare for the i th ticket, and PAX_i is the reported number of passengers travelling at that fare.

CV: The coefficient of variation, *CV*, is defined as the passenger-weighted standard deviation of fares divided by the passenger-weighted mean fare for a carrier on a route.

CFLTTOT: The observed carrier's total number of direct flights on a route per week in either direction. If there is at least one nonstop flight on the route, then all nonstop and onestop flights are included. If there is no nonstop flight on the route, then all onestop and twostop flights are included. Source: *Official Airline Guide*, May 15, 1986.

FLTTOT: The total number of direct flights on a route per week in either direction, calculated as the sum of *CFLTTOT* for all scheduled jet airlines serving the route.

FLTSHARE: The proportion of flights on a route accounted for by the observed carrier, defined as *CFLTTOT* divided by *FLTTOT*.

FLTHERF: The Herfindahl index of concentration on the observed route, using *FLTSHARE* as the measure of market share for each carrier.

ENDDOMO: A measure of endpoint dominance based on origination. *ENDDOMO* is defined as the weighted average across the endpoints of the route of the observed airline's share of passenger origination at each endpoint. An origination is the beginning of a directional trip (it differs from enplanements in that enplanements include passengers changing planes for

continuations of directional trips). The weight for each endpoint is $DIRECT_{ijk}$ - see the discussion at *APAX* for its definition.

SDCAPFLT: The standard deviation of cubed fleet utilization rates for the observed carrier on the observed route. For each scheduled flight on a route (where flights are defined by time of day and day of week), we compute the average number of aircraft the carrier has in flight system-wide during the time the flight on the observed route is scheduled (defined as from 10 minutes before scheduled takeoff to 10 minutes after after scheduled landing). This yields a measure of capacity utilization during that flight. We divide this by the maximum number of aircraft the carrier has in flight at any point during its weekly schedule to obtain a capacity utilization rate for that flight. We cube the capacity utilization rate for each flight, then compute the standard deviation of this variable across all flights for the carrier on the route to obtain *SDCAPFLT*. We also have experimented with *SDCAPF2* (based on the square of the capacity utilization rate) and *SDCAPF4* (based on the fourth power of the capacity utilization rate). Flight information is based on the *Official Airline Guide*, May 15, 1986.

SDCAPAPT: The standard deviation of cubed airport capacity utilization rates for the observed carrier on the observed route, if one or both endpoint airports are on the FAA's list of the 22 most congested airports (or is Long Beach or Orange County Airport, the two that have very restrictive local regulation). Otherwise, *SDCAPAPT* is set equal to zero. This variable is analogous to *SDCAPFLT*, except that capacity utilization rates are constructed from airport activity measures. Flight information is based on the *Official Airline Guide*, May 15, 1986.

TOURIND: A tourism index for a metropolitan area, defined as Hotel Income from Group/Tourist customers divided by Total Personal Income. **Source**: Census of Service Industries, 1977, for proportion of hotel revenues from Group/Tourist customers; Census of Service Industries, 1982, for metropolitan area hotel revenues; State and Metropolitan Area Data Book, 1985, for total personal income.

TOURIST: The weighted average of a truncated *TOURIND* for the two endpoints of the observed route. *TOURIND* is truncated at .07 for all endpoints (this downweights the index primarily for Reno and Las Vegas, where hotel revenue includes gambling income). The weight for an endpoint is the proportion of the observed carrier's passengers on the route who originated their travel at the other endpoint. For route ij , the weight for endpoint i is $(1 - DIRECT_{ijk})$; for endpoint j the weight is

$DIRECT_{ijk}$ - see the discussion at *APAX* for its definition.

TOURISTD: A dummy variable equal to one for observations with a value of *TOURIST* in excess of .02, 0 otherwise. Approximately 15 percent of the observations have values of *TOURIST* in excess of .02. We also experimented with sets of dummy variables that broke a weighted average *TOURIND* into three categories: .02 to .0499, .05 to .0799, and .08 and above. The data generally did not reject equality of coefficients across these categories.

DISTANCE: The Great Circle route nonstop mileage between the two endpoint airports on a route, calculated from airport latitude and longitude coordinates. This calculation ignores change of plane and on-flight stops. The coordinates are from the Department of Transportation's Databank 5.

AMEANPOP: The arithmetic mean of the populations of the endpoint SMSAs of the route. For SMSAs with more than one airport in the top 200, the population is apportioned to each airport according to each airport's share of total enplanements in the SMSA. Source: 1987 Statistical Abstract of the U.S.

GMEANPOP: The geometric mean of the populations of the endpoint cities of the route. See *AMEANPOP*.

GEOSHARE:

$$GEOSHARE = \frac{\sqrt{ENP_{x1} \cdot ENP_{x2}}}{\sum_y \sqrt{ENP_{y1} \cdot ENP_{y2}}}$$

where y indexes all airlines, x is the observed airline, and ENP_{y1} and ENP_{y2} are airline y 's average daily enplanements at the two endpoint airports during the second quarter of 1986.

PAX1975: The total passengers reported on the route during the year ending September 30, 1975. Source: U. S. Civil Aeronautics Board, Origin and Destination, Table 11.

XFLTHERF: Created under the assumption that the concentration of the flights on a route that are not performed by the observed airline is exogenous with respect to the price of the observed carrier, *e.g.*, that TWA's price on the JFK-Los Angeles route does not affect the division of non-TWA flights between American and United. *XFLTHERF* is the square of the fitted value for *FLTSHARE* (from its first-stage regression) plus the "rescaled" sum of the squares of all other carrier's shares. The rescaling maintains among all carriers other than the one observed the concentration of flights not performed by the observed carrier. To be concrete:

$$XFLTHERF = FLT\widehat{SHARE}^2 + \frac{FLTHERF - FLTSHARE^2}{(1 - FLTSHARE)^2} \cdot (1 - FLT\widehat{SHARE})^2$$

APAX: The adjusted total passengers for a carrier on a route. While the DB1A is supposed to reflect a random 10 percent sample of all tickets, in reality airline reporting rates often differ significantly from this. We therefore adjust the passenger counts reported in the DB1A for deviations from the 10 percent reporting rate. For each carrier, *k*, at each of the top 200 airports, *i*, we calculate the reporting rate, *REPORT*_{*i**k*}, as 10*(carrier *k* DB1A reported passenger enplanements at *i*) divided by (carrier *k* census passenger enplanements at *i*). Census passenger enplanements are from the D.O.T.'s Non-stop Market Data, which is a census of available seats, passengers enplaned, and passengers transported on every flight segment of every U.S. airline. For a carrier that reports a 10 percent sample of tickets at an airport, *REPORT* will equal 1.0. For each carrier and each route in the data set, we compute an adjustment factor, *ADJUST*_{*i**j**k*}, defined as:

$$ADJUST_{ijk} = DIRECT_{ijk} * REPORT_{ik} + (1 - DIRECT_{ijk}) * REPORT_{jk}$$

where *DIRECT*_{*i**j**k*} is the percent of carrier *k*'s passengers travelling on the route between airports *i* and *j* who originated their travel at airport *i* (i.e., *i* is the origination point of their ticket). We then compute *APAX*_{*i**j**k*} as:

$$APAX_{ijk} = (DB1A \text{ reported passengers on route } ij \text{ for carrier } k) / ADJUST_{ijk}$$

Missing or incomplete data were treated as follows: For carriers missing from the census file at an airport (apparently due to inconsistent recording of carrier codes) we assumed a reporting rate of 1.0. For carriers missing directional information (due to very small numbers of passengers or no recorded round trips), we used the aggregate (for all carriers) *DIRECT*_{*i**j*}, defined as the percent of all passengers travelling on the route who originated their travel at airport *i*.