Does Competition Reduce Price Dispersion? New Evidence from the Airline Industry

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We analyze the effects of competition on price dispersion in the airline industry, using panel data from 1993:Q1 through 2006:Q3. Competition has a negative effect on price dispersion, in line with the textbook treatment of price discrimination. This effect is pronounced for routes with consumers characterized by relatively heterogeneous elasticities of demand. On routes with a homogeneous customer base, the effects of competition on price dispersion are smaller. Our results contrast with those of Borenstein and Rose, who found that price dispersion increases with competition. We reconcile the different results by showing that the cross-sectional estimator suffers from omitted-variable bias.

I. Introduction

Traditional microeconomic theory makes clear predictions for how the extent of competition should affect price discrimination and price dispersion. A competitive firm cannot price-discriminate because it is a price taker. A firm with some monopoly power can price-discriminate,

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as long as its customers have different demand elasticities and the firm has some way of distinguishing among different customer types. Textbook theory also predicts that as more competitors enter a market, incumbent firms will find it more difficult to maintain markups over marginal cost. Hence, as the market moves toward perfect competition, the dispersion in prices charged by an individual firm in a given market will fall.

The airline industry has been the focus of several previous empirical studies on price discrimination because two important prerequisites for price discrimination are present in this market. First, customers have different demand elasticities, since demand from business travelers is less price elastic than that of leisure travelers. Second, airlines are able to distinguish between these two types with certain ticket restrictions, including advance-purchase requirements, nonrefundable tickets, and Saturday night stay-overs. Furthermore, since the deregulation of the airline industry in 1978, a great deal of publicly available data has been generated that can be used to test pricing models.

This paper uses panel data on airline prices to learn what happens to price dispersion when more carriers begin service on a particular route. As it turns out, the textbook theory does a strikingly good job of explaining the data. First, dispersion in the prices charged by an individual carrier on a particular route declines when a new entrant begins offering service on that route. Second, this effect is strongest on routes that are likely characterized by large numbers of both business and leisure travelers, that is, on the routes for which the first prerequisite of price discrimination is present. Third, price dispersion falls as a result of the high prices (likely paid by business travelers), falling to the low price levels paid (likely by leisure travelers). Fourth, the effect of entry on price dispersion is especially large during peaks in the business cycle, when dispersion is high because airlines are presumably better able to price-discriminate between business and leisure travelers.

These findings give credence to the idea that increased competitive pressures make it more difficult for incumbent carriers to price-discriminate between business and leisure travelers. Because these results confirm the conjectures of the textbook theory, one may find them not to be surprising. However, they contradict previous empirical work that supported a more complex theory of airline pricing. In a seminal paper, Borenstein and Rose (1994) found that routes with higher levels of competition were actually characterized by a greater degree of price dispersion. They argued that these results supported a pricing theory that is based on the ability of a firm to cultivate brand loyalty among some of its customers.[1] Applied to the airline industry, the brand loyalty

[1] Examples include Borenstein (1985) and Holmes (1989).

theory predicts that a new entrant will have little effect on consumers purchasing tickets in the upper tail of an incumbent's price distribution, perhaps because these high-paying customers are members of the airline's frequent-flyer rewards program. However, the new entrant will have the effect of reducing fares among the price-conscious customers purchasing tickets in the lower tail of the incumbent's price distribution. Since the new entrant reduces prices in the lower tail while having little effect on the upper tail, the brand loyalty theory predicts a positive relationship between price dispersion and competitive intensity.[2]

The existence of an alternative to the textbook theory of price discrimination in competitive markets compels us to reconcile our empirical findings with those of Borenstein and Rose. One possibility is that airline competition has changed in a fundamental way since they wrote their paper. We use data from 1993 to 2006, a period when the airline industry was shaken up by the emergence of several low-cost carriers (LCCs), whereas Borenstein and Rose used cross-sectional data from 1986, when LCCs did not exist.[3] Although our data show that the entry of an LCC such as Southwest or JetBlue reduces price dispersion more significantly than the entry of a legacy carrier—the main type of carrier that Borenstein and Rose considered—we find that entry by a legacy carrier also significantly reduces price dispersion. Thus, our analysis suggests that their exclusive focus on legacy carriers is not the reason for our different findings.

We show that the main difference between our findings and those of Borenstein and Rose is due to estimation method. Their analysis was performed with cross-sectional data, whereas we use panel data. Our estimates are therefore identified by changes in the number of carriers on a given route over time. Exploiting changes in competition over time turns out to matter because all studies of airline price dispersion need to instrument for the competitive intensity on a particular route. As higher price dispersion may draw competitors onto a specific route, there is positive bias associated with the competition variables in the estimation. As we show below, one of Borenstein and Rose's instruments—the distance between the two endpoints of a route—is corre-

[2] Frequent-flyer programs (FFPs) are an example of one possible mechanism that airlines have developed to induce and exploit brand loyalty. An important characteristic of FFPs is that, through a principal-agent structure, they were created to have a greater impact on business travelers than on leisure travelers. Since employers are often not willing to absorb the associated costs of monitoring flight costs, FFPs often lead employees to seek the benefits of staying with one airline to reap the FFP rewards for themselves. For a detailed discussion of FFPs and their effects, see Yang and Liu (2003).

[3] Borenstein and Rose used data from the Databank 1A (DB1A) of the Department of Transportation's Origin and Destination Survey for the second quarter of 1986. We use data from the Databank 1B (DB1B). The major difference between the two data sets is that the DB1B contains the publicly available domestic portion of the Origin and Destination Survey, whereas the DB1A also includes the restricted international portion.

lated with the error term in the price dispersion regression, and this correlation biases their results toward apparent support of the brand loyalty theory described above. Since distance is fixed over time, however, this invalid instrument falls out of our panel data regression, which includes route-specific fixed effects. In fact, when we estimate Borenstein and Rose's cross-sectional regressions using our data with the troublesome variable included in the instrument list, we also obtain their finding of a positive effect of competition on price dispersion. Overall, our findings suggest that the explanation of competition in monopoly markets taught in microeconomic textbooks is quite accurate.

The rest of the paper is structured as follows: Section II contains a detailed discussion of the data and our method of partitioning flights into those that are likely to contain both business and leisure travelers and those that are likely to contain predominantly leisure travelers. Section III includes our own fixed-effects panel analysis. Section IV reconciles our panel findings with those of prior cross-sectional studies. In Section V we perform a time interaction in our fixed-effects panel regression to see whether the effects of competition on price dispersion have changed over time, and in Section VI we present conclusions.

II. Data

A. Data Sources and Variable Construction

Our study focuses on domestic, direct, coach-class airline tickets over the period 1993:Q1–2006:Q3. Our sample includes nine major domestic airlines, often referred to as "legacy carriers,"[4] as well as a number of LCCs[5] and regional carriers. It is important to note that the previous literature, including Borenstein and Rose (1994), restricted the analysis to legacy carriers exclusively. We choose to include LCCs (and regional carriers) because of the important role that they have played in the airline industry over the course of our sample. Ticket prices are obtained from the DB1B database, which is a 10 percent random sample of all domestic tickets issued by airlines.[6] In addition to ticket prices, the DB1B

[4] The legacy carriers in our sample include United, US Airways, Delta, American, Alaskan, TWA, Continental, Northwest, and America West.

[5] The list of LCCs, obtained from Ito and Lee (2003), includes Air South, Access Air, AirTran, American Trans Air, Eastwind, Frontier, JetBlue, Kiwi, Morris Air, National, Pro Air, Reno, Southwest, Spirit, Sun Country, ValuJet, Vanguard, and Western Pacific. For a more detailed discussion of LCCs, see Goolsbee and Syverson (2005).

[6] The DB1B database is part of TranStats, the Bureau of Transportation Statistics' (BTS) online collection of databases, and contains coupon-specific information. A coupon is a piece of paper that indicates the itinerary of a passenger and essentially identifies a segment of travel (i.e., a one-way flight from Boston to Las Vegas that stops in Chicago would have two coupons, BOS–ORD and ORD–LAS). Even though the DB1B is only a 10 percent random sample, each quarter of the DB1B database contains a very large amount of data. For example, 1993:Q1 contains approximately 4.8 million coupons.

includes other quarterly itinerary information such as origin and destination airports, passenger quantities, number of plane changes, and fare class. Any tickets believed to be frequent-flyer tickets are eliminated.[7]

We construct a panel in which an observation is a flight conducted by a specific airline, between an origin and destination airport (route), in a specific time period (year and quarter). For example, a United Airlines direct, coach-class ticket from Philadelphia (PHL) to Chicago O'Hare (ORD) in the first quarter of 1999 is considered an observation in our data. Our direct ticket data include both one-way flights and round-trip flights. The DB1B contains numerous itineraries and fares for the same flight by the same carrier, reflecting the quarterly frequency of the data, as well as the many different fares found within the same fare class, on the same flight, at a given point in time. Thus, our data comprise distributions of prices for carrier-route itineraries.

We obtain additional route characteristics to supplement the DB1B from the BTS's T-100 Domestic Segment Database. This database contains domestic, nonstop segment data reported by all U.S. carriers, including passengers transported, origin, destination, aircraft type, available capacity, scheduled departures, departures performed, and aircraft hours. Since these are segment data, they are largely compatible with the data on direct flights that we use from the DB1B. One significant difference between the two data sets has to do with passenger counts. The T-100 data include observations on enplaned passengers, which encompass passengers who originate and end their trips at the origin and destination airports, as well as passengers who connect to and from other flights at the respective airports. The DB1B data on direct flights, however, include only passengers who originate and end their flights at the respective origin and destination airports.[8] Appendix B contains a more comprehensive discussion of data sources.

We define the ticket price as a single-direction fare, so that the prices of one-way flights are exactly as listed in the itineraries, whereas the prices of round-trip flights are one-half of the prices listed in the itin-

[7] Tickets obtained using frequent-flyer miles are typically charged handling fees between $5 and $15, depending on the airline. Thus, to be safe, we eliminate any tickets with prices under $20. These criteria are commonly used in the literature in an effort to control for ticket quality.

[8] There are a few other subtle differences between the two data sets. The DB1B data contain information on the number of plane changes but not the number of stops, whereas the T-100 data contain information on nonstop flight segments. For example, if a passenger took a flight from Boston to Los Angeles, in which the plane stopped in Chicago but the passenger did not change planes, it would be recorded as a direct flight in the DB1B but would not show up in the T-100 data set. Another difference is that the T-100 data set includes information on almost every domestic flight segment flown by domestic carriers and thus contains more routes than the DB1B data.

eraries.[9] Our analysis follows Borenstein and Rose (1994) and other studies of airline pricing in focusing on the Gini coefficient, which is equal to twice the expected absolute difference between two ticket prices drawn randomly from the population.[10] For example, a Gini coefficient of 0.25 on a given route and carrier implies an expected absolute price difference of 50 percent of the mean fare on that route. The median Gini coefficient for the entire data set is 0.22, which corresponds to an expected fare difference of 44 percent of the mean fare for two randomly selected passengers on a given carrier and route, respectively. This is slightly larger than the 36 percent difference obtained by Borenstein and Rose using data from 1986.

The data also show a large amount of variation in competition over time within the airline industry. Figure 1 shows the percentage of routes with at least one entrant and the percentage of routes with at least one exit for each year in the sample. Most years saw a considerable amount of entry and exit. Between 8 percent (2003) and 28 percent (1994) of routes experienced an entrant each year, whereas between 10 percent (1998) and 25 percent (1997) of routes experienced an exit.

B. Isolating Price Discrimination

There are a number of airline pricing strategies other than price discrimination that could explain the presence of price dispersion in our data. One strategy is "peak-load pricing," in which airlines change prices to alleviate potential capacity constraints during times of predictably high demand.[11] Another possibility is "stochastic demand pricing," which firms may implement when demand is uncertain, capacity is costly, and firms commit to a price ex ante.[12] In both of these cases, profit-maximizing behavior on the part of firms will induce a distribution of prices rather than a single price.

In our analysis, we attempt to isolate price discrimination as a cause of price dispersion by differentiating between different types of routes.[13]

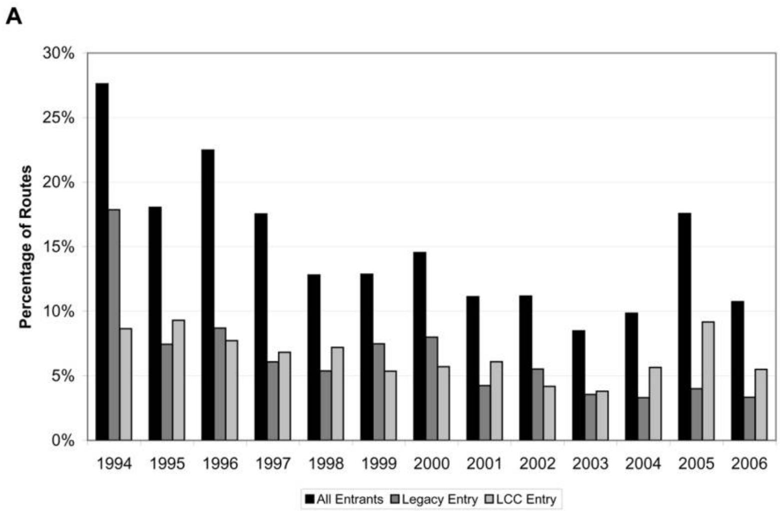
[9] This is identical to the methods of Borenstein and Rose and much of the previous literature.

[10] Hayes and Ross (1998) use the Gini coefficient, as well as the Atkinson index and Theil's index. For a comprehensive discussion of the advantages and disadvantages of different dispersion statistics, we refer the reader to Cowell (1995).

[11] See Lott and Roberts (1991) and Dana (1999) for a more detailed discussion.

[12] Prescott (1975) was the first to address this issue in the economic literature. Eden (1990) formalized Prescott's example in a setting of perfect competition, and Dana (1999) extended Eden's model to monopoly and oligopoly market structures.

[13] As the DB1B provides us with observations only at the quarterly frequency level and does not provide information regarding the exact time of departure, it is not possible to directly detect peak-load pricing or stochastic demand pricing patterns. Borenstein and Rose attempted to control for some aspects of peak-load pricing in their analysis, and we will discuss this along with our own efforts in more detail below.



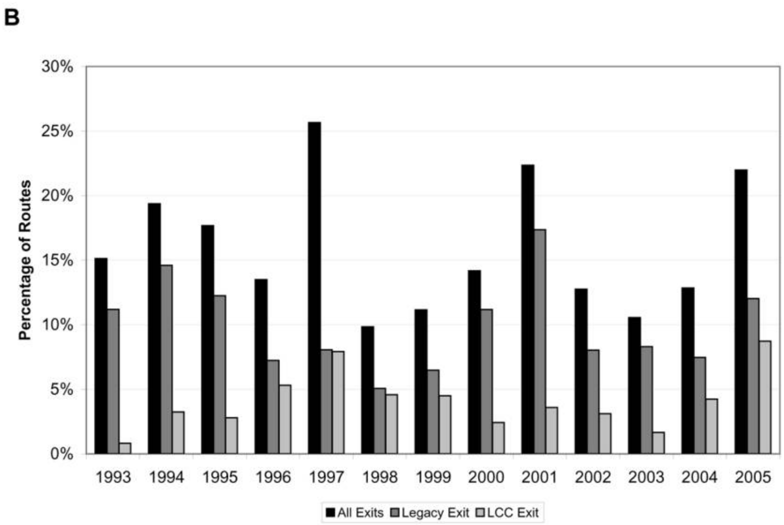


Fig. 1.—Variation in competition—entry and exit. *A*, Percentage of routes with at least one entrant. *B*, Percentage of routes with at least one exit. We divide the type of entrants between legacy carriers and LCCs.

In particular, if price discrimination is a main determinant of price dispersion, then a route with multiple types of customers should be more affected by changes in competition than a route with a more homogeneous customer base. However, peak-load pricing and stochastic demand implementation should not be affected by route type. Thus, we compare the effects of competition on price dispersion, taking into account the observable types of travelers purchasing tickets. We presume that tickets for routes to tourist destinations are mainly bought by passengers with high elasticities of demand and hence low reservation prices—leisure travelers. In contrast, we presume that tickets for routes between big cities are purchased by leisure travelers as well as by passengers with high reservation prices—business travelers. Specifically, we segment our data into “leisure routes” (routes with mainly price-sensitive leisure travelers) and “big-city routes” (routes with both leisure and price-insensitive, business travelers). Previous airline studies have allowed measures of tourism to affect only the level of prices or price dispersion.[14] However, if price discrimination is a main determinant of price dispersion, then the extent of consumer heterogeneity on a route should also affect the manner in which competition affects the distribution of prices.

We take the following steps in distinguishing between big-city and leisure routes: For each airport in our data, we calculate the ratio of accommodation earnings to total nonfarm earnings corresponding to the metropolitan area (MA) containing that particular airport for each year over the period 2001–4 and then take the median value.[15] We then sort these ratios in descending order and label as a leisure route each route that includes an airport in an MA above the 85th percentile. In addition to the airports in the 85th percentile, we include a few airports from U.S. territories for which we have no MA earnings data. These airports, which include San Juan, St. Croix, and St. Thomas, are included in the BTS’s definition of domestic and thus appear in the DB1B.[16]

Our criterion for choosing the big-city route sample is even simpler than our criterion for choosing the leisure sample. We classify a route

[14] Borenstein (1989) and Borenstein and Rose (1994) constructed a tourism index at the standard metropolitan statistical area level using the ratio of hotel income from tourist customers to total personal income. Brueckner, Dyer, and Spiller (1992) and Stavins (1996) included the absolute difference in mean January temperatures between origin and destination as a proxy for tourism in their reduced-form pricing regressions.

[15] We obtained these data from the Bureau of Economic Analysis (table SA05, Annual Personal Income by Major Source and Earnings by Industry). Since the BEA changed its industry classification system in 2000 and the new codes (North American Industry Classification System) are not readily compatible with the old (Standard Industrial Classification), we were unable to calculate this ratio for the entire span of our data.

[16] Our results are not sensitive to the 85th percentile threshold. We also estimated our models assuming both an 80th percentile and a 90th percentile threshold and did not find significantly different results.

as "big city" if that route contains both an origin and a destination airport located within the 30 largest MAs in the United States (in terms of population).[17] Our assumption is that there is a large proportion of business travelers on routes between large cities.

Figure 2 displays the distribution of coach-class fares of a big-city route—United Airlines route from Philadelphia (PHL) to Chicago (ORD)—as well as a leisure route—US Airways route from Philadephia (PHL) to Orlando (MCO)—for 1999:Q1. The big-city route is characterized by more price dispersion than the leisure route, with Gini coefficients of .303 and .248, respectively. The figure also shows that the two routes are characterized by substantially different price distributions. The leisure route has a unimodal distribution of prices, indicating that a majority of the tickets were sold for around $100. We presume that the carrier was targeting one type of consumer—leisure travelers. The big-city route, however, has a bimodal price distribution, indicating that the carrier sold a large portion of tickets for around $100 and also a large portion for around $450.

In order to shed some light on how competition affects big-city and leisure routes differently, we report in table 1 the median Gini coefficient of subsamples with different levels of competition. Specifically, we divide the entire sample into monopoly routes and competitive routes, where a monopoly route is defined to be a route on which one firm's average market share for each quarter over the entire sample period is greater than 0.95. Column 3 of the table shows that monopoly routes are characterized by slightly more price dispersion (0.23 median Gini coefficient) than competitive routes (0.21 median Gini coefficient).

In the bottom row of columns 1 and 2 of table 1 we report the median Gini coefficients for our samples of big-city and leisure routes.[18] Leisure routes are characterized by less price dispersion than big-city routes,

[17] There are a few exceptions to this criterion. We did not include airports located in Miami, Fort Lauderdale, San Diego, Tampa Bay, or Orlando on the basis that these areas are largely tourist destinations. In fact, Orlando is included in our leisure route sample. Population figures are taken from the Census Bureau and correspond to July 1, 2005. A table listing the airports in each subsample appears in online App. C (tables C2 and C3).

[18] The fact that price dispersion is higher on big-city routes than on leisure routes does not by itself prove that carriers price-discriminate to a greater extent on the former. The dispersion difference could very well be due to demand considerations and not price discrimination tactics by the firm. For example, it is possible that airlines offer the exact same distribution of prices on both route types but that consumers on leisure routes choose not to purchase expensive tickets, creating the observable difference in price dispersion between route types. The data, however, seem to refute such an explanation. If this explanation were driving the differences between price dispersion, we would expect to see lower utilization rates on leisure routes since there would be very few consumers purchasing tickets at the top part of the price distribution. However, we find that aircraft utilization rates are monotonically higher on leisure routes than on big-city routes for each year in our sample. We thank an anonymous referee for bringing up this point.

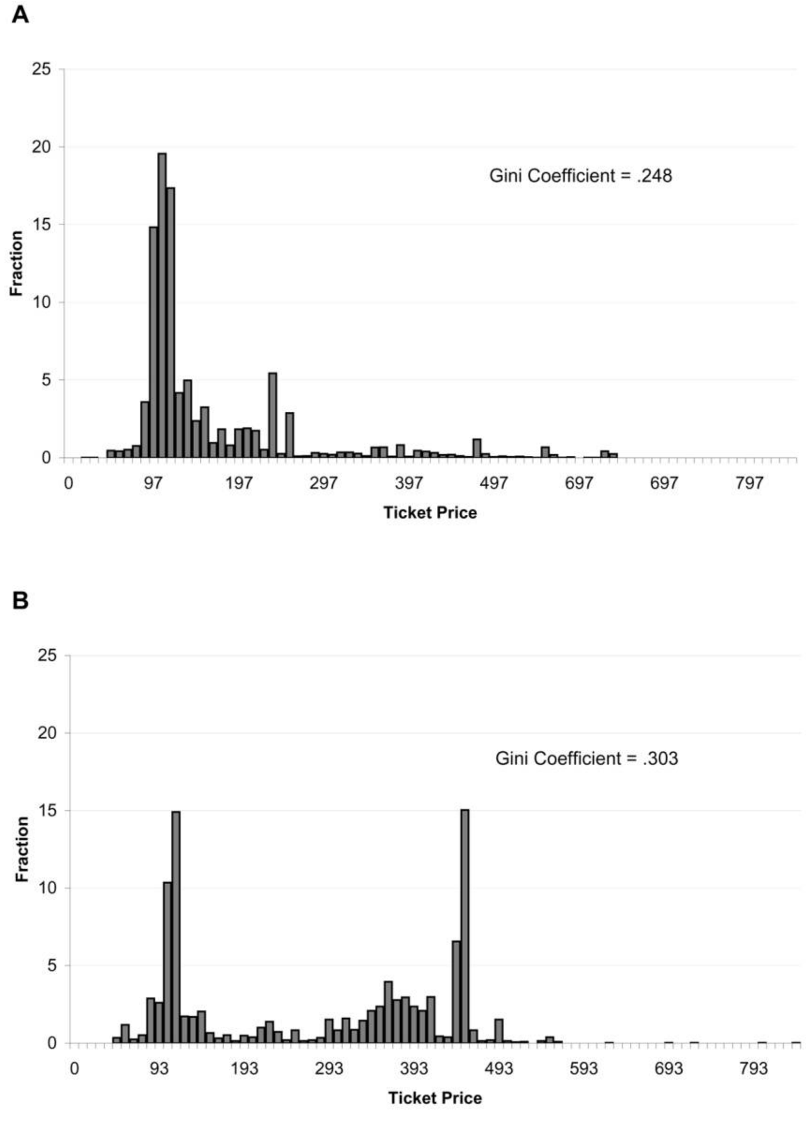


Fig. 2.—Example price distributions: histograms of coach-class fares during the first quarter of 1999. *A*, Leisure route, Philadelphia (PHL) to Orlando (MCO) on US Airways. *B*, Big-city route, Philadelphia (PHL) to Chicago (ORD) on United Airlines. Prices are in nominal U.S. dollars and are computed as directional fares (round-trip fares are divided by 2).

TABLE 1
Median Price Dispersion by Subsample

	Big-City Routes (1)	Leisure Routes (2)	All Routes (3)
Monopoly routes	.29	.19	.23
Competitive routes	.25	.18	.21
All routes	.26	.18	.22

Note.—This table reports the median Gini coefficient of domestic coach-class fares for different samples of the data. Monopoly routes are those in which the average market share over the sample period is greater than 0.95 for a single carrier.

with a median Gini coefficient of 0.18 versus a median Gini coefficient of 0.26, respectively.

Table 1 also partitions big-city and leisure routes into competitive and monopoly routes. Competitive leisure routes and monopoly leisure routes show a negligible difference in price dispersion. However, the difference in the median Gini coefficient between competitive and monopoly big-city routes is much larger. This table suggests that changes in competition may have a larger effect on price dispersion when there are distinct types of consumers purchasing tickets. This, in turn, suggests that not only is price dispersion at least partly attributable to price discrimination, but also that competition may reduce the ability of a carrier to price-discriminate. In Section III we formally test this relationship by performing a fixed-effects panel analysis that lets us identify the effect of market structure on price dispersion using variation in competition over time within a given route.

C. *Competition and Price Dynamics*

We present a few graphical examples of the dynamic price distributions that are representative of many of the leisure and big-city routes in our respective samples, paying particular attention to the role of competitive forces.

The type of route appears to play an important role in how the entry and exit of carriers, especially LCCs and regional carriers, affect the price distributions of the carriers in our sample. Figure 3*B* displays all the price deciles from the big-city route—Philadelphia (PHL) to Chicago (ORD), United Airlines. Also plotted in this figure are the 90th percentiles of two LCCs, ATA and Southwest, and a regional airline, Midway Airlines.[19] It is easiest to think of this figure as a time-series plot of the price distributions of the routes shown in figure 2.

[19] Midway and Southwest entered these routes through Midway Airport (MDW), not O'Hare International Airport (ORD).

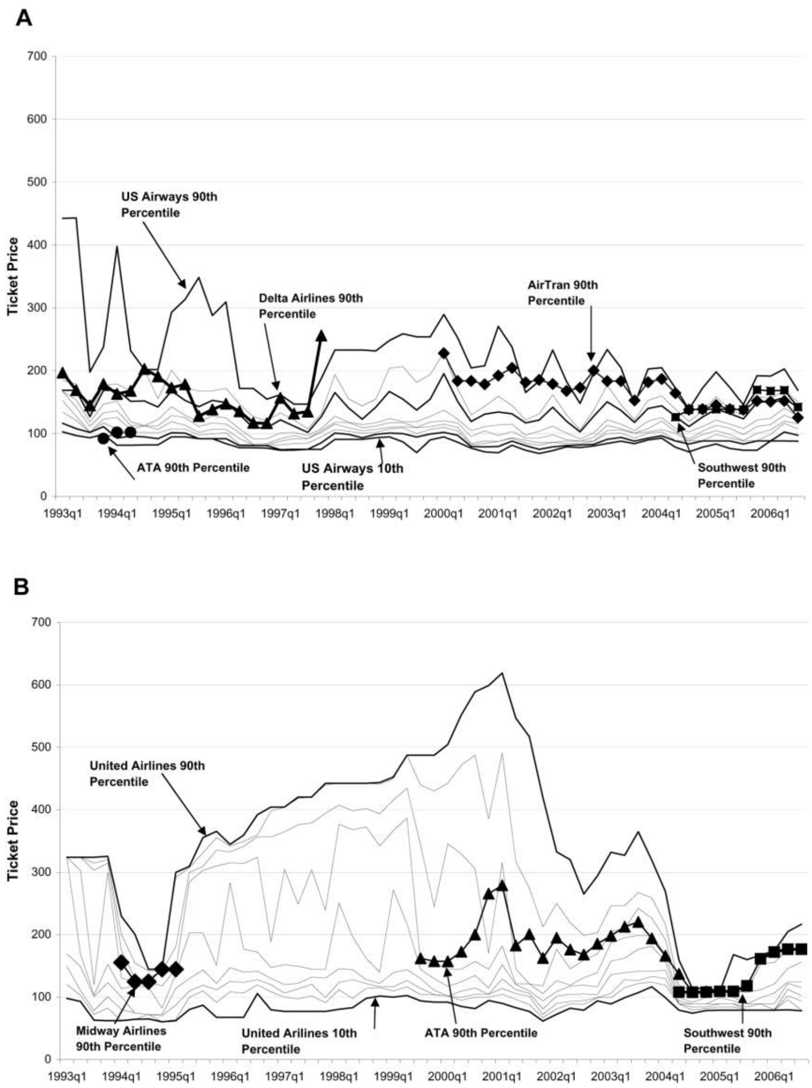


Fig. 3.—Pricing dynamics—entry and exit. *A*, Leisure route, Philadelphia (PHL) to Orlando (MCO) on US Airways. *B*, Big-city route, Philadelphia (PHL) to Chicago (ORD) on United Airlines. Depicted are the 90th percentiles of the entrants and the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles of the incumbent carrier.

Entry and exit by these carriers appear to have had significant impacts on the dynamics of United's price distribution. Entry by Midway Airlines and Southwest Airlines appears to have pulled down the upper percentiles of the distribution to a much greater extent than the lower percentiles, thereby reducing price dispersion. Figure 3*A* shows the entry and exit of carriers on the leisure route operated by US Airways from Philadelphia (PHL) to Orlando (MCO). On this route, which we believe to be characterized by a more homogeneous customer base of price-elastic, leisure travelers, entry and exit seem to have had a smaller effect on price dispersion.

While the routes shown in figure 3 are indicative of many of the routes in our big-city and leisure samples and suggest that the type of route in question may play an important role in the relationship between pricing and competition, they are only examples and, thus, must be interpreted with some caution. In the next section we conduct a more systematic analysis using panel data methods in an effort to confirm the observations from figure 3.

III. Panel Analysis

We exploit the panel dimension of our data in order to assess the effects of competition on price dispersion while controlling for time-invariant, route-specific factors. We use a fixed-effects approach, which exploits only the time-series variation along a specific route in the estimation routine.[20] Figure 1 verified that there is a considerable amount of entry and exit over the course of our sample. Hence, we take advantage of this variation by estimating the effect of competition on price dispersion using changes in the competitive structure of a given route over time.

We use two different approaches to analyze the effects of competition on the distribution of prices charged by airlines over the course of our sample. First, we use the Gini coefficient as the dependent variable to proxy for price dispersion. Second, we estimate a series of reduced-form pricing equations, similar in spirit to Borenstein (1989), in which we use the 90th and 10th percentiles of the price distribution as our dependent variables. Analyzing the top and bottom of the price distribution separately provides additional information regarding the source of the change in price dispersion.

[20] In order to determine initially whether time-invariant, route-specific effects would be important in our context, we performed Hausman tests for each sample and specification of our model. In all cases the null hypothesis of zero correlation between the residuals and the vector of explanatory variables was soundly rejected. In the next section, we show results of the pooled instrumental variable (IV), between-effects, and random-effects regressions.

A. *Gini Coefficient Regressions*

Since the Gini coefficient is bounded between zero and one, we measure price dispersion using the Gini log-odds ratio given by $G_{ij}^{\mathrm{lodd}} = \ln [G_{ij}/(1 - G_{ij})]$, which produces an unbounded statistic.[21] Specifically, we estimate the following regression:

$$G_{ijt}^{\mathrm{lodd}} = \alpha + \beta \times \mathrm{Competition}_{jt} + \theta \times X_{it} + \gamma_t + v_{ij} + \nu_{ijt}, \qquad (1)$$

where i indexes the carrier, j the route, and t the time period. Carrier-route fixed effects are represented as v_{ij}, and X_{it} is an indicator of whether airline i is in bankruptcy at time t. We control for important exogenous cost and demand effects through a full set of time dummies, γ_t.[22] For robustness purposes, we measure competition, $\mathrm{Competition}_{jt}$, in three different ways. First, we use market concentration as measured by the Herfindahl index of a given route.[23] Second, we use the logarithm of the total number of carriers operating on a given route, j, in time period t. Finally, we use two distinct variables that measure the number of legacy and low-cost carriers that operate along the route, respectively. In principle, this third measure of competition allows us to isolate the competitive effect of legacy carriers from that of LCCs. This is relevant because many previous studies analyzed the airline industry before the influx of LCCs into the market. We also broaden the definition of route to a "city pair" for this competition measure, which groups airports in a given metropolitan area together and defines a route as travel between two cities.[24]

There are potential endogeneity concerns associated with the competition variables in equation (1). As higher price dispersion may make a route more appealing for prospective entrants, estimation of equation

[21] The estimation results are not sensitive to this transformation, likely because the upper bound of the Gini coefficient is never approached in the data.

[22] We also included average variable cost (obtained from the BTS's P-52 database) of the carrier as a control, but it did not affect our estimates. We chose to leave it out because of endogeneity concerns.

[23] For comparison purposes, we report the negative value of the Herfindahl index for our measure of competition because concentration is generally inversely proportional to the number of carriers operating on a route. The Herfindahl index is calculated using passenger quantity information from the DB1B. We also calculated market shares and a Herfindahl index on the basis of passenger shares (enplaned) as well as flight shares from the T-100 Segment data, with all three measures sharing a high correlation. If plane sizes and load factors do not differ substantially across carriers on a given route, we would expect the two types of Herfindahl indexes to be similar.

[24] We do this because many LCCs entered markets through different airports (within the same metropolitan area) than those used by the legacy carriers. In order to capture the presence of these LCCs in a given market, we need to define routes as flights between cities, not between airports. Thus, we do not treat routes involving airports located in the same city as separate from one another. For example, a flight from Chicago O'Hare (ORD) to Philadelphia is considered to be on the same route as a flight between Chicago Midway (MDW) and Philadelphia.

(1) via least squares may produce a positive bias in the estimates of β. Hence, we instrument competition with total enplaned passengers on the route and two instruments used in Borenstein and Rose (1994).[25] We cluster our standard errors by route, as in Goolsbee and Syverson (2005), in order to control for both serial correlation and correlation between the pricing decisions of multiple carriers on the same route.[26] There is, of course, a possibility that the residuals are correlated across different routes within the same airline. For instance, an unaccounted-for, carrier-specific shock could affect all prices on an airline's network, producing incorrect standard errors associated with our estimates. Although we cannot account for all carrier-specific shocks, we believe that including a bankruptcy dummy, X_{it}, as a control is likely to capture some of the important carrier-specific shocks.

B. *Price Percentile Regressions*

While using the Gini coefficient seems to be the more popular approach in the literature, we see both advantages and disadvantages to this method compared with using certain percentiles of the price distribution as the left-hand-side variable. On the one hand, the use of a dispersion statistic as a dependent variable allows for a more direct interpretation of the effects from the explanatory variables on price dispersion. On the other hand, the disadvantage of this approach comes from the restrictive nature of using a single statistic to summarize an entire distribution. For example, the Gini coefficient places more emphasis on the middle part of the distribution and is not as sensitive to the tails of the distribution. Also, analyzing the percentiles sheds more information regarding the change in the shape of the price distribution.[27] For example, price dispersion can increase because of a rise in the upper portion of the price distribution relative to the lower portion, or it can increase because the lower portion falls by more than the upper portion. For this reason, we believe that studying a range of percentiles of the price distribution may be more informative than con-

[25] In the discussion below, variables that are being instrumented for are characterized by a hat. Refer to App. A for a detailed description of the instruments. We do not instrument for the competition variables in our third measure because of the lack of relevant instruments. That is, relevant instruments would each need to be correlated with N^{LEG} and N^{LCC} distinctly. In any case, the expected sign of the endogeneity bias is positive, which works in favor of the Borenstein-Rose result.

[26] Strategic behavior on the part of airlines has been well documented in the literature. For a few examples, see Berry (1990), Brueckner and Spiller (1991), and Alam, Ross, and Sickles (2001).

[27] Borenstein (1989) conducted a cross-sectional analysis in which the dependent variables were the 80th and 20th percentile prices. Our results are robust to using the 80th and 20th percentiles as opposed to the 90th and 10th percentiles.

centrating on only a single statistic. Thus, we estimate the following regressions:

$$\ln P(k)_{ijt} = \alpha + \beta \times \text{Competition}_{jt} + \theta \times X_{it} + \gamma_t + \upsilon_{ij} + \nu_{ijt}, \qquad (2)$$

where k is either the 10th or 90th percentile. If the textbook effect of how competition should affect price discrimination prevails, an increase in the number of competitors on a given route will decrease the higher-percentile prices more than the lower-percentile prices, decreasing the overall degree of price dispersion on that route. However, if the brand loyalty effect found by Borenstein and Rose dominates, an increase in the level of competition will decrease prices in the lower part of the distribution by more than those in the upper part, thereby increasing the overall degree of price dispersion.

C. *Panel Estimation Results*

Table 2 contains estimation results for all three methods of measuring competition using the Gini coefficient as the dependent variable, and table 3 shows results using the 90th and 10th percentiles of the price distribution as the dependent variables for the big-city sample and the leisure sample.[28] We report results for all direct routes in our 13-year sample.[29] In table 2, we include results for all flights in our sample (panel A), as well as results for our big-city route sample (panel B) and our leisure route sample (panel C).[30] In Section II we saw that the degree of consumer heterogeneity seems to play a role in the distribution of Gini coefficients in our sample. Performing separate estimations for big-city routes and leisure routes allows us to determine, in a more rigorous manner, whether the degree of consumer heterogeneity has any effect on the relationship between price dispersion and competition. If competition does erode the ability of carriers to price-discriminate, then we would expect to observe larger effects from competition on price dispersion on big-city routes, where we have both price-elastic and price-inelastic consumers, than on leisure routes, where we believe there to be a more homogeneous group of price-elastic consumers.

The effect of an increase in competition—as measured by market concentration $-\ln \widehat{\text{HERF}}$—on price dispersion is negative and signifi-

[28] We omit the coefficient estimates corresponding to our bankruptcy dummy, X_{it}, for the sake of brevity. There are no unexpected findings, but the results are available on request from the authors.

[29] This sample includes 112,499 carrier-route observations, covering 5,444 distinct carrier-route observations and 2,902 distinct routes.

[30] The big-city route sample consists of 32,188 carrier-route observations, covering 1,343 distinct carrier-route observations and 564 different routes; the leisure flight sample consists of 24,555 carrier-route observations, covering 1,287 distinct carrier-route observations and 621 different routes.

TABLE 2
PANEL ESTIMATES
Dependent Variable: G_{ijt}^{lodd}

	A. All Routes			B. Big-City Routes			C. Leisure Routes		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$-\ln \widehat{\text{HERF}}$	−.121***			−.229***			−.076*		
	(.022)			(.038)			(.044)		
$\ln \hat{N}$		−.177***			−.357***			−.132**	
		(.029)			(.060)			(.058)	
N^{LEG}			−.005			−.013**			−.006
			(.004)			(.006)			(.009)
N^{LCC}			−.056***			−.089***			−.034***
			(.007)			(.010)			(.012)
Observations	112,499	112,499	112,499	32,188	32,188	32,188	24,555	24,555	24,555

NOTE.—All regressions include carrier-route-specific dummies, time dummies, quarter dummies, and a dummy variable indicating whether the carrier is in bankruptcy. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route.
* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

TABLE 3
PANEL ESTIMATES
Dependent Variable: Log of 90th and 10th Percentiles

	Big-City Routes						Leisure Routes					
	ln $P90$			ln $P10$			ln $P90$			ln $P10$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$-\ln \widehat{\mathrm{HERF}}$	−.406***			−.166***			−.168***			−.119***		
	(.041)			(.027)			(.028)			(.024)		
$\ln \hat{N}$		−.652***			−.273***			−.259***			−.176***	
		(.067)			(.039)			(.041)			(.036)	
N^{LEG}			−.041***			−.025***			−.011			−.008
			(.005)			(.004)			(.008)			(.007)
N^{LCC}			−.156***			−.054***			−.090***			−.065***
			(.014)			(.007)			(.011)			(.009)
Observations	32,188	32,188	32,188	32,188	32,188	32,188	24,555	24,555	24,555	24,555	24,555	24,555

NOTE.—All regressions include carrier-route-specific dummies, time dummies, and a dummy variable indicating whether the carrier is in bankruptcy. Hats indicate that instrumental variables were used. Standard errors are in parentheses and are clustered by route to account for both autocorrelation and correlation between carriers on the same route.

* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

cant at the 1 percent significance level in the full sample as well as in the sample of big-city routes.[31] This is the opposite effect found by Borenstein and Rose in their analysis. The effect is much stronger on the big-city routes compared to the full sample. For the sample of leisure routes, the effect of competition on price dispersion is statistically significant at the 10 percent significance level but is smaller in magnitude. A look at the estimates corresponding to $-\ln \widehat{\text{HERF}}$ from the percentile regressions sheds more light on this issue. For the sample of big-city routes, the estimates show that an increase in competition decreases the 90th percentile price level by more than twice the amount that it decreases the 10th percentile price level. For the sample of leisure routes, an increase in competition decreases the 90th and 10th percentile price levels by similar magnitudes. These estimates suggest that an increase in competition has a larger negative effect on the top portion of the price distribution when there are a significant number of price-inelastic business consumers in the consumer pool. When the consumer base is more homogeneous, as in the leisure route sample, there is less disparity between the manner in which route competition affects the top and bottom portions of the price distribution.

The results from the second measure of competition show that an increase in the number of competitors, $\ln \hat{N}$, on a route is estimated to have a statistically significant, negative impact on price dispersion in the full sample.[32] The effect of $\ln \hat{N}$ on price dispersion is significant and negative for our sample of big-city routes. Specifically, the coefficient estimate (-0.357) is approximately twice the magnitude of the estimate for the full sample (-0.177). For the sample of leisure routes, the effect of competition on price dispersion is statistically significant at the 5 percent level but is much smaller in magnitude (-0.132). Focusing on table 3, we see that the 90th percentile price level falls by more than twice as much as the 10th percentile price level following an increase in competition on big-city routes. In contrast, on leisure routes, the disparity between the two percentiles is not as great. Thus, like the results found using the first model, these results suggest that, on routes with significant heterogeneity in consumer types, an increase in competition erodes the ability of carriers to charge a high markup to price-inelastic customers, lending support to the textbook theory.

Similarly, the results from the third measure of competition also pro-

[31] All instruments were relevant at the 1 percent level as measured by the Cragg-Donald statistic.

[32] As a robustness check, we ran the first and second models without instrumenting to make sure that the choice of instruments was not driving our results. The estimate on $-\ln \text{HERF}$ was $-.033$ with standard error .016, and that on $\ln N$ was $-.021$ with standard error .006. Our results are also robust when we substitute the Atkinson index in place of the Gini coefficient.

vide evidence that an increase in competition results in less price dispersion. The effect of increased competition from both LCCs and legacy carriers is larger in our big-city route sample. It is notable that the number of LCCs in a city pair has a much larger effect on a given carrier's price dispersion compared to the number of legacy carriers. For the sample of leisure routes, the number of legacy carriers has no significant effect on price dispersion. In contrast, the estimates are negative and significant for our sample of big-city routes. The results from the price percentile regressions (table 3) verify that for the big-city routes, the number of both LCCs and legacy carriers lowers the 90th percentile price level by more than the 10th percentile price level. This suggests that the presence of an LCC, and to a much smaller extent a legacy carrier, reduces the ability of the incumbent carrier to charge a high markup to price-inelastic consumers relative to the markup it can charge to price-elastic consumers.

Overall, the fixed-effects, panel estimates provide evidence of a negative relationship between competition and price dispersion in the airline industry. Furthermore, the results show that competition has a much larger effect on price dispersion in the sample of big-city routes compared to the sample of leisure routes. These results are suggestive of increased competition eroding the ability of the incumbent to price-discriminate.[33]

IV. Reconciliation with Cross-Sectional Studies

The fixed-effects panel analysis found that increased competition on a given route over time reduces the extent of price dispersion for an incumbent carrier. This result accords well with the textbook explanation of competition in monopoly markets discussed above, but it contradicts the findings of previous empirical airline studies. These found that, in the cross section, more competitive routes were characterized by more price dispersion.[34]

In this section, we reconcile the differences between our panel analysis

[33] A fall in price dispersion from an increase in competition could also be the result of changes in consumer demand. For instance, when a competitor enters, the incumbent may not lower the high fares; instead price-inelastic consumers may simply stop purchasing tickets at the top part of the price distribution. If this explanation were driving the results, we would expect to see airplane utilization rates fall in response to increases in competition as tickets offered at the top end of the distribution are not purchased. As a robustness check, we estimate $\ln(\text{util}) = \theta_0 + \beta \times \ln \hat{N}_{jt} + \alpha \times X_{it} + \gamma_t + v_{ij} + \nu_{ijt}$. The coefficient β was estimated to be .041 with standard error .014. This positive coefficient indicates that the incumbents' planes fill up as competitors enter a route, giving more credence to the idea that the falling price dispersion is a supply-side phenomenon.

[34] In addition to Borenstein and Rose (1994), empirical studies that have found such an effect include Stavins (1996) for the airline industry and Busse and Rysman (2005) for *Yellow Pages* advertising.

and the cross-sectional analysis of Borenstein and Rose (1994). There are two possible reasons for the different findings. First, the two sets of results could differ because of the different time periods encompassed by the respective data sets: Borenstein and Rose analyzed 1986 data, whereas this study uses data between 1993 and 2006. As the airline industry has evolved between the two time periods, it is quite conceivable that the manner in which competition affects price dispersion has also changed. Second, the two sets of results could differ because of differences in the estimation techniques. This study estimates the effect of competition on price dispersion using panel data methods, whereas Borenstein and Rose's paper incorporated a cross-sectional analysis. The fixed-effects, panel analysis controls for time-invariant, route-carrier effects and estimates the effect of competition on price dispersion using variation in the competitive structure of a given route *over time*. In contrast, a cross-sectional analysis estimates the effect of competition on price dispersion using variation in competitive structures *across routes*. This is an important difference, since identification of the effect of market competition on price dispersion using cross-sectional data is obtained only if the econometrician can control for all other differences in price dispersion across markets that are correlated with differences in market structure.

We perform similar, albeit not identical, cross-sectional regressions on separate quarters of our sample in order to distinguish between the two explanations discussed above.[35]

A. Cross-Sectional Analysis

In the cross-sectional analysis, we have two main concerns. First, we want to use measures that are consistent with those in prior studies. Second, as in the panel analysis, we want to have a battery of measures of competition so that we can examine whether our empirical findings are robust.

One major difference between the cross-sectional estimation and the fixed-effects panel estimation is the way in which we control for carrier-route-specific factors. The panel analysis included carrier-route dummies, which controlled for all the time-invariant characteristics specific to the carrier-route observation. In the cross section, however, using carrier-route dummies is not feasible since there is no time-series variation to exploit. Therefore, the econometrician must use a range of

[35] We lack a few of the cost variables used in Borenstein and Rose's original study. They obtained supplemental data from the *Official Airline Guide* to construct some of their cost variables, but we were unable to obtain access to this source. However, we were able to obtain some of those variables from the T-100 Segment database, which we will discuss in more detail below.

carrier-route- and route-specific covariates to control for carrier-route effects.[36]

1. Empirical Specification

We adopt two different specifications for the cross-sectional analysis. The first method corresponds to the method used by Borenstein (1989) and Borenstein and Rose (1994), in which the extent of competition along a route is measured with route concentration, $-\ln \mathrm{HERF}_j$, while controlling for the carrier's specific market share on the route, $\ln \mathrm{MKTSHARE}_{ij}$.[37] In this specification, market share is isolated from competition in order to hold fixed the market power specific to the carrier operating on the route. That is, this method theoretically allows the econometrician to assess the effects of competition between routes assuming that each carrier has the same amount of market power.[38]

The first model is

$$G_{ij}^{\mathrm{lodd}} = \beta_0 + \beta_1 \ln \mathrm{MKT}\widehat{\mathrm{SH}}\mathrm{ARE}_{ij} - \beta_2 \ln \widehat{\mathrm{HER}}\mathrm{F}_{ij} + \beta_3 \ln \mathrm{FL}\widehat{\mathrm{TT}}\mathrm{OT}_j + \beta_4 \ln \mathrm{TOURIST}_j + \beta_5 \mathrm{HUB}_{ij} + \beta_6 \mathrm{SMALL}_j + \alpha_i + \gamma_j + \eta_{ij}. \quad (3)$$

Like Borenstein and Rose, we specify that carrier effects, α_i, are fixed and that route effects, γ_j, are random. The variable TOURIST is the maximum of the ratio of accommodation earnings to total nonfarm earnings for the origin and destination airports; HUB is a dummy variable indicating whether the origin or the destination is a hub airport for the given carrier; SMALL is a dummy variable equal to one if the

[36] The cross-sectional regressions discussed below contain carrier-route- and route-specific variables that were not included in the fixed-effects panel regressions of Sec. III because these variables either do not vary much within a carrier-route observation over time or do not exhibit independent variation from the competition variables. For example, market power (as measured by market share) of carrier i is one such variable. Any variation in the market share of carrier i over time on a given route is generally due to a change in the degree of competition on the route, which is controlled for in the fixed-effects regression with route concentration. The density of route j (as measured by the total number of flights on route j) is another example, since most of the variation in this variable is due to differences in the number of competitors across routes rather than fluctuations over time. Indeed, there was very strong correlation between market share, market concentration, and market density within most routes over time.

[37] Again, we report the negative value of the Herfindahl estimate. The proportion of total passengers (in a given quarter) originating on route j on carrier i is used as a proxy for market share, $\mathrm{MKTSHARE}_{ij}$, which is subsequently used in the calculation of the Herfindahl index. Borenstein and Rose use flight shares—the proportion of total flights on route j on carrier i—as the relevant market share variable. Passenger shares and flight shares are highly correlated; however, passenger shares show more variation over time on a given route. Given this observation, we thought that it was the more relevant variable for the comparison in table 5. No results in this paper change if flight shares are used.

[38] Borenstein (1989) finds a statistically significant effect of market share on price. However, Evans and Kessides (1993) find that airfare is not correlated with market share.

route does not include a big city; and FLTTOT is the total number of flights on a given route and is included as a proxy for market density.[39]

The second specification measures competition using the number of competitors operating on the route but does not control for market share. This specification is given by

$$G_{ij}^{\text{lodd}} = \beta_0 + \beta_1 \ln \hat{N}_j + \beta_2 \ln \widehat{\text{FLTTOT}}_j + \beta_3 \ln \text{TOURIST}_j + \beta_4 \text{HUB}_{ij} + \beta_5 \text{SMALL}_j + \alpha_i + \gamma_j + \eta_{ij}. \tag{4}$$

We instrument for N, MKTSHARE, HERF, and FLTTOT using the same instruments used in Borenstein and Rose's analysis; these include distance, population, total passengers, and two instruments constructed by the authors.[40]

2. Cross-Sectional Estimation Results

We perform cross-sectional regressions on each of the 55 quarters in our sample in order to directly compare our results with those of Borenstein and Rose. For the sake of brevity, we report the first-quarter estimates in 6-year spans between 1993 and 2005 in table 4. Table 4 reports results from both models for these time periods.

Consistent with the results found by Borenstein and Rose, the results obtained in table 4 suggest that more competitive routes are characterized by more price dispersion. This result can be seen from the positive coefficient estimates on $-\ln \widehat{\text{HERF}}$ and $\ln \hat{N}$. These results are consistent with most of the quarters in our sample. In 53 of 55 quarters we obtain positive coefficient estimates associated with $-\ln \widehat{\text{HERF}}$, and in 49 quarters we obtain positive estimates associated with $\ln \hat{N}$, the majority of which are statistically significant at the 10 percent level or lower.

Borenstein and Rose interpreted this positive relationship between price dispersion and competition as evidence of the brand loyalty effect described above. One difference between our results in table 4 and their results is the estimated effect of market share on price dispersion. We

[39] Borenstein and Rose also include variables that control for weekly variation in fleet utilization rates and airport capacity utilization rates in order to control for predictable or "systematic" peak-load pricing, using data from the *Official Airline Guide* that are unavailable to us. We were able to construct seat capacity utilization rates at a monthly frequency using data from the T-100 Segment database, but this variable's effect is not significantly different from zero in any of the specifications we use, nor does it affect the other estimates in the model; thus, it is omitted from the estimations reported below. In online App. C (table C1), we provide a detailed table that compares the variables used in our model with those used in the analysis of Borenstein and Rose.

[40] Please refer to App. A for a detailed definition of all the variables as well as the instruments.

TABLE 4
Cross-Sectional Estimates
Dependent Variable: G_{ij}^{lodd}

	1993:Q1		1999:Q1		2005:Q1	
	(1)	(2)	(1)	(2)	(1)	(2)
$-\ln \widehat{\text{HERF}}$	.069		.337***		.179***	
	(.055)		(.058)		(.042)	
$\ln \widehat{\text{MKTSHARE}}$	.047***		.119***		.101***	
	(.015)		(.017)		(.015)	
$\ln \hat{N}$		.164***		.244***		.035
		(.038)		(.039)		(.029)
$\ln \widehat{\text{FLTTOT}}$	−.036***	−.074***	−.041***	−.084***	−.010	−.021**
	(.013)	(.013)	(.013)	(.014)	(.010)	(.010)
ln TOURIST	−.020	−.038***	−.043***	−.059***	−.030***	−.029***
	(.014)	(.014)	(.013)	(.013)	(.009)	(.009)
HUB	.054*	.140***	.133***	.320***	.108***	.208***
	(.028)	(.026)	(.034)	(.029)	(.027)	(.024)
SMALL	−.129***	−.067*	−.191***	−.149***	−.058**	−.061**
	(.034)	(.037)	(.034)	(.036)	(.025)	(.025)
Observations	1,993	1,993	2,085	2,085	2,053	2,053

Note.—All regressions include carrier-specific dummies. Route-specific effects are considered random in these regressions. Hats indicate that instrumental variables were used. Robust standard errors are in parentheses.
* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

find a statistically significant, positive effect of a carrier's market share on price dispersion in all three of the time periods. In the first quarter of 1993, a 10 percent increase in market share is estimated to increase the Gini log-odds ratio by 4.7 percent on average. This finding is consistent with the textbook theory, since an increase in a firm's market power is expected to increase its ability to segment the market. In contrast, Borenstein and Rose find a positive but not statistically significant effect of market share on price dispersion in their estimation.[41] Nevertheless, our cross-sectional estimates are generally consistent with their original analysis.

B. *The Role of Carrier-Route-Specific Factors*

In table 5 we report estimates from pooled, between-effects, random-effects, and fixed-effects panel regressions with the same specification as the cross-sectional regressions. We performed Hausman tests between the random-effects and fixed-effects models. In all cases the null hypothesis of zero correlation between the residuals and the vector of explanatory variables was rejected. The table suggests that a positive bias on the coefficient estimates associated with competition is coming

[41] One explanation for why our standard error associated with the coefficient on market share is smaller than that obtained by Borenstein an Rose might be a larger sample size.

TABLE 5
PANEL ESTIMATES
Dependent Variable: G_{ijt}^{lodd}

	Pooled	Between Effects	Random Effects ($\theta = .59$)	Fixed Effects ($\theta = 1$)
$-\ln \widehat{\text{HERF}}$	.116***	.380***	−.035***	−.105***
	(.007)	(.051)	(.012)	(.032)
$\ln \widehat{\text{MKTSHARE}}$	.092***	.154***	.086***	.066***
	(.003)	(.012)	(.006)	(.018)
$\ln \widehat{\text{FLTTOT}}$	.002	.042***	.040***	.034***
	(.002)	(.007)	(.003)	(.011)
ln TOURIST	−.050***	−.089***	−.068***	
	(.002)	(.007)	(.006)	
HUB	.132***	.254***	.274***	
	(.004)	(.018)	(.013)	
SMALL	−.122***	−.124***	−.173***	
	(.004)	(.019)	(.015)	
Observations	112,499	112,499	112,499	112,499

NOTE.—All four regressions include time-specific dummies. The pooled regression includes carrier-specific dummies. The panel variable for between, random, and fixed effects is carrier-route. The between-effects estimator measures the variation between carrier-routes. The term θ indicates the quasi-difference parameter of the random-effects model. A quasi-difference parameter of 0.59 indicates that the random-effects specification is controlling for 59 percent of the carrier-route-specific variation. The value of θ is constrained to one for the fixed-effects regression by construction. Hats indicate that instrumental variables were used. Standard errors are clustered by route in the fixed-effects regression.

* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

from the cross-sectional component of the data, as indicated by the large, positive estimate of competition (measured by $-\ln \widehat{\text{HERF}}$) from the between-effects regression. This result suggests that time-invariant, route-specific effects are responsible for biasing the coefficient estimates associated with the competition variables in the cross-sectional analysis. In this subsection, we discuss a particular route-specific effect—the distance of the route—that we believe may play a significant role in creating bias.

In the cross-sectional regressions performed by Borenstein and Rose, route effects, γ_j, are treated as random and distance is included in the instrument set, on the grounds that it should be a good instrument for route density, or the total number of flights on a route, FLTTOT_j. Including distance as an instrument is valid as long as it is not correlated with either of the error terms, η_{ij} or γ_j, in equation (3). In the following discussion we show that such a correlation is in fact present in our data, and it is responsible for biasing the estimates on the competition variables in the cross-sectional analysis.

For simplicity, we consider the univariate case in which competition_j corresponds to the level of competition on route j, and dist_j corresponds to the distance of route j. If we use distance as an instrument for com-

TABLE 6
DISTANCE, COMPETITION, AND PLANE SIZE

	$\overline{N}$	$\overline{\text{HERF}}$	$\overline{\text{ASEATCAP}}$
Distance < 450	2.49	.78	128
450 ≤ distance < 818	2.23	.77	128
818 ≤ distance < 1,240	2.85	.73	139
1,240 ≤ distance	3.16	.72	167

NOTE.—Each row represents a quartile of our sample, based on distance. The term $\overline{N}$ is the average number of competitors, and $\overline{\text{ASEATCAP}}$ is the average seat capacity of routes in each quartile.

petition in a two-stage least-squares regression, we can write the probability limit of the resulting IV estimator as

$$p\lim_{n\to\infty}\tilde{\beta} = \beta_0 + \frac{\text{Cov}\,(\text{dist}_j,\ u_j)}{\text{Cov}\,(\text{dist}_j,\ \text{competition}_j)}. \tag{5}$$

We argue that the sign of the ratio of covariances in equation (5) is positive for the following reasons: Carriers tend to use larger planes on longer routes because of fuel considerations. Furthermore, because of improved technology in aircraft fuel consumption, it is only in recent years that smaller aircraft have become capable of making long-distance trips.[42] This suggests a positive correlation between plane size and route distance, which we see in the data (see table 6). Price dispersion is also likely related to the size of the plane, since larger planes contain more seats and thus provide an airline with a greater opportunity to implement strategies that create more price dispersion. This suggests a positive relationship between plane size and price dispersion. However, plane size is omitted from the regressions estimated by Borenstein and Rose, so its effect is embedded in the error term, u_{ij}, and implies that the numerator, Cov (dist$_j$, u_j), is positive. We also find a positive correlation between the distance of a route and the degree of competition, which suggests that the denominator, Cov (dist$_j$, competition$_j$), is positive. Specifically, when we segment routes on the basis of distance, we find that the average number of effective competitors (inverse of the Herfindahl index) as well as the number of competitors rises with distance (see table 6).[43] While we are not certain about the source of this positive relationship between competition and distance, we believe that it may be due to the effect of route density. With a few exceptions, such as the Northeast, large cities in the United States tend to be located at relatively

[42] Average seat capacity for routes above the median distance (762 miles) has fallen by 5 percent, whereas for routes below this distance, average seat capacity has increased by 3 percent over the course of the sample period

[43] We also performed univariate regressions of competition on distance and obtained positive and significant coefficient estimates. These results are omitted from the paper but are available from the authors on request.

TABLE 7
CROSS-SECTION ROBUSTNESS ESTIMATES: 1993:Q1
Dependent Variable: G_{ijt}^{lodd}

	(1)	(2)	(3)	(4)
$-\ln \widehat{\text{HERF}}$	.069		−.065	
	(.055)		(.064)	
$\ln \widehat{\text{MKTSHARE}}$	.047***		−.006	
	(.015)		(.018)	
$\ln \hat{N}$		.164***		−.010
		(.038)		(.048)
$\ln \widehat{\text{FLTTOT}}$	−.036***	−.074***	−.075***	−.077***
	(.013)	(.013)	(.015)	(.015)
ln TOURIST	−.020	−.038***	−.113***	−.116***
	(.014)	(.014)	(.018)	(.018)
HUB	.054*	.140***	.103***	.089***
	(.028)	(.026)	(.035)	(.031)
SMALL	−.129***	−.067*	.003	.004
	(.034)	(.037)	(.042)	(.044)
ln ASEATCAP			1.428***	1.423***
			(.117)	(.123)
Observations	1,993	1,993	1,993	1,993

NOTE.—All regressions include carrier-specific dummies. Route-specific effects are considered random. Hats indicate that instrumental variables were used. Robust standard errors are in parentheses.
* Significant at the 10 percent significance level.
** Significant at the 5 percent significance level.
*** Significant at the 1 percent significance level.

long distances from each other. Since demand for air travel increases with the population of endpoint cities, we would expect, ceteris paribus, more competition on long-distance routes between large cities.[44] Equation (5) therefore suggests that the sign of the bias is positive.[45]

To address this potential bias in our cross-sectional regressions, we add a measure of plane size (average number of seats for carrier i on route j) as an additional endogenous explanatory variable in our cross-sectional regressions. In essence, we are instrumenting for plane size with distance in an attempt to remove the correlation between distance and the error term. Table 7 reports results from 1993:Q1 (the first quarter of our sample) and shows that when average seat capacity, $\ln \widehat{\text{ASEATCAP}}$, is included in the regression,[46] its coefficient estimate is positive and significant. More important, its inclusion causes the estimated effect of competition on price dispersion to reverse sign. More

[44] We thank an anonymous referee for this explanation. The effect of route density may also contribute to the use of larger planes along long-distance routes.

[45] Borenstein and Rose intended to use distance to instrument for the number of flights on a route, not for the competition variables. However, in a setting with multiple endogenous variables and multiple instruments, it is not possible to assign specific instruments to specific endogenous variables.

[46] The T-100 Segment database contains information on the total number of monthly departures and the total number of available seats. We divide seats by departures to construct a variable corresponding to the average number of available seats per departure, which is our proxy for plane size, ASEATCAP.

generally, when the proxy for plane size is included, the estimated effect of competition—as measured by the negative Herfindahl—on price dispersion falls in all 55 quarters of the sample.

Figure 4 helps illustrate this finding by plotting the coefficient estimates associated with $-\ln \widehat{\mathrm{HERF}}$ before and after the inclusion of $\ln \widehat{\mathrm{ASEATCAP}}$ as an explanatory variable. The figure, which displays estimates for the first quarter of each year, clearly shows how the coefficient estimates significantly fall with the inclusion of plane size. This indicates that there is indeed a significant bias induced by the correlations between plane size, distance, and competition. In particular, the bias is in the direction hypothesized.[47]

While this discussion has focused on the effects of distance and plane size, they are only one potential source of bias in the cross-sectional analysis. It is certainly possible that other time-invariant factors besides distance are also biasing the cross-sectional estimates of the effects of competition on price dispersion. This suggests that the appropriate estimation method for this question is a fixed-effects panel estimator.

V. Fixed-Effects Time Interaction

Over the course of our sample the U.S. domestic airline industry has experienced changes in competition, demand, and cost. Large increases in the price of oil, beginning in the early 2000s, have placed severe upward pressure on airlines' input costs. The latest business cycle, characterized by the information technology boom in the late 1990s and the subsequent recession in the early 2000s, and further incited by the September 11 terrorist attacks, also has had an effect on the demand for domestic air travel. Finally, the emergence of the LCCs has increased competitive pressures on the legacy carriers. Thus, as a final exercise, we include year-dummy interactions with our competition variable, $-\ln \widehat{\mathrm{HERF}}$, in our fixed-effects panel estimation to see whether the effect of competition on price dispersion has changed over the course of the sample period.

We plot the estimates of $-\ln \widehat{\mathrm{HERF}}$ from the year-dummy interactions

[47] We also performed regressions in which we included distance as a right-hand-side variable. In most of the time periods, distance entered with a positive and significant coefficient estimate, and its inclusion subsequently lowered the estimate for $\ln \widehat{\mathrm{HERF}}$ and $\ln \hat{N}$. We also found a significant reduction in the *J*-statistic—which tests the overidentification of the instrument set—when we removed distance from the instrument set and also when we left distance in the instrument set but included average seat capacity in the regression under standard IV estimation. For example, in 1993:Q1 (under model 1), the *J*-statistic falls from 256.8 to 87.4 when we remove distance from the instrument set. It falls to 11.7 when we put distance back into the instrument set but include $\ln \widehat{\mathrm{ASEATCAP}}$ as an explanatory variable. These results suggest that distance is highly correlated with the error term when plane size is not included in the regression.

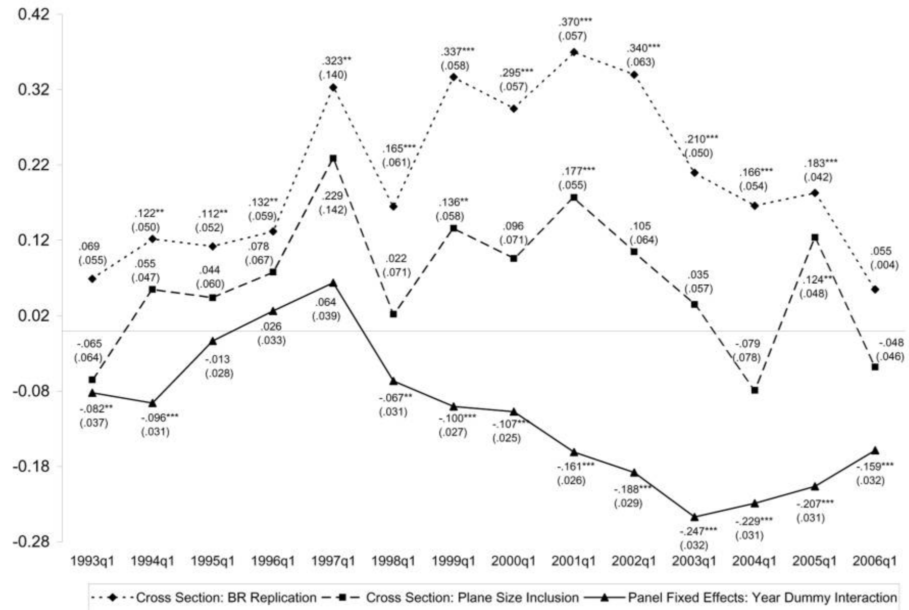


FIG. 4.—The effects of competition on price dispersion. The figure shows estimates (for three different regressions) of the coefficient on competition as measured by $-\ln \widehat{HERF}$. Diamonds indicate estimates of $-\ln \widehat{HERF}$ under equation (4) for quarter 1 of each year in our sample, squares indicate estimates of the same equation including average seat capacity as an endogenous explanatory variable, and triangles indicate estimates on the year-dummy interactions of the fixed-effects panel analysis. Robust standard errors are in parentheses. One, two, and three asterisks indicate significance at the 10 percent, 5 percent, and 1 percent significance level, respectively.

in figure 4. First, it is notable that for each year in the sample, the estimates fall monotonically below the cross-sectional estimates that include plane size. The inclusion of fixed effects therefore removes all of the bias induced by time-invariant, route-carrier effects, over and above plane size.

The pattern of the point estimates from the interaction terms is also notable. The yearly estimates of $-\ln \widehat{\mathrm{HERF}}$ plotted in figure 4 move to magnitudes that are not statistically different from zero for the early to mid 1990s and then return to magnitudes that are negative and statistically different from zero in the late 1990s and the early 2000s, before subsequently falling after 2003. An explanation that is consistent with this pattern is that airlines are able to price-discriminate less during troughs in the business cycle than they can during peaks. This would be the case if price dispersion is procyclical.[48] This suggests that during troughs in the business cycle (when airlines price-discriminate less) the effect of competition on price dispersion is less than during peaks in the business cycle (when airlines price-discriminate more).[49] Therefore, the negative effect of competition on price dispersion will be larger when price discrimination is ostensibly present.

VI. Conclusion

In this study, we perform a panel analysis of the effect of competition on price dispersion in the airline industry, in which we use fixed-effects estimation to control for time-invariant, carrier-route-specific factors. This enables us to identify the effects of changes in the competitive structure of a route on price dispersion over time. Our results show that an increase in competition over time along a route results in a decrease in price dispersion.

In addition, we find that an increase in competition on a route significantly reduces price dispersion in markets that we identify as having a heterogeneous mixture of business travelers and leisure travelers. Specifically, an increase over time in the number of carriers on these routes lowers the prices at the top of the price distribution to a greater extent than it lowers prices at the bottom of the price distribution, resulting in a decline in overall price dispersion. On routes to leisure destinations,

[48] In other work (Gerardi and Shapiro 2007), we document that price dispersion in the airline industry is procyclical. Morrison and Winston (1995) document the evolution of price dispersion from the end of deregulation through the early 1990s.

[49] As a robustness check, we interacted $\ln \widehat{\mathrm{HERF}}$ with the output gap, a measure of the business cycle, in a fixed-effects panel regression. We found the interaction term to be positive and significant, indicating that the effect of competition on price dispersion is inversely proportional to the cycle.

where we believe that the consumer base is more homogeneous, the effects of competition on price dispersion are much smaller.

Finally, we find that the negative relationship between competition and price dispersion has changed over time and, in particular, appears to be dependent on the business cycle. In particular, the effect of competition on price dispersion is mitigated during troughs in the business cycle, when the ability of airlines to price-discriminate is likely less, whereas it is enhanced during peaks in the business cycle, when the ability of airlines to price-discriminate is likely greater.

Our findings strongly suggest that prices charged to price-inelastic travelers are more affected by increased competition than prices charged to price-elastic travelers. This loss in price dispersion therefore suggests that an increase in competition erodes the carrier's ability to segment markets. It is clear that this erosion is due to a loss of market power that typically accompanies the entry of a new competitor, which supports the traditional textbook treatment of the relationship between competition and price discrimination.

We reconcile our findings with the results of the seminal study conducted by Borenstein and Rose (1994) by performing cross-sectional regressions on each quarter of our data. For a large majority of the cross sections, we obtain similar results, finding a positive relationship between the degree of competition and price dispersion across markets. The analysis shows that the cross-sectional estimates differ from the panel estimates in our sample because of omitted variable bias induced by time-invariant, route-carrier effects. When we control for route-carrier characteristics using panel data methods, we find that increased competition results in decreased price dispersion for incumbent airlines along a given route. The magnitude of the effect is significantly stronger when a change in the competitive structure of the market is induced by a low-cost carrier, suggesting that the influx of LCCs into the airline industry in the 1990s and 2000s likely bolstered the effects of competition on price dispersion. However, the negative effect of competition on price dispersion is robust to the entrance of legacy carriers. Thus, our study suggests that much of the difference between our findings and those of Borenstein and Rose is due to differences in estimation technique as opposed to differences in the competitive structure of the sample periods.

Appendix A

Variable Definitions

G_{ijt}^{lodd}: The Gini log-odds ratio, given by $G_{ijt}^{\text{lodd}} = \ln[G_{ij}/(1 - G_{ij})]$, where G_{ijt} is the Gini coefficient of carrier i's price distribution on route j in period t, calculated using data from the DB1B.

$\ln P(k)_{ijt}$: The logarithm of the kth price percentile of carrier i on route j in period t, obtained from the DB1B.

$\ln \text{MKTSHARE}_{ijt}$: The logarithm of the share of total passengers originating on route j operated by carrier i in period t, calculated from the DB1B.

$\ln \text{HERF}_{jt}$: The logarithm of the Herfindahl index of route j in period t, calculated using passenger shares obtained from the DB1B.

$\ln N_{jt}$: The logarithm of the total number of carriers operating on route j in period t, obtained from the DB1B.

$\ln \text{FLTTOT}_{jt}$: The logarithm of the total number of departures performed on route j in period t, obtained from the T-100 Domestic Segment Databank.

HUB_{ij}: A dummy variable indicating whether either the origin or destination of route j is a hub airport of carrier i.

SMALL_j: A dummy variable indicating if both the origin and the destination airports are not in our list of big cities.

$\ln \text{TOURIST}_j$: The logarithm of the maximum of the ratio of accommodation earnings to total nonfarm earnings for the origin and destination cities on route j, obtained from the BEA.

$\ln \text{ASEATCAP}_{ij}$: The logarithm of average seat capacity (total available seats divided by total number of departures) on route j by carrier i obtained from the T-100 Domestic Segment Databank.

N_{jt}^{LEG}: The number of legacy carriers on route j in period t obtained from the DB1B.

N_{jt}^{LCC}: The number of low-cost carriers on route j in period t obtained from the DB1B.

Instruments

$\ln \text{DISTANCE}_j$: The logarithm of nonstop distance in miles between endpoint airports of route j.

AMEANPOP: The arithmetic mean of the metropolitan population of endpoint cities taken from the 2000 U.S. Census.

GMEANPOP: The geometric mean of the metropolitan population of endpoint cities taken from the 2000 U.S. Census.

$\ln \text{PASSRTE}_{jt}$: The logarithm of total enplaned passengers on route j in period t from the T-100 Domestic Segment Databank.

IRUTHERF: This instrument is identical to one used by Borenstein and Rose (1994). This variable is the square of the fitted value for MKTSHARE_{ijt} from its first-stage regression, plus the rescaled sum of the squares of all other carrier's shares. See Borenstein and Rose (1994) for a more detailed explanation. It is equal to

$$\widehat{\text{MKTSHARE}}^2_{ijt} + \frac{\text{HERF}_{jt} - \text{MKTSHARE}^2_{ijt}}{(1 - \text{MKTSHARE}_{ijt})^2} \times (1 - \widehat{\text{MKTSHARE}}_{ijt})^2.$$

GENSP: $\sqrt{\text{ENP}_{j1} \times \text{ENP}_{j2}} / \sum_k \sqrt{\text{ENP}_{k1} \times \text{ENP}_{k2}}$, where k indexes all airlines, j is the observed airline, and ENP_{k1} and ENP_{k2} are airline k's average quarterly enplanements at the two endpoint airports. This instrument is similar to one used by Borenstein and Rose (1994), with the difference being that Borenstein and Rose use average daily enplanements, whereas we use average quarterly enplanements, as a result of data availability. Data on enplanements were obtained from the T-100 Domestic Segment Databank.

Appendix B

Data Construction

In this appendix, we discuss our methods and assumptions involved in constructing our panel of airline-route ticket observations from the DB1B and T-100 Domestic Segment databases maintained by the BTS at its online Web site, Transtats. There are three different subcomponents to the DB1B data set. They are market data, coupon data, and ticket data, and we combine variables from all three sources.[50]

We use only domestic, coach-class itineraries and keep only tickets containing direct flights.[51] Direct flights typically account for 30 percent of the itineraries in the DB1B over the course of our sample, with no apparent trend. The maximum percentage was 34.2 in 2006:Q1, and the minimum percentage was 22.8 in 1994:Q2.

The BTS includes a variable that describes the reliability of each ticket price ("dollar cred"). The variable takes on a value of zero if the fare is of questionable magnitude, on the basis of a set of limits defined by the BTS, and it takes a value of one if it is credible. We drop all tickets for which this variable takes a value of zero.

The DB1B also provides limited information regarding the fare class of each ticket. Each ticket is labeled as either coach-class, business-class, or first-class, and we eliminated all first-class and business-class itineraries. Unfortunately, the DB1B does not have any direct way of identifying frequent-flyer tickets, but there are indirect methods that have been used in the previous literature, and we follow these in our analysis. First, we drop all fares coded as 0. Next, we dropped all fares that are less than or equal to \$20 (\$10 for one-way tickets).

In addition to eliminating frequent-flyer tickets and higher-class tickets, we also eliminate tickets in which the operating and ticketing carriers are different because of code-sharing arrangements. Code sharing is a practice in which a

[50] For further reference, see the BTS's Web site (http://www.transtats.bts.gov).

[51] The sample of direct flights encompasses both nonstop flights and flights in which there is a stop but no change of plane.

flight operated by an airline is jointly marketed as a flight for one or more other airlines. Owing to the uncertainty regarding the actual airline that is setting the price schedule in such an arrangement, we decided to eliminate these itineraries. Code sharing first appears in the data in 1998:Q1. Table B1 displays for each quarter in the sample the total number of direct tickets, the number of tickets included in the analysis after the filtering process described above, the number of unique directional routes, and the number of airlines. On average, approximately 80 percent of the original number of direct tickets in the DB1B is retained in the analysis.

After filtering the ticket data for each quarter of the DB1B, we combined tickets from all 55 quarters and collapsed the data into airline-route observations. For example, if we had 10,000 United Airline tickets between Boston and Los Angeles in 1993:Q1, we calculated summary statistics (such as the Gini coefficient) and collapsed the data into a single observation corresponding to a United Airlines flight between Boston and Los Angeles in 1993:Q1. This left us with 606,015 airline-route observations between 1993:Q1 and 2006:Q3.

After merging all 55 quarters of the DB1B airline-route data with supplemental data from the T-100 Segment data, we were left with 274,821 airline-route observations, which encompass 8,850 distinct directional routes. The merge between the DB1B and T-100 Segment databases was not exact (around 45 percent matched). First, since the DB1B does not provide complete coverage for all airlines and routes, there are a number of direct routes in the T-100 data that we do not find in the DB1B (especially low-volume routes). Second, the DB1B does not allow us to distinguish between a nonstop, direct ticket and a ticket that involves a stop without a plane change. For example, if a passenger takes a flight from Boston to Orlando that stops in Atlanta but does not involve a plane change, his itinerary will look identical to that of a passenger who flies from Boston to Orlando without any stops. For this reason, we identified some airline routes as direct in the DB1B that are not nonstop and therefore do not have segment information in the T-100 data. While we lose many airline-route observations during the merge as a result, we believe that this merge actually provides a nice filter, since we would ideally like to use only nonstop, direct flights. Thus, by merging data between the DB1B and the T-100, we likely eliminate a large proportion of flights that are direct but not nonstop because of a plane change.

In an effort to eliminate possible coding errors, we drop certain airline-route observations from the data that we believe do not have adequate coverage to calculate reliable price dispersion statistics. We drop any airline-route observation that does not have at least 100 passengers in the DB1B. Furthermore, for each airline-route observation, we calculate the average number of passengers over time in both the DB1B and the T-100 Segment databases. If the number of passengers on an airline-route in a given quarter falls below 25 percent of its mean over time in one of the databases but not in the other, then we drop the observation from our data, on the basis that its value is most likely measurement error. However, if the number of passengers on an airline-route in a given quarter falls below 25 percent of its mean in both the DB1B and the T-100 Segment databases, then we keep the observation in our data. This leaves us with 222,261 airline-route observations.

TABLE B1
SAMPLE DETAILS

	Direct Tickets	Included in Sample	Distinct Routes	Distinct Airlines
1993:Q1	454,111	409,592	8,194	52
1993:Q2	583,547	513,098	10,893	58
1993:Q3	552,335	502,207	14,459	55
1993:Q4	576,828	523,697	14,515	53
1994:Q1	387,282	349,189	12,386	52
1994:Q2	383,384	345,349	8,332	63
1994:Q3	401,413	362,361	8,033	68
1994:Q4	432,410	393,533	7,883	60
1995:Q1	469,002	425,397	7,694	55
1995:Q2	457,736	419,642	7,685	60
1995:Q3	510,481	471,504	7,154	67
1995:Q4	593,578	541,742	7,289	67
1996:Q1	657,938	603,981	7,210	69
1996:Q2	511,920	468,429	7,488	69
1996:Q3	526,814	485,863	7,135	65
1996:Q4	562,184	521,332	7,113	62
1997:Q1	531,477	490,869	7,085	69
1997:Q2	563,734	524,267	7,347	74
1997:Q3	560,201	521,747	6,977	81
1997:Q4	546,913	508,082	6,790	66
1998:Q1	501,953	409,537	5,703	55
1998:Q2	554,740	461,818	6,262	55
1998:Q3	582,489	481,740	6,104	60
1998:Q4	664,039	554,610	5,952	57
1999:Q1	639,660	524,465	5,924	50
1999:Q2	654,209	532,586	6,150	49
1999:Q3	665,357	535,958	6,005	54
1999:Q4	731,422	594,379	6,049	46
2000:Q1	775,568	628,215	5,828	49
2000:Q2	812,520	648,177	6,184	59
2000:Q3	746,563	591,353	5,873	58
2000:Q4	811,146	648,436	6,028	55
2001:Q1	721,673	581,410	5,863	51
2001:Q2	793,630	622,636	5,651	51
2001:Q3	703,509	560,749	5,457	55
2001:Q4	684,265	535,549	5,327	50
2002:Q1	711,821	559,115	5,137	42
2002:Q2	736,101	564,072	5,584	46
2002:Q3	707,322	537,743	5,339	46
2002:Q4	687,208	534,078	5,301	44
2003:Q1	641,494	474,793	5,185	38
2003:Q2	748,889	548,439	5,380	41
2003:Q3	654,838	476,012	5,100	42
2003:Q4	771,144	561,482	5,264	42
2004:Q1	716,075	519,456	5,163	43
2004:Q2	822,045	583,893	5,362	40
2004:Q3	747,004	517,737	5,176	41
2004:Q4	858,826	603,091	5,476	44
2005:Q1	825,845	578,224	5,317	53
2005:Q2	931,194	643,535	5,490	47
2005:Q3	903,656	630,225	5,329	51

TABLE B1
(*Continued*)

	Direct Tickets	Included in Sample	Distinct Routes	Distinct Airlines
2005:Q4	923,978	626,871	5,162	47
2006:Q1	910,009	620,542	5,070	46
2006:Q2	1,023,672	670,066	5,158	43
2006:Q3	954,459	599,844	5,135	41

Finally, we addressed the issue of "double counting." Since we defined a route as a directional trip in our data, any round-trip ticket would count twice. For example, a round-trip fare from Boston to San Francisco would appear twice in the data: once as BOS–SFO and once as SFO–BOS. Since this would have no effect on the consistency of our estimates but a significant effect on the size of our standard errors, we chose to drop one of the directions. Of course, the drawback of this assumption is that some one-way fares were dropped from the data as a result. In our judgment, the first issue outweighed the second issue. Dropping one of the directions decreases our sample to 112,499 carrier-route observations, covering 5,444 distinct carrier-route observations and 2,902 distinct routes.

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