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# IS THE EFFECT OF COMPETITION ON PRICE DISPERSION NONMONOTONIC? EVIDENCE FROM THE U.S. AIRLINE INDUSTRY

Mian Dai, Qihong Liu, and Konstantinos Serfes\*

Abstract—We investigate the effect of competition on price dispersion in the airline industry. Using panel data from 1993 to 2008, we find a nonmonotonic effect of competition on price dispersion. An increase in competition is associated with greater price dispersion in concentrated markets but with less price dispersion in competitive markets—an inverse-U relationship. Our empirical findings are consistent with an oligopolistic second-degree price discrimination model and encompass contradictory findings in the literature

#### I. Introduction

HE typical intuition when firms practice price discrimination is that market power increases their ability to implement price discriminatory strategies, which implies a negative association between competition and price dispersion. A number of research papers have investigated empirically the relationship between competition and price dispersion in the U.S. airline market, but with different conclusions. Borenstein and Rose (1994), using cross-sectional data from 1986, and Stavins (2001), using a data set from 1995 with detailed information on individual tickets, find a positive effect of competition on price dispersion (more price dispersion in more competitive routes). However, Gerardi and Shapiro (2009), by assembling a panel from 1993 to 2006. uncover a negative effect of competition on price dispersion.<sup>1</sup> In this paper, we reexamine the link between price dispersion and market structure by developing a theoretical model that generates a nonmonotonic relationship.<sup>2</sup> Our empirical analysis reveals the existence of such a relationship in the U.S. airline industry.3

With the help of an oligopolistic second-degree price discrimination theoretical model, we identify two opposing

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<sup>1</sup> The mixed role of competition on price dispersion has been documented in other markets such as Yellow Pages advertising (Busse & Rysman, 2005) and detergents (Clerides & Michis, 2006).

<sup>2</sup> If the true effect of competition is nonmonotonic and the empirical model is restricted to be monotonic, then the estimated effect can be either positive or negative depending on where the data are concentrated.

<sup>3</sup> Most empirical models look at the relationship between price dispersion and concentration with log-log or log-linear specifications. While these models allow for nonlinearity, nonmonotonicity is precluded. One specification in Borenstein and Rose (1994)— the one that uses market structure indicators—can accommodate nonmonotonicity. However, they did not actively look for nonmonotonicity, and their results indicate a monotonic relationship.

forces of competition on price dispersion.<sup>4</sup> More intense competition directly affects prices (the direct price effect), resulting in a higher price dispersion. At the same time, competition also affects prices through firms' optimal quality choices (the indirect quality effect), which lowers price dispersion.<sup>5</sup> Overall, the net effect of competition on price dispersion depends on which effect dominates. We show that in our model, the direct price effect dominates at high concentration levels, and the indirect quality effect dominates at low concentration levels. This gives rise to an inverse-U-shaped relationship between competition and price dispersion.

Using a rich data set from the U.S. airline markets in 64 quarters between 1993 and 2008, we test for the existence of a nonmonotonic association between competition and price dispersion. Our empirical results show that price dispersion indeed increases with competition in concentrated markets and decreases with competition in less concentrated markets. Consistent with our theoretical intuition, the nonmonotonicity is driven by differential rates of price declines for lowand high-end products. In concentrated markets, prices of low-end products decline faster with competition, while in less concentrated markets, prices of high-end products drop faster. While our results encompass the findings in Borenstein and Rose (1994), Stavins (2001), and Gerardi and Shapiro (2009), we highlight the differential impact of competition in shaping the observed pricing patterns and offer a new perspective on the relationship between market structure and price dispersion.

The paper is organized as follows. Section II presents the theoretical model and the intuition behind the nonmonotonic relationship. Section III introduces the data, and section IV offers descriptive evidence consistent with nonmonotonicity. Section V presents the empirical model and results. Section VI concludes. The proof of the theoretical result, sample construction, and a description of the instruments are in the appendix.

<sup>4</sup> The airline industry is arguably replete with second-degree price discrimination. In a second-degree price discrimination model, firms offer a menu of products to consumers without directly observing their preferences. Consumers, in turn, self-select. Ticket characteristics, which are used to induce separation of different types of travelers, in this case consist of (a) refundable or not; (b) time of the day and day of the week for flight; (c) advance purchase (how advance); and (d) (our data span both) Saturday night stayover (in the past) as well as seats with more leg room (more recent). Firms set a lower price (discount) for the high-end product (ticket) than what they would have charged had they known the exact preferences of the consumers (and distort the low quality downward).

<sup>5</sup> The direct price effect causes the price for low-quality products to decline faster (in percentage) than the price of high-quality products. This increases price dispersion. Contrary to the direct effect, the indirect quality effect causes the price of the high-quality product to decline faster. This shrinks the price gap between high- and low-quality products and lowers price dispersion. A detailed intuition is provided in section IIA.

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# II. Theoretical Model and Intuition for the Nonmonotonic Relationship

We construct a theoretical model of oligopolistic seconddegree price discrimination that offers an explanation for why the effect of competition on price dispersion may be nonmonotonic.

We focus on two types of travelers: business and leisure travelers. Business travelers value quality more and are less price sensitive than leisure travelers. Multiple studies have shown that airlines separate leisure travelers from business travelers using sophisticated strategies such as advance purchase discounts (Dana, 1998) and Saturday night stay-overs (Stavins, 2001). In our model, we summarize all vertical nonprice characteristics of the ticket into a single variable, quality q. The marginal cost of producing a good of quality q, is assumed to be  $aq^2/2$  (with a>0), while for simplicity, we set the fixed cost of quality equal to 0. Firm i endogenously chooses  $q_{i\ell}$  (low) and  $q_{ih}$  (high) with  $q_{ih}>q_{i\ell}\geq 0$  and i=1,2. As is standard in quality competition models, we assume firms first choose qualities and then compete on prices.

High-valuation business travelers (h) and low-valuation leisure travelers ( $\ell$ ) differ in  $\theta$ , their preference for quality, with  $\theta_h > \theta_\ell$  (leisure travelers generally care less about quality). There are two firms (i=1,2), located at two end points of a Hotelling line [0,1]. Transportation cost is quadratic in the distance a consumer has to travel to consume a good. We further assume that the per unit transportation cost, which is used to capture the intensity of competition, is higher for business travelers ( $t_h > t_\ell$ ).

A type  $\ell$  consumer located at point x who buys firm 1's low-quality product will enjoy a utility of  $V + \theta_{\ell}q_{1\ell} - p_{1\ell} - t_{\ell}x^2$  and a utility of  $V + \theta_{\ell}q_{2\ell} - p_{2\ell} - t_{\ell}(1-x)^2$  if he or she then buys firm 2's low-quality product. The utilities of the consumers who are buying high-quality products can be derived similarly. Each type of consumer is uniformly distributed on the [0, 1] interval. The fraction of  $\ell$  type consumers is  $\sigma$  and that of h type is  $1 - \sigma$ . Finally, we assume that in the equilibrium, each firm will produce both qualities.<sup>8</sup>

<sup>6</sup>We believe that a discrete type is a good approximation to the airline industry. Several papers estimate airline demand using a two-type discrete choice model (Berry & Jia, 2010, Ciliberto & Williams, 2013). The two-type airline demand model fits the data quite well. The intuition from our two-firm model can be extended to *N*-firms.

<sup>7</sup>The Hotelling-type model captures that the airlines usually enjoy some local market power by fostering brand loyalty through frequent flyer programs, travel agent commission override programs, and so on. The Hotelling assumption is also consistent with Berry and Jia (2010), who use a differentiated Bertrand model to recover marginal cost of major airlines, and Brueckner (2010), who looks at schedule competition.

<sup>8</sup> Our framework is built on similar models developed in Stole (1995), Villas-Boas and Schmidt-Mohr (1999), Desai (2001), Rochet and Stole (2002), and Yang and Ye (2008). Using models similar to ours, Hernandez and Wiggins (2008) and Hernandez (2011) derive and test the predictions of a second-degree price discrimination model using a unique data set of airline ticket transactions, while Alderighi et al. (2010) look at the differential impact of full-service carriers (FSC) and low-cost carriers (LCC) in European airline market. Finally, Alderighi (2010) simulates three popular models to evaluate their ability to generate substantial fare dispersions.

Firm i's problem is

$$\begin{split} \max_{\langle q_{i\ell},q_{ih},p_{i\ell},p_{ih}\rangle} \pi_i &= \sigma \left[ \left( p_{i\ell} - \frac{aq_{i\ell}^2}{2} \right) d_{i\ell} \right] \\ &+ (1-\sigma) \left[ \left( p_{ih} - \frac{aq_{ih}^2}{2} \right) d_{ih} \right] \\ \text{subject to:} \quad p_{ih} - p_{i\ell} &\leq \theta_h (q_{ih} - q_{i\ell}) \quad \text{(IC high type)} \\ \text{and} \quad p_{ih} - p_{i\ell} &\geq \theta_\ell (q_{ih} - q_{i\ell}) \quad \text{(IC low type)} \end{split}$$

where  $d_{i\ell}$  and  $d_{ih}$  are the demand functions for its low- and high-quality product, respectively.

Equations (IC high type) and (IC low type) are the incentive compatibility (IC) constraints, which guarantee that an h-type consumer does not have an incentive to misrepresent his type and buy the low-quality product, and an  $\ell$ -type consumer has an incentive to stay with the low-quality product. To reduce the number of cases that we would have to analyze, we assume that V is sufficiently high. This assumption, coupled with the fact that competition restrains equilibrium prices, implies that the individual rationality constraints are automatically satisfied (covered market). This corresponds to the full-scale competition case in Villas-Boas and Schmidt-Mohr (1999). Proposition 1 states the main theoretical result:

**Proposition 1:** The relationship between the unit transportation cost (intensity of competition) and equilibrium price dispersion (measured by the Gini coefficient) is nonmonotonic and can be inverse U-shaped.

**Proof.** See the appendix.

#### A. Intuition for the Nonmonotonic Relationship

For simplicity, we set  $t_h = ct_\ell = ct$  for some c > 1. Hence, a singe parameter t can be used to represent the intensity of competition in the market. Assume that the market becomes more competitive: that is, t, starting from a high value, decreases. We are interested in the effect it has on price dispersion. Increasing competition has two opposing effects on prices: a direct price effect and an indirect quality effect. The direct price effect refers to the change in prices holding qualities fixed, and the indirect quality effect looks at the impact of quality change on prices.

As is standard in second-degree price discrimination models, the incentive compatibility constraint for the high type (IC-H) is binding:  $p_{ih} - p_{i\ell} = \theta_h(q_{ih} - q_{i\ell}), i = 1, 2.9$  The direct effect will increase price dispersion because the price difference is constant (since qualities are held constant), while price levels, due to competition, are falling.<sup>10</sup>

The indirect effect leads to lower price dispersion for the following reason. As competition intensifies, firms compete

<sup>&</sup>lt;sup>9</sup> This constraint ensures that high-end consumers (business travelers) do not find the low-end ticket (designed for leisure travelers) appealing. Once this constraint is binding, the IC constraint for the low type is automatically satisfied.

<sup>&</sup>lt;sup>10</sup> We measure price dispersion in percentages, which is what matters for the Gini coefficient.

more vigorously by increasing the quality offered to the low group (the level of quality offered to the low consumer group is already distorted downward relative to its efficient level). Higher quality offered to the low group means higher marginal cost, which puts a constraint on how fast the price for the low group is declining. As is typical in these models, the quality offered to the high group is fixed at its efficient level (no distortion at the top). A smaller difference between high and low qualities, combined with the IC-H constraint  $p_{ih} - p_{i\ell} = \theta_h(q_{ih} - q_{i\ell})$ , implies that the price differential between the high and the low group,  $p_{ih} - p_{i\ell}$ , must be shrinking. Given that the indirect quality effect restrains the rate of decrease of the low price, it must be that the high price is decreasing faster. Therefore, price dispersion declines.

So far, we have two opposing effects of competition on price dispersion. The question then is which effect is stronger and when. The direct effect dominates on price levels (so prices, as expected, decline as competition intensifies) but not necessarily on price dispersion. In terms of the effect on price dispersion, our results show that the strength of the indirect effect increases when t goes down (thus giving rise to an inverted U-shape when price dispersion is plotted as a function of competition; see figure 3).<sup>11</sup> Next, we take this theoretical prediction to the data.<sup>12</sup>

#### III. Data

The data on airline ticket prices comes from the Airline Origin and Destination Survey (DB1B) maintained by the Bureau of Transportation Statistics. DB1B are a 10% random sample of airline itineraries from reporting carriers in each quarter. To reach itinerary, DB1B records the ticketing and operating carriers, all connecting airports (including origin and destination), itinerary fare, and service class. We use DB1B to construct measures of price dispersion, fare quantiles, and market shares. Following the previous literature (Borenstein & Rose, 1994; Goolsbee & Syverson, 2008; Gerardi & Shapiro, 2009); we build our sample from

<sup>11</sup> The intuition behind the inverse U-shape is as follows. When t is high, competition is not very intense, and firms offer low levels of quality for the low-quality product. Hence, the marginal cost of production (which depends positively on the level of quality) is low and the indirect quality effect is weak. The price effect is stronger in this region, and a lower t increases dispersion. When t is low, firms compete more aggressively on prices and qualities. The low quality is now higher, and the marginal cost associated with it is higher as well. Hence, the indirect quality effect is stronger. A further reduction in t leads to less price dispersion. Overall, we can obtain an inverse U-shape relationship.

12 In the theoretical model, there is no factor other than second-degree price discrimination, which can cause price dispersion. This is not true in the data, however. There may exist factors (such as peak-load pricing) other than price discrimination that also contribute to price dispersion. These factors enter into quality and affect companies' costs. In the empirical part of the paper, we focus on price dispersion since we do not have a good measure of quality to test for price discrimination directly. Nevertheless, the variation of price dispersion in the data is consistent with nonmonotonicity, a prediction of our price discrimination model.

<sup>13</sup>The first operating carrier for a given itinerary is responsible for reporting data. The operating carrier can be different from reporting carrier when airlines market their tickets under a code share agreement.

domestic, one-way or round-trip, nonstop, coach class itineraries. Since we use both one-way and round-trip tickets, we define the ticket price based on the one-way fare and divide the fare of round-trip itineraries by two. We also drop the return portion of round-trip itineraries to avoid double-counting. <sup>14</sup> (In section A2 in the appendix, we offer a detailed description of how we process the data and build the sample.)

We supplement the DB1B data with carrier characteristics from the Air Carrier Financial Reports (Form 41 Financial Data). These reports contain quarterly balance sheet information such as operating cost, nonoperating income, and total current assets, for U.S. carriers with operating revenues of \$20 million or more. Smaller carriers constitute about 0.7% of the observations and are excluded from our analysis.<sup>15</sup>

Additional route characteristics come from the T-100 domestic segment database. T-100 is a 100% monthly census of traffic (both passenger and cargo) and operational data for U.S. carriers. It contains nonstop segment information: carrier, origin, destination, aircraft type and service class for transported passengers, freight and mail, available capacity, scheduled departures, departures performed, aircraft hours, and load factor. To combine the monthly T-100 with quarterly DB1B data and Air Carrier Financial Reports, we aggregated T-100 into quarterly data. Although T-100 data are largely consistent with DB1B, the match between them is not 100% for several reasons. First, DB1B samples passengers who originate and end their trips between two airports, while T-100 records all passengers traveling between two airports, including connecting passengers. Second, DB1B does not distinguish between a nonstop flight and a connecting flight without a plane change. 16 Thus, merging T-100 and DB1B helps eliminate some connecting tickets and provides a more accurate sample for nonstop segments. Finally, since DB1B is a random sample, the coverage is not 100%, especially for low-volume markets.

Finally, we obtain airport location and the associated demographics (such as population) from the Federal Aviation Administration's Passenger Boarding Data for U.S. Airports and from the U.S. Census.

An observation in our data set represents a carrier that operates (issuing nonstop tickets) on a route (from the origin to destination airport) at a specific time (quarter and year). For example, U.S. Airways—operated flights from Philadelphia (PHL) to Los Angeles (LAX) in the fourth quarter of 2008 represent one observation in our data, while the same airline in the same time period flying from Los Angeles to Philadelphia is a different observation. Although many studies define route based on the two end-point airports, a few papers (see Morrison, 2001; Berry & Jia, 2010) discuss possible

<sup>&</sup>lt;sup>14</sup> For example, without this treatment, a round-trip ticket from Philadelphia to Boston would appear as two tickets in the sample.

<sup>15</sup> Although some balance sheet information for smaller carriers can be found in schedule B-1.1 of the Air Carrier Financial Reports, they are available only semiannually and contain many missing values.

<sup>&</sup>lt;sup>16</sup> For example, an itinerary from Philadelphia to Los Angeles that stops in Chicago without changing plane will be recorded the same as a nonstop itinerary from Philadelphia to Los Angeles.

competition between adjacent airports. For example, both O'Hare and Midway are located in the Chicago metropolitan area, and if consumers can easily substitute between them, carriers in Midway will directly compete against those in O'Hare. To address this concern, we also present our results after combining the observations in close-by airports.<sup>17</sup>

Our final sample contains 56 different carriers in 6,015 distinct routes over the 64 quarters between 1993 and 2008. Many studies of the airline industry (Borenstein & Rose, 1994; Goolsbee & Syverson, 2008; Orlov, 2011) restrict the analysis to major airlines. 18 Our analysis also incorporates many medium-sized and regional carriers, which have played increasingly important roles by connecting passengers from smaller communities to the nationwide airline network. During our sample period, 2,531 of 6,015 routes experienced at least one entry, and 2,603 experienced at least one exit. These dynamics, driven in part by the emergence of regional carriers, generate varying degrees of competition across many routes, which is helpful in identifying the effect of competition on price dispersion.

### IV. Descriptive Evidence for Nonmonotonicity

Following the literature (Borenstein & Rose, 1994; Gerardi & Shapiro, 2009), we adopt the Gini coefficient as the measure of price dispersion,

$$Gini_i = \frac{2}{n^2 \overline{fare}} \sum_{j=1}^n \left( j - \frac{n+1}{2} \right) fare_j,$$

where *i* is the carrier route <u>quarter</u> combination, *j* indexes the fare from low to high, and *fare* is the mean fare. The Gini coefficient is a unit-free measure of the fare inequality across the entire range of fares paid. For example, our sample median Gini of 0.23 implies a 23% price difference (relative to mean fare) between two itineraries drawn at random from the population. It is close to that of 0.22 in Gerardi and Shapiro (2009) during the 1993–2006 period.

To investigate how the Gini coefficient varies with market structure, we divide our sample routes into three groups: monopoly, duopoly, and competitive. <sup>19</sup> Table 1 displays the average Gini coefficient, HHI, and number of carriers for each group. The distributions of concentration, firm counts, and our group classification are quite consistent with each other. On monopoly routes, both the mean firm counts and HHI are very close to 1. An average duopoly route is populated by 2.1

TABLE 1.—PRICE DISPERSION BY MARKET STRUCTURE

|             | Gini   | нні               | N      |
|-------------|--------|-------------------|--------|
| Monopoly    | .228   | .992              | 1.10   |
|             | (.090) | (.031)            | (.330) |
| Duopoly     | .238   | .560              | 2.07   |
| • •         | (.086) | (.092)            | (.280) |
| Competitive | .223   | .443              | 3.41   |
| •           | (.076) | (.111)            | (.858) |
| All         | .230   | .794 <sup>°</sup> | 1.72   |
|             | (.087) | (.237)            | (.925) |
|             |        |                   |        |

N represents carrier counts. Definitions of monopoly, duopoly, and competitive route are in note 19. Standard deviations are in parentheses. Number of observations is 248,513.

carriers with HHI equal to 0.56. The concentration in a competitive route is 0.443 with an average carrier count of 3.4. Overall, the mean HHI equals 0.79 for the full sample, and it is comparable to the HHI in Gerardi and Shapiro (2009).<sup>20</sup>

The distribution of the Gini coefficient shows suggestive evidence of a nonmonotonic relationship between competition and price dispersion. Duopoly markets exhibit the highest level of price dispersion, with the average Gini coefficient equal to 0.238. By contrast, the Gini coefficient in either a monopoly (0.228) or competitive market (0.223) is lower.<sup>21</sup> This suggests an inverse-U relationship. The Gini coefficient first rises with competition and then declines. Consequently, airlines exhibit more price dispersion in duopoly markets relative to monopoly and competitive markets.

While the overall trends in the data display a certain degree of nonmonotonicity, we next demonstrate the nonmonotonicity with a representative route. We look at two major carriers (U.S Airways and AirTran) flying between Orlando (MCO) and Philadelphia (PHL).<sup>22</sup> Figure 1 shows the scatter plot of Gini, HHI, and a local polynomial smooth. It is quite evident that the relationship between competition and price dispersion is inverse U-shaped. When the market is competitive (HHI is low), price dispersion increases with concentration. When the market is concentrated (HHI is high), price dispersion decreases with concentration.

In the next section, we confirm the existence of nonmonotonic relationship between competition and price dispersion by introducing statistical rigor.

## V. Panel Analysis

#### A. Nonmonotonic Effect of Competition

We exploit the panel structure of the data to control for the time-invariant route and carrier heterogeneities. We introduce

<sup>&</sup>lt;sup>17</sup> We combine the following close-by airports: DFW (Dallas–Fort Worth) and DAL (Love Field); LGA (La Guardia), EWR (Newark) and JFK (J. F. Kennedy); AZA (Phoenix-Mesa Gateway) and PHX (Phoenix Sky Harbor); TPA (Tampa) and PIE (St. Petersburg Clearwater); DCA (Reagan) and IAD (Washington Dulles); ORD (O'Hare) and (MDW) Midway.

<sup>&</sup>lt;sup>18</sup> A notable exception is Gerardi and Shapiro (2009).

<sup>&</sup>lt;sup>19</sup> Following Borenstein and Rose (1994), a route is considered a monopoly if the share of a single carrier is greater than 90%. A route is considered a duopoly if it is not a monopoly and the sum of shares from the two leading carriers is greater than 90%. A market is considered competitive if it is neither monopoly nor duopoly.

<sup>&</sup>lt;sup>20</sup> Gerardi and Shapiro (2009) find the average HHI of airline routes is between 0.72 and 0.78 over 1993–2006. The average HHI in our sample is slightly higher because we use generous sampling criterion and cover many small markets with high concentration. For example, Gerardi and Shapiro (2009) cover 2,902 routes while we cover 6,015 routes.

<sup>&</sup>lt;sup>21</sup> The *t*-tests strongly reject the mean equality of the Gini coefficient between any two groups.

<sup>&</sup>lt;sup>22</sup> Though several other carriers operated between MCO and PHL (for example, Delta), they do not remain in the market long enough to generate informative plots. However, their entries and exits generate variation in competition that results in a wide spectrum of HHIs.

FIGURE 1.—AN EXAMPLE OF NONMONOTONICITY. THE CURVES SHOW A SECOND-ORDER POLYNOMIAL SMOOTH.
U.S. AIRWAYS IS THE INCUMBENT, AND AIRTRAN BEGAN TO FLY THE ROUTE IN 2000

TABLE 2.—CONTROL VARIABLES

| Variable            | Definition           | Mean   | SD    |  |
|---------------------|----------------------|--------|-------|--|
| lasset              | Logged total assets  | 14.22  | 1.354 |  |
| lasset <sup>2</sup> | Lasset squared       | 204.1  | 35.62 |  |
| cash                | Cash available       | 0.148  | 0.214 |  |
| opexp               | Operating expenses   | 0.561  | 2.190 |  |
| otherinc            | Nonoperating income  | -0.011 | 0.123 |  |
| bankr               | Bankruptcy indicator | 0.066  | 0.248 |  |

Number of observations is 248,513. cash, opexp, and otherinc are computed as percentage of total

carrier and route fixed effects and year-quarter fixed effects in all of our specifications. This prevents cross-sectional variations from driving our results. The time-invariant route and carrier characteristics (such as hub status and brand loyalty in hub markets) will not bias our estimates.

We investigate the effect of competition on price dispersion by estimating the following equation:

$$Gini_{ijt} = \beta_1 HHI_{jt} + \beta_2 HHI_{jt}^2 + \alpha X_{it} + \varepsilon_{ij} + \varepsilon_t + u_{ijt}, \quad (1)$$

where *i* indexes airline, *j* indexes route, and *t* indexes year and quarter combinations.<sup>23</sup>  $X_{it}$  are time-varying carrier characteristics such as airline size and operating expenses. The full set of control variables is presented in table 2. The airline-route specific time-invariant unobservable  $\varepsilon_{ij}$  and shocks  $\varepsilon_t$  that are common to all carriers will be absorbed by the fixed effects.

The key variables of interest are  $\beta_1$  and  $\beta_2$ . We choose a quadratic specification since alternative specifications such as log-linear and log-log could admit only monotonic (and nonlinear) relationships. The empirical model, equation (1), implies that when the relationship between competition and price dispersion is nonmonotonic, the sign of  $\beta_1$  should be different from  $\beta_2$ . As our theory suggests, if price dispersion first increases with competition before it decreases, we expect  $\beta_1$  to be positive and  $\beta_2$  to be negative.

Estimating equation (1) with OLS can be problematic because concentration is endogenously determined by the extent of the market. For example, it is possible that carriers are less likely to enter the routes with low price dispersion. To address this concern, we adopt the instrumental variable approach. Based on the instruments introduced by Borenstein and Rose (1994) and Gerardi and Shapiro (2009), we include the arithmetic and geometric means of Metropolitan Statistics Area (MSA) population of end-point cities and the total passengers enplaned on a route, as well as the squared counterpart. These market-level variables affect the concentration through an airline's entry and product positioning choices and are otherwise assumed to be unrelated to price dispersion. (The full list of instruments is summarized in the appendix.) Nevertheless, we believe that the inverse-U relationship we are trying to establish through equation (1) is less susceptible to endogeneity bias. This is because in order for the bias to drive the results, the unobserved factors must be nonmonotonic in both competition and price dispersion. If the inverse-U relationship is spurious, the unobserved factors, such as the traveler's willingness to pay, must be more prominent in highly concentrated and highly competitive routes. It is hard to imagine that monopoly and competitive routes share more attributes with one another than they do with the intermediately competitive market. For example, if a market with a wider price dispersion attracts more entry,  $u_{iit}$  will be negatively correlated with HHI and bias both  $\beta_1$  and  $\beta_2$  downward. However, this kind of bias is less likely to cause the sign of  $\beta_1$  to be different from  $\beta_2$ . Finally, as a technical note, the dependent variable Gini is route and airline specific, while HHI varies at the route level. Hence, we adjust our standard errors to account for within-route correlation.

As a baseline, we estimate equation (1) without the quadratic term. Column 1 in panel A of table 3 displays the instrumental variable results. The effect of competition appears to be insignificant. This is not unexpected. If the effect of competition exhibits an inverse-U shape, the marginal effect of competition will be positive before reaching a threshold and become negative afterward. This may result in an overall zero effect if we force a monotonic relationship. To see this, the instrumental variable results from the full specification of equation (1) are displayed in column 2 of panel A.<sup>24</sup> With an additional quadratic term, the

<sup>24</sup> We estimate the IV model using 2SLS. In the first stage, we predict the values of *HHI* and *HHI*<sup>2</sup>, respectively (it is not a forbidden regression).

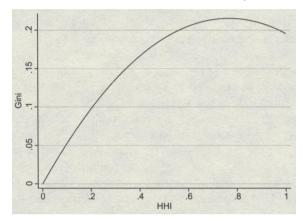
 $<sup>^{23}</sup>$  Several papers (see Gerardi & Shapiro, 2009) focus on Gini log-odds ratio in the empirical analysis.  $G^{lodds} = \ln(Gini/1 - Gini)$  is an unbounded monotonic transformation of Gini while Gini is between 0 and 1. Our results are robust to this transformation. The estimates for Gini log-odds ratio are available on request.

|              | A. Airport Pairs |                   |                  | B. City Pairs   |         |                   |                  |                  |
|--------------|------------------|-------------------|------------------|-----------------|---------|-------------------|------------------|------------------|
|              | (1)              | (2)               | (3)              | (4)             | (1)     | (2)               | (3)              | (4)              |
| ĤĤI          | .003<br>(.005)   | .561***<br>(.116) |                  |                 | .014*** | .536***<br>(.096) |                  |                  |
| ĤHI²         | (1111)           | 365***<br>(.075)  |                  |                 | (1111)  | 344***<br>(.062)  |                  |                  |
| mono         |                  | (13.5)            | 011***<br>(.003) |                 |         | (1002)            | 013***<br>(.003) |                  |
| comp         |                  |                   | 035***<br>(.005) |                 |         |                   | 044***<br>(.006) |                  |
| Ñ            |                  |                   | (.000)           | 003**<br>(.001) |         |                   | (.000)           | 006***<br>(.001) |
| Observations | 248,513          | 248,513           | 248,513          | 248,513         | 239,729 | 239,729           | 239,729          | 239,729          |

TABLE 3.—NONMONOTONIC EFFECT OF COMPETITION

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The dependent variable is Gini, and the hat represents the instrumented endogenous variable. Carrier-route and year-quarter fixed effects are included in all specifications. Robust standard errors in parentheses are adjusted for correlation within market. Control variables are log(asset), log²(asset), cash (as % of asset), operating cost (as % of asset), and nonoperating net income (as % of asset), a dummy indicator if the carrier is under bankruptcy protection. The list of instruments can be found in section A3.

FIGURE 2.—NET EFFECT OF COMPETITION ON PRICE DISPERSION. THE GRAPH IS BASED ON SPECIFICATION 2 IN TABLE 3, PANEL A



estimated effects of competition become highly significant. This is strong evidence in favor of a nonmonotonic relationship.  $\beta_1 \,>\, 0$  and  $\beta_2 \,<\, 0$  imply an inverse-U shape. We calculate and plot the net effect of competition in figure 2. It is quite evident that price dispersion increases with competition when HHI approaches 1 and decreases with competition when HHI approaches 0. The implied marginal effect of competition is  $\beta_1 + 2\beta_2 HHI = 0.561 - 0.73 HHI$ , and the estimates suggest that carriers display the highest level of price dispersion when HHI is about 0.77 (the market is neither too concentrated nor too competitive). Hence, at our sample mean HHI = 0.79, the marginal effect of competition is quite close to 0. As a robustness check, we combine the observations in close-by airports and reestimate equation (1). Column 2 in panel B of table 3 displays the results. Combining airports reduces the number of observations from 248,513 to 239,729. The estimated  $\beta_1$  and  $\beta_2$  in column 2 of panel B imply a similar nonmonotonic relationship, and the magnitude of the coefficients is close to their counterparts in panel

We further investigate the nonmonotonic relationship between competition and price dispersion using market structure indicators as an alternative measure of competition. Each route jt is assigned to one of the three markets: mono (monopoly), duo (duopoly), and comp (competitive).<sup>25</sup> We estimate

$$Gini_{ijt} = \beta_m mono_{jt} + \beta_c comp_{jt} + \alpha X_{it} + \varepsilon_{ij} + \varepsilon_t + u_{ijt}.$$
(2)

The omitted category is duopoly. If the relationship between competition and price dispersion is truly nonmonotonic and inverse-U shaped, we expect  $\beta_m < 0$  and  $\beta_c < 0$ : carriers exhibit less price dispersion in either monopoly or competitive routes relative to the intermediately competitive duopoly routes. Similar to our previous analysis, we use instrumental variables with fixed effects to estimate equation (2). The results are displayed in column 3 of panel A in table 3. The estimated effects of  $\beta_m$  and  $\beta_c$  are both negative and highly significant, consistent with an inverse-U relationship. If the underlying relationship between competition and price dispersion was monotonic (or U-shaped), there would be no reason for carriers facing intermediate competition to exhibit more price dispersion. The market structure analysis also suggests that the nonmonotonicity established in equation (1) is not merely driven by the quadratic specification. A closer look at the estimates shows that  $\beta_c = -0.035$  is smaller than  $\beta_m = -0.011$ . This implies that price dispersion is least common in competitive routes, followed by monopoly and then duopoly. The results are consistent with the distribution of mean Gini in table 1, where the average Gini is smallest in a competitive market followed by monopoly and duopoly. When we estimate the same specification after combining close-by airports, we find similar results.

Finally, column 4 of panels A and B of table 3 shows the estimated results using firm counts as measure of competition. By construction, nonmonotonicity is not allowed in this specification. We find that carriers generally display less price dispersion with more competitors. This is consistent with the findings in several other papers.<sup>26</sup>

<sup>&</sup>lt;sup>25</sup> The definitions of *mono*, *duo*, and *comp* can be found in note 19; they are similar to Borenstein and Rose (1994).

<sup>&</sup>lt;sup>26</sup> If we focus on a monotonic nonlinear relationship and use the log-log specification similar to Gerardi and Shapiro (2009), the coefficient estimate

We also perform the following two robustness checks: (a) we remove a carrier/route observation if fewer than 100 itineraries are sampled by DB1B (which may have issues with measurement error)<sup>27</sup> and (b) we weight the sample using the route and passenger counts similar to the approach in Goolsbee and Syverson (2008). The estimated coefficients are robust to these treatments, and we still find strong evidence that supports the existence of nonmonotonicity (we do not report the estimates from these robustness checks, but they are available in the online appendix, tables 1–3).

#### B. Price-Level Analysis

According to the intuition from our theoretical model, the nonmonotonicity in price dispersion is driven by the differential rates of price declines in high- and low-end segments. We formally test this intuition with the following equations:

$$\log(P90)_{ijt} = \beta_1^{P90} duo_{jt} + \beta_2^{P90} comp_{jt} + \alpha^{P90} X_{it} + \varepsilon_{ij} + \varepsilon_t + u_{ijt}$$
(3)  
$$\log(P10)_{ijt} = \beta_1^{P10} duo_{jt} + \beta_2^{P10} comp_{jt} + \alpha^{P10} X_{it} + \varepsilon_{ii} + \varepsilon_t + u_{iit},$$

where the dependent variables log(P90) and log(P10) represent the logged 90th and 10th price percentile. duoit and comp<sub>it</sub> are indicators for duopoly and competitive route, and the omitted category is monopoly. In price equation (3),  $\beta_1$  captures the effect of increasing competition from monopoly to duopoly, while  $\beta_2 - \beta_1$  measures the effect of increasing competition from duopoly to competitive. The intuition from the theoretical model implies that increasing competition in concentrated markets causes price to decline more (percentage wise) for price-sensitive, low-valuation consumers. We expect to find  $\beta_1^{P10} < \beta_1^{P90} < 0$ . By contrast, intensified competition in less concentrated duopoly markets reduces the price for high-valuation consumers more. Consequently, we expect  $\beta_2^{P90} - \beta_1^{P90} < \beta_2^{P10} - \beta_1^{P10} < 0$ . To estimate equation (3), we use an instrumental variable with fixed effects. The results are displayed in table 4. The estimates confirm the theoretical intuition.  $\beta_1^{P90} = -0.049$ suggests that compared to monopoly market, P90 in duopoly market is 4.9% lower, while  $\beta_1^{P10} = -0.122$  suggests P10 in the duopoly market is 12.2% lower. Thus, increasing competition in a concentrated market (from monopoly to duopoly) causes P10 to decline more than P90 (12.2% versus 4.9%), and increasing competition in a less concentrated market (from duopoly to competitive) causes P90 to drop more than P10 (44.1% versus 15.4%). An analysis by city pairs reaches

TABLE 4.—EFFECT OF COMPETITION ON PRICE LEVEL

|                    | Airpo    | rt Pairs | City Pairs |          |  |
|--------------------|----------|----------|------------|----------|--|
| Dependent Variable | log(P90) | log(P10) | log(P90)   | log(P10) |  |
| duo                | 049***   | 122***   | 043**      | 136***   |  |
|                    | (.017)   | (.012)   | (.019)     | (.013)   |  |
| comp               | 490***   | 276***   | 581***     | 301***   |  |
| •                  | (.028)   | (.020)   | (.030)     | (.018)   |  |
| Observations       | 248,513  | 248,513  | 239,729    | 239,729  |  |

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. P90 represents the 90th percentile fare, and P10 represents the 10th percentile fare. The hat represents the instrumented endogenous variable. Carrier-route and year-quarter fixed effects are included in all specifications. Robust standard errors in parentheses are adjusted for correlation within market. Control variables are log(asset),  $\log^2(asset)$ , cash (as % of asset), operating cost (as % of asset), nonoperating net income (as % of asset), and a dummy indicator if the carrier is under bankruptcy protection. The list of instruments is in section A3.

TABLE 5.—DISTRIBUTION OF CONCENTRATION BY TRAFFIC VOLUME

|              | Low    | Medium  | High   |  |
|--------------|--------|---------|--------|--|
| ННІ          | .965   | .819    | .575   |  |
|              | (.115) | (.218)  | (.195) |  |
| N            | 1.13   | 1.59    | 2.60   |  |
|              | (.365) | (.716)  | (1.05) |  |
| Observations | 62,632 | 125,245 | 62,633 |  |

N represents carrier counts. Standard deviations are in parentheses.

the same conclusion. We also check the robustness of percentile regression by examining different price quantile pairs (for example, P80 and P20, P75 and P25). The findings are very similar. In robustness checks (similar to those performed in section VA; available in the online appendix, tables 4–6), we also confirm that our results are not driven by the low-volume routes and carriers and are robust when we weight routes by passenger counts. Overall, the effect of competition on price levels is consistent with our theory intuition.

#### C. Differential Effect of Competition by Markets

To understand how the effect of competition differs in different types of markets, we divide the sample according to air traffic volume. We consider routes with high, medium, and low traffic volume, where the cutoffs for high- and low-volume markets are the 25th and 75th percentiles in the distribution of enplanement across all airlines routes. In general, the intensity of competition increases with air traffic. As shown in table 5, in markets with high traffic volume, there are on average 2.6 operating carriers with mean HHI equal to 0.58, while in markets with low traffic volume, the average number of airlines is 1.1 and mean HHI is 0.96. We investigate the net effect of competition in each type of market by estimating

$$Gini_{iit}^{\nu} = \beta^{\nu} \log(HHI)_{jt} + \alpha X_{it}^{\nu} + \varepsilon_{ii}^{\nu} + \varepsilon_{t}^{\nu} + u_{iit}^{\nu}, \tag{4}$$

where v = H, M, L for high-, medium-, and low-volume markets. If the relationship between competition and price dispersion is consistent with nonmonotonicity, we expect the net effect of competition to be positive ( $\beta < 0$ ; price dispersion increases with competition) in the more concentrated low-volume markets. Price dispersion should decrease with competition ( $\beta > 0$ ; price dispersion decreases with competition) in the competitive high-volume markets. For medium

of log(HHI) is 0.074. It is highly significant at 1% and reasonably close to 0.121 found by Gerardi and Shapiro (2009).

<sup>&</sup>lt;sup>27</sup> This corresponds to fewer than 1,000 tickets sold by a given carrier in the market since DB1B is a 10% random sample. Removing low-volume carriers and routes from our sample effectively eliminates 52,345 observations from the airport-pair analysis and 51,660 observations from the city-pair analysis.

TABLE 6.—HETEROGENEOUS EFFECT OF COMPETITION

|                       | (a)    | (a) Airport Pairs |         |        | (b) City Pairs |         |  |
|-----------------------|--------|-------------------|---------|--------|----------------|---------|--|
|                       | Low    | Medium            | High    | Low    | Medium         | High    |  |
| $\widehat{\log(HHI)}$ | 029*** | .011**            | .033*** | 030*** | .027***        | .029*** |  |
|                       | (800.) | (.005)            | (800.)  | (.007) | (.005)         | (.010)  |  |
| Observations          | 60,753 | 124,421           | 62,275  | 58,703 | 120,025        | 60,076  |  |

\*\*\*p < 0.01, \*\*p < 0.05, \*p < 0.1. The hat represents the instrumented endogenous variable. Carrier-route and year-quarter fixed effects are included in all specifications. Robust standard errors in parentheses are adjusted for correlation within market. Control variables are log(asset), log² (asset), cash (as % of asset), operating cost (as % of asset), and nonoperating net income (as % of asset), a dummy indicator if the carrier is under bankruptcy protection. The list of instruments can be found in section A3.

markets, the net effect of competition is ambiguous and we expect the slope of competition to be less steep than either high- or low-volume markets. Similar to our previous analysis, we adopt instrumental variables with fixed effects in our estimation. The results are presented in table 6. The estimates confirm our conjecture. In the concentrated low-volume markets, we find  $\beta^L = -0.029 < 0$  and is highly significant: price dispersion increases with competition. In competitive routes with high traffic volume, we find  $\beta^H = 0.033 > 0$ , and this implies that price dispersion decreases with competition. For the medium-volume market, the effect of competition is significant at the 5% level with  $\beta^M = 0.011$ , and it is less steep than either the high- or low-volume markets. We find similar results after combining the close-by airports in column (b).

#### VI. Conclusion

This paper offers a simple intuition that explains why equilibrium price dispersion can vary nonmonotonically with the intensity of competition. We identify two competing forces, the direct price effect and the indirect quality effect, that lie at the heart of this nonmonotonicity. The direct price effect focuses on the direct impact of a change in the level of competition on prices for given quality levels. The indirect quality effect focuses on the impact of a change in the level of competition on quality and the consequent impact on prices. An additional important element of the analysis is the (binding) incentive compatibility constraint, which sets the price differential between high- and low-quality products equal to the quality differential valued by the high-type consumers. If competition in the market intensifies, prices drop and the incentive compatibility constraint forces the low-end price to go down by the same absolute amount as the high-end price, but because the low-end price is lower, its percentage decline is higher, resulting in higher price dispersion. This is the direct price effect. An increase in competition also causes the qualities of low-end products to increase (qualities of high-end products are fixed and equal to the efficient level). Higher lowend quality implies a higher low-end product price, and the incentive compatibility constraint then dictates that high-end price cannot increase by the same absolute amount, resulting in lower price dispersion. This is the indirect quality effect. Overall, price dispersion varies nonmonotonically with the intensity of competition and can be inverse U-shaped.

Using carrier-route-level data from 1993 to 2008, we establish a nonmonotonic relationship between competition and

price dispersion (inverse U-shape). Price dispersion increases with concentration in competitive markets and decreases with concentration in less competitive markets. Consistent with our intuition, we find that different rates in price decline are the source of nonmonotonicity. The price of the low-end product declines faster with competition in concentrated markets, while the price of the high-end product declines faster in less concentrated market. We further confirm the existence of nonmonotonicity by dividing our sample into three groups according to traffic volume. The effect of concentration is negative in the less competitive low-volume markets, implying that price dispersion increases with competition; it is positive in the more competitive high-volume markets, implying that price dispersion decreases with competition.

Our paper contributes to the literature on the airline industry and the literature on price discrimination. We identify a novel relationship between competition and price dispersion that encompasses different empirical findings in multiple industries. Competition affects both the average price and price dispersion, which in turn affect consumer welfare. Consequently, future studies could use our results to shed new light on the impact of market structure on consumer welfare.

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#### **APPENDIX**

#### AI. Proof of Proposition 1

We proceed to prove our main theoretical result as follows. First, we look for a symmetric candidate equilibrium in pure strategies where the IC constraint for the high type is binding, while for the low type it is slack.<sup>28</sup> Second, we demonstrate that price dispersion can be nonmonotonic with respect to competition and in particular inverse U-shaped. We provide an intuition and demonstrate the role of the incentive compatibility constraints. Third, we show that the candidate equilibrium prices and qualities constitute an equilibrium by ensuring that global deviations are unprofitable. General results are extremely cumbersome to present, so our approach is to demonstrate that an equilibrium exists by assigning different sets of numerical values to our key parameters.29

Candidate equilibrium prices and qualities. The marginal consumer  $\hat{x}_i$ from group  $j=h,\ell$ , who is indifferent between firm 1 and 2, must satisfy  $V+\theta_jq_{1j}-p_{1j}-t_j\hat{x}_j^2=V+\theta_jq_{2j}-p_{2j}-t_j(1-\hat{x}_j)^2$ . This yields the demand functions of firm 1, located at point 0

$$d_{1\ell} = \frac{\theta_{\ell} (q_{1\ell} - q_{2\ell}) - (p_{1\ell} - p_{2\ell}) + t_{\ell}}{2t_{\ell}} \text{ and}$$

$$d_{1h} = \frac{\theta_{h} (q_{1h} - q_{2h}) - (p_{1h} - p_{2h}) + t_{h}}{2t_{h}}.$$
(A1)

The demand functions of firm 2, located at point 1, are  $d_{2\ell} = 1 - d_{1\ell}$  and  $d_{2h} = 1 - d_{1h}$ . Since the IC constraint for the high type (IC-H) is binding, prices and qualities must satisfy  $p_{1h} - p_{1\ell} = \theta_h(q_{1h} - q_{1\ell})$  for firm 1 and  $p_{2h} - p_{2\ell} = \theta_h(q_{2h} - q_{2\ell})$  for firm 2. We solve the IC-H constraints with respect to  $p_{1h}$  and  $p_{2h}$  and substitute these prices, along with the demand functions  $d_{ii}$  given by equation A5, into firm i's profit function: 30

$$\pi_{i} = \sigma \left[ \left( p_{i\ell} - \frac{aq_{i\ell}^{2}}{2} \right) d_{i\ell} \right] + (1 - \sigma) \left[ \left( p_{ih} - \frac{aq_{ih}^{2}}{2} \right) d_{ih} \right]. \tag{A2}$$

Firms compete on qualities and prices sequentially. We normalize  $\theta_{\ell}$  = 1. We differentiate  $\pi_i$  with respect to  $p_{i\ell}$ , i=1,2 and solve the system of first-order conditions to derive the equilibrium prices as a function of

 $^{28}\,\rm This$  is the standard case in a monopoly market, and it can be reasonably extended in a duopoly market, for example, Villas-Boas and Schmidt-Mohr (1999). Competition, however, can give rise to other cases, such as an equilibrium where all incentive compatibility constraints are slack (for more

details, see Rochet & Stole, 2002).

29 All derivations were performed using Maple software. All Maple files are available on request.

30 Our model allows for competition between firms for the same-quality products and within a firm for products of different qualities, but not between firms for products of different qualities. This, however, emerges endogenously in the model. Each consumer has four options in terms of buying either quality of product (low or high) from either firm (1 or 2), but, for example, for a high-type consumer who is closer to firm 1, buying the low-quality product of firm 2 is always strictly dominated.

qualities (Second-order conditions are also satisfied.) The price of firm 1. designed for the high consumer group, is given by

$$\begin{aligned} p_{1h} &= \\ &\frac{\left(\begin{array}{c} \theta_{h}q_{1h}\left(2t_{\ell}\left(1-\sigma\right)+6t_{h}\sigma\right)-6t_{h}\sigma\theta_{h}q_{1\ell}+2t_{h}\sigma\left(q_{1\ell}-q_{2\ell}\right)+\\ t_{\ell}a\left(1-\sigma\right)\left(2q_{1h}^{2}+q_{2h}^{2}\right)+\sigma t_{h}a\left(2q_{1\ell}^{2}+q_{2\ell}^{2}\right)-2t_{\ell}\theta_{h}\left(1-\sigma\right)q_{2h}+6t_{\ell}t_{h}}\right)}{6\left(t_{\ell}\left(1-\sigma\right)+t_{h}\sigma\right)}, \end{aligned}}{6\left(t_{\ell}\left(1-\sigma\right)+t_{h}\sigma\right)}, \tag{A3}$$

while the price of firm 1 for the low group can be derived from the IC constraint,  $p_{1\ell} = p_{1h} - \theta_h(q_{1h} - q_{1\ell})$ . The equilibrium prices of firm 2 can be similarly expressed using symmetry. Then we substitute the equilibrium prices back into the profit function  $\pi_i$  and obtain the first-order conditions with respect to qualities. At this stage, we impose the symmetry condition, that is,  $q_{1h}=q_{2h}$  and  $q_{1\ell}=q_{2\ell}$ . We find that firms choose the efficient quality level for the high type,  $q_{ih}^*=\theta_h/a$ , which depends positively on the quality preference parameter  $\theta_h$  and negatively on the marginal cost of quality parameter a, (for example, Desai, 2001), but it is independent of the degree of competition in the market, that is,  $t_h$  and  $t_\ell$ . This is the standard "no distortion at the top" result, whereas firms distort the quality offered to the low group downward. The equilibrium quality (and the distortion) depends on the competition parameters  $t_h$  and  $t_\ell$ , as follows:

$$q_{1\ell}^* = \frac{at_h - 3at_h\sigma + 3\theta_h - 3t_\ell a - 3\theta_h^2 + 3t_\ell\sigma a + 3\theta_h^2\sigma - 3\sigma\theta_h + (a(9t_\ell^2 a + t_h^2 a - 18t_\ell^2\sigma a + 9t_\ell^2\sigma^2 a + 9\sigma^2t_h^2 a - 12\sigma t_h + 24t_h\sigma\theta_h - 24t_h\theta_h - 6\sigma t_h^2 a - 6t_ht_\ell a + 12t_h\theta_h^2 + 24t_\ell t_h a\sigma - 12t_h\sigma\theta_h^2 - 18at_ht_\ell\sigma^2 + 12t_h))}{3a(1 - \sigma)(1 - \theta_h)}$$

By substituting  $q_{ij}^*$  into A3, we can derive the equilibrium prices  $p_{ij}^*$ , j = $\ell$ , h and i = 1, 2.31

The Gini coefficient. We derive the Gini coefficient for equilibrium price dispersion as follows. First, we define

$$x \equiv \frac{\sigma p_{1\ell}^*}{\sigma p_{1\ell}^* + (1 - \sigma) p_{1h}^*}.$$

Then the Gini coefficient is

$$Gini \equiv 1 - x\sigma - (1 + x)(1 - \sigma).$$

The expression for the Gini coefficient is very complicated unless we assign specific numerical values to the parameters. We assign the following values to the parameters:  $\sigma \in \{1/2, 3/4\}, \theta_h \in \{2, 5, 10\}, a \in \{1/2, 1\}, \text{ and }$  $\frac{t_h}{t_h} \in \{2, 3, 5\}$ . These give us 36 combinations of parameter values. The only free parameter is  $t_{\ell}$ , which is set equal to t and measures the intensity of competition in the market. We find that Gini is inverse U-shaped for all these combinations of parameters. For example, if  $\sigma = 3/4$ ,  $\theta_h = 2$ , a = 1/2, and  $t_h = 3t_\ell = 3t$ , it can be shown that the Gini coefficient becomes

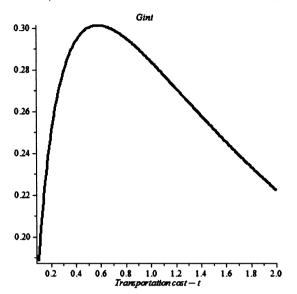
$$Gini = \frac{15}{4} \left( \frac{-3t + \sqrt{t(8+9t)}}{20 + 87t - 15\sqrt{t(8+9t)} - 27t\sqrt{t(8+9t)} + 81t^2} \right).$$

Figure 3 shows that Gini is inverse U-shaped. We offer a general intuition

Existence of an equilibrium. To establish the existence of an equilibrium, we have to examine all possible unilateral deviations. Due to symmetry, we check only firm 1's incentive to deviate. There are various types of deviations. In a type 1 deviation, firm 1 deviates in prices only. In a type 2 deviation, firm 1 deviates in qualities but still sells two qualities of products. After observing the new qualities, firms choose prices simultaneously. Depending on whether the IC-H constraints are binding, it is divided into four cases. Neither firm's IC-H constraint is binding in type 2a deviation,

<sup>31</sup> We have focused on symmetric equilibria for simplicity and tractability and because it is a natural focal point given that firms are ex ante symmetric (in terms of cost and consumer distribution). When we examine deviations (to establish the existence of an equilibrium), we do allow for asymmetric strategies.

FIGURE 3.—GINI COEFFICIENT AS A FUNCTION OF THE INTENSITY OF COMPETITION, MEASURED BY THE TRANSPORTATION COST PARAMETER t.



while both firms' IC-H constraints are binding in type 2b deviation. In type 2c and 2d deviations, one firm's IC-H constraint is binding, while the other firm's is not. In type 3 deviation, firm 1 deviates and chooses to sell a single quality of product. After observing the new quality, both firms choose prices simultaneously. There are two cases depending on whether firm 2's IC-H constraint is binding.

We assign the following values to the parameters-2, a = 1/2 and  $t_{\ell} = 1$ ,  $t_h \in \{2, 3\}$ —and check whether firm 1 has incentive for any of the deviations. Our results show that for all type 1 and type 2 deviations, we either recover the initial candidate equilibrium or the IC-H constraint is violated, in which case IC-H needs to assumed to be binding, and then we recover the equilibrium candidate as well. We also find that both cases of type 3 deviations lower firm 1's profit; thus, firm 1 has no incentive to deviate. In sum, for these two sets of parameter values, firms have no incentive to deviate from the candidate equilibrium. We have not checked the profitability of all these unilateral deviations for other parameter values. Existence of an equilibrium is of secondary importance, and given that we have proved that it exists for some parameter values and that the inverse U-shape result holds for a wide range of parameters, the added benefit of proving it for even more parameter values is small.

Therefore, the main message is that in a second-degree price discrimination model, the relationship between competition and price dispersion is possible to be nonmonotonic and, in particular, inverse U-shaped (due to the presence of the two opposing effects: the direct price effect and the indirect quality effect).

#### A2. Sample Construction

Our data are constructed from DB1B, T-100 domestic segment and Air Carrier Financial Reports database.

The price and quantity information comes from DB1B. Like many other studies using the DB1B database, we use domestic, one-way or round-trip, nonstop, coach class itineraries.<sup>32</sup> The fare charged by a carrier is defined as a one-way fare, and we divide the fare by two for round-trip tickets. In addition, we use the following criterion to screen the itinerary. We eliminate the itinerary if (a) the one-way fare is less than \$10 or above the 99th percentile of the route carrier fare distribution,<sup>33</sup> (b) the dollar credibility is questioned by BTS, (c). the operating carrier is different from the ticketing carrier on either segment of the itinerary, (d) any segment of the itinerary is in first or business class, 34 any segment of the itinerary involves connecting flights, or (f) ticketing carrier change occurs in either segment of the itinerary. Finally, we drop the return portion of the round trip tickets to avoid double-counting.<sup>35</sup> Overall, the direct passengers account for approximately 62% of total passengers. The portion of direct passengers for the sampling period is presented in the second column of table A1 (which appears in the online appendix). On average, 3,547,130 passengers travel on direct flight in each quarter, and we cover 2,118,260. Additional details of our sample coverage are presented in the online appendix (see table A1).

After screening the itineraries with these criteria, we collapse them into airline-route observations and merge them with T-100 and Air Carrier Financial Reports. We drop the carrier-route observations if (a) we cannot find the match in T-100,36 (b) the available seats equal 0, (c) the number of departures performed equals 0, (d) the carrier financial information is missing, (e) the MSA population in either of the two end-point airports is missing, or (f) fewer than ten itineraries are recorded in a route-carrier-quarter.<sup>38</sup> The final sample contains about 56% of the route-carrier observations from DB1B with non-0 price dispersion.

#### A3. Instruments

log(amsapop): log arithmetic mean of Metropolitan Statistics Area (MSA) population of end-point cities. We obtain MSA population from the Census. This instrument is introduced by Borenstein and Rose (1994). log<sup>2</sup>(amsapop): log(amsapop) squared.

log(gmsapop): log geometric mean of msa population of end-point cities. This instrument is introduced by Borenstein and Rose (1994).

log2(gmsapop): log(gmsapop) squared.

genp:  $\sqrt{enp_{j1} * enp_{j2}} / \sum_k \sqrt{enp_{k1} * enp_{k2}}$  where k indexes all airlines, enp<sub>1</sub> and enp<sub>2</sub> are quarterly enplanement at two end-point cities from T-100. This instrument is introduced by Borenstein and Rose (1994). genp<sup>2</sup>: genp squared.

log(totpas): total passengers enplaned on a route from T-100. This instrument is introduced by Gerardi and Shapiro (2009).

 $log^2(totpas)$ : log(totpas) squared.

- 32 Domestic tickets are associated with flights in the lower 48 states (the value of itinerary geography type equals 2 in DB1B).
- <sup>33</sup> Abnormal fares are usually frequent flier tickets or key punch error.
  <sup>34</sup> Since all itineraries issued by Southwest and JetBlue are reported as either first class or business class, we code them as coach class.

  35 Gerardi and Shapiro (2009) have a detailed discussion about double-
- counting.
- <sup>36</sup> As discussed in section III, merging with T-100 results in the loss of many carrier-route observations. However, it helps eliminate the connecting passengers without a plane change from our sample.

<sup>37</sup> If the airport is in a rural county, the corresponding MSA population is

considered as missing.

38 This corresponds to fewer than 100 tickets sold by a carrier in a quarter.