Is the Effect of Competition on Price Dispersion Non-Monotonic? Evidence from the U.S. Airline Industry*

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Abstract

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

JEL Classification: D43, L11, L93

Keywords: Price Dispersion; Second-Degree Price Discrimination; Airline Industry.

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1 Introduction

The typical intuition when firms practice price discrimination is that market power increases a firm's ability to implement price discriminatory strategies, which implies a negative association between competition and price dispersion. Many research papers have investigated empirically the relationship between competition and price dispersion in the US airline market, but with different conclusions. Borenstein and Rose (1994), using cross-sectional data in 1986, and Stavins (2001), using a dataset in 1995 with detailed information on individual tickets, find a *positive* effect of competition on price dispersion (i.e. more price dispersion in more competitive routes). However, Gerardi and Shapiro (2009) uncover a *negative* effect of competition by assembling a panel from 1993 to 2006.[1] In this paper, we re-examine the link between price dispersion and market structure by developing a theoretical model that generates a non-monotonic relationship.[2] Our empirical analysis reveals the existence of such a relationship in the US airline industry.[3]

With the help of an oligopolistic second-degree price discrimination theoretical model, we identify two opposing forces of competition on price dispersion.[4] More intensive 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.[5] 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 dataset from the US airline markets in 64 quarters from 1993 to 2008, we test for the existence of a non-monotonic association between competition and price dispersion. Our empirical

[1] The mixed role of competition on price dispersion has been documented in other markets such as yellowpage advertising (Busse and Rysman (2005)) and detergents (Clerides and Michis (2006)).

[2] If the true effect of competition is non-monotonic and the empirical model is restricted to be monotonic, then the estimated effect can be either positive or negative depending on where the data is concentrated.

[3] Most empirical models look at the relationship between price dispersion and concentration with log-log or log-linear specifications. While these models allow for non-linearity, non-monotonicity is precluded. One specification in Borenstein and Rose (1994)–namely, the one that uses market structure indicators–can accommodate non-monotonicity. However, they didn't actively look for non-monotonicity and their results indicate a monotonic relationship.

[4] 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 (1) refundable or not; (2) time of the day and day of the week for flight; (3) advance purchase (how advance); (4) 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 downwards).

[5] 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 2.1.

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 non-monotonicity is driven by differential rates of price declines for low- and 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 2 presents the theoretical model and the intuition behind the non-monotonic relationship. Section 3 introduces the data and Section 4 offers descriptive evidence consistent with non-monotonicity. Section 5 presents the empirical model and results. Section 6 concludes. The proof of the theoretical result, sample construction and a description of the instruments are in the Appendix.

2 Theoretical Model and Intuition for the Non-Monotonic Relationship

We construct a theoretical model of oligopolistic second-degree price discrimination that offers an explanation for why the effect of competition on price dispersion may be non-monotonic.

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 non-price characteristics of the ticket into a single variable called 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 zero. 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 (ℓ) differ in θ, their preference for quality, with $\theta_h > \theta_\ell$ (i.e. leisure travelers generally care less about quality).[6] There are

[6] 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 (e.g. Berry and Jia (2010), Ciliberto and Williams (2010)). The two-type airline demand model fits the data quite well.

two firms ($i = 1, 2$), located at two end points of a Hotelling line $[0, 1]$.[7,8] 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 (i.e., $t_h > t_\ell$).

A type ℓ consumer located at point x if he 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 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 ℓ type consumers is σ and that of h type is $1 - \sigma$. Finally, we assume that in the equilibrium each firm will produce both qualities.[9]

Firm i's problem is

$$\max_{\langle q_{i\ell}, q_{ih}, p_{i\ell}, p_{ih} \rangle} \pi_i = \sigma \left[\left(p_{i\ell} - \frac{a q_{i\ell}^2}{2} \right) d_{i\ell} \right] + (1-\sigma) \left[\left(p_{ih} - \frac{a q_{ih}^2}{2} \right) d_{ih} \right]$$

$$\text{subject to:} \qquad p_{ih} - p_{i\ell} \leq \theta_h (q_{ih} - q_{i\ell}) \qquad \text{(IC high type)}$$

$$\text{and} \qquad p_{ih} - p_{i\ell} \geq \theta_\ell (q_{ih} - q_{i\ell}) \qquad \text{(IC low type)}$$

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 ℓ 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 restraints equilibrium prices imply 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). The next Proposition states the main theoretical result.

Proposition 1 *The relationship between the unit transportation cost (intensity of competition)*

[7] The intuition from our two-firm model can be extended to N-firms.

[8] 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 etc. 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.

[9] 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 (forthcoming) derive and test the predictions of a second-degree price discrimination model using a unique dataset of airline ticket transactions, while Alderighi et al. (2010) looks 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.

and equilibrium price dispersion (measured by the Gini coefficient) is non-monotonic and can be inverse U-shaped.

Proof. See Appendix. ∎

2.1 Intuition for the Non-Monotonic Relationship

For simplicity, let's 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: $p_{ih} - p_{i\ell} = \theta_h (q_{ih} - q_{i\ell})$, $i = 1, 2$.[10] 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.[11] The indirect effect, on the other hand, leads to lower price dispersion for the following reason. As competition intensifies, firms compete more vigorously by increasing the quality offered to the low group (the level of quality offered to the low consumer group is already distorted downwards relative to its efficient level). Higher quality offered to the low group means higher marginal cost and hence a higher price for the low group. On the other hand, 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, implies that the price for the high type group cannot increase as much as the price for the low group. 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),

[10] 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.

[11] We measure price dispersion in percentages, which is what matters for the Gini coefficient.

see Figure 1 in Section A.1.[12] Next, we take this theoretical prediction to the data.[13]

3 Data

The data on airline ticket prices comes from the Airline Origin and Destination Survey (DB1B) maintained by the Bureau of Transportation Statistics. DB1B is a 10% random sample of airline itineraries from reporting carriers in each quarter.[14] For each itinerary segment, 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 (e.g. Borenstein and Rose (1994), Goolsbee and Syverson (2008), Gerardi and Shapiro (2009)), we build our sample from 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.[15] The data Appendix of the paper offers 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). The Air Carrier Financial Reports contain quarterly balance sheet information (e.g. operating cost, non-operating income, total current asset etc.) 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.[16]

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 including carrier, origin, destination, aircraft type and service

[12] 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 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.

[13] 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 (e.g., peak-load pricing) other than price discrimination which 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 which we can use to test for price discrimination directly. Nevertheless, the variation of price dispersion in the data is consistent with non-monotonicity, a prediction of our price discrimination model.

[14] 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.

[15] For example, without this treatment, a roundtrip ticket from Philadelphia to Boston would appear as two tickets in the sample.

[16] Although some balance sheet information for smaller carriers can be found in Schedule B-1.1 of the Air Carrier Financial Reports, they are only available semi-annually and contain many missing values.

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 is 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.[17] Thus, merging T-100 and DB1B helps eliminate some connecting tickets and provides a more accurate sample for nonstop segments. Lastly, 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 (e.g. population) from the Federal Aviation Administration's Passenger Boarding Data for U.S. Airports and from the U.S. Census.

An observation in our dataset represents a carrier who 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 4th quarter of 2008 represents 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 ((e.g. Morrison (2001), Berry and Jia (2010)) discuss possible 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.[18]

Our final sample includes 56 different carriers in 6015 distinct routes over the 64 quarters between 1993 and 2008. Many studies of the airline industry (e.g. Borenstein and Rose (1994), Goolsbee and Syverson (2008), Orlov (2011)) restrict the analysis to major airlines.[19] Our analysis also incorporates many medium sized and regional carriers who have played increasingly important roles by connecting passengers from smaller communities to the nation-wide airline network. During our sample period, 2531 out of 6015 routes experienced at least one entry while 2603 experience at least one exit. These

[17] 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.

[18] We combine the following close-by airports: DFW (Dallas-Ft 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.

[19] A notable exception is Gerardi and Shapiro (2009).

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.

4 Descriptive Evidence for Non-monotonicity

Following the literature (e.g. Borenstein and Rose (1994), Gerardi and 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 quarter combination, j indexes the fare from low to high and $\overline{fare}$ 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 1993-2006.

To investigate how the Gini coefficient varies with market structure, we divide our sample routes into three groups: monopoly, duopoly and competitive.[20] Table 1 displays the average Gini coefficient, HHI and number of carriers for each group. The distribution 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 one. An average duopoly route is populated by 2.1 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).[21]

The distribution of the Gini coefficient shows suggestive evidence of a non-monotonic 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.[22] This suggests an inverse-U relationship. The Gini coefficient first rises with competition and then declines. Consequently, airlines exhibit more price dispersion in the intermediately competitive duopoly markets relative to monopoly and competitive

[20] 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.

[21] Gerardi and Shapiro (2009) finds the average HHI of airline routes is between 0.72 and 0.78 during 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) covers 2,902 routes while we cover 6,015 routes.

[22] The t-tests strongly reject the mean equality of the Gini coefficient between any two groups.

markets.

While the overall trends in the data display a certain degree of non-monotonicity, we will next demonstrate the non-monotonicty with a representative route. We look at two major carriers (U.S Airways and Airtran) flying between Orlando (MCO) and Philadelphia (PHL).[23] Figure 2 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 non-monotonic relationship between competition and price dispersion by introducing statistical rigor.

5 Panel Analysis

5.1 Non-Monotonic Effect of Competition

We exploit the panel structure of the data to control for the time-invariant route and carrier heterogeneities. We introduce 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 (e.g. hub status, brand loyalty in hub markets) will not bias our estimates.

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

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

where i indexes airline, j indexes route, and t indexes year and quarter combinations.[24] X_{it} are time varying carrier characteristics such as airline size, the operating expenses etc. The full set of control variables are presented in Table 2. The airline-route specific time invariant unobservable ε_{ij} and shocks ε_t that are common to all carriers will be absorbed by the fixed effects.

The key variables of interest are β_1 and β_2. We choose a quadratic specification since alternative specifications such as log-linear and log-log could only admit monotonic (and non-linear) relationship. The empirical model (1) implies that when the relationship between competition and price dispersion

[23] Though several other carriers operated between MCO and PHL (e.g. Delta), they do not remain in the market long enough to generate informative plots. However, their entries/exits generate variation in competition that results in a wide spectrum of HHIs.

[24] Several papers (e.g. Gerardi and 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 upon request.

is non-monotonic, the sign of β_1 should be different from β_2. As our theory suggests, if price dispersion first increases with competition before it decreases, we expect β_1 to be positive and β_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's possible that carriers are less likely to enter the routes with low price dispersion. To address this concern, we adopt the instrumental variable approach as in Borenstein and Rose (1994) and Gerardi and Shapiro (2009). We use instruments similar to the ones in Gerardi and Shapiro (2009), as well as their squared counterparts. The list of instruments can be found in the Appendix, Section A.3. 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 non-monotonic in both competition and price dispersion. If the inverse-U relationship is spurious, the unobserved factors (e.g. 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_{ijt} will be negatively correlated with HHI and bias both β_1 and β_2 downwards. However, this kind of bias is less likely to cause the sign of β_1 to be different from β_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 afterwards. 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 (1) are displayed in Column (2) of panel (a). With an additional quadratic term, the estimated effects of competition become highly significant. This is strong evidence in favor of a non-monotonic relationship. $\beta_1 > 0$ and $\beta_2 < 0$ imply an inverse-U shape. We calculate and plot the net effect of competition in Figure 3. It is quite evident that price dispersion increases with competition when HHI approaches one and decreases with competition when HHI approaches zero. The implied marginal effect of competition is $\beta_1 + 2\beta_2 * HHI$ and the estimates suggest that carriers display more price dispersion when HHI is around 0.77 (i.e. the market is neither too concentrated nor too competitive). At our sample mean HHI=0.79, the marginal effect of competition is quite close to zero. As a robustness check, we combine the observations in close-by airports and re-estimate equation (1). Panel (b) column (2) of Table 3 displays the results.

Combining airports reduces the number of observations from 248,513 to 239,729. The estimated β_1 and β_2 in column (2) of panel (b) imply a similar non-monotonic relationship and the magnitude of the coefficients are close to their counterparts in panel (a).

We further investigate the non-monotonic 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).[25] We estimate:

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

The omitted category is duopoly. If the relationship between competition and price dispersion is truly non-monotonic and inverse-U shaped, we expect $\beta_m < 0$ and $\beta_c < 0$, i.e. 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 Table 3 panel (a). The estimated effects of β_m and β_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 carriers facing intermediate competition to exhibit more price dispersion. The market structure analysis also suggests that the non-monotonicity established in (1) is not merely driven by the quadratic specification. Looking closer at the estimates, $\beta_c = -0.035$ 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 Table 3 shows the estimated results using firm counts as measure of competition. By construction, non-monotonicity is not allowed in this specification. We find that carriers generally display less price dispersion with more competitors. This is consistent with the existing findings in several papers.[26]

We also perform the following two robustness checks: 1) we remove a carrier/route observation if less than 100 itineraries are sampled by DB1B (which may have issues with measurement error)[27] and

[25] The definitions of *mono*, *duo* and *comp* can be found in footnote 20 and they are similar to Borenstein and Rose (1994).

[26] If we focus on a monotonic non-linear relationship and use the log-log specification similar to Gerardi and Shapiro (2009), the coefficient estimate of log(HHI) is 0.074. It is highly significant at 1% and reasonably close to 0.121 found by Gerardi and Shapiro (2009).

[27] This corresponds to less than 1000 tickets sold by a given carrier in the market since DB1B is a 10% random sample. Removing low volume carrier/routes from our sample effectively eliminates 52,345 observations from the airport-pair analysis and 51,660 observations from the city-pair analysis.

2) we weight the sample using the route/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 non-monotonicity (we do not report the estimates from the robustness checks).

5.2 Price Level Analysis

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

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

where the dependant variables $log(P90)$ and $log(P10)$ represent the logged 90th and 10th price percentile. duo_{jt} and $comp_{jt}$ are indicators for duopoly and competitive route while the omitted category is monopoly. In price equation (3), β_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 theory intuition 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 (3), we use 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 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% vs. 4.9%). On the other hand, increasing competition in a less concentrated market (from duopoly to competitive) causes $P90$ to drop more than $P10$ (44.1% vs. 15.4%). An analysis by city-pairs reaches the same conclusion. We also check the robustness of percentile regression by examining different price quantile pairs (e.g. $P80$ and $P20$, $P75$ and $P25$ etc.). The findings are very similar. In robustness checks (similar to those performed in Section 5.1), we also confirm that our results are not driven by the low volume routes/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.

5.3 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 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:

$$Gini_{ijt}^{v} = \beta^{v} \log(HHI)_{jt} + \alpha X_{it}^{v} + \varepsilon_{ij}^{v} + \varepsilon_{t}^{v} + u_{ijt}^{v} \tag{4}$$

where $v = H, M, L$ for high, medium and low volume markets. If the relationship between competition and price dispersion is consistent with non-monotonicity, we expect the net effect of competition to be positive (i.e. $\beta < 0$, price dispersion increases with competition) in the more concentrated low volume markets. Price dispersion should decrease with competition (i.e. $\beta > 0$, price dispersion decreases with competition) in the competitive high volume markets. For medium 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, i.e. 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 marginally significant with $\beta^{M} = 0.011$ and it is less steep than either high or low volume markets. Our results are robust to inclusion of the close-by airports.

6 Conclusion

This paper offers a simple intuition that explains why equilibrium price dispersion can vary non-monotonically with the intensity of competition. We identify two competing forces: the direct price effect and the indirect quality effect, which lie at the heart of this non-monotonicity. 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, on the other hand, 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 then 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 low-end 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 non-monotonically with the intensity of competition.

Using carrier-route level data from 1993 to 2008, we establish a non-monotonic 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 non-monotonicity. 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 non-monotonicity 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.

A Appendix

A.1 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.[28] *Second*, we demonstrate that price dispersion can be non-monotonic with respect to competition and in particular inverse U-shaped. We provide an intuition and we 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 $\hat{x}_j$ from group $j = h, \ell$, who is indifferent between firm 1 and 2, must satisfy $V + \theta_j q_{1j} - p_{1j} - t_j \hat{x}_j^2 = V + \theta_j q_{2j} - p_{2j} - t_j (1 - \hat{x}_j)^2$. This yields the demand functions of firm 1 who is located at point 0

$$d_{1\ell} = \frac{\theta_\ell (q_{1\ell} - q_{2\ell}) - (p_{1\ell} - p_{2\ell}) + t_\ell}{2t_\ell} \text{ and } d_{1h} = \frac{\theta_h (q_{1h} - q_{2h}) - (p_{1h} - p_{2h}) + t_h}{2t_h}. \tag{5}$$

The demand functions of firm 2, who is 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 we substitute these prices, along with the demand functions d_{ij} given by (5), into firm i's profit function[30]

$$\pi_i = \sigma \left[\left(p_{i\ell} - \frac{a q_{i\ell}^2}{2} \right) d_{i\ell} \right] + (1 - \sigma) \left[\left(p_{ih} - \frac{a q_{ih}^2}{2} \right) d_{ih} \right]. \tag{6}$$

Firms compete in qualities and prices sequentially. We normalize $\theta_\ell = 1$. We differentiate π_i with respect to $p_{i\ell}$, $i = 1, 2$, and we solve the system of first-order conditions to derive the equilibrium prices as a function of qualities. (Second-order conditions are also satisfied.) The price of firm 1, designed for the high consumer group, is given by

$$p_{1h} = \frac{\left(\begin{array}{c} \theta_h q_{1h} (2t_\ell (1 - \sigma) + 6t_h \sigma) - 6t_h \sigma \theta_h q_{1\ell} + 2t_h \sigma (q_{1\ell} - q_{2\ell}) + \\ t_\ell a (1 - \sigma) \left(2q_{1h}^2 + q_{2h}^2 \right) + \sigma t_h a \left(2q_{1\ell}^2 + q_{2\ell}^2 \right) - 2t_\ell \theta_h (1 - \sigma) q_{2h} + 6t_\ell t_h \end{array} \right)}{6 (t_\ell (1 - \sigma) + t_h \sigma)}, \tag{7}$$

[28] This is the standard case in a monopoly market and it can be reasonably extended in a duopoly market, e.g., 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 and Stole (2002)).

[29] All derivations were performed using Maple software. All Maple files are available upon request.

[30] Our model allows for competition between firms for the same quality products and within a firm for products of different qualities, but does not allow for competition 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.

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 π_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 θ_h and negatively on the marginal cost of quality parameter a, e.g., Desai (2001), but it is independent of the degree of competition in the market, that is, t_h and t_ℓ. This is the standard "no distortion at the top" result, whereas firms distort the quality offered to the low group downwards. The equilibrium quality (and the distortion) depends on the competition parameters t_h and t_ℓ, as follows

$$q^*_{1\ell} = \frac{\left(\begin{array}{c} at_h - 3at_h\sigma + 3\theta_h - 3t_\ell a - 3\theta_h^2 + 3t_\ell \sigma a + 3\theta_h^2\sigma - 3\sigma\theta_h + \\ \sqrt{\begin{array}{c} (a(9t_\ell^2 a + t_h^2 a - 18t_\ell^2 \sigma a + 9t_\ell^2\sigma^2 a + 9\sigma^2 t_h^2 a - 12\sigma t_h + 24 t_h \sigma\theta_h - \\ 24 t_h\theta_h - 6\sigma t_h^2 a - 6t_h t_\ell a + 12 t_h\theta_h^2 + 24 t_\ell t_h a\sigma - 12 t_h\sigma\theta_h^2 - 18 a t_h t_\ell \sigma^2 + 12 t_h)) \end{array}} \end{array} \right)}{3a(1-\sigma)(1-\theta_h)}.$$

By substituting q^*_{ij} into (7) 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: $\sigma \in \{1/2, 3/4\}$, $\theta_h \in \{2, 5, 10\}$, $a \in \{1/2, 1\}$ and $\frac{t_h}{t_\ell} \in \{2, 3, 5\}$. These give us a total of 36 combinations of parameter values. The only free parameter is t_ℓ 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 $\sigma = 3/4$,

[31] We have focused on symmetric equilibria for simplicity/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.

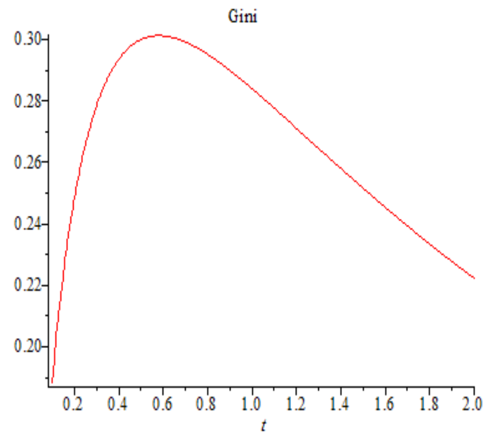


Figure 1: Gini coefficient as a function of the intensity of competition, measured by the transportation cost parameter t

$\theta_h = 2$, $a = 1/2$ and $t_h = 3t_\ell = 3t$, it can be shown that the Gini coefficient becomes

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

Figure 1 shows that Gini is inverse U-shaped. We offer a general intuition in Section 2.1.

Existence of an equilibrium. To establish the existence of an equilibrium, we have to examine all possible unilateral deviations. Due to symmetry, we only check firm 1's incentive to deviate. There are various types of deviations. In type 1 deviation, firm 1 deviates in prices only. In 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 or not, it is divided into 4 cases. Neither firm's IC-H constraint is binding in type 2a) deviation 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 or not.

We assign the following values to the parameters: $\sigma = 3/4$, $\theta_h = 2$, $a = 1/2$ and $t_\ell = 1$, $t_h \in \{2, 3\}$, and check whether firm 1 has incentive for any of the above 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 non-monotonic and in particular inverse U-shaped (due to the presence of the two opposing effects: the direct price effect and the indirect quality effect).

A.2 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 studies using DB1B database, we use domestic, one-way or round-trip, non-stop, coach-class itineraries.[32] The fare charged by a carrier is defined as one-way fare and we divide the fare by two for round-trip tickets. Additionally, we use the following criterion to screen the itinerary. We eliminate the itinerary if: 1. the one-way fare is less than $10 or above the 99th percentile of the route-carrier fare distribution;[33] 2. the dollar credibility is questioned by BTS; 3. the operating carrier is different from the ticketing carrier on either segment of the itinerary; 4. any segment of the itinerary is in first or business class;[34] 5. any segment of the itinerary involves connecting flights; 6. 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.[35] 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. 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 Table A1.

After screening the itineraries with the above 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 1. we cannot find the match in T-100;[36] 2. the available seats equal zero; 3. the num-

[32] Domestic tickets are associated with flights in the lower 48 states (i.e. the value of itinerary geography type equals 2 in DB1B).

[33] Abnormal fares are usually frequent flier tickets or key punch error.

[34] 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.

[36] As discussed in Section 3, merging with T-100 results in the loss of many carrier-route observations. However, it

ber of departures performed equals zero; 4. the carrier financial information is missing; 5. the MSA population in either of the two endpoint airports is missing;[37] 6. if less than 10 itineraries are recorded in a route-carrier-quarter.[38] The final sample contains about 56% of the route-carrier observations from DB1B with non-zero price dispersion.

A.3 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^2(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).

log^2(gmsapop): log(gmsapop) squared.

genp: $\sqrt{enp_{j1} * enp_{j2}}/\sum_k \sqrt{enp_{k1} * enp_{k2}}$ where k indexes all airlines, enp_1 and enp_2 are quarterly enplanement at two end-point cities from T-100. This instrument is introduced by Borenstein and Rose (1994).

$genp^2$: genp squared.

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

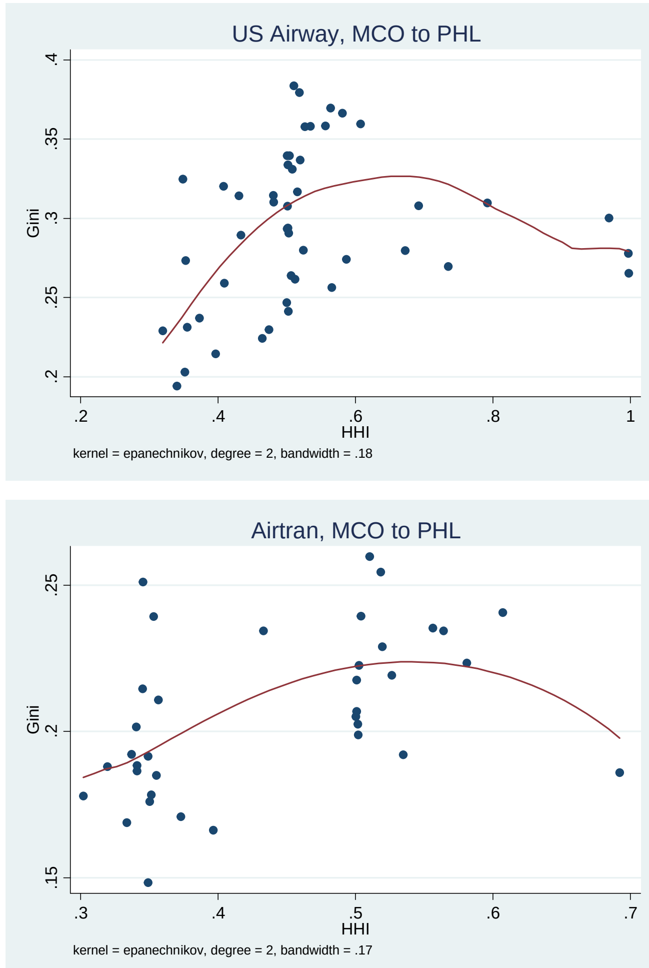
log^2(totpas): log(totpas) squared.

helps eliminate the connecting passengers without a plane change from our sample.

[37] If the airport is in a rural county, the corresponding MSA population is considered as missing.

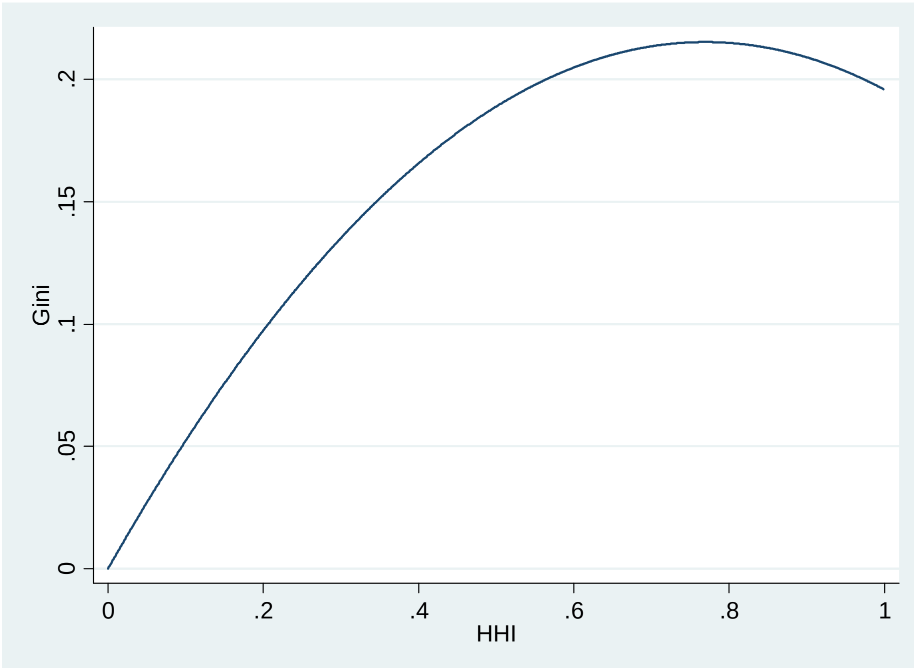
[38] This corresponds to less than 100 tickets sold by a carrier in a quarter.

Figure 2. An Example of Non-monotonicity



Note: The curve shows a second order polynomial smooth. U.S Airways is the incumbent and Airtran began to fly the route in 2000.

Figure 3. Net Effect of Competition on Price Dispersion



Note: The graph is based on specification (2) of Table 3 (a).

Table 1. Price Dispersion by Market Structure

	Gini	HHI	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	1.72
	(.087)	(.237)	(.925)

Note: N represents carrier counts. Definition of Monopoly, Duopoly and Competitive route appear in footnote 20. Standard deviations are in parentheses. Number of observation is 248,513.

Table 2. Control Variables

Variable	Definition	Mean	Std. Dev.
lasset	logged total assets	14.22	1.354
lasset^2	lasset squared	204.1	35.62
cash	cash available	0.148	0.214
opexp	operating expenses	0.561	2.190
otherinc	non-operating income	-0.011	0.123
bankr	bankruptcy indicator	0.066	0.248

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

Table 3. Non-monotonic Effect of Competition

	(a) Airport-Pairs				(b) City-Pairs			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
$\widehat{HHI}$	.003	.561***			.014***	.536***		
	(.005)	(.116)			(.005)	(.096)		
$\widehat{HHI}^2$		-.365***				-.344***		
		(.075)				(.062)		
$\widehat{mono}$			-.011***				-.013***	
			(.003)				(.003)	
$\widehat{comp}$			-.035***				-.044***	
			(.005)				(.006)	
$\widehat{N}$				-.003**				-.006***
				(.001)				(.001)
Obs	248,513	248,513	248,513	248,513	239,729	239,729	239,729	239,729

Note: *** p<0.01, ** p<0.05, * p<0.1. Dependant variable is Gini. 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), non-operating net income (as % of asset), a dummy indicator if the carrier is under bankruptcy protection. The list of instruments can be found in Appendix A.3.

Table 4. Effect of Competition on Price Level

	(a) Airport-Pairs		(b) City-Pairs	
Dependant Var.	log(P90)	log(P10)	log(P90)	log(P10)
$\widehat{duo}$	-.049***	-.122***	-.043**	-.136***
	(.017)	(.012)	(.019)	(.013)
$\widehat{comp}$	-.490***	-.276***	-.581***	-.301***
	(.028)	(.020)	(.030)	(.018)
Obs	248,513	248,513	239,729	239,729

Note: *** p<0.01, ** p<0.05, * p<0.1. P90 represents 90th percentile fare and P10 represents 10th percentile fare. 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), non-operating net income (as % of asset), a dummy indicator if the carrier is under bankruptcy protection. The list of instruments can be found in Appendix A.3.

Table 5. Distribution of Concentration by Traffic Volume

	low	medium	high
HHI	.965	.819	.575
	(.115)	(.218)	(.195)
N	1.13	1.59	2.60
	(.365)	(.716)	(1.05)
Obs	62632	125245	62633

Note: N represents carrier counts. Standard deviation in parenthesis.

Table 6. Heterogeneous Effect of Competition

	(a) Airport-Pairs			(b) City-Pairs		
	low	medium	high	low	medium	high
$\widehat{log(HHI)}$	-.029***	.011**	.033***	-.030***	.027***	.029***
	(.008)	(.005)	(.008)	(.007)	(.005)	(.010)
Obs	60,753	124,421	62,275	58,703	120,025	60,076

Note: *** p<0.01, ** p<0.05, * p<0.1. 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), non-operating net income (as % of asset), a dummy indicator if the carrier is under bankruptcy protection. The list of instruments can be found in Appendix A.3.

Table A1. Sample Coverage

Year	Quarter	Direct%	Direct Passenger	Included in Sample
1993	1	61%	2,347,325	1,552,025
1993	2	60%	2,732,743	1,845,573
1993	3	62%	2,808,783	1,924,035
1993	4	63%	2,826,413	1,959,490
1994	1	62%	2,742,757	1,913,821
1994	2	61%	3,059,764	2,149,515
1994	3	62%	3,296,834	2,272,259
1994	4	63%	3,264,309	2,344,988
1995	1	63%	3,050,977	2,169,525
1995	2	63%	3,404,277	2,375,728
1995	3	63%	3,424,686	2,324,551
1995	4	64%	3,331,087	2,299,081
1996	1	64%	3,340,096	2,341,196
1996	2	64%	3,684,842	2,531,306
1996	3	64%	3,697,765	2,539,549
1996	4	64%	3,681,909	2,648,695
1997	1	65%	3,514,741	2,490,587
1997	2	64%	3,816,307	2,722,339
1997	3	64%	3,817,751	2,752,356
1997	4	64%	3,701,143	2,681,515
1998	1	64%	3,456,168	2,276,095
1998	2	63%	3,913,433	2,655,346
1998	3	60%	3,315,715	1,989,588
1998	4	61%	3,343,274	2,055,060
1999	1	61%	3,136,115	1,948,767
1999	2	60%	3,508,712	2,082,621
1999	3	61%	3,597,405	2,180,426
1999	4	62%	3,560,581	2,172,298
2000	1	62%	3,344,426	2,042,844
2000	2	61%	3,870,791	2,314,505
2000	3	61%	3,747,983	2,219,665
2000	4	62%	3,639,652	2,225,034
2001	1	62%	3,373,946	2,050,941
2001	2	61%	3,725,593	2,127,941
2001	3	60%	3,320,010	1,954,184
2001	4	59%	2,874,623	1,574,578
2002	1	59%	2,838,981	1,593,684
2002	2	60%	3,311,236	1,815,891
2002	3	60%	3,290,827	1,794,290
2002	4	60%	3,180,164	1,727,419
2003	1	60%	2,929,783	1,527,719
2003	2	59%	3,295,265	1,762,191

Year	Quarter	Direct%	Direct Passenger	Included in Sample
2003	3	59%	3,288,868	1,706,621
2003	4	61%	3,378,497	1,879,730
2004	1	62%	3,249,169	1,749,516
2004	2	61%	3,739,937	2,064,304
2004	3	61%	3,746,179	2,008,342
2004	4	62%	3,759,416	2,031,568
2005	1	62%	3,546,753	1,995,086
2005	2	63%	4,154,046	2,212,991
2005	3	63%	4,120,411	2,255,096
2005	4	64%	4,018,775	2,121,540
2006	1	64%	3,854,482	2,027,572
2006	2	64%	4,338,909	2,171,215
2006	3	63%	4,182,650	2,054,404
2006	4	64%	4,222,630	2,101,583
2007	1	65%	3,977,024	2,009,419
2007	2	64%	4,518,411	2,255,648
2007	3	63%	4,333,628	2,173,927
2007	4	65%	4,224,005	2,245,330
2008	1	66%	4,017,621	2,158,301
2008	2	64%	4,381,260	2,329,006
2008	3	62%	4,038,621	2,102,713
2008	4	63%	3,805,847	1,985,485

Note: Direct% is the percent of direct passengers out of total passengers.

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