Competition and Price Dispersion in the U.S. Airline Industry: An Analysis with Explicit Quality Differentiation

Master Thesis
M.Sc. Economics and Business
Specialization Urban, Port and Transport Economics (UPTE)

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Table of contents

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ABSTRACT

We re-examine the relationship between competition and price dispersion in the airline industry. Quality competition models in the literature so far have restricted their attention to coach class passenger data, thereby not explicitly modelling quality differentiation in their empirical applications. We tackle the mismatch between theory and application by introducing quality dispersion in our analysis with the use of a sample that includes both coach class and business class passengers. In addition to introducing quality differentiation, we evaluate the consistency of our results across specifications in which competition is measured by airline market shares based on passenger tickets sold, passenger enplanement and flight departure data. Using a rich panel of airline ticket and competition data from 1993 to 2014, we find robust evidence for a non-monotonic relationship between competition and price dispersion. Additionally, we provide preliminary evidence that the strength of the non-monotonic relationship is influenced by the concentration of monopoly routes in the data.

I. Introduction and background

THE effect of competition on price dispersion has varied significantly in the empirical literature in spite of the clear predictions of economic theory. Traditional microeconomic theory suggests that the ability of firms to engage in price discrimination practices goes hand in hand with increased market power, indicating a negative relationship between competition and price dispersion: the lower the degree of competition in a market, the higher the market power of a given firm and the greater its ability to exploit potential differences in the demand elasticity of separable sub-markets by price discriminating.

Nevertheless, the empirical literature examining the relationship between competition and price dispersion in the U.S. airline market has neither delivered robust conclusions on the magnitude nor on the direction of this relationship. In a first attempt to analyse price dispersion in U.S. airline fares, Borenstein and Rose (1994) identify a positive relationship between competition and price dispersion with the use of cross-sectional data from 1986. Stavins (2001) also reports similar findings (i.e. higher price dispersion in more competitive routes) by using a more recent data set from 1995. However, Gerardi and Shapiro (2009) challenge those results by establishing a negative relationship between competition and price dispersion, providing thus support to the standard microeconomic prediction. By means of a fixed effects estimation and a rich panel of airline data from 1993 to 2006 they find competition to be putting downward pressure on the prices at the top of the price distribution to a larger extent than to those at the bottom, resulting in a decline in the overall price dispersion. They contrast their findings to those of Borenstein and Rose (1994) and by replicating their cross-sectional analysis, attribute their different result to the existence of omitted variable bias induced by time invariant, route and carrier specific effects.

Furthermore, Dai et al. (2014) encompass the two different outcomes by advocating the relationship between price dispersion and competition to be non-monotonic (i.e. inverse-U-shaped). They test their hypothesis empirically and provide evidence for a different impact of competition on price dispersion that depends on the level of competition in the market: in highly concentrated markets, price dispersion increases with competition, while in less concentrated markets price dispersion decreases with competition[1]. Dai et al. (2014) devise two opposing effects in order to explain the different levels of price dispersion in their data. In particular, they argue that the non-monotonic relationship is driven by the relative strength of a direct-price and indirect-quality effect[2].

Indeed, the non-monotonicity claim provides an interesting ground for explaining the mixed findings on the relationship between competition and price dispersion in the literature. Since the impact of competition on price dispersion has been restricted to

* We thank Peran van Reeven and Enrico Pennings for their invaluable guidance, feedback and corrections that led to the final version of this paper.

[1] The terms high (low) competition and low (high) market concentration are used complementary in this paper.

[2] We explain the working of the two effects in detail in Section II of this paper, together with our motivation for re-examining the non-monotonic relationship.

being linear or monotonic[3], the estimated effect can be found to be either positive or negative depending on the concentration of the market in the dataset employed.

Although the empirical findings of Dai et al. (2014) provide support for a non-monotonic relationship between competition and price dispersion, we challenge their empirical design and argue that their results have to be interpreted with care as they do not constitute empirical support for the theoretical model developed by the authors. In particular, Dai et al. (2014) violate an important assumption of their theoretical model by their choice of data[4], namely that different quality levels are characterised by different levels of marginal cost. Two important questions therefore arise as to (i) whether their empirical results can be disregarded even though they provide robust evidence for a non-monotonic relationship between competition and price dispersion, and (ii) whether the theoretical model of Dai et al. (2014) can be empirically supported in the data.

In this paper, we first explain the empirical results of Dai et al. (2014) using the framework of Gale (1993) and then proceed to re-examine the relationship of competition and price dispersion in the U.S. airline industry in line with the model developed in Dai et al. (2014). Using the same sources of data, we extend the timeframe of Dai et al. (2014) to include more recent years and re-model the quality dispersion by including business class passengers in the analysis. By means of an instrumented variable, fixed effects model on a panel of 88 quarters set between 1993 and 2014, we re-test the existence of a non-monotonic relationship between competition and price dispersion. In addition, we evaluate the robustness of this result by examining alternative measures of concentration in line with literature on frequency competition (Brueckner and Flores-Fillol, 2007; Brueckner, 2010). We deem re-examination of this relationship – with explicit quality differentiation and additional robustness checks – to be essential for the following two reasons: (i) to address the consistency of the non-monotonic relationship in an appropriately defined empirical application of a quality competition model[5], and (ii) to shed more light on the drivers of the relationship by examining the intuition of the direct-price and indirect-quality effect of Dai et al. (2014).

Our empirical results are consistent with Dai et al. (2014) with respect to the non-monotonicity; increasing quality dispersion does not alter the estimated type of relationship. However, the intuition of a direct-price and indirect-quality effect is not robust in our analysis. This suggests that the theoretical intuition of Dai et al. (2014) might not be appropriate in explaining the non-monotonic relationship. Indeed, we offer an alternative explanation of the non-monotonic relationship that is closer to the framework of Gale (1993). By re-evaluating the measurement of market concentration in our empirical specifications, we provide preliminary evidence that the strength of the non-monotonic relationship is influenced by the concentration of monopoly routes in the data[6].

The paper is structured as follows. Section II discusses the empirical findings of Dai et al. (2014) and elaborates on the theoretical background that motivates the existence of a non-monotonic relationship between competition and price dispersion. Section III introduces the different sources of data employed, while Section IV presents the empirical model employed. Section V provides some descriptive statistics, and presents and discusses the results of the main specifications used. Finally, section VI concludes. More details on the construction of the final dataset and the results of the remaining specifications and robustness checks are provided in the appendix.

II. Motivation for re-examining the non-monotonic relationship

In this section, we start by outlining the key elements of the theoretical model of Dai et al. (2014) in order to explain the mismatch between the developed theory and empirical application. We proceed by using the framework of Gale (1993) on price dispersion in advance-purchase markets to clarify their empirical results. Finally, we present the main intuition of the model of oligopolistic second-degree price discrimination of Dai et al. (2014), which will prove useful for our own analysis.

Dai et al. (2014) distinguish between two types of passengers: business and leisure passengers. They assume that airlines separate business from leisure passengers based on their price sensitivity and value for quality. Previous literature (Dana, 1998; Stavins, 2001) and practical evidence suggests that airlines will offer such products as advance purchase discounts, Saturday night or weekend stay-overs, thereby restricting the flexibility of the ticket sold. By assumption, leisure passengers will prefer buying those tickets given their high price sensitivity and low valuation of quality. On the contrary, business passengers, with a high valuation of time and lower price sensitivity will prefer the flexibility of the non-discount fare[7].

[3] Borenstein and Rose (1994) compare the results of a log-log and a linear specification, Stavins (2001) uses a log-linear specification, while Gerardi and Shapiro (2009) also specify a log-log model.

[4] Dai et al. (2014) restrict their attention to coach class passengers in their data, distinguishing in quality between restricted and unrestricted coach class fares. However, marginal cost is modelled as a quadratic function of quality, meaning that the high-quality ticket should also be characterised by a higher marginal cost compared to the low-quality ticket. This assumption is arguably not applicable given their choice of data, since a restricted ticket on the same fare class is a damaged version of the full, unrestricted coach class ticket.

[5] That is, in contrast to a market of advances purchases, as put forward in Gale (1993). We highlight the main features of each theoretical model in Section II of this paper.

[6] We show that the higher the percentage of monopoly routes included in the sample examined, the stronger the inverse-U-curve estimated in the data. In particular, we observe that it is the concentration of monopoly routes in the examined sample and *not* the overall variance of price dispersion between fare classes that is driving the strength of the predicted non-monotonic relationship.

[7] Practical evidence suggests that airlines distinguish at least between business and coach passengers. In recent years, discrimination in more sub-

Dai et al. (2014) model all non-price ticket characteristics such as ticket flexibility by using a single variable, quality q, and use a parameter θ to measure consumer preference for quality. In addition, they assume marginal cost to be increasing in quality using the rule $MC = aq^2/2$, while fixed costs are set equal to zero for simplicity. As is common in quality competition models, the authors assume that firms first set qualities and then compete on prices. Using this specification and defining the intensity of competition to be equal to t[8], the authors prove that utility maximizing leisure (business) passengers will always prefer the low (high) quality product. As a result, a profit maximizing firm will set prices that in equilibrium produce a non-monotonic (i.e. inverse-U-shaped) relationship between the intensity of competition parameter and price dispersion as measured by the Gini coefficient.

The caveat of Dai et al. (2014) does not lie in the theoretical formulation of the model but in its empirical application. In particular, the authors assume marginal costs to be increasing with quality on a quadratic rate in their model, while using a sample with no quality dispersion. Dai et al.'s (2014) sample includes only coach class passengers and defines different quality levels by distinguishing between restricted and unrestricted coach class tickets. By doing so, however, an important assumption of the theoretical model is violated, namely that different quality levels are also characterised by different levels of marginal cost. However, a restricted coach class ticket is arguably a damaged good that facilitates price discrimination. Since restricted and unrestricted fare category passengers receive the same product offering (excluding the ticket flexibility), both fare classes should be characterised by the same marginal cost of production. In other words, restricting the ticket flexibility should not entail the airline to be incurring additional costs. As a result, there is no quality dispersion in the empirical application of Dai et al. (2014), despite the quality dispersion in their theoretical model.

Despite the mismatch between the theoretical model and the empirical application, the results of Dai et al. (2014) should not come as a surprise. Gale (1993) developed a theoretical model for the behaviour of price dispersion in advance-purchase markets that shares the same prediction. Indeed, Gale (1993) shows that price dispersion between advance-purchase (restricted) tickets and regular (unrestricted) tickets is increasing with competition but is higher in a duopoly than in a monopoly. This implies that the relationship between price dispersion and competition can be non-monotonic. He does that by using a model where consumers are uncertain as to which product to choose for *ex ante*, but where there is horizontal differentiation *ex post*. He argues that there is an *ex post* incentive for price discrimination as a result of the consumer uncertainty. He shows that an expected profit maximizing duopolist would sell more advance-purchase (restricted) tickets at a lower price compared to an expected profit maximizing monopolist. At the same time, the regular (high) price set by the duopolist would be at least as high as the one of the monopoly, implying a higher price dispersion in the duopoly than in the monopoly case.

It is evident that the model of Gale (1993) is the only appropriate in explaining the behaviour of price dispersion when looking at fare classes of different "quality" offerings but an equal marginal cost of production (e.g. restricted vs. unrestricted coach class tickets). In order to empirically test the model of Dai et al. (2014) it is therefore essential to increase the quality dispersion of the examined fare classes. This is done in this paper by creating a sample where business class passengers are also included. Explicit introduction of quality differentiation is necessary for an appropriately specified empirical application of the theoretical model in Dai et al. (2014). Indeed, looking at the price difference between business and coach class meets both necessary criteria: (i) the two fare classes constitute quality offerings that are distinctly classifiable as "high" and "low"; furthermore, (ii) the superior quality fare class (business) is also characterised by a higher marginal cost of production, as assumed in the model[9].

In addition to introducing quality differentiation, we check the robustness of the estimated relationship in specifications with alternative measures of market concentration. This is important, especially given the extent to which the results in the literature so far have been susceptible to changing market concentration in the employed samples. In that respect, we are also interested in investigating how robust the intuition of Dai et al. (2014) is, according to which the non-monotonic relationship is driven by a direct-price and indirect-quality effect.

We provide the main intuition behind the working of the two effects below. According to the direct-price effect, when competition is increasing price dispersion also increases because prices of high-class tickets are decreasing at a *lower* rate compared to prices of low-class tickets. Moreover, according to the indirect quality effect, when competition is increasing firms choose to compete by offering a better quality low-class product instead of lowering their prices further. This is possible assuming that the quality of the low-class product was distorted downwards in order to price discriminate[10]. Increasing the quality of the low-class product implies an increase in its marginal cost of production, which reduces the rate at which prices of low-class tickets are

categories in the spectrum of business (first) to coach class is becoming increasingly popular with airlines in an effort to reduce costs and tailor their offerings to passenger needs. A number of new passenger categories have arisen, from Basic Economy to Premium and Exclusive Economy, with distinguishing features offerings such as more leg space, additional baggage allowance, meals on board, etc.

[8] The authors model intensity of competition t as the transportation cost that uniformly distributed consumers incur on a Hoteling line [0,1] with each of the two firms situated at one of the two end points.

[9] It can be assumed that a business class seat is associated with significantly higher marginal cost of production compared to a coach class seat, as a result of the better features and service it includes (e.g. better meals, bigger seats, exclusive personnel etc.).

[10] The model of Dai et al. (2014), similar to other quality competition models, assumes that a profit maximizing firm sets the high-class product at the efficient quality level and distorts the quality of the low-class product downwards in order to price discriminate effectively.

decreasing as a result of competition. Therefore, the indirect-quality effect suggests that price dispersion is decreasing as competition increases because prices of high-class tickets are decreasing at a *higher* rate compared to prices of low-class tickets. According to Dai et al. (2014), the relative strength of the two opposing effects eventually determines the direction of the relationship between competition and price dispersion.

III. Data

A. Sources of data

We employ multiple sources of data in order to create the final sample used in the panel analysis.

The largest part of the data comes from the Transtats database of the Bureau of Transportation Statistics of the U.S. Department of Transportation [11]. We obtain information on ticket prices, fare class and the operating route and carrier from the Origin and Destination Survey (DB1B). DB1B is a 10% sample of airline tickets of reporting carriers. The dataset also includes information on the origin, destination and other itinerary details of passengers transported. In addition, we obtain supplementary characteristics for each route from the T-100 Domestic Segment (T-100) database. T-100 contains domestic non-stop segment data reported by U.S. air carriers on a monthly basis. It includes information on both passengers and cargo transported: carrier, origin, destination, aircraft type and service class for transported passengers, freight and mail transported, available capacity, scheduled departures, departures performed and load factor. Similar to Dai et al. (2014) and consistent with previous literature (Gerardi and Shapiro, 2009; Borenstein and Rose, 1994) we use domestic segment data to restrict our attention to direct flights of which both origin and destination airports are located within the United States.

We use the following sources of data in order to construct the instruments and control variables employed in our specifications. We obtain financial data from the Air Carrier Financial Reports (Form 41 Financial Schedule) of the Transtats database. Form 41 Financial Schedule consists of financial information of large U.S. air carriers and reports among others cash flows, employment, income statements, fuel cost and consumption, and operating expenses. We only use data from schedules B-1 and P-1.2, which contain quarterly operating balance sheet statements and profit and loss accounts of U.S. air carriers with annual operating revenues of $20 million or more. As done in Dai et al. (2014), we exclude smaller carriers from our analysis since they only constitute a small portion (about 1%) of our final sample [12]. We also include a bankruptcy indicator in our specifications, for which we combine information from the UCLA-LoPucki Bankruptcy Research Database (BRD)[13] and the bankruptcy list on the website of the Air Transportation Association (ATA) [14]. The BRD contains Chapter 11 bankruptcy filings of public companies with assets over $100 million, while ATA lists both Chapter 7 and 11 bankruptcy filings regardless of the size of the airline[15]. Finally, we obtain information on the metropolitan population of origin and destination airports from the Metropolitan Statistical Areas (MSA) database of the U.S. Census[16].

B. Construction of the final sample

We combine the sources of data defined in the previous section as outlined below. A detailed description of the construction of the final sample (including details on the control variables and instruments employed) can be found in the appendix of this paper.

We reduce the original DB1B to include only domestic market, direct (non-stop), one-way and return flights. We drop the return portion of the flight in line with Dai et al. (2014) and Gerardi and Shapiro (2009) in order to avoid double counting. The sample employed in our main specifications that are presented in the results section contains both coach and business class passengers, in contrast to Dai et al. (2014). We also generate a sample that includes only coach passengers in order to replicate their findings – the results of those specifications are presented in the appendix of this paper.

The data from DB1B is merged with the T-100 dataset after transforming the T-100 from monthly to quarterly data. Following the merge, a large proportion of the data is not perfectly matched and therefore not part of the final sample. This happens for the following reasons: (i) T-100 includes passengers with connecting flights, who were already dropped from DB1B as part of the initial filtering, and (ii) DB1B does not distinguish between a direct (non-stop) flight and a connecting flight with a stop but without a plane change. Thus, merging the two datasets facilitates as an additional filter for obtaining a sample of only direct (non-stop) itineraries (Dai et al., 2014). Finally, we merge the combined dataset with the Form 41 Financial Schedule and the Metropolitan Statistical Area (MSA) population data. The final sample only includes observations for which the financial data and MSA population data is not missing[17].

[11] All Transtats databases are available on the website of the Bureau of Transportation statistics: http://www.transtats.bts.gov/homepage.asp.

[12] Financial data for U.S. carriers with annual operating revenues of $20 million or less (small carriers) is available only on a semi-annual basis on schedules B-1.1 and P-1.1 and contains many missing values.

[13] The UCLA-LoPucki Bankruptcy Research Database (BRD) is available at: http://www.webbrd.com/bankruptcy_research.asp.

[14] The database on U.S. Bankruptcies and Service Cessations of the ATA is available at: http://airlines.org/data/u-s-bankruptcies-and-services-cessations.

[15] Chapter 7 of the United States Code dictates liquidation processes in the event of a bankruptcy under the bankruptcy laws of the United States. In contrast, Chapter 11 governs the process of reorganization of a debtor in the event of a bankruptcy.

[16] The Metropolitan Statistical Areas (MSA) database of the U.S. Census is available at: http://www.census.gov/population/metro.

[17] As explained in the appendix of this paper, the population of rural areas (counties) is considered as missing.

Each observation in our final sample is unique on a route-carrier-quarter basis. For example, a Delta Airlines (DL) flight from New York John F. Kennedy airport (JFK) to Los Angeles International airport (LAX) in the first quarter of 2014 is a unique observation in our sample. In that sense, a United Airlines (UA) flight from JFK to LAX in the same quarter (Q1 2014) is a separate observation in our final sample, similar to a DL flight on the same route but in a different quarter. Similar to Dai et al. (2014) we define origin and destination both on an airport-pair as well as a city-pair basis in our analysis. That is in line with previous literature advocating potential competition between airports that serve the same metropolitan areas, for instance John F. Kennedy International (JFK), LaGuardia (LGA) and Newark Liberty International (EWR) serving the New York metropolitan area (Morrison, 2001; Berry and Jia, 2010).

IV. Methodology and empirical specifications

In this section, we present the empirical method and specifications employed in the panel analysis. Our empirical specifications are, except from any deviations explicitly mentioned, in line with Dai et al. (2014). We first discuss the motivation for using instrumental variables and a two-stage least squares model in our panel. We then proceed to the empirical specifications, each one of which is presented and discussed in a separate sub-section.

The comparison of cross-sectional and panel data results in Gerardi and Shapiro (2009) provides strong support in favour of the panel. Indeed, exploiting the panel structure of the data allows to control for time-invariant route and carrier specific heterogeneity. In addition, our specifications include quarter fixed effects for all years to control for time-specific heterogeneity. In that respect, we eliminate the possibility that our estimates are biased as a result of, e.g. the hub status of the airline or passenger loyalty (Dai et al., 2014). Gerardi and Shapiro (2009) also identify an additional threat to consistent estimates: potential changes in the competitive intensity of particular routes over time. In particular, if higher price dispersion draws more competitors onto a specific route, a positive bias would be introduced when estimating the effect of competition on price dispersion. In accordance to previous literature, we tackle this issue by introducing instrumental variables (Borenstein and Rose, 1994) and estimating a two-stage least squares fixed effects model (Gerardi and Shapiro, 2009; Dai et al., 2014). Finally, since price dispersion (Gini coefficient) is calculated on a route-carrier basis while competitive intensity (Herfindahl-Hirschman Index) varies on a route basis, we need to account for serial correlation at the route level. We thus correct our standard errors by clustering observations at the route level.

In addition to the quarter fixed effects, all specifications include the following set of control variables. In line with Dai et al. (2014), we control for the size and financial health of the airline by including measures of total assets, cash available and non-operating income. Also, in order to distinguish between demand-induced and cost-driven price discrimination it is essential to control for variable costs incurred by the airline. For this purpose, we include a measure of operating expenses as an additional control variable.

Moreover, we instrument the competitive intensity (or market structure, respectively) of a route in a similar manner to Dai et al. (2014). As a result, the following instruments are employed (introduced in Borenstein and Rose, 1994; Gerardi and Shapiro, 2009): arithmetic and geometric means of the MSA population of end-point cities, quarterly enplanement at the origin and destination airports and total enplanement on a route. Although these variables affect route entry and the output choices of airlines, they can be assumed to be unrelated to price dispersion (Dai et al., 2014).

A summary of descriptive statistics is provided in Section V, while a full list of the controls and instruments employed can be found in the appendix of this paper. We present the empirical specifications in detail in the sub-sections below.

A. Competitive intensity and price dispersion

We estimate the following equation in order to directly examine the effect of competition on price dispersion[18]:

$$Gini_{ijt} = \beta_1 HHI_{jt} + \beta_2 HHI_{jt}^2 + \gamma X_{it} + a_{ij} + a_t + \varepsilon_{ijt} \qquad \textbf{(1)}$$

In the above equation, i indexes the airline, j the route and t the time period (88 unique quarters from 1993 to 2014). Vector X_{it} includes the control variables introduced in the previous section (full list in the appendix). The route specific, time invariant part of the error is denoted as a_{ij}, while a_t is the quarter (time) specific unobservable. By construction of the empirical specification, these two error terms are fully modelled as a result of the panel structure of the data and the inclusion of the quarter fixed effects. The error term of the regression is therefore reduced to ε_{ijt} in the above equation. As evident in equation (1), price dispersion is measured by the Gini coefficient ($Gini_{ijt}$), while competition is measured by the Herfindahl-Hirschman Index (HHI_{jt}) – the formulas for their calculation are provided in the appendix of this paper. We calculate HHI_{jt} by using market shares based both on passengers transported and on departures performed, and compare results. We also compare results of models that are specified at an airport-pair basis and a city-pair basis (by clustering adjacent airports[19]).

[18] Equation (1) is the second stage of our two-stage least squares IV model. In the first stage, we regress HHI_{jt} and HHI_{jt}^2 on the instruments (listed in the appendix of this paper) in order to predict their values. Both competition variables in equation (1) are the predicted terms of this first stage regression ($\widehat{HHI_{jt}}$, $\widehat{HHI_{jt}^2}$), while the error term ε_{ijt} is the composite error term that is uncorrelated with $\widehat{HHI_{jt}}$, $\widehat{HHI_{jt}^2}$ and the control variables in X_{it}.

[19] Adjacent airports are airports that serve the same metropolitan area, as defined in the Metropolitan Statistical Areas (MSA) of the U.S. Census.

In addition, we estimate equation (1) with and without the quadratic term in order to verify that the relationship between price dispersion and competition is not linear. In accordance with our non-monotonicity hypothesis, we expect the coefficient of HHI_{jt} to be positive and the coefficient of HHI_{jt}^2 to be negative. That is, price dispersion is initially increasing and then decreasing in a market where competitive intensity moves from perfect competition to monopoly.

B. Market structure and price dispersion

We compliment the results of equation (1) by investigating the relationship between different market structures and price dispersion. In specific, we define three levels of market structure: competitive ($comp_{jt}$), duopoly (duo_{jt}) and monopoly ($mono_{jt}$) . These are defined in line with Dai et al. (2014) in order to facilitate comparison[20]. We estimate the following equation[21]:

$$Gini_{ijt} = \beta_1 mono_{jt} + \beta_2 comp_{jt} + \gamma X_{it} + a_{ij} + a_t + \varepsilon_{ijt} \quad \textbf{(2)}$$

where the notation follows the one introduced in equation (1). Duopoly (duo_{jt}) is the reference category in the above specification.

If the relationship between competition and price dispersion is non-monotonic, we should expect the coefficients of both monopoly (β_1) and competitive (β_2) to be negative. In that respect, price dispersion is expected to be higher in the duopoly case for the relationship to be inverse-U-shaped. For robustness, we compare results of models that are specified at an airport-pair basis and a city-pair basis by clustering adjacent airports. We also calculate HHI_{jt} by using market shares based on the departures performed at a given route.

C. Price-level estimation

In order to explicitly test the intuition in Dai et al. (2014) of a direct price and indirect quality effect we need to examine the percentage changes of prices at different ends of the fare distribution. Examining the differential rates at which prices are changing is especially interesting in our case because of the increase in the quality dispersion we introduce by including business class passengers. This is done, similar to Dai et al. (2014), by specifying the following model[22]:

$$\begin{aligned} \ln p90_{ijt} &= \beta_1^{p90} duo_{jt} + \beta_2^{p90} comp_{jt} + \gamma^{p90} X_{it} \\ &\quad + a_{ij} + a_t + \varepsilon_{ijt} \\ \ln p10_{ijt} &= \beta_1^{p10} duo_{jt} + \beta_2^{p10} comp_{jt} + \gamma^{p10} X_{it} \\ &\quad + a_{ij} + a_t + \varepsilon_{ijt} \end{aligned} \quad \textbf{(3)}$$

where the notation follows the one introduced in equation (1). Our dependent variables are the logarithm of the 90th ($\ln p90_{ijt}$) and the 10th ($\ln p10_{ijt}$) price percentile of a given route fare distribution respectively. The independent variables of this specification follow the notation of equation (2), while the reference category is monopoly ($mono_{jt}$).

The intuition behind a non-monotonic relationship suggests that increasing competition from monopoly to duopoly should lead to a higher percentage reduction in price at the *lower* ($\ln p10_{ijt}$) compared to the *higher* ($\ln p90_{ijt}$) end of the route fare distribution. That would imply that price dispersion is increasing. We therefore expect to find $\beta_1^{p10} < \beta_1^{p90} < 0$ in this case. On the contrary, we expect that increasing competitive intensity starting from a duopoly should lead to a higher percentage reduction in price at the *higher* ($\ln p90_{ijt}$) compared to the *lower* ($\ln p10_{ijt}$) end of the route fare distribution. That would imply that price dispersion is decreasing. We therefore expect to find $\beta_2^{p90} - \beta_1^{p90} < \beta_2^{p10} - \beta_1^{p10} < 0$ [23]. As thus far done in our analysis, we compare results of models that are specified at an airport-pair basis and a city-pair basis.

V. Results and discussion

In this section, we provide summary statistics and describe the main features of the data. In addition, we present the results of the main specifications discussed in section IV.

Unless otherwise indicated, the summary statistics, result tables and discussion thereof concern the sample consisting of coach class and business class passengers and market shares constructed based on passenger data from DB1B ("DB1B base sample"). We explicitly specify using the following adjusted samples in our analysis: (i) a sample of coach class and business class passengers and market shares constructed based on T-100 passenger data ("T-100 passenger sample") [24], (ii) a sample of coach class and business class passengers and market shares constructed based on departures

[20] We define market structure by using the following rule: a monopoly route is defined as a route in which the share of a single carrier is higher than 90%. As a duopoly we classify routes that are not a monopoly and in which the sum of shares of the two leading carriers is higher than 90%. Finally, routes that are not classified as a monopoly or a duopoly are defined to be competitive.

[21] Equation (2) is the second stage of our two-stage least squares IV model. In the first stage, we regress $mono_{jt}$ and $comp_{jt}$ on the instruments (listed in the appendix of this paper) in order to predict their values. Both market structure variables in equation (2) are the predicted terms of this first stage regression ($\widehat{mono}_{jt}$, $\widehat{comp}_{jt}$), while the error term ε_{ijt} is the composite error term that is uncorrelated with $\widehat{mono}_{jt}$, $\widehat{comp}_{jt}$and the control variables in X_{it}.

[22] The first stage of this two-stage least squares fixed effects IV regression is estimated in a similar manner to the one of equation (2) for the respective market structure categories. Additional details are provided in note number 21.

[23] With monopoly ($mono_{jt}$) being the reference category in equation (3), β_1 measures the effect of increasing competition from monopoly to duopoly, while β_2 measures the effect of increasing competition from monopoly to competitive. In order to measure the effect of increasing competition from duopoly to competitive, we therefore need to estimate $\beta_2 - \beta_1$.

[24] Dai et al. (2014) compute market shares and quantity information from passenger data in DB1B. For robustness, we re-calculate the quantity information using passenger enplanement data from T-100. Given that DB1B is a 10% random sample of all tickets issued by registered carriers, the match is expected to be close but not perfect. Indeed, our results (found in the appendix of this paper) are similar and thus corroborate the non-monotonicity hypothesis.

performed in T-100 in line with the literature on frequency competition ("T-100 departure sample"), and (iii) a sample of coach class passengers *only* that replicates the sample employed in Dai et al. (2014) ("DB1B replication sample"). Finally, for each specification we summarize the results obtained using both airport-pairs and city-pairs when defining routes in our analysis.

A. Description of the data and summary statistics

We summarize the most important features of the data in Table 1. The data summarised is calculated based on the DB1B base sample for airport-pairs. In addition, Table 2 presents summary statistics (mean and standard deviation) of the main control variables and instruments used in our two stage least squares fixed effect model.

Based on 345,482 unique observations from Q1 1993 to Q4 2014 we obtain a sample mean Gini coefficient close to 0.24, which implies a price dispersion of approximately 24% relative to the mean fare. This is slightly larger but similar to the values reported in Dai et al. (2014) and Gerardi and Shapiro (2009) – these are 0.23 and 0.22 respectively. Furthermore, the mean HHI value (based on passenger market shares) is close to 0.77 with an average of 2.2 carriers per route, indicating a highly concentrated market.

In order to get an insight on the variability of price dispersion at different market structures we tabulate the respective mean and standard deviation of Gini under monopoly, duopoly and competitive [25]. Indeed, we observe the mean Gini value reaching a peak in duopoly (0.249) and then falling again as competition decreases to monopoly (0.24). This provides some preliminary evidence for a non-monotonic relationship. The mean HHI values are consistent with the definitions of the sub-groups. Specifically, the mean HHI value is 0.985, 0.584 and 0.38 for monopoly, duopoly and competitive, respectively. The average number of carriers on a route decreases from approximately 4.2 in competitive to 2.7 in a duopoly and finally to 1.4 in a monopoly. These values are consistent with the summary statistics reported in Dai et al. (2014), which indicates a comparable sample in terms of competitive intensity.

Finally, we highlight the differences between the DB1B base and replication samples by reviewing the fare distribution of coach and business class tickets respectively and offering an insight into our extended sample. About 17% of total tickets in the DB1B base sample consist of tickets in business class, with the remaining 83% being coach class tickets [26]. Given the average seat capacity of the two fare classes, the split of coach and business in our sample is considered to be representative of reality. In addition, examining the price distribution of the two fare classes is particularly

Table 1: Sample means by market structure

	Gini	HHI	Carriers	Observations
Full sample	.244	.768	2.20	345,482
	(.085)	(.246)	(1.31)	
Monopoly	.240	.985	1.38	181,177
	(.087)	(.036)	(.693)	
Duopoly	.249	.584	2.70	118,523
	(.083)	(.093)	(.949)	
Competitive	.248	.380	4.15	45,782
	(.078)	(.078)	(1.29)	

The summary statistics are calculated from the DB1B base, airport-pairs sample. Market structure groups are defined in note 17. Standard errors are in parentheses, while summary statistics for the following variables are provided: Gini (the Gini coefficient used to measure price dispersion), HHI (Herfindahl-Hirschman Index) and Carrier (number of carriers operating on a route).

Table 2: Control variables and instruments

	Description	Mean	St. Deviation
ln_asset	Logged total assets	15.78	1.513
ln_asset2	Squared log total assets	251.3	44.27
cash	Cash available	.0555	0.081
opexpenses	Operating expenses	.2128	.1682
nonopinc	Non-operating income	-.0047	.0432
bankr_id	Bankruptcy identifier	.0086	.0925
ln_totroute	Logged passengers enplaned	10.52	1.086
genp	Enplanement instrument	.6871	.3225
ln_amean	Logged arithmetic mean MSA	15.00	.7146
ln_gmean	Logged geometric mean MSA	14.77	.6883

The summary statistics for the control variables and instruments are calculated from the DB1B base, airport-pairs sample. The variables cash, opexpenses and nonopincome are computed as a percentage of total assets. For a full list and detailed description of the construction of our instruments, refer to the appendix of this paper. The number of observations is 345,482.

interesting, especially since coach class is over-represented in our sample. The mean coach class fare is equal to \$210.6, while 50% and 75% of coach class fares are below \$164.5 and \$260, respectively[27]. Moreover, the mean business class fare is close to double the mean coach class fare and equal to \$414.4, with 50% of business class fares being higher than \$322 and 25% higher than \$595[28]. Therefore, our sample consists of business class fares that are significantly higher compared to coach class. This ensures that quality differentiation is appropriately modelled with the inclusion of business class passengers in our empirical application.

B. Competition, market structure and price dispersion

We start by highlighting the most important findings of the main specifications on competitive intensity, market structure and price dispersion.

Using the DB1B base sample and defining routes on an airport-pair basis, yields the estimates presented in Table 3A. We observe that the linear specification in model (1) yields significant results, however, the estimated effect is very close to zero. Adding the quadratic term in model (2) produces highly significant results and coefficients that suggest a non-monotonic relationship between competition and price dispersion. The predicted marginal effect of competition on price dispersion is $\beta_1 + 2\beta_2 HHI = 0.635 - 0.832HHI$, which is

[25] The market structure indicators were defined in note number 20.

[26] The relative percentage of coach and business class fares in the full sample is also representative of the division of coach and business class tickets on a given route. Business class fares are therefore uniformly spread in our sample and are not concentrated on particular routes.

[27] The equivalent statistics for the DB1B replication sample are: mean coach class fare equal to \$210.5, and 25%, 50% and 75% of coach class fares below \$109, \$164 and \$260, respectively. In both DB1B base and replication samples, 90% of coach class fares are below \$404.

[28] 90% of business class fares are below \$895. The equivalent fare percentile for coach class is at \$404.

Table 3A: DB1B base sample - Airport pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.019***	0.635***		
	(0.004)	(0.085)		
$\widehat{HHI^2}$		-0.416***		
		(0.057)		
$\widehat{mono}$			-0.005**	
			(0.003)	
$\widehat{comp}$			-0.051***	
			(0.006)	
$\widehat{Ncarr}$				-0.008***
				(0.001)
Observations	344,267	344,267	344,267	344,267
Unique routes	12,060	12,060	12,060	12,060
Adj. R-squared	0.090	0.043	0.053	0.082

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Table 3B: DB1B base sample - City pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.021***	0.463***		
	(0.005)	(0.079)		
$\widehat{HHI^2}$		-0.309***		
		(0.055)		
$\widehat{mono}$			-0.009**	
			(0.004)	
$\widehat{comp}$			-0.046***	
			(0.007)	
$\widehat{Ncarr}$				-0.003**
				(0.002)
Observations	302,235	302,235	302,235	302,235
Unique routes	10,335	10,335	10,335	10,335
Adj. R-squared	0.091	0.054	0.047	0.088

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

equal to zero when HHI is close to 0.76 – this effect is illustrated in Figure 1. That is when the effect of competition on price dispersion reaches its peak. The estimated coefficients of the city-pair analysis presented in Table 3B are very similar[29]. However, the estimated coefficients in model (2) yield a relatively flatter curve compared to the one of the airport-pair analysis; this is also illustrated in Figure 1.

In addition, Table 3A summarizes the estimated coefficients of the market structure specification in model (3) and a (linear) specification where competition is measured by the number of carriers on a route in model (4). The negative coefficients of $mono_{jt}$ and $comp_{jt}$ are in accordance with a non-monotonic relationship between the competitive structure and price dispersion. That is, price dispersion, as measured by the Gini coefficient, is significantly higher in the case of a duopoly, followed by monopoly and competitive. Also, the coefficient in model (4) suggests that price dispersion decreases as the number of carriers increases on a particular route. That is in line with the findings of Gerardi and Shapiro (2009). Despite them being highly significant, the estimated coefficients are relatively small in magnitude. Finally, we observe that the coefficients of models (3) and (4) from the city-pair analysis presented in Table 3B are almost identical to the airport-pair case.

The results of the T-100 departure sample are to a large extent consistent with the previous results, which adds to the robustness of our analysis (refer to Tables 4A and 4B). The coefficient of the linear model in model (1) of the airport-pair analysis becomes even weaker in size and is significant only at the 10% level. In addition, the coefficients of HHI_{jt} and HHI_{jt}^2 are reduced to 0.315 and –0.210 respectively, indicating a flatter parabola compared to the ones estimated in the DB1B base sample. The predicted marginal effect of competition on price dispersion in this case is $\beta_1 + 2\beta_2 HHI = 0.315 - 0.42HHI$, which is equal to zero when HHI is close to 0.75. The estimated type of relationship is similar to the ones from the DB1B base sample – however, the strength of the non-monotonic relationship is significantly weaker in the T-100 departure sample[30]. The non-monotonic relationship is still significant at the 1% level. The results from the city-pair specifications can be found in Table 4B and are very similar to the ones described above.

The market structure specifications (models 3 and 4) in Table 4A are also consistent with the ones estimated from the DB1B base sample. The negative coefficients of $mono_{jt}$ and $comp_{jt}$ are again highly significant and indicate higher price dispersion in duopoly, followed by monopoly and then competitive. The city-pair analysis of the T-100 departure sample (refer to Table 4B) also yields highly comparable results.

C. Price-level analysis

We present here the results of the specifications of the price-level analysis. Our goal was to investigate the differential rates at which prices are changing at different ends of the carrier-fare distribution. As before, we first present the estimates from the DB1B base sample followed by the estimates of the T-100 departure sample.

The results of the price-level specifications from the DB1B base sample are summarized in Table 5. The estimated coefficients corroborate the non-monotonicity hypothesis: specifically, we see that when competition increases from monopoly to duopoly, prices at the lower end of the fare distribution are decreasing faster (7.3% decrease) compared to prices at the higher end of the fare distribution (3% decrease) since $\beta_1^{p10}(= -0.073) < \beta_1^{p90}(= -0.030) < 0$. The estimated coefficients are statistically significant at the 1% and 5% level, respectively. Therefore, increasing competition from monopoly to duopoly will increase price dispersion, in accordance with the non-monotonic relationship.

In addition, increasing competition from duopoly to competitive results to a higher price decline at the higher end compared to the lower end of the fare distribution. Since $\beta_2^{p90} - \beta_1^{p90} = -0.633$ and $\beta_2^{p10} - \beta_1^{p10} = -0.377$, prices at

[29] Clustering adjacent airports (serving the same metropolitan area) reduces our sample from 344,267 to 302,325 unique observations and from 12,060 to 10,335 unique routes, respectively.

[30] To facilitate easy comparison of the estimated net effects of competition on price dispersion between the different specifications, we also plot this estimated relationship in Figure 1.

Table 4A: T-100 departure sample - Airport pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.005*	0.315***		
	(0.003)	(0.033)		
$\widehat{HHI^2}$		-0.210***		
		(0.022)		
$\widehat{mono}$			-0.008***	
			(0.002)	
$\widehat{comp}$			-0.033***	
			(0.003)	
$\widehat{Ncarr}$				-0.004***
				(0.001)
Observations	344,267	344,267	344,267	344,267
Unique routes	12,060	12,060	12,060	12,060
Adj. R-squared	0.090	0.066	0.062	0.087

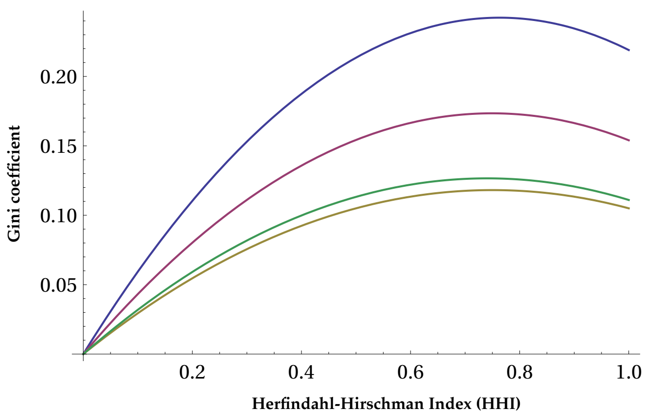
Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Table 4B: T-100 departure sample - City pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.005*	0.342***		
	(0.003)	(0.033)		
$\widehat{HHI^2}$		-0.231***		
		(0.023)		
$\widehat{mono}$			-0.014***	
			(0.002)	
$\widehat{comp}$			-0.040***	
			(0.004)	
$\widehat{Ncarr}$				-0.006***
				(0.001)
Observations	302,325	302,325	302,325	302,325
Unique routes	10,335	10,335	10,335	10,335
Adj. R-squared	0.090	0.057	0.048	0.073

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Figure 1: Effect of competition on price dispersion



The figure above illustrates the net estimated effect of competition on price dispersion of our main quadratic specifications. The net estimated effects are, in order of strength (i.e. from top to bottom), from the following sample specifications: DB1B Airport-pairs base sample (blue line), DB1B City-pairs base sample (purple line), T-100 City-pairs departure sample (green line), T-100 Airport-pairs departure sample (yellow line).

the higher end decline by approximately 63.3%, while prices at the lower end decline by approximately 37.7%. This implies that price dispersion is decreasing in this case, as non-monotonicity suggests. Finally, the results of the city-pair analysis are very similar with one exception: the coefficient β_1^{p90} in this specification is estimated to be very close to zero and becomes insignificant. Nevertheless, the results of this panel continue to provide additional robustness to the non-monotonicity hypothesis.

The estimated coefficients from the T-100 departure sample are summarized in Table 6. Measuring competition in terms of the departures performed yields price reductions that are smaller in magnitude compared to the previous case, where competition was measured based on passenger market shares. In fact, increasing competition from monopoly to duopoly is now estimated to be *increasing* prices at the higher end of the fare distribution. This price increase is equal to 5% in the airport-pairs sample and 8.5% in the city-pairs sample. These effects are significant at the 5% and 1% level respectively. At the same time, prices at the lower end of the fare distribution are not significantly different between monopoly and duopoly according to both airport-pair and city-pair specifications. When increasing competition from duopoly to competitive we continue to observe that prices at the the higher end decline faster compared to the ones at the lower end of the fare distribution (44.1% vs. 25.8% decrease in the airport-pairs sample and 50.4% vs. 28.7% decrease in the city-pairs sample). However, the estimated price decline is significantly lower compared to the one predicted by the DB1B base sample.

The T-100 departure sample results continue to suggest a non-monotonic relationship: price dispersion is increasing when competition increases from monopoly to duopoly (prices at the higher end increase while prices at the lower end remain constant) and price dispersion is decreasing when competition increases from duopoly to competitive. However, it no longer empirically supports the intuition behind a direct-price and indirect-quality effect at high levels of market concentration. Indeed, although we find non-monotonicity to be consistent in our different specifications, we find empirical evidence for the direct-price and indirect-quality effects driving this relationship *only* in the DB1B specifications [31]. We elaborate on the implications of this in the following sub-section in which we discuss the results of our analysis.

D. Discussion

Overall, our results provide robust evidence for a non-monotonic relationship between competition and price dispersion.

To be specific, we obtain significant results in some of the linear specifications, however, these are not robust in the different samples examined, while most importantly the estimated effect is very close to zero. Indeed, when the quadratic term is added to the model our results are highly significant and the signs of the coefficients very consistent across the variety of

[31] All specifications in which market shares are constructed using T-100 passenger or departure data do not corroborate the intuition of a direct-price and indirect-quality effect. At the same time, these specifications consistently predict a weaker non-monotonic relationship (flatter inverse-U-curve) compared to the DB1B specifications. We present and discuss a number of those specifications in Table 7 and in the appendix of this paper.

specifications employed. With β_1 strictly positive and β_2 strictly negative, we obtain robust evidence for a non-monotonic relationship between competition and price dispersion. Moreover, the market structure models consistently predict that price dispersion is highest in duopoly, closely followed by monopoly and then a competitive market. This suggests a parabolic relationship that peaks at duopoly and decreases further as the market becomes monopolised. Finally, our price-level analysis also indicates that price dispersion is increasing when competition increases from monopoly to duopoly, and decreasing when competition increases from duopoly to competitive.

The relationship between competition and price dispersion is thus estimated to be non-monotonic both in the quality dispersion model we examine and the case of an advance-purchase market that is put forward in Gale (1993) and empirically tested in Dai et al. (2014). Therefore, explicit modelling of quality differentiation with the inclusion of business class passengers does not change the estimated type of relationship[32]. This is not surprising given that both models suggest an inverse-U-relationship between competition and price dispersion.

Despite the robustness of non-monotonicity across the different specifications in our analysis, we do not find consistent evidence of a direct-price and indirect-quality effect driving this result at high levels of market concentration. Indeed, the results of the T-100 departure sample in Table 6 suggest that a duopoly will sell the high class tickets at a significantly greater price compared to a monopoly. This is in contrast to the intuition of a direct-price effect that would suggest duopoly prices to be falling at both ends of the fare distribution.

The results of our robustness checks[33] suggest that non-monotonicity does *not* stem from the differential rates at which prices decrease between fare classes as competition increases. Instead, pricing decisions seem to be unique to the degree of market concentration in the context of the predictions of Gale (1993). According to his model, a profit maximizing duopolist will choose a greater (or at least equal) high class fare, while selling more low class tickets compared to a profit maximizing monopolist. Price dispersion, in this case, does not stem from a competitive reaction as a result of the decrease in market concentration. On the contrary, higher price dispersion in duopoly markets is nested in the different competitive structure, and in turn, optimal pricing decisions of a profit maximizing monopoly and duopoly, respectively. Arguably, a monopoly constitutes a unique market structure that cannot be viewed as the top end of a continuum of increasing market concentration.

Table 5: Price-level analysis – DB1B base sample

	Airport pairs		City pairs	
Dependent	**ln(p90)**	**ln(p10)**	**ln(p90)**	**ln(p10)**
$\widehat{duo}$	-0.030**	-0.073***	-0.009	-0.080***
	(0.013)	(0.012)	(0.021)	(0.018)
$\widehat{comp}$	-0.663***	-0.450***	-0.705***	-0.517***
	(0.038)	(0.028)	(0.041)	(0.031)
Observations	344,267	344,267	302,325	302,325
Unique routes	12,060	12,060	10,335	10,335

Dependent variable is indicated on the legend and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Table 6: Price-level analysis – T-100 departure sample

	Airport pairs		City pairs	
Dependent	**ln(p90)**	**ln(p10)**	**ln(p90)**	**ln(p10)**
$\widehat{duo}$	0.050**	-0.009	0.085***	-0.001
	(0.009)	(0.008)	(0.013)	(0.010)
$\widehat{comp}$	-0.391***	-0.258***	-0.419***	-0.287***
	(0.018)	(0.014)	(0.019)	(0.014)
Observations	344,267	344,267	302,325	302,325
Unique routes	12,060	12,060	10,335	10,335

Dependent variable is indicated on the legend and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

We attempt to explain the strength of the estimated non-monotonic relationship by giving preliminary evidence of the following result: the higher the percentage of monopoly routes included in the sample examined, the stronger is the inverse-U-curve estimated in the data. In particular, we observe that it is the concentration of monopoly routes in the examined sample and *not* the overall variance of price dispersion between fare classes that is driving the strength of the predicted non-monotonic relationship.

In order to demonstrate this, we summarize the following information from the DB1B base, DB1B replication, T-100 departure and T-100 replication samples in Table 7[34]: the mean, and 25th, 50th and 75th percentiles of the distribution of route HHI, and the estimated coefficients of our quadratic specifications. We observe that both in the DB1B base and DB1B replication samples (samples 1 and 2, respectively), more than 50% of the routes in the sample are considered to be a monopoly[35]. In contrast, the T-100 departure and T-100 replication samples (samples 3 and 4, respectively) consist of a significantly lower number of monopoly routes. As evident in Table 7, the samples with the lower concentration of monopoly routes are also the ones in which the weaker non-monotonic relationship is estimated. This result is consistent in our robustness checks of both competition and market structure, and price-level analysis specifications.

[32] We compare that by re-estimating our models and not including business passengers in our final sample. This sample is meant to replicate the one used in the empirical models of Dai et al. (2014). We use the term "replication sample" to refer to the sample employed in this analysis. The results of those specifications can be found in the appendix of this paper.

[33] The robustness checks of our competition and market structure specifications are available in the appendix of this paper. Table 7 also summarizes some of the estimated coefficients of those specifications.

[34] The T-100 replication sample is a sample of coach class passengers *only*, replicating the sample of Dai et al. (2014), with market shares constructed from T-100 departure data (instead of DB1B passenger data). We use this sample to highlight that the strength of the estimated non-monotonic relationship is directly related to the distribution of HHI, irrespective of the quality differentiation in the data.

[35] Our definition of monopoly can be found in note 20, where we define the different market structure variables that are employed in our analysis. A monopoly route is defined as a route in which the share of a single carrier is higher than 90%.

Table 7: Cross-sample comparison of the quadratic specification

Sample	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.635***	1.012***	0.315***	0.269***
	(0.085)	(0.138)	(0.033)	(0.033)
$\widehat{HHI^2}$	-0.416***	-0.679***	-0.210***	-0.187***
	(0.057)	(0.092)	(0.022)	(0.023)
Mean HHI	0.768	0.786	0.697	0.687
25^{th} percentile	0.525	0.539	0.494	0.474
50^{th} percentile	0.886	0.959	0.622	0.605
75^{th} percentile	1	1	1	1

Samples are indicated as follows: (1) DB1B base sample, (2) DB1B replication sample, (3) T-100 departure sample and (4) T-100 replication sample. Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

We therefore advocate that the erratic strength of the estimated non-monotonic relationship is not the result of the explicit quality differentiation. This is directly related to the representation of monopoly routes in the examined sample. Indeed, it would be possible for price dispersion to be linearly increasing with market concentration as competition decreases to a duopoly (Gerardi and Shapiro, 2009). However, if monopoly routes *in particular* exhibit significantly lower price dispersion (e.g. as a result of the unique market structure), then a non-monotonic relationship between competition and price dispersion could be erroneously estimated in the data. As a result, it would be interesting for future literature to examine isolating monopoly routes in the data and studying the implications on the relationship between competition and price dispersion. This could further test the robustness of the non-monotonic relationship.

VI. Conclusion

This paper re-examines the relationship between competition and price dispersion in the airline market in light of the findings of Dai et al. (2014), which suggest a non-monotonic relationship. We argue that there is a mismatch between the quality dispersion model developed by the authors and their empirical application. We explain their result using the framework of an advanced-purchases market in Gale (1993) that also stipulates non-monotonicity. In order to empirically test the quality dispersion model of Dai et al. (2014), we extend the sample of coach class passengers to include business class passengers, thereby introducing quality dispersion to the analysis. In addition, we test the consistency of our results by using a variety of specifications, in which market share (and therefore competition) is measured by the number of passengers transported or the number of departures performed by an airline. We argue that explicit quality differentiation and additional robustness checks are essential for an appropriate empirical application of the theoretical model, and an understanding of the intuition behind a direct-price and indirect-quality effect in Dai et al. (2014).

Using a panel from 1993 to 2014 defined on a route-carrier level, we find evidence for non-monotonicity in the relationship between competition and price dispersion. Our results indicate that an increase in concentration will have the following effect, starting from a highly competitive market: price dispersion initially increases at a decreasing rate, reaches a peak in duopoly and then starts decreasing as the market is being monopolised. As a result, explicit quality differentiation does not deliver new insights on the type of relationship between competition and price dispersion. That is, a non-monotonic relationship is consistent in the data both in an advanced-purchase market model with ticket restrictions (Dai et al., 2014) and a quality competition model with explicit quality differentiation, as shown in this paper.

However, we do not find consistent evidence of a direct-price and indirect-quality effect driving the non-monotonicity at high levels of market concentration. In particular, our robustness checks show that the variability of price dispersion does *not* stem from the differential rates at which prices decrease at the lower and higher end of the fare distribution as competition increases. Instead, the strength of the non-monotonicity of price dispersion seems to be directly related to the concentration of monopoly routes in the examined sample. We show that the higher the percentage of monopoly routes included in the sample examined, the stronger is the inverse-U-curve estimated in our analysis. We advocate that a monopoly constitutes a unique market structure that may not be appropriate to be viewed as the top end of a continuum of increasing market concentration. We argue that a non-monotonic relationship between competition and price dispersion when HHI ranges from 0 to 1, would be consistent with the following: price dispersion that increases linearly with competition from highly competitive routes to duopoly, and monopoly routes that exhibit significantly lower price dispersion.

Segregating monopoly routes in the data is, however, not in the scope of our analysis. We believe it is important for future literature to further examine the impact of competition on price dispersion without taking into account monopoly routes, so as to verify the consistency of the non-monotonic relationship. In addition to segregating monopoly routes, it is important to test the robustness of this relationship in other markets, potentially with a different mix of market concentration. We expect those extensions to shed more light on the drivers of non-monotonicity in the data, and in turn on the complex relationship between competition and price dispersion.

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APPENDIX

A1. Construction of the final sample

In this section, we describe in more detail the construction of the sample employed in our empirical specifications. We discuss the procedure concerning the DB1B base sample and highlight (when necessary) the differences compared to the construction of the DB1B replication sample.

We start by screening the data from the Origin and Destination Survey (DB1B) of the Bureau of Transportation Statistics (BTS). Before merging the three components of DB1B (Coupon, Ticket and Market sub-databases) we filter the data as follows: we only keep observations with 2 or less ticket coupons and 1 market coupon[36] and drop any observations for which the recorded distance covered is equal to zero[37]. We then merge the sub-databases in the following order: we first merge DB1B Coupon and Market and then the combined dataset with DB1B Ticket. The last part of this merge ensures that only one leg of a return flight remains part of our final sample. In accordance with Dai et al. (2014) and Gerardi and Shapiro (2009), we drop the return portion of the trip to avoid double counting. Finally, we drop all observations for which (i) there is a change of ticketing carrier recorded, (ii) the ticketing carrier is different from the operating carrier, (iii) the fare category is considered to be bulk, or (iv) the dollar credibility of the carrier, as measured by the BTS, is equal to zero. Additionally, we divide all roundtrip fares by 2 and drop any itinerary fares that are lower than \$10 or higher than the 99th percentile of the route-carrier fare distribution[38]. At this stage, we only keep observations for which all segments of a trip are in coach class when replicating the sample of Dai et al. (2014). Our base sample includes all fare class tickets.

We continue with the procedure followed in preparing the T-100, Form 41 Financial Data and MSA databases. First, we drop all observations from the T-100 for which the recorded seats, distance covered or departures performed are equal to zero. In addition, we only keep route-carrier observations for which more than 10 departures were performed or more than 100 tickets were issued in a given quarter. We then prepare the MSA population data by merging the corresponding databases for the years 1990-99, 2000-09 and 2010-14. The population data is then manually merged with the airport list from the T-100 on the basis of the City Market ID of a particular airport. At this stage, we drop all route-carrier observations for which the MSA population data is missing[39]. Finally, we merge the Form 41 Financial Data with the T-100 and MSA and only keep carrier observations for which the financial data is not missing[40].

The final sample is created by merging the adjusted DB1B and extended T-100 database. Approximately 62% of the route-carrier observations in the extended T-100 are perfectly matched and thus part of our final sample.

A2. Measurement of price dispersion and competition

As evident in our analysis, we measure price dispersion by using the Gini coefficient and competition by means of the Herfindahl-Hirschman Index (HHI). In this section, we present the formulas that were used for the calculation of the two indices.

We calculate the Gini coefficient by using the following equation:

$$Gini_{ijt} = \frac{2}{n^2\overline{p}} \sum_{k=1}^{n} \left(k - \frac{n+1}{2}\right) p_k$$

In the above equation, $Gini_{ijt}$ is the dependent variable employed in our empirical specifications, where i indexes the airline, j the route and t the time period. The average fare price is denoted by $\overline{p}$, while k indexes fare prices from low to high within the n observations of a unique route-carrier.

The Herfindahl-Hirschman Index (HHI) is calculated by using the following formula:

$$HHI_{jt} = \sum_{i=1}^{N} s_i^2$$

In the above equation, i indexes the airline, j the route and t the time period. The number of carriers on a specific route is denoted by N, while the market share of carrier i is denoted by s_i. In the DB1B base and replication samples, these market shares are constructed based on passenger ticket data from DB1B. Market shares are constructed based on passenger enplanement from T-100 and departures performed from T-100 in the T-100 passenger sample and T-100 departure sample, respectively.

[36] A flight coupon is issued for every segment of an itinerary without a plane change. In addition, a market is defined as a unique one-way itinerary (including potential stopovers). That is, a return flight ticket from A to B consists of two separate markets in the DB1B sample: one for the trip from A to B and another one for the trip from B to A. Restricting our sample to include only ticket coupon ≤ 2 and market coupon ≤ 1 is a filter for obtaining only direct, non-stop flights. By keeping observations with 2 or less ticket coupons, we restrict our sample to the following itinerary types: one-way direct non-stop flights, return direct non-stop flights and one-way flights with a single stopover with a plane change. Finally, keeping observations with 1 market coupon reduces the itinerary types to one-way and return direct non-stop flights.

[37] Observations with an itinerary distance equal to zero (origin airport = destination airport) are considered to be recorded by error and contain many missing values.

[38] This helps eliminate tickets that are part of promotional offers or frequent flyer programs and key punch errors (Dai et al., 2014).

[39] This results to eliminating airports that are located in rural areas or counties. A similar filter was implemented by Dai et al. (2014) and Gerardi and Shapiro (2009).

[40] This results to some small carriers (approximately 1% of the final sample) being eliminated.

Table A1.A: T-100 passenger sample - Airport pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.006**	0.278***		
	(0.003)	(0.031)		
$\widehat{HHI^2}$		-0.184***		
		(0.021)		
$\widehat{mono}$			-0.006***	
			(0.002)	
$\widehat{comp}$			-0.031***	
			(0.003)	
$\widehat{Ncarr}$				-0.004***
				(0.001)
Observations	344,267	344,267	344,267	344,267
Unique routes	12,060	12,060	12,060	12,060
Adj. R-squared	0.090	0.073	0.067	0.087

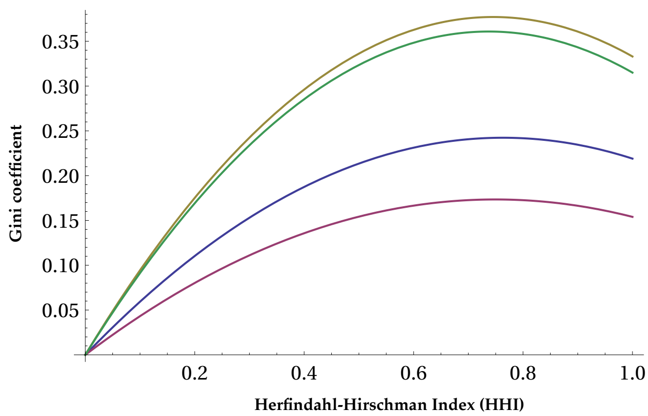
Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Table A1.B: T-100 passenger sample - City pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.006**	0.345***		
	(0.003)	(0.033)		
$\widehat{HHI^2}$		-0.231***		
		(0.023)		
$\widehat{mono}$			-0.012***	
			(0.002)	
$\widehat{comp}$			-0.038***	
			(0.004)	
$\widehat{Ncarr}$				-0.006**
				(0.001)
Observations	302,235	302,235	302,235	302,235
Unique routes	10,335	10,335	10,335	10,335
Adj. R-squared	0.090	0.061	0.055	0.073

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Figure A1: Effect of competition on price dispersion



The figure above illustrates the net estimated effect of competition on price dispersion and compares the different outcomes of a sample including both coach class and business class passengers and a sample of coach class passengers only. The net estimated effects are, in order of strength (i.e. from top to bottom), from the following sample specifications: DB1B Airport-pairs replication sample (yellow line), DB1B City-pairs replication sample (green line), DB1B Airport-pairs base sample (blue line), DB1B City-pairs base sample (purple line).

A3. Control variables and instruments

We employ the following set of control variables in all of our specifications:

ln_asset	Logarithm of total assets
ln_asset2	Square of the logarithm of total assets
cash	Cash available as % of total assets
opexpenses	Operating expenses as % of total assets
nonopinc	Non-operating income as % of total assets
bankr_id	Bankruptcy identifier

We instrument endogenous dependent variables in all of our specifications by means of the following instruments in the first stage regression of the TSLS fixed effects model:

ln_totroute	Logarithm of the total passengers enplaned on a particular route from T-100
ln_totroute2	Square of the logarithm of total passengers enplaned on a route
ln_amean	Logarithm of the arithmetic mean of the Metropolitan Statistical Area (MSA) population of the end-point airport-pairs or city-pairs
ln_amean2	Square of the logarithm of the arithmetic mean of MSA end-point population
ln_gmean	Logarithm of the geometric mean of the Metropolitan Statistical Area (MSA) population of the end-point airport-pairs or city-pairs
ln_gmean2	Square of the logarithm of the geometric mean of MSA end-point population
genp	Enplanement instrument, which is calculated as follows: $genp = \sqrt{enpl_{j1}enpl_{j2}}/\sum_k \sqrt{enpl_{k1}enpl_{k2}}$, where j indexes a given airline, k all airlines and $enpl_1$, $enpl_2$ are quarterly enplanement at the given end point airport-pairs or city-pairs
genp2	Square of the enplanement instrument

The following instruments are introduced by Borenstein and Rose (1994): *ln_amean*, *ln_gmean*, *genp*. Gerardi and Shapiro (2009) introduced *ln_totroute* in their empirical specification. All instruments are also employed in the analysis of Dai et al. (2014).

A4. Additional specifications

In this section, we present and shortly discuss the results of our empirical specifications from the T-100 passenger sample and the DB1B replication sample. T-100 passenger is the sample of both coach class and business class passengers with market shares calculated using passenger enplanement data from T-100, while DB1B replication is the sample of coach class passengers *only* that replicates the sample used in Dai et al. (2014).

The results of the T-100 passenger sample are summarized in Tables A1.A and A1.B (airport-pairs and city-pairs, respectively). The results are highly comparable to the ones from the T-100 departure sample specifications. We continue to observe a non-monotonic relationship between competition and price dispersion that is weaker compared to the one predicted by the DB1B base sample. The market structure specification in model (3) also yields highly robust results. Price dispersion continues to be the highest in the duopoly case, followed by monopoly and competitive. This effect is significant at the 1% level in both airport-pair and city-pair specifications. We attribute the different estimated net effect in model (2) to the structure of DB1B. As argued in the paper, the strength of the estimated non-monotonic relationship is influenced by the concentration of monopoly routes in the examined sample. Being a 10% random sample of ticket prices, DB1B might underrepresent particular route-carrier characteristics (e.g. particular routes or tickets issued by smaller carriers) or distort passenger shares in high-density routes (Dai et al., 2014). We therefore argue that using passenger data from T-100 is superior to calculating market shares from DB1B. This is highlighted by the robustness of our T-100 specifications in terms of the net effect estimated. We do, however, present the results of the DB1B base sample as part

Table A2.A: DB1B replication sample - Airport pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.003	1.012***		
	(0.006)	(0.138)		
$\widehat{HHI^2}$		-0.679***		
		(0.092)		
$\widehat{mono}$			-0.019***	
			(0.003)	
$\widehat{comp}$			-0.083***	
			(0.011)	
$\widehat{Ncarr}$				-0.003
				(0.002)
Observations	298,204	298,204	298,204	298,204
Unique routes	11,680	11,680	11,680	11,680
Adj. R-squared	0.086	0.018	0.004	0.084

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

Table A2.B: DB1B replication sample - City pairs

Model	(1)	(2)	(3)	(4)
$\widehat{HHI}$	0.009	0.979***		
	(0.007)	(0.171)		
$\widehat{HHI^2}$		-0.664***		
		(0.117)		
$\widehat{mono}$			-0.024***	
			(0.005)	
$\widehat{comp}$			-0.098***	
			(0.015)	
$\widehat{Ncarr}$				0.000
				(0.002)
Observations	261,648	261,648	261,648	261,648
Unique routes	10,064	10,064	10,064	10,064
Adj. R-squared	0.084	0.052	0.102	0.084

Dependent variable is Gini and the hats indicate instrumented endogenous variables. All specifications include the set of control variables and quarter fixed effects described in the methodology section. Robust standard errors can be found in parentheses, while significance is indicated as follows: *** for p<0.01, ** for p<0.05, and * for p<0.1.

of our main specification to facilitate comparison with previous literature.

Finally, we present the results of the DB1B replication sample in Tables A2.A and A2.B (airport-pairs and city-pairs, respectively). We attempt to replicate the empirical specification of Dai et al. (2014) in order to compare the net estimated effects predicted by an advanced-purchases market model and our quality dispersion model. The main difference in the reported results is the strength of the estimated relationship. To be specific, the net estimated effect of the DB1B replication sample suggests a stronger non-monotonic relationship between competition and price dispersion. We illustrate this in Figure A1 to facilitate easy comparison. As argued in the paper, we attribute this to the presence of relatively more monopoly routes in the passenger share samples from DB1B.