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Market heterogeneity and the relationship between competition and price dispersion: Evidence from the U.S. airline market

Charles Howell [a,b,*], Emili Grifell-Tatjé [c]

[a] Department of Business, Universitat Autònoma de Barcelona, Spain
[b] University of Nebraska Omaha, United States
[c] Department of Business, Universitat Autònoma de Barcelona, Spain

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ABSTRACT

Previous studies agree that competition influences price dispersion, however there is disagreement on the direction of the effect. To explain this contradiction in findings we include a measure not typically considered in competitive analysis, the level of market heterogeneity. We find that the response of price dispersion to changes in competition is conditioned by differentiation. When products in a market are homogenous, increasing competition reduces price dispersion, while in a market with heterogeneous products, the same increase in competition increases price dispersion. We include an output attribute index as a control for market heterogeneity and test our method on 73,981 observations of airfare data from 2002 through 2016. The implication of our findings for policymakers is that the traditional measures of market concentration do not determine the level of competition alone. Decisions on allowing or disallowing mergers should consider market heterogeneity, not just concentration. The results of this work contribute toward extending knowledge on the effect of competition on price dispersion and introduce a method of measuring market differentiation.

1. Introduction

The relationship between market structure and price dispersion has interested economists since merchants first posted prices. Textbook theory argues that as a market becomes competitive dispersion will evaporate as all prices converge on marginal cost. However, this is not reflected in real-world markets where persistent price dispersion can be observed in markets of all structures. The relationship between market structure and price dispersion has been documented in markets for products such as groceries (Kaplan et al., 2016; Eden 2018), retail gasoline (Lach and Moraga-González, 2017; Shepard, 1991), auto insurance (Dahlby and West, 1986), and U.S. domestic airline fares (Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Dai et al. 2014). Despite this depth of study, the relationship between market structure and dispersion remains unclear. The lack of clarity is particularly obvious in relation to U.S. domestic airline fares, where the three articles cited come to widely differing conclusions.

In one of the first studies on market structure and dispersion of airline fares, Borenstein and Rose (1994) find that price dispersion increases with competition. This finding is contradicted by Gerardi and Shapiro (2009), who argue the textbook model and find that competition strictly reduces price dispersion. Dai et al. (2014) find an inverse-U-shaped relationship between competition and price dispersion, with dispersion initially growing as a concentrated market becomes competitive, but then declining at higher levels of competition. Understanding why these conclusions differ can significantly impact how policies and regulations are formed. To contribute to this understanding, we consider the qualitative characteristics associated with the product. Based on these characteristics—which Ray and Mukherjee (1996) refer to as "output attributes"—we introduce a new measure of market heterogeneity grounded in index number theory.

In this paper, we identify the cost premium driven by a higher level of output attributes and use this premium to measure market differentiation. Price dispersion arising from cost differences is not considered discrimination, so this premium is removed from the fare price creating a more homogenous product. Remaining price dispersion is measured and analyzed. This study answers three research questions. First, how much price dispersion is driven by cost differences resulting from a wide range of output attributes? Second, how does the level of competition affect price dispersion after accounting for output attribute cost-driven price dispersion? Third, are the direction and magnitude of competition's effect on price dispersion dependent on the level of output attribute differentiation in the market?

The U.S. domestic airline market is ideal for empirically testing the

* Corresponding author.
E-mail address: cbhowell@unomaha.edu (C. Howell).

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relationship between market structure and price dispersion. Airlines can sort passengers by product valuation using ticket characteristics such as advance-purchase discounts, round trip, or refundability. There is also heterogeneity between airlines in output attributes such as on-time performance, departure frequency, or load factor. Additionally, the U. S. market is dynamic and includes routes with a wide range of carriers and competitive levels.

We find that by including the measure of market heterogeneity we can explain the contradictions in previous results. In short, we find that in markets where the product is more homogenous, the textbook effect of a reduction in price dispersion is associated with increases in competition. While in more heterogeneous markets, an increase in competition leads to an increase of dispersion. These results form the basis for policy recommendations. They show that introducing a measure of market heterogeneity as a complement to the Herfindahl–Hirschman Index (HHI) of market concentration is imperative when regulators examine potential mergers. For example, in the current business press there is speculation on “mergers of equals” like Spirit and Frontier Airlines, or JetBlue and Alaska Airlines. As we show in this paper, market concentration alone is not sufficient to understand the impact of these potential mergers. In addition, when policy is based on the findings of applied economics, it is important to understand and resolve contradictions. In a recent article on trends in air transportation policy, Button (2019) notes that there is a lack of replication in air transport work which can lead to credibility issues. To that end, in this paper we show how these contradictions can be resolved without invalidating previous work.

We make two major contributions in this paper. First, we introduce a general method of measuring market heterogeneity. This method can be applied in any empirical research that controls for levels of market power. Second, our results from the applied section contribute to the research line on understanding the relationship between market structure, competition, and price dispersion. The paper is structured as follows. In section 2 we provide a motivational discussion and background on price dispersion and market structure. In section 3 we introduce a measure of differentiation based on output attributes and apply it to fare prices. In section 4 we outline the data and variable construction and in section 5 present the results. Finally, we cover conclusions, policy recommendations, and ideas for further research in section 6.

2. Background

2.1. Price dispersion

The study of price dispersion has a long history because its existence runs counter to the textbook model of most market forms. Standard theory allows for price dispersion in a monopoly market where firms can sort consumers and price discriminate, but under perfect competition, all firms accept a single market price. Between the polar cases, most oligopoly models allow for little to no dispersion in price, and in models of monopolistic competition, price dispersion is driven by product cost differences. Theoretical explanations for price dispersion include costly information search, uncertain demand, price discrimination, and cost differences.

In one of the earliest studies, Stigler (1961, p. 214) focuses on the role of information and search stating, “Price dispersion is a manifestation—and, indeed, it is the measure—of ignorance in the market.” Stigler shows that cost of search, changing supply and demand conditions, and the difficulty of updating prices generate the observed price dispersion. In the same vein of information and search, Stahl’s (1989) model of temporal price dispersion shows that sales and intentional price fluctuations allow retailers to generate price dispersion by capitalizing on uninformed consumers.

The second common source of dispersion is price discrimination, which results from exploiting differences in consumers’ willingness to pay. Borenstein (1985) introduced a model of third-degree price discrimination in differentiated product markets, showing that market power is not a requirement for discrimination. The model was formalized by Holmes (1989), who demonstrated that firm-level elasticity of demand can be decomposed into two components, industry elasticity and cross-price elasticity. Industry elasticity is based on consumer valuation of the basic product whereas cross-price elasticity is based on the price of a substitute. The distinction between these two forms is important for our analysis because they result in a different amount of price dispersion, a distinction we expand on later in this section.

Cost-driven price variances are not considered price discrimination, nor dispersion, and distinguishing between the two makes empirical work difficult. Shepard (1991) works around this difficulty by exploiting a situation where firms have similar production costs but differ in their ability to price discriminate. Shepard compares price differentials between full-service and self-service gasoline, at stations that offer both products, with the price differentials between full-service and self-service gasoline at stations that offer only one or the other. Results show that the differential is greater in multi-product stations.

The product of the airline industry, a seat on a flight, is perishable in nature and has uncertain demand. Considering these characteristics, Dana (1999) models a system where the firm must establish prices and quantities (inventory of seats) prior to knowing what demand will be. Equilibrium in the model is found by establishing multiple price points with a limited number of seats available at each point. Dana’s model shows that as competition increases, the average price level falls and the degree of price dispersion increases. Also looking at the airline industry, Stavins (2001) studies dispersion due to price discrimination. Using the marginal implicit price of ticket restrictions in interaction with market concentration, Stavins examines restrictions used to separate consumers by valuation of convenience and flexibility. The model shows that the marginal effect of restrictions is less on concentrated routes, or in other words, the same ticket restriction yields a greater discount on a more competitive route.

As shown in the section, there are multiple theoretical explanations for observed price dispersion. In this paper, we focus mainly on price discrimination and cost differences, expanding on price discrimination in the next section and on cost differences in section 3.

2.2. Market structure and price dispersion

Borenstein (1985) builds on a generalized price discrimination model introduced by Salop (1979) by developing a characteristic space model of monopolistic competition. In this model, brand characteristics and consumer preferences differ on one dimension and are represented as equidistant points on a unit-circumference circle. Through reservation price, the model allows for two forms of price discrimination, sorting consumers by preferred brand or by basic utility. The first form is termed “monopoly-type discrimination” because only one brand can provide a positive consumer surplus. Under this form of discrimination, the firm sorts consumers based on industry elasticity and basic valuation of the brand; high-valuation consumers are charged a higher price while low-valuation consumers receive a discount. Under the second form, “competitive-type discrimination”, multiple firms can provide consumer surplus. Here it is more effective for the firm to segment by cross-price elasticity, providing a discount to customers on the verge of switching brands. The model shows that price dispersion is greater under competitive-type discrimination than under monopoly-type discrimination. Applying this model to price dispersion in airline fares, Borenstein and Rose (1994) find that competitive-type discrimination dominates and that price dispersion increases as airline markets become more competitive.

In contrast, Gerardi and Shapiro (2009) find that increasing competition strictly reduces price dispersion in airline fares. Citing traditional microeconomic theory, they argue that as competitors enter the market, incumbents will find it difficult to price discriminate. Using panel data, they analyze the effect of competition on price dispersion in

U.S. airfares between 1993 and 2006 and find that competition has a negative effect on price dispersion.

In another panel data study of airfares, Dai et al. (2014) find that the effect of competition on price dispersion has a non-monotonic inverse-U-shaped relationship. They point to two opposing effects, first a direct price effect which increases dispersion as a highly concentrated market becomes more competitive, and then an indirect "quality" effect that leads to reduced dispersion as less concentrated markets become even more competitive.

The three studies noted above have all been of the U.S. domestic market; however, this question has been looked at in other markets as well. In a study of the market connecting the U.K. and Ireland, Gaggero and Piga (2011) find a negative relationship between competition and price dispersion. In their work, they also discuss monopoly-type and competitive-type price discrimination, finding evidence of monopoly-type. Obermeyer, Evangelinos, and Püschel (2013) move the empirical setting for this same question to the European airline market. Their results support the argument for a non-monotonic relationship, with the effect of further competition depending on the current degree of concentration.

This paper considers a variable of market structure that is not typically included in this type of analysis: differentiation and the degree of firm heterogeneity in the market. By adding this variable, we contribute to understanding the relationship between market structure, competition, and price dispersion.

3. Methodology

In this section, we show how the presence of a wide or narrow range of output attributes can alter the response of price dispersion to a change in competition. In homogenous markets where firms have similar levels of output attributes, monopoly-type discrimination dominates, while in heterogeneous markets that exhibit differentiation, competitive-type discrimination is stronger. For example, imagine that the Seattle–Salt Lake City (SEA–SLC) route is served by Delta and Alaska Airlines, and assume that they have similar output attributes. With little to differentiate between brands, consumers are sorted on reservation price as under monopoly-type discrimination. Compare this with a second route, Philadelphia to Raleigh-Durham (PHL–RDU) served by American Airlines and Frontier. On this route, if we assume market heterogeneity based on differing output attributes, then the possibility of competitive-type discrimination exists. To control for this difference by route, we introduce an output attribute index that allows us to categorize markets as heterogeneous or homogenous, and we compare price dispersion on these two types of routes. The comparison lets us explore our first research question: How much price dispersion is driven by cost differences resulting from a wide range of output attributes?

Moving to a dynamic analysis, and our second research question, we look at changes in the level of competition and examine the effect on price dispersion after controlling for differences in output attribute levels. Returning to the SEA–SLC route, assume there is an increase in competition coming from a third airline that provides attributes similar to the incumbents, JetBlue for example. The model would predict a decrease in price dispersion following the increase in competition. However, if instead the change in competition on the SEA–SLC route comes from an airline with lower output attributes, Frontier for example, the opportunity for competitive-type discrimination is created allowing customers to be sorted by output attribute preference. The model would now predict an increase in price dispersion following the increase in competition, as hypothesized by Borenstein and Rose (1994). Comparing the effect of competition on routes that vary by output attribute index sheds light on the second question: How does the level of competition affect price dispersion after controlling for output attribute cost-driven price dispersion?

Comparing routes that vary in competition and in the level of product differentiation also lets us answer our third research question: Are the direction and magnitude of the effect of competition on price dispersion dependent on the level of output attribute differentiation in the market? We believe that answers to these three research questions will contribute to understanding the relationship between price dispersion and market structure and may be able to explain contradictions found by previous work.[1].

3.1. A cost approach

When production of a scalar output has associated qualitative output attributes, Ray and Mukherjee (1996) note that these attributes affect the maximum output quantity producible from a given input bundle, or in the dual problem, the minimum cost achievable.[2] Ignoring these output attributes when measuring and comparing the cost of production processes can result in underestimating or overestimating costs. Beginning with standard notation, we denote output as $y \in \mathbb{R}_+$, the vector of output attributes as $q \in \mathbb{R}_+^m$, the vector of inputs as $x \in \mathbb{R}_+^n$, the vector of input prices as $w \in \mathbb{R}_+^n$ and the vector of output prices as $p \in \mathbb{R}_+^i$. Note that one output can be associated with multiple prices. The production possibility set that defines the output and associated output attributes possible for a given set of inputs is noted as

$$T = \{(x, y, q) : x \text{ can produce } y \text{ with output attributes } q\}. \tag{1}$$

Given technology set T, we now define the set of inputs x required for every output quantity y with the level of output attributes q as $L(y, q) = \{x : (x, y, q) \in T\}$. Technology set T defines all the possible input vectors that can produce a specific output at a given output attribute level. With the addition of input prices w, we move from input quantities to production cost and can define the least expensive bundle of inputs required to generate a specified quantity of output and level of output attributes. For an output quantity y, output attribute vector q and input prices w, the firm allocates the inputs to generate the required quantity of output at a minimum cost, defined as

$$c(w, y, q) = \min\{w^T x : x \in L(y, q)\} \tag{2}$$

Including the transpose of the input price vector "T," we express the minimum cost as $w^T x(q)$, where $w^T x(q) = c(w, y, q)$. As defined in (2), more inputs x would be required to create either a greater quantity of y at the same level q or an equal quantity of y with a greater output attribute level q. Comparing one output quantity y at two output attribute levels q and q^0, where $q \geq q^0$, we would find that $x(q) \geq x(q^0)$ and $w^T x(q) \geq w^T x(q^0)$.

From (2) we derive the minimum cost of providing output quantity y, with output attributes q and input prices w. However, the cost between periods for a single firm, or between individual firms in a single period, can vary greatly based on the scale of operations. For this reason, we move to a unit or average cost function to better understand the effect of changes in output attributes. The move to a unit or average cost function is also useful when applying cost changes to unit prices. With output defined as y, we can find a unit or average cost function $ac(w, y, q)$ as

$$ac(w, y, q) = \frac{c(w, y, q)}{y}. \tag{3}$$

[1] An alternative approach would be to control for the number of full-service carriers (FSCs) and low-cost carriers (LCCs) in the market. The drawbacks would be that there is no distinction between carriers in each group, less distinction between markets, and that the approach would not allow for change over time as carriers adjust their product offerings.

[2] An alternative approach was introduced by Spady and Friedlaender (1978). In their hedonic cost-function approach, an effective output is calculated such that $C = C(\psi(y, q), w)$ where $\psi(y, q)$ is a vector of functions that defines an effective output and where $\psi^i = \psi^i(y, q_1^i, \ldots, q_1^i)$. We adopted the Ray and Mukherjee (1996) approach in this paper because it more easily adapts to multiple outputs.

Since our interest lies in capturing the cost premium of providing a greater level of output attributes, we measure cost differences between different attribute levels for the same firm and period. Extending (3), we define $ac(w_h, y_h, q_h)$ $h = 1, \ldots, k$ as the average minimum cost given w, y, and output attribute level q, which defines the attribute level currently provided by firm h in a specific market. Similarly, $ac(w_h, y_h, q^0)$ $h = 1, \ldots, k$ is the minimum cost for the same output quantity and price level, but with the lowest level of output attributes in the market q^0, where $q^0 = \{q_1^0, \ldots, q_m^0\}$ and $q_j^0 = Min\ \{q_{jh}^0, h = 1, .., k\}, j = 1, .., m$.[19]

3.2. Output attribute index

In the literature, changes in average cost are thought to come from a limited number of sources. Capturing the change from the price of inputs, Konüs (1939) defines a theoretical input price index as a scalar function that compares input price vectors w^0 and w^1 for a given output y in the context of a cost function.[3] Building on the Konüs approach, Grifell-Tatjé and Lovell (2015) discuss the drivers of unit cost change. They show that a difference in average cost can come from only two sources, a change in the price of inputs or a change in productivity. In this paper, we extend these concepts by introducing an *output attribute index* which collects the impact on the unit cost of changes between the level of output attributes q and q^0 as

$$\begin{aligned} Q(w_h, y_h, q_h, q^0) &= \frac{ac(w_h, y_h, q^0)}{ac(w_h, y_h, q_h)}; \ h = 1, .., k \\ &= \frac{c(w_h, y_h, q^0)}{c(w_h, y_h, q_h)} \ ; \ h = 1, .., k. \end{aligned} \tag{4}$$

The index of output attribute differentiation defined in the first row holds output quantities and input prices equal, allowing measurement of the impact on unit cost of a change in the output attributes from q to q^0. Remember that q^0 has been defined in the previous section 3.1 as the vector with the lowest level of output attributes. The second row, after simplifying by dropping y, shows that the impact on the total minimum cost of a change in the output attributes from q to $q^0$is equal to the unit cost result from the first row. These results show that the output attribute index can be calculated on either minimum unit cost or minimum cost, meaning the model can be easily applied to the case of multiple outputs as well.[4].

Recalling that q_h represents the observed level of output attributes for a firm in a market and that q^0 represents the lowest level of observed attributes in the market, then for all cases where $q_h \geq q^0$ and consistent with (4), $ac(w_h, y_h, q_h) \geq ac(w_h, y_h, q^0)$ as well as $c(w_h, y_h, q_h) \geq c(w_h, y_h, q^0)$, thus $Q(w_h, y_h, q_h, q^0) \leq 1$. An index value of 1 signifies that the cost of firm h reflects the lowest level of attributes, while a value of 0.5 would indicate that firm h has a unit cost that is double that of providing the lowest level of attributes.[5] In section 4, we discuss moving this measure to the market level to measure market heterogeneity. Note that the output attribute index $Q(w, y, q, q^0)$ is bounded between 0 and 1 with the same result ranking as the HHI and the Gini coefficient have.

3.3. Implementing the output attribute index

In this section we outline implementing both a parametric and non-parametric approach to estimate and construct the empirical production frontier needed to estimate minimum cost $c(w_h, y_h, q_h)$.

3.3.1. A non-parametric approach

The non-parametric data envelopment analysis (DEA) method was introduced by Charnes et al. (1978) and moved to the economic context by Färe et al. (1985).[6] Non-parametric models estimate the frontier using the minimum extrapolation method and require minimal assumptions of the functional form of production. With our focus on finding the minimum cost for a given level of output and output attributes, we use a cost minimization model with variable returns to scale. The minimum cost is found by solving the DEA linear programming problem for one observation h with output quantity y_h and output attribute level q.

$$\begin{aligned} c(w_h, y_h, q) = &\min w_h^T x\, s.t. \sum_{l=1}^{k} \lambda_l x_{li} \leq x \ i = 1, \ldots, n; \sum_{l=1}^{k} \lambda_l y_l \geq y_h; \sum_{l=1}^{k} \lambda_l q_{lj} \geq q \ j \\ &= 1, \ldots, m; \sum_{l=1}^{k} \lambda_l = 1; \ \lambda_l \geq 0. \end{aligned} \tag{5}$$

The minimum cost is solved for twice, first with q taking the value of observed q_h to find $c(w_h, y_h, q_h)$ and then as q^0 to find $c(w_h, y_h, q^0)$. The applied part of the paper follows the non-parametric approach.

3.3.2. A parametric approach

The cost function and $Q(w_h, y_h, q_h, q^0)$ in (4) can also be estimated by a parametric method, where the model is defined a priori and requires assumptions on the functional form of production. The form most common in airline cost functions is the translog (Christensen et al., 1973). Regarding the estimation method of airline cost functions, previous literature includes the application of both deterministic parametric frontiers (Gillen et al., 1990; Johnston and Ozment, 2013) and stochastic parametric frontiers (Ahn and Sickles, 2000; Assaf, 2009). A deterministic linear programing approach for the estimation of parametric functions is also possible (Aigner and Chu, 1968). We define C as the total cost per firm at time t, w as the price of inputs, y as output, and q as output attributes, and include a time trend variable (t) to account for the panel nature of our data. Assuming the standard restrictions to

[3] A Konüs (1939) price index is in the literature considered a theoretical index in contrast with the alternative classification as an empirical index. As a theoretical index, a Konüs price index is defined directly from the underlying production technology, and it inherits the desirable properties from it. Consequently, because the underlying production technology is unobserved, a Konüs price index is also unobserved, and must be estimated. Empirical index numbers, like the well-known Laspayres, Paasche, Fisher, or Edgeworth-Marshall, are constructed from observable market transactions and can therefore be calculated directly. Their calculation depends on both prices and quantities and, because this information is not fully observable in the case of output attributes, the empirical index numbers are not a suitable alternative in this study. Balk (2018) provides a comprehensive introduction to empirical index numbers. The original formulation of a Konüs price index is $K(w^0, w^1, y) = c(w^1, y)/c(w^0, y)$, in which $c(w^1, y)$ and $c(w^0, y)$ are cost frontiers without output attributes. The Konüs price index converts a comparison of two input price vectors w^0 and w^1 to a ratio of two scalars. $K(w^0, w^1, y) \gtreqless 1$ and it shows if the cost of producing y is more expensive, equally expensive, or less expensive with input prices of w^1 than w^0. Grifell-Tatjé and Lovell (2015, Ch 5) provide a discussion of the Konüs price index, and the implicit input quantity index and its decomposition. The output attribute index defined in (4) is similar to a theoretical Konüs price index.

[4] In addition to multiple outputs, this method could be applied to a revenue function to capture differentiation by input attribute.

[5] The output attribute index can be formulated in the form of difference instead of ratio. The formulation is based on the first row of (4) and is given by.$ac(w_h, y_h, q_h) - ac(w_h, y_h, q^0) \geq 0$.

[6] See Liu et al. (2013) for a general survey of DEA or Schefczyk (1993) for a detailed discussion of this technique applied to airlines.

ensure input price linear homogeneity and symmetric cross effects,[7] the translog cost function to be estimated is

$$\ln C_{ht} = \sum_{i=1}^{n} \alpha_i \ln w_{iht} + \tfrac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} \ln w_{iht} \ln w_{jht} + \sum_{i=1}^{l} \alpha_{iy} \ln y_{iht}$$
$$+ \tfrac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_{ijy} \ln y_{iht} \ln y_{jht} + \sum_{i=1}^{n} \sum_{j=1}^{l} \alpha_{ijwy} \ln w_{iht} \ln y_{jht}$$
$$+ \sum_{k=1}^{m} \alpha_{kq} \ln q_{kht} + \alpha_t t + \varepsilon_{ht}.$$

Given the log nature of the translog cost function, the value $Q(w_h, y_h, q_h, q^0)$ in (4) can be directly calculated after parameters $\hat{\alpha} = \{\hat{\alpha}_i, \hat{\alpha}_{ij}, \hat{\alpha}_{iy}, \hat{\alpha}_{ijy}, \hat{\alpha}_{ijwy}, \hat{\alpha}_{kq}, \hat{\alpha}_t\}$ are estimated. Recalling (4) as $Q(w_h, y_h, q_h, q^0) = c(w_h, y_h, q^0)/c(w_h, y_h, q_h)$, we have

$$Q(w_h, y_h, q_h, q^0) = \exp[\ln c(w_h, y_h, q^0) - \ln c(w_h, y_h, q_h)]$$
$$= \exp\left[\sum_{k=1}^{m} \hat{\alpha}_{qk} \ln q^0_{kt} - \sum_{k=1}^{m} \hat{\alpha}_{qk} \ln q_{kht}\right]. \quad (6)$$

Using expression (6), we find the cost premium of providing a higher level of attributes. It is worth mentioning that the form of the previous expression is linked to the specification of a translog function. However, the specification of other functional forms may have associated a different formulation of expression (6), an aspect that is open to future research. A drawback of any parametric approach is that the functional form must be defined prior to estimation. Because the interaction of output attributes, output, and inputs is not well-defined, in the applied part of this paper we use the non-parametric DEA approach defined in Section 3.3.1.

3.4. Estimating market price dispersion and the effect of competition

Using expression (5), we find the cost premium of providing a higher level of attributes and remove it from price, allowing us to measure the amount of price dispersion resulting from differentiation by output attributes. Beginning with observed prices by market and quarter, $p_h(q_h)$ represents a vector of observed prices for firm h in a specific market and quarter. Noting the definition of the output attribute index from (4), we use the formula below to generate the vector $p_h(q^0)$ that equalizes prices for differences in output attributes between firms and removes any cost premium for differentiation by output attribute:

$$p_h(q^0) = p_h(q_h) \cdot Q(w_h, y_h, q_h, q^0) \quad i = 1, .., l; \ h = 1, .., k. \quad (7)$$

An alternative way of explaining formula (7) is that the unit margin, defined here as $\alpha_h = \frac{p_h(q_h)}{ac(w_h, y_h, q_h)}$, can be applied to the minimum unit cost with the lowest level of attributes to find an adjusted price $p_h(q^0) = \alpha_h \cdot ac(w_h, y_h, q^0)$.

We now move the analysis from the firm to the market level, and the focus to changes in price dispersion over time. With $p(q)$ as the vector of all observed prices in a market and $p(q^0)$ as the vector of all adjusted prices, we define $S_{jt}(p(q))$ as the observed price dispersion in market j at time period t, and define $S_{jt}(p(q^0))$ as dispersion of adjusted prices. The method of measuring price dispersion will be defined in the next section. Hereafter we note price dispersion as $S_{jt}(\cdot)$, to signify either $S_{jt}(p(q))$ or $S_{jt}(p(q^0))$.

Following the structure of previous literature, we define $S_{jt}(\cdot)$ as dependent variables and *competition* (*Com*) as the independent variable. We also include dummy variable χ_{jt} as a control for the presence of a bankrupt carrier in the market.[8] Market fixed effects are represented as υ_j and we include a full set of quarterly time dummies as γ_t to control for exogenous demand and cost effects. Residuals are captured by. ε_{jt}.

Because we are measuring product-level price dispersion rather than brand-level dispersion,[9] we add a control variable for the carriers present in the market. Firms differ in their pricing strategies and vary in their amounts of price discrimination. When measuring brand-level dispersion, firm strategy would be captured in the fixed effects, but in the case of product-level dispersion it must be accounted for. To control for firm strategy, we add a dummy variable for each of the carriers represented in our study as δ_{ht}. The following panel regression is then estimated as a baseline,

$$S_{jt}(\cdot) = \beta_1 Com_{jt} + \theta \chi_{jt} + \delta_{ht} + \gamma_t + \upsilon_j + \varepsilon_{jt}, \quad (8)$$

which measures the effect of competition on price dispersion over time as coefficient β_1, but does not account for the level of market heterogeneity.

To account for the level of market heterogeneity, we add Q_{jt} to the estimation as the value of the output attribute index, expression (4), for market j in time period t. In the previous section, we defined $Q(w_h, y_h, q_h, q^0)$ as a firm-level output attribute index; moving this measure to the market level is discussed in subsection 4.5. The addition of this variable is unique to the literature and contributes to understanding the relationship between market structure, competition, and price dispersion. The following panel regression addresses our first two research questions and is estimated with the same control variables as are used in (8):

$$S_{jt}(\cdot) = \beta_1 Com_{jt} + \beta_2 Q_{jt} + \theta\chi_{jt} + \delta_{ht} + \gamma_t + \upsilon_j + \varepsilon_{jt}. \quad (9)$$

Our third research question focuses on the effect of the interaction between competition and product differentiation on price dispersion. Specifically, when the market is homogenous (low differentiation) the effect of an increase in competition is thought to reduce price dispersion, but when the market is heterogeneous (high differentiation) the effect of increasing competition is an increase in price dispersion. To capture this effect, we add the interaction of *Com* and Q_{jt} to equation (9) and estimate the following panel regression with the same control variables as are used in (8):

$$S_{jt}(\cdot) = \beta_1 Com_{jt} + \beta_2 Q_{jt} + \beta_3 (Com \cdot Q)_{jt} + \theta\chi_{jt} + \delta_{ht} + \gamma_t + \upsilon_j + \varepsilon_{jt}. \quad (10)$$

To address potential problems of endogeneity with the competition

[7] To impose homogeneity of degree one input prices, we divide total cost C and all input prices w by one of the input prices. We also require that $\sum_{k=1}^{m} \alpha_k = 1$, $\sum_{k=1}^{m} \alpha_{kj} = \sum_{k=1}^{m} \alpha_{jk} = \sum_{k=1}^{m} \alpha_{ky} = 0$. We apply Shephard's lemma to obtain the share of input k in total cost: $S_k = \partial \ln C / \partial \ln w_k = \alpha_k + \sum_{k=1}^{m} \alpha_{jk} \ln w_{jht} + \alpha_{ky} \ln y_{ht}; k = 1, \ldots, m$, where $S_k = w_k x_c / C$ it follows that $\sum_{k=1}^{m} S_k = 1$.

[8] As noted by Ciliberto and Schenone (2012), during a bankruptcy, airlines lower route-specific prices, and increase them after emerging from bankruptcy.

[9] The terms "product-level price dispersion" and "brand-level price dispersion" are often referred to as "inter-firm price dispersion" and "intra-firm price dispersion." In this paper we focus more on product-level, or inter-firm, price dispersion. The output attributes we use in this paper are experienced by all consumers equally and allow firms to differentiate their products. For example, all passengers, first class and coach, experience the same arrival time. The question of how the presence of output attributes affects intra-firm price dispersion would be a promising area for future research.

variables in formulas (8–10), we adopt the instrumental variable approach.[10] In the empirical section, instrumented variables are denoted by a hat.

4. Data

In this section we provide a discussion of the sources and construction of the data used in the applied portion of this study. All data are provided by the Bureau of Transportation Statistics (BTS), [11] an independent statistical agency within the U.S. Department of Transportation. Our unit of analysis is a non-stop, coach-class flight between two city pairs. Non-stop refers to a flight with no intermediate stops between city pairs. The market is defined by a set of city pairs which we term a *route*. For example, three airlines service the route San Francisco (SFO) to Salt Lake City (SLC) with non-stop flights: Delta, Alaska Airlines, and United Airlines. We measure the price dispersion of all carriers on the route, in this example, the prices of Delta, Alaska, and United. We combine observations in cities with close-by airports that are easily substitutable. For example, O'Hare (ORD) and Midway (MDW) are both located in the Chicago metropolitan area, so observations for these airports are treated as a single location; therefore, flights from San Francisco to O'Hare (SFO–ORD) or Midway (SFO–MDW) constitute a single route.[12].

4.1. Flight operations, output quantities, and output attributes

Flight operations data used to generate our best-practice production frontier and to derive minimum costs are sourced from BTS Form 41. Traffic data are reported monthly and financial data are collected quarterly and include statistics on traffic, capacity, cost, income, and balance sheet accounts.

To measure output, a number of airline studies have used measures of output generated, such as ton miles available or seat miles available (Assaf, 2011; Arjomandi and Seufert, 2014; Lee and Worthington, 2014), while others have focused on the revenue-generating measures of revenue passenger miles (RPM) or revenue ton miles (Färe et al., 2007; Wang et al., 2014). With our focus on passenger ticket prices, we have chosen to use RPM, calculated as the number of paying passengers multiplied by the miles traveled, as our measure of output (y).[13].

Three variables were chosen for output attribute vector q: i) on-time arrival performance, ii) flight frequency, and iii) load factor. Numerous previous studies (see Borenstein, 1989; Douglas and Miller, 1974; Ippolito, 1981; Suzuki, 2000; Gayle and Yimga, 2018) have identified these attributes as important in differentiating air carriers. We source on-time arrival data from the BTS On-Time Performance database. From this data set we build a panel of quarterly on-time performance measures for each carrier for each of the sixty quarters analyzed. A flight is considered on-time if it arrives within 15 min of its scheduled arrived time. Average on-time arrival performance over the period was 80.6%, with a minimum of 11.5%, a maximum of 100%, and a standard deviation of 8.3%. Flight frequency is sourced from the T-100 Domestic Segment table, collected as part of Form 41. We calculate it as the average number of daily flights provided by the carrier.[14] On the previously mentioned SFO–SLC market route, in Q4 2016, United Airlines averaged 0.86 flights per day, Alaska Airlines 1.02, and Delta Airlines 2.37.

Load factor, the proportion of aircraft seats with revenue-paying passengers, is also sourced from the T-100 Domestic Segment table. Because passengers prefer a lower load factor, the output attribute is measured as (1 – load factor) to be consistent with other output attributes. Average load factor during the period under observation was 73% with a standard deviation of twelve percentage points. We measure the output attributes of on-time performance and load factor at the carrier level and flight frequency at the carrier-route level. An extended description of output, on-time performance, frequency, load factors, and routes by carrier can be found in Table 1. Output is presented as average passenger miles per quarter and route, and we can see significant

Table 1
Statistics of output, output attributes, and routes – average route.

Carrier	Passenger Miles	On-Time Arrival	Flight Frequency	Load Factor	Routes
	y (millions)	$q1$ (%)	$q2$ (#)	$q3$ (%)	(#)
AirTran Airways Co.	31	79	2.7	24	119
Alaska Airlines Inc.	56	83	2.5	21	87
America West Airlines Inc.	65	81	3.2	23	83
American Airlines Inc.	105	79	4.3	19	208
ATA Airlines	64	78	2.1	26	35
Continental Air Lines Inc.	86	79	3.3	19	120
Delta Air Lines Inc.	79	82	3.6	18	260
Envoy Air	10	78	3.8	29	169
ExpressJet Airlines Inc.	10	78	2.6	25	209
Frontier Airlines Inc.	35	78	2.2	15	68
Hawaiian Airlines Inc.	90	93	4.0	13	23
JetBlue Airways	65	77	2.9	17	97
Mesa Airlines Inc.	7	81	1.8	21	154
Northwest Airlines Inc.	52	79	3.0	20	197
PSA Airlines Inc.	4	70	1.8	30	92
SkyWest Airlines Inc.	9	82	2.4	21	336
Southwest Airlines Co.	43	82	3.5	24	455
Spirit Air Lines	31	73	1.2	15	147
United Air Lines Inc.	95	80	3.4	17	197
US Airways Inc.	61	81	3.5	20	160
Virgin America	95	81	3.1	18	27

[10] Higher price dispersion can make a market attractive to prospective entrants. This attraction can create reverse causation and positive bias in the least-squares estimates of β. Although, a Hausman endogeneity test did not indicate this bias, we have chosen to follow the previous literature in using instrumental variables to keep our results consistent. Endogeneity can also arise from omitted variables, a problem also solved by the instrumental approach. We used market-level variables of distance between end points, arithmetic and geometric mean of endpoint populations, total enplaned passengers, and two variables introduced by Borenstein and Rose (1994). We also used the Hausman test to check for endogeneity in our Q variable and found no evidence of endogeneity.

[11] https://www.transtats.bts.gov/homepage.asp (Accessed February 15, 2022.).

[12] The following close-by airports are combined in the results: DFW (Dallas–Fort Worth) and DAL (Love Field); LGA (LaGuardia), EWR (Newark) and JFK (J. F. Kennedy); AZA (Phoenix–Mesa Gateway) and PHX (Phoenix Sky Harbor); TPA (Tampa) and PIE (St. Pete–Clearwater); DCA (Reagan) and IAD (Washington Dulles); ORD (O'Hare) and (MDW) Midway.

[13] By using only passenger miles, we are ignoring freight and mail as an output; however, because passenger revenue is typically 98% of total revenue for this group of carriers, the impact of freight and mail is negligible.

[14] As carriers can enter or exit a market during a quarter, we find the average number of daily flights for each month the carrier was active in the market, then find the average for the quarter based only on the months they were active. For example, if Delta entered a market in March, its flight frequency for that quarter would be based only on the number of daily flights performed in March.

variation in values.

4.2. Inputs

We use the standard airline inputs of fuel, labor, flight capital, and purchased materials and services (see Oum et al., 2005; Färe et al., 2007; Wu et al., 2013; Wang et al., 2014). These form our input quantity vector x and input price vector w. Fuel data are sourced from Form 41 schedule P-12(a) and are measured as total gallons of fuel consumed. The price is calculated as a ratio of total cost to gallons of usage. Regarding labor, we use the number of full-time equivalents (FTE) as the measure of labor. Total salary and benefits divided by the number of FTE provides the labor price. For flight capital, we follow a process similar to that of Färe et al. (2007) and define capital as the total number of seats available based on the number of planes in service and the seat configuration used by the carrier. The cost of capital comes from two sources, leasing rates and capital depreciation, and the price is calculated as the ratio of the total cost of capital to quantity. The final input is purchased materials and services, which is calculated as total operating expenses less the cost of all other identified inputs. The result is deflated by the Bureau of Labor Statistics (BLS) producer price index (PPI) of air transportation support activities to obtain quantities, and the price is set equal to the index value.[15] Table 2 provides a quarterly average of inputs by carrier and the average route. As with outputs, we can observe a significant amount of variation.

4.3. Competition and market structure

Following previous works, we use two proxy measures for competition, the HHI and the number of carriers on a route. The HHI, a measure of market concentration, varies from 0.0 to 1.0 and is calculated as the sum of the squares of market shares of all firms in the market.[16] Our definition of a market as non-stop flights between two city pairs is relatively narrow, which is reflected in the average HHI score of 0.76 over the period of analysis.[17] This value is in line with the 0.79 HHI reported by Dai et al. (2014) and the 0.72 to 0.78 noted by Gerardi and Shapiro (2009). To facilitate comparison of the HHI value and the number of carriers, we follow Gerardi and Shapiro (2009) and use the negative of the log of the HHI, noted in our estimation as the instrumented variable $-\ln \widehat{HERF}$.

4.4. Ticket data

We analyze coach-class tickets over the fifteen-year period of the first quarter 2002 to the fourth quarter 2016. Ticket price data come from the Airline Origin and Destination Survey (DB1B), a 10% quarterly sample collected by the BTS that is reported by all U.S. carriers that have at least 1% of the total scheduled-service domestic passenger revenue. The reporting group changed over the period of observation, ranging from ten to eighteen firms as carriers entered and exited the group.

Following previous airline literature (see Borenstein and Rose, 1994; Gerardi and Shapiro, 2009; Dai et al., 2014), we include non-stop, coach-class itineraries for flights within the U.S. We include both one-way and round-trip tickets, but define ticket price as a one-way fare, thus round-trip tickets are included as half of the full fare. Itineraries costing less than $10 are excluded to eliminate frequent flyer tickets, promotional tickets, or non-revenue passengers. We also exclude fares that the BTS has flagged as questionable.

Following previous work, we use the Gini coefficient as our primary measure of dispersion $S(\cdot)$ for estimations (8–10), and this Gini coefficient takes a value between 0 and 1.[18] Our calculation for the Gini coefficient of fares follows the formula established by Borenstein and Rose (1994) and Gerardi and Shapiro (2009).[19] Because the Gini coefficient is bounded between zero and one, we follow Gerardi and Shapiro and use the log-odds ratio given by $S(\cdot) = \ln[\text{Gini}/(1-\text{Gini})]$, which provides an unbounded statistic. To further understand how competition affects price and dispersion, we also look at the 10th percentile price (P10), the 90th percentile price (P90), and the spread between these two prices (P90–P10). The fifteen-year period between 2002 and 2016 provides 73, 981 separate quarterly route observations with 20 individual carriers and 2079 routes represented. At 0.23, the overall Gini measure is in line with the measure in previous studies.[20].

4.5. Differentiation

As defined in (4), the output attribute index $Q(w_h, y_h, q_h, q^0)$ measures the impact on the unit cost of a change between output attribute level q_h and q^0. However, for the purpose of (8–10), we need a measure at the market level to indicate the degree of differentiation by output attribute in the market. Forsund and Hjalmarsson (1979) demonstrated that it was possible to create a firm representative of an industry based on the arithmetic average of all firm inputs, outputs, and output attributes q_h. The value for q^0 is already at the market level and does not need to be averaged. A similar approach was used by Yu et al. (2018) in their study of ferry transportation. Following these examples, we create a representative carrier for each route and quarter and calculate a market output attribute index defined as $Q(w, y, q, q^0)$ where w, y, and q are the average of all carriers in the market. The interpretation of $Q(w, y, q, q^0)$ at the market level is the same as for the case of firm h provided after expression (4). Over the period observed, the average value for $Q(w, y, q, q^0)$ was 0.95 with a standard deviation of 0.09. For the purpose of our estimation, we want a value that increases with differentiation to match the value of $-\ln \widehat{HERF}$ which increases with competition, so we use the inverse value noted as $Q(w, y, q, q^0)^{-1}$.

5. Results

5.1. Descriptive results

Results for observed and adjusted fare and price dispersion values are presented in Table 3. To provide detail and context, we have separated the results by degree of market concentration. Following Borenstein and Rose (1994), we are grouping together markets where one carrier has a

[15] https://www.bls.gov/data/Series PPI industry group data for air transportation support activities, not seasonally adjusted.

[16] $HHI = \sum_{h=1}^{k} s_h^2$ where s is the share of firm h in the market and k is the number of firms.

[17] The U.S. Department of Justice guidelines for horizontal mergers consider an HHI below 0.15 as indicating a non-concentrated market, between 0.15 and 0.25 moderate concentration, and above 0.25 high concentration. https://www.justice.gov/atr/horizontal-merger-guidelines-08192010 (Accessed February 9, 2022.).

[18] The Gini coefficient is a value between 0 and 1 and is equal to twice the expected absolute difference as a proportion of the mean price between any two randomly drawn ticket prices. For example, a Gini coefficient of 0.20 would indicate an expected absolute price difference of 40% of the mean fare for any two randomly drawn tickets.

[19] $GINI = 1 - 2\,x \left(\sum_{i=1,N} fare_i \; x \; \frac{PAX_i}{total\ Revenues}\right) x \left[\frac{PAX_i}{total\ PAX} \; x \left(1 - \sum_{j=1,i} \frac{PAX_j}{total\ PAX}\right)\right]$

here N is the number of different fare-level tickets reported by a carrier on a specific route, $fare_i$ is the fare for the ith ticket, and PAX_i is the number of passengers. traveling at that fare.

[20] Borenstein and Rose (1994), using Q2 1986 data, calculated a Gini of 0.18, Gerardi and Shapiro (2009) calculated 0.22 for the 1993–2006 period, and Dai et al. (2014) calculated 0.23 for the 1993–2008 period.

Table 2
Statistics of input quantity and input prices (route average).

	Fuel ($x1$)		Labor ($x2$)		Flight Capital ($x3$)		Other Material ($x4$)	
Carrier	Gal (000's)	Price ($)	FTE (#)	Price ($)	Seats (#)	Price ($)	Quantity	Price ($)
AirTran Airways Co.	661	2.00	62	15.69	29	17.51	9	141.51
Alaska Airlines Inc.	1,037	2.02	113	22.96	47	14.51	22	143.73
America West Airlines Inc.	1,222	1.05	133	14.32	56	18.15	24	123.41
American Airlines Inc.	2,162	1.88	254	21.49	96	11.64	49	143.73
ATA Airlines	1,160	1.43	138	14.29	55	22.64	28	131.10
Continental Air Lines Inc.	1,566	1.68	203	20.10	72	16.65	60	135.55
Delta Air Lines Inc.	1,496	2.00	175	24.02	69	11.94	52	143.73
Envoy Air	352	1.85	55	12.31	17	13.80	6	137.50
ExpressJet Airlines Inc.	222	1.46	28	16.45	14	17.95	4	141.12
Frontier Airlines Inc.	770	2.38	76	16.80	30	21.69	13	153.56
Hawaiian Airlines Inc.	1,424	2.13	134	23.22	73	19.04	29	151.11
JetBlue Airways	1,236	2.19	112	20.89	50	13.03	17	149.31
Mesa Airlines Inc.	155	2.64	16	10.99	10	26.82	3	150.74
Northwest Airlines Inc.	1,242	1.52	131	23.21	58	9.89	31	131.46
SkyWest Airlines Inc.	126	2.50	28	14.89	11	23.93	2	149.31
Southwest Airlines Co.	834	1.79	85	24.96	40	10.34	11	143.73
Spirit Air Lines	431	1.66	30	22.22	21	21.15	6	167.44
Trans World Airlines	1,461	0.90	198	15.98	65	23.17	26	114.18
United Air Lines Inc.	1,720	1.90	237	20.65	77	11.89	63	143.73
US Airways Inc.	1,196	1.92	156	18.83	60	15.59	43	140.57
Virgin America	1,553	2.23	94	27.05	66	28.23	28	164.01

Table 3
Statistics by market structure and output attribute index (average weighted by number of passengers).

Market	Output Attribute Index		Avg Fare per Mile ($)		Avg Gini		Count of
Structure	Range	Avg	Observed	Adjusted	Observed	Adjusted	Markets
Monopoly	1.00–1.01	1.00	0.29	0.28	0.249	0.249	18,794
	1.01–1.05	1.02	0.37	0.36	0.246	0.246	15,747
	1.05–1.10	1.07	0.42	0.39	0.234	0.234	7,314
	1.10–1.15	1.12	0.42	0.37	0.225	0.225	3,407
	1.15 +	1.38	0.40	0.30	0.189	0.189	8,526
	Average	1.07	0.34	0.32	0.238	0.238	53,788
Duopoly	1.00–1.01	1.00	0.24	0.24	0.245	0.246	5,659
	1.01–1.05	1.03	0.23	0.22	0.254	0.257	4,672
	1.05–1.10	1.07	0.26	0.24	0.253	0.257	2,138
	1.10–1.15	1.12	0.30	0.26	0.245	0.253	916
	1.15 +	1.27	0.35	0.26	0.224	0.239	1,423
	Average	1.05	0.25	0.24	0.247	0.250	14,808
Competitive	1.00–1.01	1.00	0.17	0.17	0.250	0.250	2,698
	1.01–1.05	1.03	0.17	0.16	0.262	0.265	1,576
	1.05–1.10	1.07	0.22	0.20	0.277	0.281	610
	1.10–1.15	1.12	0.28	0.24	0.274	0.281	217
	1.15 +	1.30	0.43	0.32	0.255	0.269	284
	Average	1.04	0.19	0.18	0.257	0.260	5,385
All Market	1.00–1.01	1.00	0.24	0.24	0.248	0.248	27,151
Structures	1.01–1.05	1.03	0.27	0.26	0.253	0.254	21,995
	1.05–1.10	1.07	0.31	0.29	0.251	0.254	10,062
	1.10–1.15	1.12	0.35	0.30	0.242	0.247	4,540
	1.15 +	1.34	0.39	0.29	0.209	0.215	10,233
Overall	Average	1.06	0.28	0.26	0.245	0.247	73,981

90% or greater share as *Monopoly*, markets where the top two carriers combined have a 90% or greater share as *Duopoly*, and then all other markets as *Competitive*. These groupings are not intended to infer specific market characteristics, but simply to group together markets of similar concentration. Results are further categorized into five levels of market differentiation using the value of $Q(w, y, q, q^0)^{-1}$. The first grouping contains markets we would consider homogenous. To allow for some slack in consumers' ability to discern differences, we define a market as homogenous when minimum unit costs at attribute levels q and q^0 are equal or no more than 1% different.[21] In other words, the value of $Q(w, y, q, q^0)^{-1}$ is between 1.00 and 1.01. The next four groupings are considered heterogeneous: markets with $Q(w, y, q, q^0)^{-1}$ values between 1.01 and 1.05, then those with values between 1.05 and 1.10, those with values between 1.10 and 1.15, and finally those with a value

[21] For context, a 1% difference in unit costs adds roughly $1.00 to the total cost per passenger on a flight of average length.

greater than 1.15. The higher the value of $Q(w, y, q, q^0)^{-1}$ the greater the level of market heterogeneity.

We observe a sharp difference in per mile fares between the three market structures. In the *Competitive* group average fares are \$0.19 per mile. Fares rise by 32% to an average fare of \$0.25 in the *Duopoly* group, and then increase by another 35% to an average of \$0.34 per mile in the *Monopoly* group. Fares that have been adjusted to remove the costs of a higher level of attributes are lower but retain a similar difference between concentration levels. We can also observe that generally per mile fares increase as market heterogeneity increases.

The level of price dispersion, given by the average Gini coefficient in the third column, also varies by levels of market concentration and differentiation. The table shows a first glimpse of the relationship between market concentration and level of differentiation, which is one of the objects of this study that the econometrical analysis in the next section will help to clarify. The values for the adjusted Gini coefficient show an overall increase, which highlights a shortcoming of the adjusted Gini as a measure of dispersion for our use. As a measure of dispersion, the Gini measures dispersion across the whole range of fares and can be sensitive to changes in the middle. There are often common fare points used by all carriers in a market. For example, multiple carriers may offer a \$145 advance-purchase fare. Our method of adjustment may move one or all carriers off that point, creating more dispersion. To better understand the data, we have added a second measure of dispersion that is more focused on the tails of the dispersion, the 10th (P10) and 90th (P90) percentile price per mile and the spread between them. We define the spread (P90–P10) as simply the 90th percentile price per mile less the 10th percentile price per mile. An increase in the spread value indicates a wider dispersion.

Our first research question compares the levels of dispersion in markets with a wide and narrow range of attributes. To explore this question, we perform a comparison of means and outline the results in Table 4. Using the definition of *homogenous* as a value of $Q(w, y, q, q^0)^{-1}$ between 1 and 1.01 and *heterogeneous* as values greater than 1.01, we calculate weighted means of dispersion on the Gini coefficient and the (P90–P10) spread. Our test establishes the null hypothesis that the mean dispersion in a homogenous market is greater than or equal to the mean dispersion in a heterogeneous market. We reject the null hypothesis and accept the alternative that dispersion is greater in heterogeneous markets in every case except the Gini measure in the *Monopoly* structure.[22].

We also looked at the dispersion of prices that had been adjusted in concordance with (7) by removing the cost of providing a higher level of attributes, and found mixed results. In terms of the Gini measure, we see an increase in dispersion, but the (P90–P10) spread shows a reduction in dispersion. These results may be explained by the existence of common fare points noted earlier.[23].

5.2. Fixed-effects panel estimation results

Table 5 contains estimation results using the HHI as the measure of competition and the Gini log-odds ratio as the measure of dispersion, while Table 6 presents the same measure of competition but with the (P90–P10) as the measure of dispersion.[24] In Table 5 baseline estimation (8), we see that effect of competition on price dispersion, measured as $-\ln\widehat{HERF}$, is negative and significant, echoing Gerardi and Shapiro (2009). These findings are reinforced in Table 6 where we see that an increase in competition reduces the (P90) price by more than the (P10) price, resulting in a narrower spread and a reduction in dispersion. We also see in the second column of Table 5 that the effect of competition on price dispersion, after removing the cost of product differentiation, is stronger than the coefficient on observed price. This result would be expected because adjusted prices reflect a market that is more homogenous in terms of output attributes. For brevity's sake, we do not report adjusted values in Table 6, but results mirror those of Table 5.[25]

Results for estimation (9), which bridges (8) and (10), are interesting, but not very informative. We see that the significantly negative effect of competition on price dispersion is strengthened over (8) once the level of differentiation is accounted for. Although the negative coefficient on $Q(w, y, q, q^0)^{-1}$ was unexpected, in fact our model did not make predictions on what happens within a market when the level of differentiation changes.

Turning to formula (10), we now address the question of the interaction effect of competition on price dispersion in homogenous and heterogeneous markets. As can be seen in both Table 5 and 6, the interaction effect is significant and positive. To verify the validity of the interactive term, we performed a Wald test on the results of estimations (9) and (10) and found that in addition to being significant, it adds to the model. With an F value of 52.21, we reject the null hypothesis that model (9) is as good as (10). A similar test was run based on both measures of competition and both measures of dispersion. All showed the same validity of the interactive measure.

Understanding the question of interaction requires a more detailed level of information that is provided by the rewriting of expression (10), and the specification of different levels of market differentiation in concordance with Table 3. To simplify interpretation, we provide Table 7 as the resulting coefficient on competition at various levels of $Q(w, y, q, q^0)^{-1}$. Table 7 can be interpreted as reducing formula (10) to the formula below, and then finding $(\beta_1 + \beta_3 Q)$ at various levels of Q:

$$S_{jt}(\cdot) = (\beta_1 + \beta_3 Q_{jt})\, Com_{jt} + \beta_2\, Q_{jt} + \theta\chi_{jt} + \delta_{ht} + \gamma_t + \upsilon_j + \varepsilon_{jt}. \tag{11}$$

Results in Table 7 show that considering interactive effects, the effect of competition on dispersion is negative in homogenous markets, but turns positive when the market becomes more differentiated in terms of output attributes. This result can be seen in the Gini measure and in the relative changes of the (P10) and (P90) coefficients and the resulting (P90–P10) spread. In both measures, the effect of competition on dispersion changes sign at a $Q(w, y, q, q^0)^{-1}$ value of about 1.10. As noted in our discussion of the Borenstein (1985) model in section 2.1, dispersion reduction in homogenous markets is driven from monopoly-type discrimination when firms compete based on market elasticity. While in the more heterogeneous markets, the increase in dispersion arises from competitive-type discrimination and more cross-price elasticity competition.

Estimations from Table 5, 6, and 7 are reproduced in Table 8, 9 and 10 with the log of the number of carriers in the market ($\ln\widehat{N}$) as the measure of competition. Here we see in Table 8 that the effect of competition has almost no effect on price dispersion and the coefficient is not significant. In fact, it is not until we add the interactive effects of formula (10) and allow for differences by level of differentiation that the

[22] One possible explanation for this is that in the more highly concentrated Monopoly markets carriers providing a higher level of output attributes do not offer price reductions and engage in limited price discrimination. This explanation is supported by Table 4, where that same group has a per mile fare significantly higher than any other group's per mile fare. This difference also may explain the 0.410 measure for the (P90–P10) spread in this group, many higher price tickets, and only a few lower-priced tickets.

[23] On prices that have been adjusted, the Gini value for all market structures together is 0.248 for homogenous markets and 0.246 for heterogeneous markets. For the (P90–P10) spreads, these values are 0.259 and 0.304.

[24] In tests of instrument validity, we found all instruments were significant, and with an F-test value of 6962, we can reject that they are weak instruments.

[25] As in Table 5, the reduction in dispersion is greater on the adjusted prices. The (P90–P10) spread is −0.511 on observed prices and −0.546 on adjusted prices.

Table 4
Independent samples weighted unequal variances T-test.

	Mean Observed Gini Coefficient			Mean Observed (P90–P10) Spread		
	Monopoly	Duopoly	Competitive	Monopoly	Duopoly	Competitive
Homogenous	0.249	0.245	0.250	0.316	0.260	0.182
Heterogeneous	0.229	0.248	0.266	0.410	0.286	0.250
P-Value	1.00	0.00	0.00	0.00	0.00	0.00
Reject H_0	No	Yes	Yes	Yes	Yes	Yes

Table 5
Panel Estimates Dep Var: Gini log-odds ratio (Observed or Adjusted Prices).

Estimation Formula:	Observed	Adjusted	Observed	Observed
	(8)	(8)	(9)	(10)
$-\ln\widehat{HERF}$	−0.164**	−0.253***	−0.222***	−2.380***
	(0.068)	(0.068)	(0.069)	(0.338)
$Q(w, y, q, q^0)^{-1}$			−0.208***	−0.286***
			(0.009)	(0.015)
Interaction Variables				
$-\ln\widehat{HERF} \cdot Q(w, y, q, q^0)^{-1}$				2.234***
				(0.067)
Observations	73,981	73,981	73,981	73,981

Notes: All regressions include quarter and carrier dummies, and a dummy variable indicating whether any carrier in the market was currently in bankruptcy. Standard errors are in parentheses.
* Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

coefficient becomes significant. Results from Table 9, using the (P10) and (P90) to measure dispersion, closely mirror those of Table 6 in terms of sign, coefficient value, and significance. In Table 9, the effect of competition is significant and negative even before controlling for differentiation. Finally, Table 10 reports the effective coefficient based on interactive effects at various levels of $Q(w, y, q, q^0)^{-1}$. Under this measure of competition, we see the effect of competition on the Gini coefficient, and the (P90–P10) changes sign when $Q(w, y, q, q^0)^{-1}$ values are greater than 1.15.

5.3. Robustness checks

In this section we test the robustness of the output attribute index $Q(w, y, q, q^0)$ we introduced. As discussed in section 4, the values for the output attributes of on-time arrival and load factor are measured at the carrier level, whereas the value for flight frequency is measured at the route level. An alternative would be to measure all output attributes at the route level. The logic being that although the information is less accessible at the route level, it is the route-level output attribute that directly affects consumers. To test for robustness, we replicate the method with this alternative measure and find that results are essentially unchanged, though not as statistically strong. The loss in statistical significance is largely because a significant number of routes are served by a single carrier. When differentiation by output attribute is measured at the route level, these single-carrier routes show no differentiation, masking the true level of heterogeneity in service levels.

In addition to testing the robustness of the output attribute index, we check for robustness in our regression results from formula (10). Our presented results are based on a static fixed-effects panel within the estimator. Because there is a fair amount of persistence in the measure

Table 7
Coefficient ($\beta_1 + \beta_3\, Q$) on *Com* ($-\ln\widehat{HERF}$) at Different Output Attribute Index Levels Dependent Variable: Gini log-odds ratio, 10th Percentile Price or 90th Percentile Price.

Output Attribute Index		$-\ln\widehat{HERF}$		$-\ln\widehat{HERF}$	
Range	Avg	Gini	(P10)	(P90)	(P90–P10)
1.00–1.01	1.00	−0.146	−0.600	−1.053	−0.453
1.01–1.05	1.03	−0.079	−0.445	−0.750	−0.305
1.05–1.10	1.07	0.010	−0.238	−0.346	−0.108
1.10–1.15	1.12	0.122	0.021	0.159	0.139
1.15 +	1.34	0.614	1.158	2.382	1.223

Table 6
panel estimates dep var: Log of 10th or 90th percentile observed price.

Estimation Formula:	Log(P10)	Log(P90)	Log(P10)	Log(P90)	Log(P10)	Log(P90)
	(8)	(8)	(9)	(9)	(10)	(10)
$-\ln\widehat{HERF}$	−1.044***	−1.555***	−1.076***	−1.603***	−5.772***	−11.155***
	(0.060)	(0.059)	(0.061)	(0.061)	(0.064)	(0.103)
$Q(w, y, q, q^0)^{-1}$			−0.096***	−0.224***	−0.257***	−0.562***
			(0.009)	(0.009)	(0.018)	(0.022)
Interaction Variables						
$-\ln\widehat{HERF} \cdot Q(w, y, q, q^0)^{-1}$					5.172***	10.102***
					(0.366)	(0.443)
Observations	73,981	73,981	73,981	73,981	73,981	73,981

Notes: All regressions include quarter and carrier dummies, and a dummy variable indicating whether an carrier in the market was currently in bankruptcy. Standard errors are in parentheses.
* Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 8
Panel Estimates Dep Var: Gini log-odds ratio (Observed or Adjusted Prices).

Estimation Formula:	Observed	Adjusted	Observed	Observed
	(8)	(8)	(9)	(10)
$\ln\widehat{N}$	0.007	−0.072	−0.020	−1.041***
	(0.074)	(0.074)	(0.073)	(0.186)
$Q(w, y, q, q^0)^{-1}$			−0.194***	−0.260***
			(0.008)	(0.013)
Interaction Variables				
$\ln\widehat{N} \cdot Q(w, y, q, q^0)^{-1}$				0.893***
				(0.144)
Observations	73,981	73,981	73,981	73,981

Notes: All regressions include quarter and carrier dummies, and a dummy variable indicating whether any carrier in the market was currently in bankruptcy. Standard errors are in parentheses.
* Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

Table 9
Panel estimates dep var: Log of 10th or 90th percentile observed price.

Estimation Formula:	Log(P10)	Log(P90)	Log(P10)	Log(P90)	Log(P10)	Log(P90)
	(8)	(8)	(9)	(9)	(10)	(10)
$\ln\widehat{N}$	−0.985***	−1.269***	−0.991***	−1.293***	−2.959***	−5.241***
	(0.056)	(0.051)	(0.056)	(0.051)	(0.185)	(0.187)
$Q(w, y, q, q^0)^{-1}$			−0.029***	−0.124***	−0.187***	−0.419***
			(0.008)	(0.007)	(0.013)	(0.013)
Interaction Variables						
$\ln\widehat{N} \cdot Q(w, y, q, q^0)^{-1}$					2.137***	3.983***
					(0.144)	(0.146)
Observations	73,981	73,981	73,981	73,981	73,981	73,981

Notes: All regressions include quarter and carrier dummies, and a dummy variable indicating whether any carrier in the market was currently in bankruptcy. Standard errors are in parentheses.
* Significant at the 10 percent level, ** Significant at the 5 percent level, *** Significant at the 1 percent level.

replicate the estimation with instrumented competition, the effect is stronger at −0.015. These results might indicate that there are indirect effects of competition on dispersion through Q. A simple way to test for these results is suggested by Judd and Kenny (1981). They suggest comparing the result coefficient between a model that includes the mediator and one that does not, subtracting one from the other. We have found these values already as equations (8) and (9). Using the results from Table 5, we find that the indirect effect of competition on dispersion, through Q, is 0.031 compared with the direct effect of −0.222.[26].

5.4. Reconciliation with previous studies

In this section, we reconcile our results with those of previous studies and explore how our findings can help explain some of the contradictions between those studies. Like previous researchers, we perform a panel analysis of the effect of competition on price dispersion using fixed-effects estimation to control for time-invariant market-specific factors. However, we introduce a measure of market differentiation and its interaction with competition, showing that the effect of competition on price dispersion differs depending on whether the market is homogenous or heterogeneous based on output attributes.

Our results from estimation formula (8) are in line with those of Gerardi and Shapiro (2009). The difference is our extension of the model to include the level of market heterogeneity in formula (9) and the interaction effect in formula (10). Our extension refines their work, because of our finding that the effect of competition can differ based on the degree of differentiation. However, in a sample where markets are predominantly more homogenous, the result would indicate a negative relationship, just as Gerardi and Shapiro (2009) found.

Dai et al. (2014) find an inverse-U-shaped relationship, with price dispersion increasing as a highly concentrated market initially becomes more competitive, but decreasing when a less concentrated market becomes even more competitive. They do not control for the level of differentiation. What we find does not contradict their results but can provide further insight into what is happening in the market. When a monopoly market first receives a second carrier, there is a move from highly concentrated to more competitive. Concurrent with that change there is a probability of an increase in differentiation and therefore an increase in dispersion. For markets that are already less concentrated, differentiation is more likely to have peaked and competition increases

for dispersion in any given market, we first test our results with the addition of a lag of the dependent variable. As might be expected, the lagged variable is highly significant both statistically and economically. However, our main results for competition, differentiation, and the interaction are robust to the addition of this lag.

We test further and use dynamic panel data methods to account for the possibility of correlation between the transformed lagged variable and the transformed error term. We test several specifications, including the Arellano and Bond (1991) difference generalized-method-of-moments (GMM) estimator, the Blundell and Bond (1998) system GMM estimator, and the Arellano and Bover (1995) system GMM with forward orthogonal deviations from Roodman (2003). This last specification, which differences observations by subtracting the mean of future observations, fits our data well. Because airlines can enter or exit a market easily, or switch between direct and connecting service, our panel has many gaps. The forward orthogonal deviation method retains observations that would have been lost through first differences. Though the absolute value of coefficients varies somewhat between the methods, again our main results for competition, differentiation, and the interaction hold up.

As a further check for robustness, we test for the existence of indirect effects of competition on dispersion through our measure of heterogeneity Q. A concern would be that heterogeneity has no effect on its own, but only through mediation of competition. As a first step in this check, we run a simple regression with competition predicting heterogeneity Q. We find that the relationship is statistically significant at the 5% level but has a small effect, with a coefficient of 0.005, on competition. If we

[26] We also tested the presence of an LCC as a method of measuring market heterogeneity. In neither estimation (9) nor (10) was the measure significant, nor was the model fit as good as that of the base model.

Table 10

Coefficient ($\beta_1 + \beta_3 Q$) on Com ($\ln \widehat{N}$) at Different Output Attribute Index Levels Dependent Variable: Gini log-odds ratio, 10th Percentile Price or 90th Percentile Price.

Output Attribute Index		$\ln \widehat{N}$	–		$\ln \ln \widehat{N}$	
Range	Avg	Gini		(P10)	(P90)	(P90–P10)
1.00–1.01	1.00	−0.148		−0.822	−1.258	−0.436
1.01–1.05	1.03	−0.121		−0.758	−1.139	−0.381
1.05–1.10	1.07	−0.085		−0.672	−0.979	−0.307
1.10–1.15	1.12	−0.041		−0.566	0.780	−0.214
1.15 +	1.34	0.156		−0.095	0.096	0.192

are likely to come in the form of battles between carriers serving the same niche. We see this effect in the descriptive data of Table 3 in the column Avg Gini Observed. In the competitive structure, as markets become more differentiated, dispersion increases from 0.250 to 0.277, but then begins decreasing, dropping to 0.255 at the highest levels of heterogeneity. A similar effect is seen in the duopoly structure.[27].

Reconciling our findings with those of Borenstein and Rose (1994), we look to two particular points, the difference in econometric methods and the lack of a variable controlling for differentiation. Gerardi and Shapiro (2009) provide a full discussion on the differences between the cross-section method and the fixed-effects panel method used by Borenstein and Rose (1994). In short, they show that the cross-section method would bias the coefficient on competition. They also note several time-invariant factors that could cause this bias. We would argue that the level of differentiation in the market is one of the most important of these. To test this theory, we run a cross-section estimation on our data set and find a positive relationship between competition and dispersion. However, once we add $Q(w, y, q, q^0)^{-1}$ to the estimation, either on its own or as an interaction variable, the sign on competition turns negative.[28].

6. Conclusions

In this study we have introduced an output attribute index which collects the cost impact of various changes in levels of output attributes. Our new method allows us to measure the amount of product differentiation that is due to output attributes. Markets with a wide range of output attributes are categorized as heterogeneous markets, whereas those with a narrow range of output attributes are classified as homogenous markets.

Returning to our research questions, we can now draw conclusions. First, price dispersion is greater in heterogeneous markets. This is true both for observed price dispersion and for price dispersion after removing cost differences due to product differentiation. Second, we find that if we control for the level of product differentiation, competition has a strictly negative effect on price dispersion. Finally, using a fixed-effects panel estimation with interactions, we find that the direction and magnitude of the effect of competition on price dispersion is dependent on the level of product differentiation in the market. We also find that at higher levels of differentiation, an increase in competition can increase price dispersion.

Whereas homogeneity is an absolute, heterogeneity is gradable and has levels. We see that the switch from price dispersion decreasing to increasing as competition grows occurs only at a certain level of differentiation. This finding might imply that although these results can be generalized to other industries, the point at which the affect occurs may be different. We also reconcile our study's findings with findings in previous research and helps to explain the contradictory results.

Our findings provide regulators information to consider when reviewing potential mergers. Typically, regulators focus on the HHI and how the merger will affect market concentration. However, as we have shown, the market HHI alone is not enough when trying to understand changes related to pricing. Regulators should also consider the level of differentiation provided by the firms and how a merger might affect differentiation in the markets they are part of. A merger or horizontal alliance between two carriers with similar attributes can result in a greater increase in fare price, and in price dispersion, than the increases that would result from a merger between two carriers with quite different attributes. A further consideration for policymakers is that market concentration alone does not determine the level of competition. A market with two carriers of similar attributes will be more competitive than one where the carriers have quite different attributes, since market power is not determined by market concentration alone.

Between April 2008 and November 2013, the U.S. Department of Justice approved four separate airline mergers. In a review of this decision, Gifford and Kudrle (2017) conclude that a contributing factor to this decision was the belief by the U.S. Justice Department that potential entry and competition by a low-cost carrier (LCC) would restrain any price increases. As measured by price dispersion, we find that belief to be flawed. Some evidence can be seen in the strong growth in airline profitability following these mergers.[29] Had our findings here been considered, perhaps some of these mergers would not have been approved.

From a strategic perspective, these results can provide carriers some direction when choosing routes to enter or exit. Entering a route where the current competitors are similar to the potential entrant would be less attractive, unless the potential entrant could adjust its product offering. On the other side, entering a route where the current carriers are dissimilar will allow the entrant greater latitude to price discriminate and generate higher fares.

Our study has focused on the effects on price dispersion. Further research using our techniques could analyze the effect on average prices and price deciles to further understand how changes in competition affect markets, conditioned on the level of differentiation. This analytical method could also be applied to other economic models to understand how explicitly controlling for the level of differentiation by output attribute affects model outcomes. Some possible examples may be productivity analysis, a hedonic price equation, or other models where market power plays a significant role.

Author statement

Charles Howell: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft. **Emili Grifell-Tatjé:** Writing – Review & Editing, Supervision, Conceptualization and Methodology.

[27] To validate our findings, we have adjusted formula (10) to allow for the nonmonotonic effect found by Dai et al. (2014). We replaced the measure $-\ln\widehat{HERF}$ ith HHI and HHI^2 and introduced interactions of $Q(w,y,q,q^0)^{-1}$ ith the HHI terms. Without the interaction, we found a coefficient of 0.283 on HHI and −0.211 on HHI^2, compared with the 0.536 and −0.344 found by Dai et al. (2014) on a different time period. Adding the interaction term we find a significant result of −0.195 on the interaction with HHI and −0.148 with HHI^2. Recalling that the HHI is a measure of concentration (higher values indicate less competition), this validation supports our conclusion that at higher levels of differentiation, an increase in competition can add to dispersion, while in the more homogenous markets, competition reduces price dispersion.

[28] As an additional step to ensure the validity of our findings, we followed the same methodology as Borenstein and Rose used (1994) and ran a series of cross-sectional regressions on each quarter in our sample. Using this method, we found a median coefficient of 0.144 on competition, compared to their 0.323. We then added the interaction measure $-\ln\widehat{HERF}\cdot Q(w,y,q,q^0)^{-1}$ to the cross-sectional regressions and found the median coefficient on competition to be −2.517, similar to our results in Table 5. With this method, the median value of the coefficient on the interaction variable is 0.264. These values differ from our findings using panel data, but the direction, signs, and conclusion would be the same.

[29] U.S. domestic airline profitability rose from 1.05 in 2008 to 1.20 by 2016.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tranpol.2022.06.001.

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