Mark Israel, Bryan Keating, Daniel L. Rubinfeld* and Bobby Willig Airline Network Effects and Consumer Welfare

Abstract: In this paper we develop a methodology to quantify the value to consumers of the non-price characteristics of airline networks. Our research demonstrates that analyses that ignore the quality effects associated with expanded airline networks generate incorrect findings and thus should not form the basis for policy decisions regarding airline transactions. Appropriately incorporating quality effects into quality-adjusted fares reverses the conclusion that hub airports yield lower consumer welfare due to generally higher fares than other airports. From the perspective of consumer welfare in this industry, to evaluate potential airline mergers, alliances, slot swaps or other transactions, one should not focus solely on the effect of concentration on nominal fares, rather, one should account for the welfare-enhancing effects of larger airline networks.

Keywords: airlines; mergers; network effects.

*Corresponding author: Daniel L. Rubinfeld, University of California, Berkeley, Law School Berkeley, USA, e-mail: drubinfeld@law.berkeley.edu

Mark Israel and Bryan Keating: Compass Lexecon, District of Columbia, USA Bobby Willig: Princeton University, Woodrow Wilson School Princeton, New Jersey, USA

1 Overview

It has long been recognized that airlines experience economies of scale and scope from the spreading of fixed and common costs across a larger network of flight operations. However, there has been little recognition (and some real resistance) accorded to the equally intuitive idea that airline passengers benefit from the higher quality service provided by airlines that have more extensive networks.¹ Furthermore, there have been claims that hub-and-spoke airlines have

¹ As we describe in more detail below, the concept that air carriers compete on dimensions of quality and that effects on quality should be balanced against effects on price has been recognized in the economics literature at least since Douglas and Miller (1974). However, these concepts have not been consistently applied to policy related to air travel.

substantial market power, which is exhibited in the form of relatively high fares for flights into and out of hub airports. Yet, as many airlines have grown, airline network effects have increasingly provided passengers with improved connectivity and more convenient schedules, whether or not they are flying out of hubs. Can these contrasting views of airline market power on the one hand and valued network effects on the other be rationalized?

This paper shows empirically that airline network effects are highly valued by consumers. These network benefits should be viewed as important in the assessment of public policies that affect airlines' network architectures. We also show that once network benefits are taken into account, the relatively high hub fares are largely offset and counterbalanced by the greater quality of services that are offered. As a consequence, a substantial portion of the seeming nominal hub market power of airlines can be attributed to the consumer benefits that those hubs offer.

To evaluate these important network issues, we model consumer demand for airline itineraries as a function of price and various other characteristics of flights and associated airline networks. We find that network characteristics have effects that are both statistically significant and economically important. We then go a step further by utilizing consumer demand theory to integrate the economic impacts of nominal price and service characteristics into a quality-adjusted price of service. The quality-adjusted price reflects the monetary value to consumers of the qualities of service that are revealed by consumers' purchasing behavior. For example, the quality-adjusted price of an itinerary is higher when the nominal price is higher and is lower when the network effects on the itinerary are more beneficial to consumers.

We utilize our methodology for measuring quality-adjusted prices to evaluate network effects empirically. We find that taking into account the impact of network effects on consumer welfare reverses some important elements of conventional wisdom regarding the airline industry.² Our findings overturn the conventional wisdom that increased airline concentration brought about by mergers or acquisitions necessarily creates anti-competitive output restrictions or consumer harm. We focus attention on two specific applications:

 We reexamine the traditional measures of higher nominal prices for flights out of hubs, the so-called "hub premia." We show that the literature's conventional finding of a pattern of higher prices at hub airports is overturned

² The concepts of quality-adjusted prices and consumer welfare are closely related. Indeed if there were only one product in the market, the quality adjusted price (Equation 5) would be identical to the consumer surplus (Equation A1). See generally Willig (1978).

when one considers the quality benefits that are associated with flights that depart from hubs. If anything, quality-adjusted prices tend to be lower at hub airports.³

We examine the implications of network effects for the prospective evaluation of mergers between competing carriers.⁴ Focusing on the recent Delta-Northwest merger, we show that even on the non-stop overlap routes, where the traditional literature predicts the greatest increases in nominal fares, the quality changes flowing from the larger networks engendered by the merger predict reduced quality-adjusted fares and increased consumer welfare. This conclusion is also consistent with large quality improvements predicted from the merger on connecting overlap routes on which there would have been no predicted significant effects on nominal fares.

In today's dynamic air-traffic world, researchers, regulators, and policy-makers share responsibility for evaluating airline industry transactions that would lead one airline (or one alliance of airlines) to serve a larger share of the traffic at a particular airport or on a particular route. Such transactions include mergers, slot exchanges, changes in alliance structure or immunity status, and joint ventures. We conclude that an appropriate evaluation of any such transaction from the perspective of consumer welfare must incorporate "network effects" in the airline industry – such as the facts that an airline with a larger share of traffic at one airport can offer a more complete network of service to more destinations, and that an airline with a larger share of service on one route can offer a more convenient schedule of flights. Unfortunately, discussions of airline policy often dwell narrowly on potential price increases without considering the benefits that larger airline networks provide to consumers. Such discussions also fail to recognize that any associated price increases may largely reflect the improved quality of airline service created by an expanded network. For this reason, it is critical that evaluations of airline industry transactions and policies explicitly recognize and account for the quality advantages to consumers of large airline networks.

³ To be clear, this paper does not offer an analysis of the sources of possible hub market power, which may be accounted for by the specifics of the current regulatory environment, including elements that encourage entry.

⁴ This paper focuses on presenting methods for evaluating prospective airline mergers. Evaluating actual mergers on a retrospective basis is beyond the scope of this paper. Mehta and Miller (2012) and Luo (2013) have both evaluated the impact on fares of the Delta-Northwest merger and concluded that it led to no substantial increases in nominal fares.

2 Network Effects and Hub Market Power

That the structure of the domestic airline industry in the US has generated substantial network effects has been well understood for decades, based in part on the earlier insights of Levine (1987, 1992), and running through a number of thoughtful analyses by Borenstein (1989, 2005, 2013) and a host of others. This has, in turn, led to a continuing debate as to the sources of hub market power and its magnitude and implications for consumer welfare.⁵ Many authors such as Borenstein (1989) and Lederman (2008) evaluate hub market power in the context of reduced-form regressions in which price is regressed on a hub dummy (or a proxy for "hubness" such as airport concentration) and a variety of relevant covariates.⁶ Berry (1990) uses the number of destinations served from the origin and destination of each route as proxies for hubness and includes these proxies in both the demand and cost functions. Berry and Jia (2010) take a slightly different approach, including a hub dummy in their marginal cost equation.

Even this early literature raises questions about the source of the market power at hub airports and whether it harms or benefits consumers on net. For example, Borenstein (1989) notes that hub carriers are able to charge higher fares without creating an "umbrella" effect, whereby competing carriers at the same airport are also able to charge higher prices. This finding suggests that one explanation for higher nominal fares charged by hub carriers may be that they offer welfare-enhancing high-quality services that both benefit air travelers and impose a competitive constraint on rival carriers.⁷

In this paper, we break from much of the prior literature by, in effect, accounting for the impact of hubs through the demand equation. Using a structural analysis of the network characteristics that consumers value, we are not only able to evaluate the nominal market power that hubs generate, but also to measure

⁵ The most recent estimates indicate that even the nominal hub premia have been declining in recent years.

⁶ Numerous authors have investigated the fare effects of airline hubs, including Borenstein (1989, 2005, 2013), Berry (1990), Brueckner et al. (1992), Evans and Kessides (1993), Lee and Luengo Prado (2005), Lederman (2007, 2008), Borenstein and Rose (2013), Berry and Jia (2010), and Ciliberto and Williams (2010).

⁷ Indeed, Borenstein (1989) notes: "Though the link between airport dominance and high fares seems clear, a welfare analysis of increased airport concentration must also include the benefits that may accrue from hub operations. [note omitted] ... Greater flight frequency, easier connections, and more nonstop flights may also be associated with these route systems. In this regard, the estimated impact of these quality factors on price, presented in the previous section, should not be interpreted as hedonic prices. [note omitted] These possible benefits of mergers or other increases in airport shares should be weighed against the higher prices that seem likely to result."

the hub-generated consumer benefits.⁸ Our analysis focuses on the relationship between hub fares and network effects. We begin with a description of the underlying demand model. This is followed by the empirical analyses that generate the core results relating to consumer benefits.

We note that a complete analysis of the sources of nominal hub market power is beyond the scope of this paper. Here, we neither assess the magnitude of relevant price-cost margins over time nor do we attempt to evaluate all of the market- and regulatory-based sources of any existing hub market power (see, e.g., Lederman (2007 and 2008) for an evaluation of the impact of frequent flyer programs and Ciliberto and Williams (2010) for an analysis of the role of access to airport facilities).

3 The Demand Model

Discrete choice demand models – that define products in terms of a set of characteristics (for example, price and quality) and model demand for each product attribute – are a natural way to analyze demand for airline products, as customers typically pick from a menu of multiple products that each offer differentiated features. The economics literature on airlines (for example, Peters 2006; Berry and Jia 2010) as well as the airlines' own internal planning models (for example, Coldren et al. 2003) have typically modeled demand using discrete choice (logit-based) models. However, standard logit models impose confining restrictions on substitution patterns across products.⁹ Most of the literature assumes that markets are defined as either city-pairs or airport-pairs and does not allow for flexible substitution patterns across airports within a geographic area. This assumption artificially restricts substitution patterns across airports in the same city. One exception is Peters (2006), which estimates a generalized extreme value (GEV) model that allows for imperfect substitution patterns across airports.¹⁰

Following the traditions just described, our empirical evidence is derived from an econometric analysis of the consumer demand for specific itineraries

⁸ Our approach is closest to Berry (1990).

⁹ Most papers estimate either a nested logit model with the outside good in one nest and all inside goods in another nest or a simple logit model with no outside good. For a general description of the restrictive substitution patterns implicit in the logit functional form, see Berry (1994). **10** Peters (2006) points to only one other working paper that allows for imperfect substitution across airports.

on specific airlines, with which we estimate the value that passengers place on airline and itinerary characteristics, including the size of the airline's network at the relevant airports and the convenience of its schedule on the relevant routes.

The model is formulated as follows. On route *r*, a consumer *i* may choose from *F* flights corresponding to *J* itineraries. Each itinerary *j* offers F_j flights. The utility of consumer *i* from choosing flight *f* (belonging to itinerary *j*) is given by:

$$u_{iif} = \delta_{ii} + \varepsilon_{iif} \tag{1}$$

where $\delta_j = \alpha p_j + X_j \beta + \xi_j$, p_j is the price of itinerary j, X_j is a vector of characteristics for itinerary j, ξ_j captures unobserved characteristics of itinerary j, α and β are a vector of parameters (where $\alpha < 0$) and the term ε_{ijf} captures the idiosyncratic preferences of consumer i for flight f on itinerary j.¹¹

Logit models come in a variety of different "flavors," corresponding to different assumptions about the distribution of ε .¹² In our model, we allow substitution patterns to depend upon the airport pair.^{13,14} With this assumption, the GEV model is equivalent to a multi-level nested logit model, where the outside good forms one nest and products operating on different airport pairs form separate nests within the nest of inside goods.

12 The GEV model proposed by Peters (2006) allows substitution patterns to depend on two product characteristics: i) whether the product was non-stop or connecting; and ii) the origin and destination airports. However, the modeling of flexible substitution patterns across multiple product dimensions substantially increases the computational burden. In particular, with multiple overlapping nests, the market shares cannot be inverted analytically so the computation requires a contraction mapping algorithm. See Berry (1994).

13 Formally, using the notation of Peters' (2006), we assume that $\rho_{D} = \rho_{0}$. As a result, *a*=1 and the market share equation in the appendix collapses to the equation shown below.

14 In our model, consumer heterogeneity enters only through the error term. Armantier and Richard (2008) and Berry and Jia (2010) are two notable papers that estimate more flexible functional forms that allow for greater consumer heterogeneity. Those papers suggest that price sensitivity is negatively correlated with the strength of preferences for non-price (quality) attributes. As a result, welfare estimates based on averages across all passengers such as those presented here are likely to understate the magnitude of impact from improvements in quality.

¹¹ For simplicity, we suppress the *f* subscript since we only observe itinerary-level data and not flight-level data. For a similar model, see Ackerberg and Rysman (2005).

The model allows a consumer's preferences for flights within the same itinerary to be correlated. This specification allows each consumer to realize a draw from the logit error distribution for each flight in addition to each itinerary. The intuition is that each consumer has idiosyncratic preferences over each flight, perhaps because actual and preferred departure times vary. Note that this means that consumers only receive a different number of draws from the error distribution for flights in the event of a merger if the merger results in addition (or subtraction) of flights. If a merger were to simply "smush" the networks of the merging carriers, then consumers would receive an identical number of draws from the error distribution for flights.

We decompose the error term as follows:

$$\varepsilon_{ij} = \phi_{iG} + \rho_0 \mu_{ig} + \rho_A \nu_{ij}, \tag{2}$$

where ϕ , μ , and ν are independently drawn from a unique distribution.¹⁵ For each individual *i*, all itineraries share the same taste shock ϕ , all itineraries within each airport pair (denoted by *g*) share the same taste shock μ , and each itinerary receives an idiosyncratic taste shock ν . The parameter ρ_0 lies in the interval (0, 1] and captures the correlation of the error terms amongst the inside goods. As ρ_0 approaches zero, there is no substitution between the inside and outside goods. The parameter ρ_A lies in the interval $(0, \rho_0]$ and captures the correlation of the error terms amongst the correlation of the error terms amongst the inside goods. The parameter ρ_A lies in the interval $(0, \rho_0]$ and captures the correlation of the error terms amongst the itineraries in the same airport pair *g*. As ρ_A approaches zero, there is no substitution across airport pairs within the same city pair. When ρ_A equals ρ_0 , the model corresponds to a nested logit with a single inside-good nest and the outside good in a separate nest. When both ρ_A and ρ_0 equal one, the model corresponds to a simple logit model (that is, a logit model with no nests).

In this model, share is given by:¹⁶

$$s_{j} = \frac{\exp\left(\frac{\delta_{j}}{\rho_{A}}\right)}{\sum_{j'} \exp\left(\frac{\delta_{j'}}{\rho_{A}}\right)} \times \frac{\left[\sum_{j'} \exp\left(\frac{\delta_{j'}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}}{\sum_{A} \left[\sum_{j'} \exp\left(\frac{\delta_{j'}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}} \times \frac{\left[\sum_{A} \left[\sum_{j'} \exp\left(\frac{\delta_{j'}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}}{1 + \left[\sum_{A} \left[\sum_{j'} \exp\left(\frac{\delta_{j'}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}}$$
(3)
$$\equiv s_{j|A_{i}} \times s_{A_{i}|A} \times s_{A}$$

By normalizing $\delta_{_0}$ to be equal to zero, $^{\scriptscriptstyle 17}$ the equation above can be manipulated to show: $^{\scriptscriptstyle 18}$

16 Own-price elasticity with respect to price can be derived from the share equation as:

$$\varepsilon_{j} = \frac{\alpha}{\rho_{A}} p_{j} \left(1 - \left(1 - \frac{\rho_{A}}{\rho_{0}} \right) \mathbf{s}_{j|g_{j}} - \frac{\rho_{A}}{\rho_{0}} (1 - \rho_{0}) \mathbf{s}_{j|g_{j}} \times \mathbf{s}_{g_{j}|G} - \rho_{A} \mathbf{s}_{j} \right).$$

17 This is a standard assumption in the discrete choice literature; see Berry (1994).

18 We use linear instrumental variable methods to minimize the difference between observed and predicted shares. We compute observed shares as the ratio of the number of passengers choosing a given product in a quarter to the geometric mean of the endpoint MSA-level populations.

¹⁵ Formally, we assume that the idiosyncratic error term, ε_{ijt} , is distributed Type I Extreme Value. For further details, see Cardell (1997).

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$$\ln\left(\frac{s_{j}}{s_{0}}\right) = \delta_{j} + 1(1 - \rho_{A}) \ln(s_{j|g_{j}}) + (1 - \rho_{0}) \ln(s_{g_{j}|G})$$
(4)

Intuitively, the model identifies the parameter ρ_A from changes in the group-level share as the number of products changes. In the extreme case in which ρ_A equals zero, the group-level share does not change as the number of products within the group changes.

We use data on fares and quantities for itineraries from the first quarter of 2009 through the fourth quarter of 2010, obtained from the Department of Transportation's Origin and Destination Survey (DB1B), a 10% random sample of tickets from reporting carriers in the US. We also use scheduling data from the Official Airline Guide (OAG) for the second Thursday of the second month of each quarter to determine nonstop itineraries and to construct plausible connecting itineraries.¹⁹ To build connecting itineraries, we apply the following rules: i) all segments must be flown by the same operating carrier or carriers in a codeshare alliance;²⁰ ii) connection times must be between 45 min and 4 h; iii) for each segment and routing, we keep the minimum connection time; iv) we eliminate routings that start and end in the same location; and v) we eliminate circuitous routings.²¹

We define route *r* as a directional origin and destination city pair, for example, SF2-CH2-SF2 is a different route from CH2-SF2-CH2.²² We define product *j* by an itinerary (ordered sequence of airports, for example, SF0-STL-ORD-STL-SF0), ticketing and operating carrier(s), and time period.²³

¹⁹ Our approach is similar to that used by Berry and Jia (2010).

²⁰ We assign regional operating carriers to their mainline parent on a route-by-route basis using OAG data.

²¹ For example, for distances <350 miles, circuity must be <4.15, while for distances >2000 miles, circuity must be <1.45.

²² We define the following cities with multiple airports: CH2 (Chicago O'Hare (ORD) and Chicago Midway (MDW)), CL2 (Cleveland Hopkins International (CLE) and Akron Canton (CAK)), DA2 (Dallas/Ft. Worth (DFW) and Dallas Love Field (DAL)), HO2 (George Bush Intercontinental (IAH) and Hobby (HOU)), LA3 (Los Angeles International (LAX), Burbank (BUR), and Long Beach (LGB)), MI2 (Miami International (MIA) and Ft. Lauderdale (FLL)), NY3 (LaGuardia (LGA), Newark (EWR), and John F. Kennedy (JFK)), SF2 (San Francisco (SFO) and Oakland (OAK)), DC3 (Reagan National (DCA), Washington Dulles (IAD), and Baltimore-Washington (BWI)), and TA2 (Tampa International (TPA) and St. Petersburg/Clearwater International (PIE)).

²³ Note that because we define a product by the ticketing carrier, we treat code-shared flights as separate products. For example, suppose NW and DL codeshare on a particular route that is operated by DL. This would show up in the data as two sets of observations, one for a flight operated by DL and ticketed by NW and a second for a flight operated by NW and ticketed by NW. In general, the physical characteristics of the two flights will be identical, but ticketing characteristics (*for example*, price and a fixed effect for ticketing carrier) will be different.

To create the estimation sample, we apply a number of screens to the data.²⁴ First, we keep round-trip tickets with at most four segments. Second, we eliminate itineraries with non-credible or bulk fares or round-trip fares below \$50. Third, we eliminate itineraries that include a non-US marketing or operating carrier segment.²⁵ Fourth, we eliminate itineraries with multiple marketing carriers. Fifth, we eliminate products with fewer than 30 passengers per quarter.²⁶ We separate round-trip itineraries into directional segments and divide the round-trip fare by two.²⁷ Finally, we focus on routes with end-point population >500,000.²⁸

We model demand as a function of fare, scheduling convenience, network quality, non-stop status, distance, average connection time, codeshare status, marketing carrier fixed effects, year-quarter fixed effects, and route fixed effects.²⁹ We also control for the flight frequency (in logs) of each itinerary. In the context of estimating the effects of mergers, it is important to control for flight frequency in order to avoid a mistaken conclusion that simply consolidating the number of frequencies on a single carrier (conditional on the overall convenience of the schedule) generates a consumer benefit. As described below, a merger generates consumer benefits to the extent that it increases traffic *conditional* on frequency (e.g., by generating a more convenient schedule) or actually increases the number

²⁴ These screens are standard in the literature. See, for example, Borenstein (1989); Peters (2006).

²⁵ We also eliminate routes that do not have both endpoints in the continental US.

²⁶ Peters (2006) applies a similar screen. The reason for doing so is that the logit model assumes that choice probabilities (shares) are integrated over multiple individuals, each with her own *i.i.d.* logit error term. Without sufficient product-level observations, it is not possible to differentiate between the product-level unobservable quality and the individual idiosyncratic error term. For example, suppose we observe a product with just one passenger in the quarter. Further, suppose that the reported fare for this product is twice the average fare on the route, while other observable characteristics are equal to the average values on the route. With just a single individual observation, the model cannot determine whether the individual chose to fly on the flight – despite its high price – because the product itself has a high level of unobserved quality or because the individual has an idiosyncratic preference for the product and is therefore willing to pay a high fare. With multiple observations, the logit model integrates over the idiosyncratic error term in order to identify the unobserved quality.

²⁷ We estimate the model using the outbound segment of the round-trip itinerary.

²⁸ Our results are substantively similar when we examine all routes.

²⁹ Our "discrete choice" model of demand similar to that used by many economists and operations research specialists who have studied airline demand. See, for example, Morrison et al. (1989), Berry (1990), Coldren et al. (2003), Peters (2006), Armantier and Richard (2008), and Berry and Jia (2010). The route fixed effects in the model generate a route-specific constant term. This route-specific constant term captures the aggregate level of flying (relative to the outside good) on a route-by-route basis. We assume that the quality of the outside good stays constant over the sample period.

of frequencies (e.g., if the merged carrier would be likely to add frequencies to the schedule). 30

We focus our analysis on round-trip flights. We measure quality variables based on the outbound leg of the trip. For the airport breadth variables, it is intuitive that consumers would care most about the quality of the network at the point of sale. While the convenience of the schedule will vary between the outbound and return legs, we have found that when we include an additional variable reflecting convenience on the return leg, the coefficient on that variable is not statistically significant while the coefficients on the other variables are largely unchanged.

Our measures of the quality of each airline's network on a given route and at a given airport are as follows:

- Route Level "Inconvenience": This variable measures the average time it takes a customer wishing to go from point A to point B to make the journey on the airline in question, relative to the desired time of departure. In particular, for each hour of the day, it answers the question: "what is the soonest a passenger at point A could make it to point B on the airline." This variable accounts both for the wait until the next departure and the time-in-transit (influenced by any required connections). To establish a single measure for the airline on the route, we compute a weighted average of these hourly figures, with weights taken from Delta Airlines' data on the distribution of consumers' preferred departure flight times during the day.
- Airport-Level Network Breadth: We use two variables to measure network breadth – the number of destinations that can be reached via non-stop service and via one-stop service from the origin airport on the airline in question. These variables allow for the possibility that consumers prefer airlines that offer a wide breadth of service from the airport (perhaps due to higher-quality loyalty programs or familiarity with particular terminals or airline operations).

The model relies on variation in product characteristics and shares to estimate the relative importance of each product characteristic in explaining demand. This allows us to compute the dollar value that consumers place on various flight, itinerary, and network characteristics. In essence, we find the extra market share that a carrier gains by adding a particular characteristic to an itinerary, and compare that to the share gain associated with a price reduction: If adding a given characteristic attracts as much share on average as a \$50 price cut, then that characteristic is measured to be worth \$50.³¹ In this way, we calculate the value to consumers

³⁰ See note 11 for a description of our econometric treatment of frequency.

³¹ For the development of this methodology, see Willig (1978).

that is generated by network effects via more convenient schedules on relevant routes and by more breadth of service at relevant airports. As the methodology expresses the value of changing quality characteristics in terms of dollars per itinerary flown, these changes can also be compared to changes in fares to assess the net impact on quality-adjusted fares and on consumer welfare.

Table 1 reports summary statistics for the data in our sample weighted by passengers. We treat fares, frequency, convenience, and the nested logit terms as endogenous and instrument for them. We treat all network variables as exogenous, since they are based on the structure of the network and are not driven by prices of particular flights. We create several sets of instrumental variables for the endogenous variables listed above. Table 2 summarizes these instruments.

Our first set of instruments follows Peters (2006) and relies on the fact that a number of connecting itineraries may make use of any given segment. Segments that are used by many itineraries are more likely to be flown more frequently and to lead to more convenient schedules. Our instruments consist of the geometric mean of the number of itineraries making use of each segment at the carrier-itinerary level (the level of aggregation at which we measure frequency) and the carrier-route level (the level of aggregation at which we measure convenience). Similarly, itineraries on more populous routes are likely to lead to greater demand at the segment level. We construct analogous instruments at the carrier-itinerary and carrier-route level based on the geometric mean of the endpoint populations of the itineraries making use of each segment. Greater flow traffic (as captures by the number and size of routes that flow through a particular segment) is likely to

Variable	Mean	Min	Max
Year	2010	2009	2010
Average Fare (\$ one-way)	171	26	2109
Frequency	5	0	26
Inconvenience (h)	7.3	0.7	112.3
Network Size (# nonstop connections)	31	1	148
Network Size (# one-stop connections)	78	0	218
Nonstop	0.71	0.00	1.00
Distance (miles 000 s)	1.1	0.0	3.8
Average connection time (min)	28	0	240
Codeshare	0.00	0.00	1.00
Market Size (millions)	4.0	0.0	15.7

Table 1 Summary Statistics.

Source: Authors' calculations using data from the Department of Transportation's Origin and Destination Survey (DB1B) and the Official Airline Guide (OAG); 1Q2009–4Q2010. Note: All statistics weighted by passengers.

Instrument	Description
Instrument 1a	Geometric mean of the number of itineraries making use of each segment at the carrier-itinerary level
Instrument 2a	Geometric mean of the endpoint populations of the itineraries making use of each segment at the carrier-itinerary level
Instrument 1b	Geometric mean of the number of itineraries making use of each segment at the carrier-route level
Instrument 2b	Geometric mean of the endpoint populations of the itineraries making use of each segment at the carrier-route level
Instrument 3	Number of products offered by rivals on route
Instrument 4	Number of rival carriers competing on route
Instrument 5	Mean of non-stop flights for rival carriers
Instrument 6	Mean of circuity for rival carriers
Instrument 7	Mean of instrument 1a for rival carriers
Instrument 8	Mean of instrument 2a for rival carriers
Instrument 9	Mean of airport-level non-stop market breadth for rival carriers
Instrument 10	Mean of airport-level conecting market breadth for rival carriers
Instrument 11	Mean of city-level non-stop market breadth for rival carriers
Instrument 12	Mean of city-level conecting market breadth for rival carriers
Instrument 13	Airport-level network breadth at destination
Instrument 14	City-level network breadth at destination
Instrument 15	Dummy indicating if destination is a hub for carrier
Instrument 16	Dummy indicating if intermediate airport is a hub for carrier
Fuel	Domestic fuel cost per gallon
Fuel imes carrier	Interaction of fuel price and carrier fixed effects
Fuel × distance	Interaction of fuel price and itinerary distance

 Table 2
 Description of Instruments.

be correlated with both quality (because more flow traffic causes a carrier to add frequencies and capacity) and price (because it shifts the demand curve for a seat outward).

We construct a second set of instruments based on the principles introduced in Berry (1994), Berry et al. (1995), and Bresnahan et al. (1997). These instruments measure the number and quality of competing carriers on a route.³² These

³² In particular, we count the number of products offered by competing carriers on a route, the percent of products offered by competing carriers on a route that are non-stop, passengerweighted mean circuity for products offered by competing carriers on a route, the mean of the number of itineraries making use of segments for competing carriers on a route, the mean of the endpoint populations for those itineraries for competing carriers on the route, the mean of non-stop network quality for products offered by competing carriers on a route, and the mean of connecting network quality for products offered by competing carriers on a route.

instruments are motivated by an implicit model of supply in which the price of any given product is motivated by the competitive conditions in which it is offered (with greater competition in the form of more or higher quality competitors leads to lower prices, all else equal). We use a third set of instruments that account for itineraries that fly to or through hubs. Berry and Jia (2010) argue that flying to or through a hub could affect the marginal costs of a flight because of economies of scale as well as congestion costs.³³ Finally, we include fuel costs as an instrument. To allow for differential effects of higher fuel prices on different carriers due to different equipment and other differences, we interact fuel costs with carrier indicator variables as well as with distance. In the estimation, we use all of these instruments jointly.³⁴ Our results are robust to a variety of instrument choices within the set of instruments just described.

4 Demand Estimation

Table 3 shows the estimated parameters from the demand model.³⁵ The results are intuitive and consistent with the previous literature. For example, previous literature has found average product-level own-price elasticities of demand of roughly -2; our comparable estimate ranges from -2.0 to -3.5.³⁶ Also consistent with the literature, our results indicate that consumers dislike more circuitous routings and longer connection times, and dislike codeshare flights relative to online itineraries.

Across the entire sample, the average (one-way) fare is approximately \$171. Our estimate of the value that consumers place on non-stop travel is fairly consistent with other findings in the literature. For example, Berry and Jia (2010) find that leisure-type travelers would pay approximately \$56 on average to avoid a connection (while holding all other flight characteristics constant), while business-type travelers would pay approximately \$510 on average to reduce

³³ By focusing on itineraries that fly to or through hubs, we eliminate the demand effects associated with flying from a hub.

³⁴ A variety of test statistics reject the null hypothesis that the instruments are weak. Specifically, the Angrist-Pischke (AP) first-stage χ^2 and F statistics reject the null hypothesis that each endogenous regressor is under- or weakly identified.

³⁵ Table 4 reports the results from the first stage regressions of the right-hand-side endogenous variables on exogenous instruments.

³⁶ Berry and Jia (2010) estimated an average own-price elasticity of –2.1 using data from 2006 and a different functional form. They estimate an average own-price elasticity of –2.9 when aggregating across certain airports within cities, a methodological choice similar to ours.

	Coefficient	Std. Err	Valuation	Std. Err
ρ_{A}	0.1014	0.0082		
$ ho_{0}$	0.2753	0.0115		
ln(Frequency)	0.1191	0.0081		
Average Fare (\$ one-way)	-0.0037	0.0001	-1.00	0.00
ln(Inconvenience) (h)	-0.0717	0.0098	-19.48	2.57
Network Size (# nonstop connections)	0.0018	0.0001	0.48	0.02
Network Size (# one-stop connections)	0.0001	0	0.02	0.01
Non-stop	0.2880	0.0224	78.29	5.97
Distance (miles 000 s)	-0.0678	0.0197	-18.43	5.34
Distance-squared	-0.0079	0.0026	-2.14	0.71
Average connection time (min)	-0.0003	0	-0.08	0.01
Codeshare	-0.0373	0.0097	-10.14	2.63

 Table 3
 Demand Model Parameter Estimates.

Source: Authors' calculations using data from the Department of Transportation's Origin and Destination Survey (DB1B) and the Official Airline Guide (OAG); 1Q2009-4Q2010. Note: Average fare is the carrier-route fare reported in the DB1B database. Frequency is the daily frequency of each itinerary. Inconvenience is the average minimum time from preferred departure time to actual arrival time at the destination for a given carrier-route combination, where the average is weighted by departure time preferences. The direct network destination variable measures the number of cities served on a non-stop basis by the given carrier from the given airport. The connecting network destination variable measures the number of incremental cities served on a one-stop basis (but not on a non-stop basis) by the given carrier from the given airport. Non-stop is a dummy variable indicating whether the itinerary is non-stop (versus connecting). Distance and distance-squared are measures of the distance flown on the itinerary. Average connection time is the average time between connecting flights, assumed to be zero for non-stop travel. Codeshare indicates whether the itinerary is a codeshare (versus online; interline itineraries are excluded). The terms ρ_{A} and ρ_{a} are nested logit terms that govern substitution patterns between adjacent airports within cities and substitution with the outside good, respectively. Valuation for a given parameter is calculated by dividing its coefficient by the fare coefficient and reversing the sign.

the number of connections on a round-trip by one. They also find that business type travelers account for approximately 49% of total passengers, suggesting an average value per round-trip of \$278. We find that the average across business and leisure travelers is approximately \$78 per leg (or \$156 per round-trip). These results are not exactly comparable because non-stop and connecting flights will have different values for other variables such as connection time (non-stops will have zero connection time, while connecting itineraries will have at least 45 min of connection time), distance (non-stop flights will travel shorter distances), and convenience (non-stop flights will be associated with more convenient schedules all else equal) and therefore the value of the non-stop coefficient will depend on

Variables	(1) اn(share _{۱۸})	(2) ln(share , , ,	(3) Fare	(4) ln(Frequency)	(5) ln(Inconvenience)
Instrument 1a	-0.002**		-0.004	-0**	-0**
	(7.99E-05)	(3.99E-05)	(4.10E-03)	(5.06E-05)	(2.30E-05)
Instrument 2a	-0.006	0.004	1.987**	0.016**	-0.017**
	(4.85E-03)	(2.42E-03)	(2.49E-01)	(3.07E-03)	(1.40E-03)
Instrument 1b	0.009**	-0.001**	0.153**	0.010**	-0**
	(5.77E-05)	(2.89E-05)	(2.96E-03)	(3.66E-05)	(1.66E-05)
Instrument 2b	0.122**	0.038**	2.132**	0.111**	-0.021**
	(2.91E-03)	(1.45E-03)	(1.49E-01)	(1.84E-03)	(8.38E-04)
Instrument 3	0.012**	-0.001**	0.197**	0.010**	0.006**
	(4.31E-04)	(2.16E-04)	(2.21E-02)	(2.73E-04)	(1.24E-04)
Instrument 4	-0.061**	0.005**	-1.047**	-0.014**	-0.008**
	(2.64E-03)	(1.32E-03)	(1.35E-01)	(1.67E-03)	(7.59E-04)
Instrument 5	0.461**	-0.137**	-19.586**	0.193**	-0.012**
	(1.38E-02)	(6.88E-03)	(7.06E-01)	(8.72E-03)	(3.96E-03)
Instrument 6	0.177**	-0.005	2.405	0.155**	-0.309**
	(2.54E-02)	(1.27E-02)	(1.30E+00)	(1.61E-02)	(7.31E-03)
Instrument 7	0.001**	-0**	-0.087**	-0	0.001**
	(1.30E-04)	(6.51E-05)	(6.68E-03)	(8.25E-05)	(3.75E-05)
Instrument 8	-0.048**	0.028**	-0.979**	0.004	-0
	(5.15E-03)	(2.57E-03)	(2.64E-01)	(3.26E-03)	(1.48E-03)
Instrument 9	0.014**	-0.003**	0.218**	0.005**	-0.001**
	(1.20E-03)	(6.00E-04)	(6.16E-02)	(7.61E-04)	(3.46E-04)
Instrument 10	-0.012**	-0.011**	-0.312**	-0.019**	0.005**
	(1.21E-03)	(6.05E-04)	(6.21E-02)	(7.67E-04)	(3.49E-04)
Instrument 11	-0.013**	0.004**	-0.122*	-0.002**	0.001*
	(1.10E-03)	(5.50E-04)	(5.64E-02)	(6.97E-04)	(3.17E-04)
Instrument 12	0.011**	0.012**	0.329**	0.019**	-0.006**
	(1.19E-03)	(5.96E-04)	(6.11E-02)	(7.55E-04)	(3.43E-04)
Instrument 13	-0.001**	0.003**	0.255**	0.005**	-0.005**
	(2.65E-04)	(1.33E-04)	(1.36E-02)	(1.68E-04)	(7.64E-05)
Instrument 14	-0.001**	-0.002**	-0.079**	-0.003**	0.002**
	(2.33E-04)	(1.16E-04)	(1.19E-02)	(1.47E-04)	(6.70E-05)
Instrument 15	0.141**	-0.141**	5.207**	0.025**	0.083**
	(1.25E-02)	(6.24E-03)	(6.39E-01)	(7.90E-03)	(3.59E-03)
Instrument 16	0.081**	0.081**	-6.746**	0.112**	0.038**
	(7.60E-03)	(3.80E-03)	(3.90E-01)	(4.81E-03)	(2.19E-03)
Fuel imes dist	0.014	0.003	15.259**	0.035**	-0.040**
	(1.05E-02)	(5.27E-03)	(5.40E-01)	(6.67E-03)	(3.03E-03)
# Destinations	0.004**	0**	0.498**	0.003**	-0.004**
(direct)	(1.39E-04)	(6.93E-05)	(7.10E-03)	(8.78E-05)	(3.99E-05)
# Destinations	0	0.001**	0.038**	0.001**	-0.002**
(connecting)	(9.75E-05)	(4.87E-05)	(5.00E-03)	(6.18E-05)	(2.81E-05)

 Table 4
 First-Stage Regression Results.

Variables	(1)	(2)	(3)	(4)	(5)
	ln(share _{jAj})	ln(share _{AjA})	Fare	ln(Frequency)	ln(Inconvenience)
Non-stop	2.878**	0.052**	-16.531**	0.154**	0.060**
	(9.54E-03)	(4.77E-03)	(4.89E-01)	(6.04E-03)	(2.75E-03)
Distance (Miles	-2.432**	-0.064**	-23.816**	-0.698**	0.445**
1000 s)	(3.23E-02)	(1.61E-02)	(1.65E+00)	(2.04E-02)	(9.29E-03)
Distance-squared	0.209**	0.023**	-2.368**	0.143**	-0.068**
	(6.30E-03)	(3.15E-03)	(3.23E-01)	(3.99E-03)	(1.82E-03)
Average	-0.003**	-0**	-0.038**	-0.001**	0.001**
Connection Time	(4.88E-05)	(2.44E-05)	(2.50E-03)	(3.09E-05)	(1.41E-05)
Codeshare	-1.082**	-0.026*	-3.416**	-0.509**	0.116**
	(2.17E-02)	(1.08E-02)	(1.11E+00)	(1.37E-02)	(6.24E-03)
Constant	-1.401**	-0.352**	269.670**	0.248	2.294**
	(2.28E-01)	(1.14E-01)	(1.17E+01)	(1.44E-01)	(6.57E-02)
Observations	346,536	346,536	346,536	346,536	346,536
R ²	0.602	0.531	0.183	0.380	0.448
Number of	7026	7026	7026	7026	7026
Routes					

(Table 4 Continued)

Source: Authors' calculations using data from the Department of Transportation's Origin and Destination Survey (DB1B) and the Official Airline Guide (OAG); 1Q2009–4Q2010. Note: Carrier, carrier × fuel, airport, and route fixed effects are included in the regression, but not reported in the table. Standard errors in parentheses. ** p<0.01, * p<0.05.

what else is controlled for. Nonetheless, our finding that passengers place a high value on non-stop travel is consistent with the findings in the literature.

Earlier papers have also estimated the utility (measured in dollars) of airline characteristics. For example, Morrison et al. (1989) estimated a multinomial logit model for air travel demand. Using a very similar methodology, they found that passengers had a high value of travel time (approximately \$0.57 per minute or \$35 per hour (in 1983 dollars)) and an even higher value of transfer time for connecting flights (approximately \$1.23 per minute or nearly \$75 per hour). In other words, they found that passengers would pay an extra \$35 to reduce travel time by 1 h and an extra \$75 if that reduction in travel time came via a reduction in transfer time. Similarly, they found that the value of a hub is more than \$25 per round-trip.³⁷

³⁷ While more recent papers such as Peters (2006), Armantier and Richard (2008), and Berry and Jia (2010) do not focus on valuing the characteristics of air travel, such values can be derived from the parameters of the logit models that they estimate. For example, Armantier and Richard (2008) find evidence on preferences for travel time that are consistent with the predictions of Morrison and Winston (1995).

Our empirical analysis also demonstrates that consumers value the services from higher quality networks on particular routes and at particular airports. For example, the estimates associated with the "*Inconvenience*" variable indicate that reducing the time required to get to a destination (relative to the consumer's desired departure time) from, for example, 6–3 h is worth as much to consumers on average as a \$13.51 reduction in the fare.³⁸ We also find that a consumer's increased preference for an airline serving 25 additional destinations (with direct service) at the origin point of sale is equivalent to a \$12.03 reduction in fare on a per-leg basis or (approximately \$24 for round-trip travel).

We note that, although the model yields estimates of the value of particular flight characteristics (for example, non-stop vs. connecting), one should not take individual estimates as indicators of which particular flights do or do not compete against one another. To the contrary, the results explicitly demonstrate that the value consumers place on a given flight itinerary depends on the combination of its price, multiple flight characteristics, and the carrier's overall network of service on the route and at the airport. So, for example, although connecting flights may be, on average, less appealing to customers than non-stop flights, consumer choices will also reflect the convenience of flight times, the carriers' overall networks of service, the relative price, and other factors that determine the relative attractiveness of the various alternative itineraries on a given route.

5 Implications of Quality Adjustments for Welfare Effects

We use the estimates of consumer preferences for quality to examine the implications for several public policy issues related to airlines.

³⁸ To see this, note that "*inconvenience*" enters the utility function in logs. The value of a change in inconvenience from 6 to 3 h is equivalent to $19.48 \times (\ln(6) - \ln(3)) = 13.51$, where 19.48 is the value coefficient reported in Table 3. We have also experimented with allowing "*inconvenience*" to enter linearly and find similar results.

The average "*inconvenience*" in our sample is approximately 7.3 h. Recall that our measure of convenience incorporates both time in transit as well as the extent to which the schedule matches desired departure times. For example, suppose a passenger desires to depart at noon on a flight that takes 3 h to travel from the origin to the destination. If a carrier that previously only offered a flight that departs at 3 PM adds a second flight that departs at noon, this would be equivalent to reducing the inconvenience of the schedule from 6 to 3 h. We separately control for the duration of the individual flight timerary with distance and connection time variables.

5.1 Hub Premia

Several studies published by government (or government-affiliated) agencies, including the Transportation Research Board (TRB), the Government Accounting Office (GAO) and the Department of Transportation (DOT), have considered "hub premia," the differences between average fares to and from hub airports and other airports (controlling for flight lengths), as "one important indicator of the possible exercise of market power."³⁹ While acknowledging multiple potential explanations for the existence of hub premia, including higher quality of service at hubs, these studies generally focus on market power as the primary cause of hub premia.⁴⁰

The economics literature, including Borenstein (1989, 2005, 2013), Evans and Kessides (1993), Lee and Luengo-Prado (2005), Lederman (2007, 2008), Borenstein and Rose (2013), and Ciliberto and Williams (2010), has explored the reasons for the existence of hub premia. The literature has traditionally concluded that flights out of hub airports, which are typically served primarily by one or two large airlines, are associated with higher nominal fares (that is, there are positive hub premia). However, the literature has also recognized that this type of service may be associated with improved quality. For example, Borenstein and Rose (2013) note:⁴¹

"Large airports with one or two dominant airlines generally are hubs and, as such, schedule a disproportionate number of flights compared to the *local* demand for air service. Improved service quality may offset part or all of the loss from higher prices resulting from airport dominance."

Using our model of consumer demand, we are able to evaluate the extent to which hub premia reflect quality differences. Because our demand estimates enable us to determine the equivalent monetary value of many salient flight/airline

³⁹ See GAO (2001). See also (1999), GAO (1989 and 1990), and DOT (2001).

⁴⁰ For example, DOT (2001) rejects quality as an explanation for higher fares based on its conclusion that hub carriers typically lower fares (and maintains quality) in response to entry at hubs by low cost carriers. The fact that airlines respond to competition is not surprising and does not undermine the conclusion that higher quality could explain part or all of the observed hub premia, especially today after significant entry by low cost carriers has already occurred.

Borenstein (2013) finds that the nomimal hub premium has declined since the mid-1990s. He attributes these declines to a number of factors, including LCC competition, decreases in costs (in part from increases in load factors), and declining market power of legacy carriers. **41** Evans and Kessides (1993) also suggest that service quality may explain at least part of the observed hub premia.

characteristics, we are able to determine the levels of the "full" or quality-adjusted fares that take into account these characteristics, and then to use these fares to compute hub premia. In this way, we are able to investigate the extent to which improved quality of service offsets any higher nominal fares on hub flights by measuring hub premia in terms of quality-adjusted fares.

Table 5 shows the "nominal fare premium" at each airport, for the 50 airports evaluated by Borenstein (2005).^{42,43} In this table, we sort the airports by the size of their nominal fare premia. Nine of the ten airports with the highest nominal fare premia are hub airports.⁴⁴ In contrast, only one of the ten airports with the lowest nominal fare premia is a hub airport. Hence, there appears to be a relationship between hub status and higher nominal fares, as the literature has found.⁴⁵

To compute hub premia, we follow the methodology described in Borenstein (2005). First, we categorize itineraries based on 50-mile origin-to-destination distance buckets. For each bucket, we compute the passenger-weighted average fare. We compute the airport premium by comparing the fares for all itineraries originating from or arriving at an airport in a given distance bucket to the average fares for all flights nationally in the corresponding bucket. We then compute a passenger-weighted average across buckets.

To compute quality-adjusted fare premiums, we first compute quality adjusted fares:

⁴² We compute hub premia, controlling for distance, following the methodology in Borenstein (2005). This method was presented to the TRB in 1999. The academic literature has often used regression analysis to more fully control for factors affecting price. (See, e.g., Evans and Kessides 1993) We follow the simpler approach for two reasons. First, our goal is to inform the policy debate. So it is helpful to use a similar starting point. Second, price regressions in the airline industry can raise subtle econometric questions, such as the endogeneity of market share measures typically used in the academic literature, which can be difficult to resolve.

⁴³ Borenstein analyzed the 50 busiest airports. To remain consistent with the rest of our analysis, which focuses on the continental US, we exclude Honolulu (HNL) and Kahului (OGG). We explain the methodology in detail in the Appendix.

⁴⁴ We note that the fare premium calculation does not account for the mix of passengers. To the extent that hubs tend to be located in commercial centers, one explanation for the higher observed average fares at some hub airports may be the presence of relatively more business travelers. See Lee and Luengo-Prado (2005).

⁴⁵ An alternative way to estimate the average nominal fare premium is to run a regression of average nominal fare (in logs) on a dummy for hub airport. We include a polynomial in non-stop distance, year-quarter fixed effects to control for the possibility that passenger distributions change across routes over time, and we weight by passengers. This approach indicates that the nominal fare hub premia is positive and significantly different from zero.

MEM MEMPHIS DL 34.0% CVG CINCINNATI DL 27.8% IAH HOUSTON (INTERNATIONAL) CO/UA 19.1% CLE CLEVELAND CO/UA 17.6% DCA WASHINGTON (REAGAN) 16.8% EWR NEWARK CO/UA 16.4% DFW DALLAS/FT.WORTH (DFW) AA 16.2% MSP MINNEAPOLIS DL 14.6% IAD WASHINGTON (DULLES) CO/UA 11.6% CLT CHARLOTTE US 11.4% BDL HARTFORD 10.7% DTW DETROIT DL 7.7% NAN NASHVILLE 5.9% ORD CHICAGO (O'HARE) AA, CO/UA 4.2% ATL ATLANTA DL 3.0% SLC SALT LAKE CITY DL 1.6% SQL SALT LAKE CITY DL 1.6% SAT SAN ANTONIO -0.1% -0.4% HOU HOUSTON<	Airport	City	Hub Carriers	Nominal Fare Premium
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EWRNEWARKCO/UA16.4%DFWDALLAS/FT.WORTH (DFW)AA16.2%MSPMINNEAPOLISDL14.6%IADWASHINGTON (DULLES)CO/UA11.6%CLTCHARLOTTEUS11.4%BDLHARTFORDDL7.7%BNANASHVILLES.9%ORDCHICAGO (O'HARE)AA, CO/UA4.2%ATLATLANTADL3.0%PHLPHILADELPHIAUS2.5%SILCSAIT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%5TLSTLST. LOUIS-0.1%HOUHOUSTON-0.4%LGANANNTONIO-0.8%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMINAA-1.4%DAYDAYTON-2.2%PDXPORTLAND, OR-3.9%KILKANSAS CITY-3.9%LAXLOS ANGELESCO/UA-3.7%INDINDIANAPOLIS-3.9%LAXLOS ANGELESCO/UA-4.8%PHXPHOENIXUS-6.8%SANSAN IDEGO-7.2%-6.8%BNBALTIMORE-7.2%-7.2%SANSAN DIEGO-7.9%PBWEST PALM BEACH-8.5%BVIBALTIMORE-11.0%CHAMPA-11.0%CHAMPA-11.0%CHAMPA-11.0%CHAMPA-11.0%	DCA	WASHINGTON (REAGAN)		16.8%
DFW DALLAS/FT.WORTH (DFW) AA 16.2% MSP MINNEAPOLIS DL 14.6% IAD WASHINGTON (DULLES) CO/UA 11.6% CLT CHARLOTTE US 11.4% BDL HARTFORD 10.7% DTW DETROIT DL 7.7% BNA NASHVILLE 5.9% ORD CHICAGO (0'HARE) AA, CO/UA 4.2% ATL ATLANTA DL 3.0% PHL PHILADELPHIA US 2.5% MSY NEW ORLEANS 1.8% SLC SALT LAKE CITY DL 1.6% ABQ ALBEQUERQUE 0.9% 51 STL ST. LOUIS -0.1% HOU HOUSTON -0.4% 1.3% BOS BOSTON -1.3% MIA MIAMI AA -1.4% DAY DAYTON -2.1% -3.3% MIA MIANIA AA -3.3% MIA	EWR	NEWARK	CO/UA	16.4%
MSP MINNEAPOLIS DL 14.6% IAD WASHINGTON (DULLES) CO/UA 11.6% CLT CHARLOTTE US 11.4% BDL HARTFORD 10.7% DTW DETROIT DL 7.7% BNA NASHVILLE 5.9% ORD CHICAGO (O'HARE) AA, CO/UA 4.2% ATL ATLANTA DL 3.0% PHL PHILADELPHIA US 2.5% MSY NEW ORLEANS 1.8% SLC SALT LAKE CITY DL 1.6% ABQ ALBEQUERQUE 0.9% 5TL 5T. LOUIS -0.1% HOU HOUSTON -0.4% -0.4% -0.4% -0.4% SAT SAN ANTONIO -1.3% -0.4% -0.4% -0.4% SAT SAN ANTONIO -1.3% -0.4% -1.4% -0.4% DAY DAYTON -2.2% -2.2% -2.2% PDX PORTLAND, OR -3.3% <t< td=""><td>DFW</td><td>DALLAS/FT.WORTH (DFW)</td><td>AA</td><td>16.2%</td></t<>	DFW	DALLAS/FT.WORTH (DFW)	AA	16.2%
IADWASHINGTON (DULLES)CO/UA11.6%CLTCHARLOTTEUS11.4%BDLHARTFORD10.7%DTWDETROITDL7.7%BNANASHVILLE5.9%ORDCHICAGO (O'HARE)AA, CO/UA4.2%ATLATLANTADL3.0%PHLPHILADELPHIAUS2.5%SSYNEW ORLEANS1.8%SLCSAT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%STLST. LOUIS-0.1%HOUHOUSTON-0.4%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMIAA-1.4%DAYDAYTON-2.2%PDXPORTLAND, OR-3.3%SNAORANGE COUNTY, CA-3.6%SFOSAN FRANCISCOCO/UA-3.7%INDINDIANAPOLIS-3.9%LAXLOS ANGELESCO/UA-4.8%JFKNEW YORK (JFK)AA, DL-6.3%SEASEATTLE-6.4%-6.4%ONTONTARIO, CA-6.8%-6.8%PHXPHOENIXUS-6.8%PHXPHOENIXUS-6.8%PHXPHOENIXUS-6.8%PHWEST PALM BEACH-8.5%BWIBALTIMORE-71.0%PHAHAMPA-11.0%	MSP	MINNEAPOLIS	DL	14.6%
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BDLHARTFORD10.7%DTWDETROITDL7.7%BNANASHVILLE5.9%ORDCHICAGO (O'HARE)AA, CO/UA4.2%ATLATLANTADL3.0%PHLPHILADELPHIAUS2.5%MSYNEW ORLEANS1.8%SLCSALT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%STLST. LOUIS-0.1%HOUHOUSTON-0.4%LGANEW YORK (LA GUARDIA)-0.8%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMIAA-1.4%DAYDAYTON-2.1%PITPITSBURGH-2.2%SNAORANGE COUNTY, CA-3.3%SNAORANGE COUNTY, CA-3.9%KCIKANSAS CITY-3.9%IAXLOS ANGELESCO/UA-4.8%JFKNEW YORK (JFK)AA, DL-6.3%SICSAN JOSE-6.8%-6.8%PHXPHOENIXUS-6.8%PHXPADENIXUS-6.8%PHXDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%	CLT	CHARLOTTE	US	11.4%
DTW DETROIT DL 7.7% BNA NASHVILLE 5.9% ORD CHICAGO (O'HARE) AA, CO/UA 4.2% ATL ATLANTA DL 3.0% PHL PHILADELPHIA US 2.5% MSY NEW ORLEANS 1.8% SLC SALT LAKE CITY DL 1.6% ABQ ALBEQUERQUE 0.9% STL ST. LOUIS -0.1% HOU HOUSTON -0.4% LGA NEW YORK (LA GUARDIA) -0.8% SAT SAN ANTONIO -1.3% BOS BOSTON -1.3% MIA MIAMI AA -1.4% DAY DAYTON -2.1% PIT PITSBURGH -2.2% PDX PORTLAND, OR -3.3% SNA ORANGE COUNTY, CA -3.6% SFO SAN FRANCISCO CO/UA -3.7% MCI KANSAS CITY -3.9% LAX LOS ANGELES <	BDL	HARTFORD		10.7%
BNANASHVILLE5.9%ORDCHICAGO (O'HARE)AA, CO/UA4.2%ATLATLANTADL3.0%PHLPHILADELPHIAUS2.5%MSYNEW ORLEANS1.8%SLCSALT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%STLST. LOUIS-0.1%HOUHOUSTON-0.4%LGANEW YORK (LA GUARDIA)-0.8%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMIAA-1.4%DAYDAYTON-2.2%PDXPORTLAND, OR-3.3%SNAORANGE COUNTY, CA-3.6%SFOSAN FRANCISCOCO/UA-3.7%INDINDIANAPOLIS-3.9%MCIKANSAS CITY-3.9%KAXLOS ANGELESCO/UA-4.8%JFKNEW YORK (JFK)AA, DL-6.3%SIASEATLE-6.4%-6.4%ONTONTARIO, CA-6.5%-6.8%PHXPHOENIXUS-6.8%PHXPHOENIXUS-6.8%PHXPHOENIXUS-6.8%PHXBALIMORE-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALIMORE-11.0%TPATAMPA-11.0%	DTW	DETROIT	DL	7.7%
ORDCHICAGO (O'HARE)AA, CO/UA4.2%ATLATLANTADL3.0%PHLPHILADELPHIAUS2.5%MSYNEW ORLEANS1.8%SLCSALT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%STLST. LOUIS-0.1%HOUHOUSTON-0.4%LGANEW YORK (LA GUARDIA)-0.8%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMIAAPITPITSBURGH-2.2%PDXPORTLAND, OR-3.3%SNAORANGE COUNTY, CA-3.6%SFOSAN FRANCISCOCO/UASATLOS ANGELESCO/UAINDINDIANAPOLIS-3.9%MCIKANSAS CITY-3.9%LAXLOS ANGELESCO/UASFASEATILE-6.4%SFASEATILE-6.4%SFASEATILE-6.4%PHXPHOENIXUSONTONTARIO, CA-6.5%SICSAN JOSE-6.8%PHXPHOENIXUSDALDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALIMORE-11.0%CPATAMPA-11.0%	BNA	NASHVILLE		5.9%
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MSYNEW ORLEANS1.8%SLCSALT LAKE CITYDL1.6%ABQALBEQUERQUE0.9%STLST. LOUIS-0.1%HOUHOUSTON-0.4%LGANEW YORK (LA GUARDIA)-0.8%SATSAN ANTONIO-1.3%BOSBOSTON-1.3%MIAMIAMIAAPITPITTSBURGH-2.1%PITPITTSBURGH-3.3%SNAORANGE COUNTY, CA-3.6%SFOSAN FRANCISCOCO/UASFOSAN FRANCISCOCO/UAINDINDIANAPOLIS-3.9%LAXLOS ANGELESCO/UAJFKNEW YORK (JFK)AA, DLONTONTARIO, CA-6.5%SJCSAN JOSE-6.8%PHXPHOENIXUSALLDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%	PHL	PHILADELPHIA	US	2.5%
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ONTONTARIO, CA-6.5%SJCSAN JOSE-6.8%PHXPHOENIXUS-6.8%DALDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%	SFA	SEATTI F	701,02	-6.4%
SIASIASJCSAN JOSEPHXPHOENIXDALDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGOPBIWEST PALM BEACHBWIBALTIMORETPATAMPA	ONT	ONTARIO CA		-6.5%
DALDALLAS/FT.WORTH (LOVE)-6.8%DALDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%	SIC	SAN IOSE		-6.8%
DALDALLAS/FT.WORTH (LOVE)-7.2%SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%	рнх	PHOENIX	lis	-6.8%
SANSAN DIEGO-7.9%PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%		DALLAS/FT WORTH (LOVE)	05	-7.2%
PBIWEST PALM BEACH-8.5%BWIBALTIMORE-11.0%TPATAMPA-11.0%	SAN	SAN DIEGO		_7.2%
BWI BALTIMORE -11.0% TPA TAMPA -11.0%	PRI	WEST PALM REACH		-7.9% _8 5%
TPA TAMPA11.0%	BWI	BAITIMORE		_11 0%
	ТРА	ТАМРА		_11.0%

 Table 5
 Airports Sorted by Nominal Fare Premia.

Airport	City	Hub Carriers	Nominal Fare
			Premium
DEN	DENVER	CO/UA	-12.2%
LAS	LAS VEGAS		-12.3%
OAK	OAKLAND		-13.2%
мсо	ORLANDO		-15.4%
FLL	FT. LAUDERDALE		-17.3%

(Table 5 Continued)

Source: Authors' calculations using data from the Department of Transportation's Origin and Destination Survey (DB1B) and the Official Airline Guide (OAG); 1Q2009–4Q2010. Note: Hub premia computed as in Borenstein (2005).

$$p_{j}^{Q} = \frac{\delta_{j}}{\alpha}$$

$$= p + \frac{X\beta + \xi}{\alpha}$$
(5)

The quality-adjusted price is the sum of the nominal price and the quality index (captured by the vector of observed characteristics *X*, the parameter vector β , and the unobserved quality index ξ and scaled by the coefficient on price (α) to put everything into equivalent dollar terms).⁴⁶ While in the logit model we normalize the mean utility (δ) of the outside good to be zero,⁴⁷ this calibration is irrelevant for the purpose of our analysis of hub premia, since we are concerned only with relative rankings of quality-adjusted fares as opposed to levels.

Once we have computed the quality-adjusted fares, it is straightforward to apply the Borenstein methodology to these fares to compute quality-adjusted fare premia across airports. Table 6 presents the same data, this time sorted by fare premia that are computed from quality-adjusted fares. Here, the pattern observed for nominal fares disappears.⁴⁸ Only one of the ten airports with the highest quality-adjusted premia is a hub airport, while nine are not hubs. In contrast, seven of the ten airports with the lowest quality-adjusted premia are hub airports, while only three are not.⁴⁹ Indeed, four of the five airports with the lowest

⁴⁶ See Willig (1978) for a discussion of the conditions under which this is appropriate.

⁴⁷ This scaling is embedded in the constant term and route fixed effects, which reflect the size of the inside goods relative to the size of the market and are captured in δ .

⁴⁸ In order to compare nominal and quality-adjusted fare premia, we measure all premia relative to nominal fares.

⁴⁹ A regression of quality-adjusted fares (in logs) on hub status, again controlling for distance and time and weighting by passengers, indicates that the average quality-adjusted hub premium is *negative* and significant.

Table 6 Airports Sorted by Quality-Adjusted Fare Premia.

Airport	City	Hub Carriers	Nominal Fare Premium	Quality-Adjusted Fare Premium
MEM	MEMPHIS	DL	34.0%	53.0%
DAY	DAYTON		-2.1%	43.5%
BDL	HARTFORD		10.7%	42.3%
PIT	PITTSBURGH		-2.2%	28.0%
BNA	NASHVILLE		5.9%	25.8%
ABQ	ALBEQUERQUE		0.9%	24.3%
DCA	WASHINGTON (REAGAN)		16.8%	23.7%
SNA	ORANGE COUNTY, CA		-3.6%	20.0%
SAT	SAN ANTONIO		-1.3%	19.1%
MSY	NEW ORLEANS		1.8%	18.6%
ONT	ONTARIO, CA		-6.5%	15.8%
STL	ST. LOUIS		-0.1%	15.7%
EWR	NEWARK	CO/UA	16.4%	14.9%
PDX	PORTLAND, OR		-3.3%	12.5%
SLC	SALT LAKE CITY	DL	1.6%	11.4%
MSP	MINNEAPOLIS	DL	14.6%	9.0%
IAH	HOUSTON (INTERNATIONAL)	CO/UA	19.1%	6.7%
SAN	SAN DIEGO		-7.9%	5.2%
MCI	KANSAS CITY		-3.9%	5.1%
SJC	SAN JOSE		-6.8%	3.6%
CLT	CHARLOTTE	US	11.4%	2.2%
CVG	CINCINNATI	DL	27.8%	0.7%
IND	INDIANAPOLIS		-3.9%	0.3%
PBI	WEST PALM BEACH		-8.5%	-0.4%
TPA	ТАМРА		-11.0%	-2.7%
DFW	DALLAS/FT.WORTH (DFW)	AA	16.2%	-5.0%
BWI	BALTIMORE		-11.0%	-5.4%
LGA	NEW YORK (LA GUARDIA)		-0.8%	-5.6%
HOU	HOUSTON		-0.4%	-7.2%
CLE	CLEVELAND	CO/UA	17.6%	-8.2%
PHL	PHILADELPHIA	US	2.5%	-8.7%
РНХ	PHOENIX	US	-6.8%	-8.9%
BOS	BOSTON		-1.3%	-9.5%
SEA	SEATTLE		-6.4%	-11.2%
ORD	CHICAGO (O'HARE)	AA, CO/UA	4.2%	-12.1%
DAL	DALLAS/FT.WORTH (LOVE)		-7.2%	-15.3%
DEN	DENVER	CO/UA	-12.2%	-15.4%
мсо	ORLANDO	·	-15.4%	-15.9%
MIA	MIAMI	AA	-1.4%	-16.6%
OAK	OAKLAND		-13.2%	-18.4%
FLL	FT. LAUDERDALE		-17.3%	-23.6%
IAD	WASHINGTON (DULLES)	CO/UA	11.6%	-31.7%
DTW	DETROIT	DL	7.7%	-35.4%

Airport	City	Hub Carriers	Nominal Fare Premium	Quality-Adjusted Fare Premium
SFO	SAN FRANCISCO	CO/UA	-3.7%	-40.4%
ATL	ATLANTA	DL	3.0%	-44.2%
LAX	LOS ANGELES	CO/UA	-4.8%	-48.4%
LAS	LAS VEGAS		-12.3%	-50.3%
JFK	NEW YORK (JFK)	AA, DL	-6.3%	-64.7%

(Table 6 Continued)

Source: Authors' calculations using data from the Department of Transportation's Origin and Destination Survey (DB1B) and the Official Airline Guide (OAG); 1Q2009–4Q2010. Note: Fare premia computed as in Borenstein (2005).

quality-adjusted premia are hubs – United's San Francisco and Los Angeles hubs, Delta's Atlanta hub, and New York's JFK airport, which serves as a hub for Delta and American.

Table 7 presents premia for the key components of the quality-adjusted prices based on the passenger-weighted average values of these variables relative to the average across all airports, controlling for distance and sorting by partially quality-adjusted fare premia (Column (10)).^{50,51} The partially quality-adjusted fares account for just those factors that are most associated with hubs, including convenience, frequency, non-stop status, and network size. Adjusting only for these factors also reverses any pattern that hub airports tend to be the most expensive. Only three of the ten airports with the highest partially quality-adjusted premia are hub airports, while seven are not hubs. In contrast, seven of the ten airports with the lowest quality-adjusted premia are hub airports, while only three are not.⁵² Of course, airports vary on other dimensions that are harder to characterize.

⁵⁰ For the purposes of results reported here, we do not consider the route-specific fixed effects, which capture the average benefits of flying versus not flying, the airport-specific fixed effects, which capture the benefits of flying to specific airports within multi-airport cities, or unobservable route-product-specific elements of quality. We do this (1) to focus most directly on the elements of quality that can be clearly interpreted and (2) in recognition of the fact (as explained in the Appendix) that we do not estimate effects on all routes and therefore do not have estimates of the value of unobserved quality for all observations. Our substantive conclusions are unchanged if we account for unobserved quality on those observations where estimates are available.

⁵¹ The "other" category captures aspects of air travel that are less directly related to hubs. This category includes factors like carrier fixed effects, which capture unobserved attributes specific to certain carriers but invariant across routes.

⁵² A regression of partially quality-adjusted fares (in logs) on hub status, again controlling for distance and time and weighting by passengers, also indicates that the average partially quality-adjusted hub premium is negative and significant.

Airport	. City	Hub Carriers	(1) Nominal Fare Premium	(2) Inconvenience	(3) Frequency	(4) Network (Direct)	(5) Network (Connect)	(6) Nonstop	(7) Partial Quality- Adjusted Fare Premium	(8) Other	(9) Quality- Adjusted Fare Premium
MEM	MEMPHIS	DL	34.0%	-0.1%	4.0%	-4.1%	-0.7%	4.7%	38.1%	15.2%	53.0%
BDL	HARTFORD		10.7%	1.1%	3.0%	3.0%	-0.3%	7.5%	26.3%	17.2%	42.3%
CVG	CINCINNATI	DL	27.8%	~6.0-	6.6%	-3.1%	-0.9%	-0.8%	26.0%	-28.0%	0.7%
DAY	DAYTON		-2.1%	2.0%	6.2%	4.6%	-0.1%	14.4%	25.8%	18.5%	43.5%
CLE	CLEVELAND	CO/UA	17.6%	0.8%	6.6%	-1.0%	-0.2%	1.0%	23.1%	-33.0%	-8.2%
BNA	NASHVILLE		5.9%	1.5%	3.7%	2.0%	0.0%	4.0%	17.6%	8.7%	25.8%
ABQ	ALBEQUERQUE		%6.0	1.6%	4.3%	2.5%	0.1%	6.3%	16.3%	8.6%	24.3%
PIT	PITTSBURGH		-2.2%	1.2%	4.3%	3.0%	-0.2%	6.5%	13.6%	15.4%	28.0%
MSY	NEW ORLEANS		1.8%	0.8%	3.1%	0.7%	-0.1%	5.4%	12.1%	6.9%	18.6%
SAT	SAN ANTONIO		-1.3%	0.9%	0.3%	2.6%	-0.1%	9.3%	12.0%	7.5%	19.1%
DCA	WASHINGTON (REAGAN)		16.8%	-1.5%	-4.2%	0.1%	-0.3%	-0.5%	11.0%	13.4%	23.7%
STL	ST. LOUIS		-0.1%	1.0%	4.0%	1.7%	-0.1%	2.8%	9.5%	6.4%	15.7%
IND	INDIANAPOLIS		-3.9%	0.4%	3.5%	3.4%	-0.2%	5.8%	8.7%	-8.7%	0.3%
ONT	ONTARIO, CA		-6.5%	1.5%	0.7%	4.3%	0.2%	5.3%	6.3%	10.3%	15.8%
MCI	KANSAS CITY		-3.9%	0.7%	1.6%	2.3%	-0.1%	4.0%	4.7%	0.5%	5.1%
EWR	NEWARK	CO/UA	16.4%	-0.5%	-3.5%	-3.9%	0.0%	-6.8%	2.4%	13.3%	14.9%
РДХ	PORTLAND, OR		-3.3%	0.8%	2.6%	3.1%	0.2%	-1.6%	2.4%	10.7%	12.5%
IAD	WASHINGTON (DULLES)	CO/UA	11.6%	-1.0%	1.1%	-1.8%	0.0%	-4.8%	2.0%	-36.7%	-31.7%
CLT	CHARLOTTE	US	11.4%	-2.0%	-3.1%	-4.5%	0.0%	0.3%	1.8%	0.1%	2.2%
SNA	ORANGE COUNTY, CA		-3.6%	0.7%	-1.6%	2.8%	0.1%	1.3%	1.0%	20.4%	20.0%
ПОН	HOUSTON		-0.4%	0.9%	-1.0%	2.2%	0.5%	-1.7%	0.5%	-7.6%	-7.2%
MSP	MINNEAPOLIS	DL	14.6%	-1.3%	-1.2%	-7.4%	-0.4%	-4.3%	0.0%	9.1%	9.0%
SLC	SALT LAKE CITY	DL	1.6%	-0.3%	1.4%	-1.3%	-0.4%	-2.8%	-1.2%	13.2%	11.4%
SJC	SAN JOSE		-6.8%	0.6%	-0.2%	4.2%	0.3%	-0.9%	-1.9%	6.3%	3.6%
IAH	HOUSTON	CO/UA	19.1%	-1.8%	-5.1%	-7.7%	0.0%	-6.7%	-2.1%	9.0%	6.7%
	(INTERNATIONAL)										
DAL	DALLAS/FT.WORTH		-7.2%	0.6%	-6.0%	5.6%	0.5%	1.0%	-5.5%	-9.8%	-15.3%
	(LOVE)										

 Table 7
 Components of Quality-Adjusted Fare Premia.

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Airport	City	Hub Carriers	(1) Nominal Fare Premium	(2) Inconvenience	(3) Frequency	(4) Network (Direct)	(5) Network (Connect)	(6) Nonstop	(7) Partial Quality- Adjusted Fare Premium	(8) Other	(9) Quality- Adjusted Fare Premium
PBI	WEST PALM BEACH		-8.5%	0.5%	0.7%	1.3%	0.1%	-0.7%	-6.2%	6.2%	-0.4%
PHL	PHILADELPHIA	US	2.5%	-0.9%	-1.6%	-2.2%	0.0%	-3.9%	-6.3%	-2.5%	-8.7%
TPA	TAMPA		-11.0%	0.9%	2.9%	1.3%	0.0%	-1.2%	-6.8%	4.5%	-2.7%
BOS	BOSTON		-1.3%	-1.2%	-2.7%	1.2%	-0.1%	-3.4%	-7.8%	-2.0%	-9.5%
SAN	SAN DIEGO		-7.9%	-0.2%	-3.2%	2.2%	0.1%	0.3%	-7.8%	13.9%	5.2%
DTW	DETROIT	DL	7.7%	-2.0%	-0.4%	-8.1%	-0.3%	-4.1%	-8.3%	-28.2%	-35.4%
BWI	BALTIMORE		-11.0%	0.8%	1.4%	1.0%	0.3%	-2.4%	-9.2%	4.5%	-5.4%
OAK	OAKLAND		-13.2%	0.6%	-3.2%	4.7%	0.5%	-2.7%	-13.0%	-5.0%	-18.4%
SEA	SEATTLE		-6.4%	-0.8%	-1.9%	0.4%	0.3%	-4.8%	-13.1%	2.1%	-11.2%
DFW	DALLAS/FT.WORTH (DFW)	AA	16.2%	-3.8%	-9.2%	-10.1%	0.1%	-6.9%	-13.5%	8.7%	-5.0%
LGA	NEW YORK (LA GUARDIA)		-0.8%	-2.1%	-7.4%	0.1%	-0.2%	-4.2%	-14.3%	9.1%	-5.6%
ХНА	PHOENIX	US	-6.8%	-0.3%	-2.2%	-0.6%	0.2%	-5.8%	-14.8%	6.6%	-8.9%
SFO	SAN FRANCISCO	CO/UA	-3.7%	-1.7%	-2.9%	0.1%	0.0%	-4.4%	-15.2%	-27.7%	-40.4%
MIA	MIAMI	AA	-1.4%	-2.1%	-4.3%	-1.8%	-0.3%	-5.1%	-15.6%	-1.6%	-16.6%
MCO	ORLANDO		-15.4%	0.5%	0.7%	0.8%	0.2%	-4.2%	-17.2%	1.6%	-15.9%
LAS	LAS VEGAS		-12.3%	-1.1%	0.0%	0.3%	0.3%	-4.8%	-17.9%	-32.7%	-50.3%
FLL	FT. LAUDERDALE		-17.3%	0.0%	1.1%	1.7%	0.3%	-4.1%	-18.2%	-5.3%	-23.6%
LAX	LOS ANGELES	CO/UA	-4.8%	-2.0%	-4.1%	0.2%	0.0%	-5.2%	-18.3%	-32.5%	-48.4%
ORD	CHICAGO (O'HARE)	AA, CO/UA	4.2%	-2.4%	-6.6%	-7.4%	-0.1%	-7.8%	-20.3%	8.1%	-12.1%
JFK	NEW YORK (JFK)	AA, DL	-6.3%	-1.9%	-1.3%	0.9%	0.3%	-9.0%	-20.8%	-47.2%	-64.7%
DEN	DENVER	CO/UA	-12.2%	-0.5%	-0.3%	-2.7%	0.2%	-7.1%	-22.2%	7.1%	-15.4%
ATL	ATLANTA	DL	3.0%	-4.2%	-9.0%	-9.8%	-0.2%	-7.1%	-28.2%	-16.9%	-44.2%
Source (OAG);	:: Authors' calculations u: 1Q2009–4Q2010.	sing data fro	im the Dep	artment of Trans	sportation's	Origin an	d Destinati	on Survey	(DB1B) and the	e Official	Airline Guide

Notes: Premia computed as in Borenstein (2005); partial quality adjustment accounts for inconvenience, frequency, network size, and availability of

nonstop flights.

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Some of these may be associated with hubs even if they do not as neatly follow our intuition. In our view, a complete comparison of quality adjusted fares across airports should account for all quality factors revealed by our demand model. When we do this, it only strengthens the conclusion that hubs are not more expensive on a quality adjusted basis as shown in Table 6.⁵³

The decomposition of the elements of quality-adjusted fares illuminates the value of hub airports. Negative values indicate that, overall, the particular airport offers more value for any given attribute. For example, although the nominal fares at Delta's Atlanta hub are slightly above average, passengers flying into or out of Atlanta also tend to be able to choose from a variety of convenient, high-frequency, non-stop flights to many destinations.⁵⁴ As a result, both partially and fully quality-adjusted fares are substantially below average. On the other hand, smaller hubs such as Memphis tend to have higher fares without offsetting quality benefits. Nonetheless, on a quality-adjusted basis, the evidence indicates that hub airports (and especially the larger hub airports) tend to provide consumers with more value than other airports.

5.2 Merger Analysis

Competition agencies often evaluate airline mergers by developing estimates of nominal fare effects derived from regressions of average fares on measures related to the competitive structure of routes (for example, counts of the number of carriers operating on a route) and applying those estimates to routes on which the merging parties offer overlapping service. These estimates of nominal fare effects are sometimes compared to aggregate measures of efficiencies (either from cost savings or quality improvements) as in Heyer et al. (2009). For example, in reviewing the Delta-Northwest merger, economists at the Department of Justice (DoJ) balanced the "modest" potential harm from their predicted increased nominal fares against estimates of quality improvements, derived from changes in traffic patterns predicted by the parties' internal planning models.⁵⁵

⁵³ We do not attempt to evaluate how the relationship between hub premia and quality-adjusted fares would affect structural changes, such as the banning of frequent-flyer programs or making airport facilities available to new entrants were made. For a discussion of the Aviation Investment and Reform Act for the 21st Century – AIR-21, see Snider and Williams (2001).

⁵⁴ Atlanta also serves as a hub for AirTran, which was recently acquired by Southwest.

⁵⁵ DoJ concluded that "[o]ur best estimates of the likely increases in consumer welfare significantly exceeded the feared harm to consumers in the overlap routes served by the two carriers." See Heyer et al. (2009).

Our proposed methodology offers a related but distinct approach to evaluating the welfare effects of airline mergers, which tightly integrates fare and quality effects into a single analysis. In particular, we use our explicit econometric model of consumer demand for airline services to estimate changes in consumer surplus due to the merger that reflect both changes in quality characteristics and changes in nominal fares.⁵⁶ As an example of this approach, we present a prospective analysis of the Delta-Northwest merger to illustrate the type of analysis that could be done as part of the process of reviewing a particular proposed merger. Here we focus on the merger's likely impact on consumer welfare on routes on which both Delta and Northwest offered non-stop service in Q3 2008, just before they merged in October 2008.

Our analysis of the Delta-Northwest merger proceeds in several steps. First, we identify the itinerary characteristics that change as a result of the larger network generated by the merger. In particular, the merger led to more convenient schedules on routes for which, pre-merger, Delta and Northwest operated flights at different times on the same route.⁵⁷ The merger also led to larger available networks at airports where, pre-merger, Delta and Northwest served different destinations. Second, we incorporate estimates of nominal fare effects derived from the most recent research in the economics literature. In particular, we apply the estimates of Brueckner et al. (2013), who find that reductions in the number of legacy nonstop carriers serving a route from two to one generate average nominal price increases of approximately 5.4% (across all carriers operating on the route, including LCCs where they are present), while reductions in the number of legacy

⁵⁶ Morrison et al. (1989) is the first paper that we are aware of to propose this approach in the context of evaluating airline mergers.

⁵⁷ We model changes in quality characteristics using scheduling data from the third-quarter of 2008. We simulate the effect of the merger by comparing stand-alone schedules to schedules in which all Northwest flights are recoded as Delta flights. This analysis therefore does not incorporate any estimates of changes in schedule resulting from the merger. As discussed above, we do not attribute any increase in consumer welfare to the combination of frequencies within the merged carrier over and above any benefits arising from other quality attributes such as scheduling convenience. To the extent that the merger would have caused the combined carrier restructure the post-merger network, these effects could also be accounted for in the analysis. Indeed, carriers often construct detailed plans for post-merger networks as part of the merger planning process. In some cases, those plans indicate reductions in capacity on some routes (e.g., where the pre-merger carriers fly similar schedules), and increased capacity on other routes (e.g., where the combined carrier produces sufficient flow to sustain increased service). In general, it is not possible to say which direction these effects will go without access to the precise schedule planning.

nonstop carriers serving a route from three to two generate average nominal price increases of approximately 1.4%.⁵⁸ Third, we compute the changes in consumer surplus resulting from changes in the product quality and changes in nominal fares using the method introduced to the literature by Small and Rosen (1981) to compute welfare effects using discrete choice models.^{59,60}

Results for all of the Delta-Northwest non-stop overlap routes with three or fewer competitors operating on the route pre-merger are presented in Table 8. Columns (1) and (2) identify the route and the number of non-stop competitors operating in the third quarter of 2008 (before the merger was completed). Columns (3) and (4) report the size of the route based on total passengers and revenues across all carriers (including LCCs where they are present), respectively. Column (5) shows the average merger-induced reduction in inconvenience per passenger who flew via either Delta or Northwest pre-merger.⁶¹ Column (6) shows the average merger-induced increase in the number of destinations served via non-stop service, per passenger who flew via either Delta or Northwest pre-merger.⁶² Column (7) reports the net annual change in consumer welfare on each

⁵⁸ See Brueckner et al. (2013), at Table 3. We base our estimates on their "market" model, which generates the highest estimate of two-to-one effects and is therefore most conservative. Our results are robust to using alternative specifications. The Brueckner et al. model controls for whether an LCC is present on a route, but does not allow the competitive effects of reducing the number of legacy carriers to vary with LCC presence. In the case of the Delta-Northwest merger, the combined carrier faced competition from Airtran, particularly on routes out of Atlanta.

⁵⁹ Our use of the Small and Rosen welfare formula is conceptually equivalent (and numerically approximately equivalent) to computing the changes in consumers' surplus due to changes in quality-adjusted prices, given the specifications of the demand functions we employ. As discussed in the Appendix, for these demand functions the Small and Rosen welfare formula permits this calculation in one integrated step. In contrast, quality-adjusted prices are a more natural way to address the literature on hub premia, which analyzes price differences across airports rather than the welfare effects of a transaction.

⁶⁰ This approach is conservative in that it increases the nominal prices of the non-merging firms without letting them respond to the improved quality of the merging carrier via enhanced quality and/or lower nominal fares. A recent paper about the price effects of the 1987 merger between USAir and Piedmont found that competing carriers did lower their nominal fares in response to the merger. The paper goes on to suggest that this pattern could occur because of "better service by the merged carrier" or "'S-curve' effects" (analogous to our network breadth benefits). *See* Kwoka and Shumilkina (2010).

⁶¹ We weight by pre-merger passengers. Negative values indicate that the schedule becomes more convenient.

⁶² We weight by pre-merger passengers.

(1) Route	(2) Type	(3) Passengers (MM)	(4) Revenues (\$ MM)	(5) Change in Inconvenience* (h)	(6) Change in Destinations Served Non-stop*	(7) Net Change in Consumer Welfare (\$ MM)	(8) Ratio of Net Change in Consumer Welfare to Revenue
ATLDTW	3 -> 2	0.23	\$35.80	-0.7	52.2	\$7.72	21.55%
ATLMEM	3 -> 2	0.12	\$16.50	-0.6	19.3	\$2.84	17.18%
ATLMSP	3 -> 2	0.22	\$38.00	-0.6	45.4	\$8.44	22.22%
CN2DTW	2 -> 1	0.01	\$1.68	-0.6	45.8	\$0.12	6.89%
CN2MSP	2 -> 1	0.05	\$15.30	-1.2	37.0	\$0.39	2.57%
DTWATL	3 -> 2	0.23	\$35.30	-0.7	40.8	\$6.72	19.05%
DTWCN2	2 -> 1	0.01	\$1.57	-0.9	58.3	\$0.13	8.53%
DTWNY3	2 -> 1	0.44	\$73.20	-0.2	5.2	\$2.03	2.78%
DTWSLC	2 -> 1	0.04	\$10.30	-1.0	42.6	\$0.90	8.67%
MEMATL	3 -> 2	0.13	\$17.30	-0.8	41.1	\$3.91	22.56%
MSPATL	3 -> 2	0.21	\$37.20	-0.7	42.8	\$6.86	18.44%
MSPCN2	2 -> 1	0.05	\$15.80	-0.8	41.5	\$0.70	4.46%
MSPNY3	3 -> 2	0.37	\$91.90	-0.6	5.6	\$4.30	4.68%
MSPSLC	2 -> 1	0.05	\$15.30	-0.7	31.5	\$1.06	6.90%
NY3DTW	2 -> 1	0.44	\$73.10	-0.2	17.2	\$4.11	5.63%
NY3MSP	3 -> 2	0.37	\$92.60	-0.5	17.1	\$4.11	4.44%
SLCDTW	2 -> 1	0.04	\$10.40	-1.0	22.1	\$0.24	2.31%
SLCMSP	2 -> 1	0.05	\$15.50	-0.4	30.5	\$0.18	1.17%
2 -> 1	2 -> 1	1.18	\$232.00	-0.4	17.2	\$9.87	4.25%
3 -> 2	3 -> 2	1.89	\$365.00	-0.6	30.0	\$44.89	12.31%
All Routes		369.50	\$69,800.00			\$390.74	0.56%
Source: Autho	ors' calculat	cions using data fi	rom the Departme	ent of Transportation'	s Origin and Destinatio	n Survey (DB1B) and t	the Official Airline Guide
(OAG); 1Q200)8-4Q2010						
Note: Passen	ger, revenue	e and welfare tota	ils based on 1Q08	3-4Q08 data. All tota	ls are reported for the c	ontinental US. Merge	r-related quality changes

 Table 8
 Delta-Northwest Net Consumer Welfare Results.

*Weighted by pre-merger passengers.

based on 3Q08 schedules.

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route due to the merger.^{63,64} Positive numbers indicate that consumers benefited from the merger, even after accounting for potentially higher nominal fares. Column (8) expresses the net change in consumer welfare as a percentage of total revenue (across all passengers) on the route.

The first 18 rows show the results for particular individual routes. The bottom rows show the results for all the routes flown by Delta and Northwest prior to the merger aggregated across three categories: i) those routes containing an airport pair with a nonstop overlap and two nonstop carriers operating pre-merger; ii) those routes containing an airport pair with a nonstop overlap and three nonstop carriers operating pre-merger; and iii) all routes.

Our ex ante analysis of the likely effects of the Delta-Northwest merger supports the finding of the Department of Justice that the merger of Delta and Northwest was likely to benefit consumers substantially.⁶⁵ Even on routes on which Delta and Northwest both offered non-stop service pre-merger, and where it is assumed that the merger causes increases in nominal fares, the predicted net effect of the merger on consumer welfare is positive (that is, quality-adjusted fares decrease). On routes with just two non-stop competitors pre-merger, consumer welfare is predicted to increase by approximately 4.25% of total revenues. On routes with three non-stop competitors pre-merger, consumer welfare is predicted to increase by approximately 12.31% of total revenues.

The reasons for the likely increase in welfare can be seen in the changes in characteristics. In particular, the convenience of the schedules improves by approximately 0.4 h on routes with two nonstop carriers pre-merger and by 0.6 h

⁶³ This measure of consumer welfare captures welfare changes realized by passengers of nonmerging carriers as well as passengers who choose one of the merging carriers. The welfare of those customers who choose non-merging carriers is impacted for two reasons. First, the nominal fares may change due to changes in the competitive structure on the route. Second, those customers benefit from the option of choosing a merged carrier with its merger-induced quality improvements. For some passengers, the improvement in quality on the merging carrier may be so great that they will be induced to switch.

⁶⁴ For the purposes of these calculations, we assume that airlines do not face capacity constraints. Airlines typically employ sophisticated "spill and recapture" algorithms that can be used to assess the extent to which capacity constraints bind. We also do not model any changes in network configuration. To the extent that airlines cannot seat all passengers desiring a seat post-merger, the welfare gains from quality improvements may be reduced. On the other hand, airlines may be able to respond to capacity constraints by flying larger aircraft on a route or adding frequencies.

⁶⁵ See US Department of Justice 2008. "Statement of the Department of Justice's Antitrust Division on its Decision to Close its Investigation of the Merger of Delta Air Lines Inc. and Northwest Airlines Corporation." http://www.justice.gov/atr/public/press_releases/2008/238849.htm (last updated October 29, 2008).

on routes with three nonstop carriers pre-merger. Similarly, the number of destinations served via non-stop service increases (on average) by 17 on routes with two nonstop carriers pre-merger and 30 on routes with three nonstop carriers pre-merger. These improvements in quality translate directly into benefits to consumers, which outweigh the assumed increases in nominal prices (based on averages from the academic empirical literature).⁶⁶

Incorporating routes with no overlap only strengthens these findings. Overall, net consumer welfare is predicted to increase by nearly \$400 million per year. This large increase in consumer welfare reflects benefits to consumers from network effects on routes where no offsetting fare effects would be expected.⁶⁷ In contrast, Brueckner et al. (2013) focus just on nominal fare effects and predict that the Delta-Northwest merger would increase fares by <\$43 million.

To see how this translates into welfare, consider the first row based on ATLDTW. The convenience benefits are worth \$3.45 per passenger while the improved network is worth \$25.13. Based on pre-merger passenger counts (that is, not allowing passengers to switch to flights that become more desirable), this accounts for \$6.6 million of the \$7.7 million in total benefits. The remaining benefits are accounted for by changes in other attributes (for example, codeshare status) and benefits to switchers (as described in the Appendix). In contrast, the offsetting fare effects are predicted to be just 1.4% of total revenue or \$0.5 million.

As shown in Equation (A1) in the Appendix, the changes in welfare depend on the changes in product characteristics and a non-linear function of shares that determines how much those changes matter. So, for example, changes in characteristics of products with low share get relatively less weight in the welfare calculation than changes in characteristics for more highly valued characteristics. As we discuss in the Appendix, we estimate our demand parameters using data from 2009–2010. Consequently, our demand model does not estimate the ξ 's for the period surrounding the DL-NW merger. To address this issue, we solve for the implicit ξ 's such that the predicted shares match the observed shares in the third quarter of 2008. Using these ξ 's allows us to weight the welfare function according to pre-merger observed shares.

67 Benefits can arise on routes where there is no non-stop overlap for a few reasons. First, some interline itineraries that were previously excluded from the model could become online itineraries, creating new options for passengers. Second, some codeshare itineraries could become online itineraries. Third, on routes on which there are connecting overlaps, convenience could improve due to better flight times. Fourth, even on routes where there is no overlap at all, to the extent that there are airport-level overlaps, benefits from improved network breadth may be realized.

⁶⁶ For example, applying the valuations from Table 3, the change in convenience implies average consumer benefits of approximately \$1–\$6 per flight (in each direction). Similarly, the increase in nonstop destinations translates into \$2–\$28 of consumer benefits on average per flight (in each direction). The variation in these benefits is driven by differences across routes in the changes in scheduling convenience and network quality as a result of the merger. Consumers get additional benefits from connecting flights as well as the conversion of codeshare itineraries to online itineraries. In contrast, the assumed increases in nominal prices based on the estimations in Brueckner et al. (2013) come to \$3–\$11 depending on the type of route.

Finally, we note that the methodology developed in this paper allows us easily to incorporate quality improvements due to expanded networks into merger simulations or related analysis.⁶⁸ In particular, we can use the explicit econometric model of consumer demand for airline services as the basis for computing quality-adjusted prices. The quality-adjusted prices also can play an important role in other techniques frequently used to assess the impact of mergers on consumer welfare such as assessments of upward pricing pressure (UPP).⁶⁹ This is an important lesson because, while UPP techniques are capable of incorporating quality changes or other efficiencies, actual analysis used in practice tend to focus narrowly on nominal prices rather than appropriately incorporating the effects of merger-induced quality changes.

6 Conclusion

Our research demonstrates that analyses that ignore the quality effects associated with expanded airline networks generate incorrect findings and thus should not form the basis for policy decisions regarding airline transactions. Appropriately incorporating quality effects into quality-adjusted fares reverses the conclusion that hub airports yield lower consumer welfare due to generally higher fares than other airports. It also suggests that the Delta-Northwest merger was likely to substantially benefit consumers, even on the limited number of routes where traditional analysis indicates that consumers face potentially higher nominal fares.

This paper does not attempt to present a retrospective analysis of the Delta-Northwest merger. A complete retrospective analysis would use a technique such as difference-in-differences analysis to control for changes that affected both supply and demand in the airline industry subsequent to the merger, such as global macro-economic shocks and a steep decline in fuel prices followed by a sharp increase in fuel prices. Such an analysis is beyond the scope of this paper. We do know, however, that by early 2010, Delta and Northwest had completed a significant portion of the integration of two carriers, including combining frequent flyer programs, consolidating and rebranding airport facilities, and integrating flight reservation systems. Delta estimated that it achieved \$700 million

⁶⁸ Merger simulations are often used for the evaluation of price effects from mergers. For more details, see, for example, Budzinski and Ruhmer (2010). However, research has shown that merger simulations can be quite inaccurate in the airline industry. See, for example, Peters (2006).

⁶⁹ Willig (2011) shows how quality-adjusted prices can be incorporated into UPP analysis.

in "[m]erger synergy benefits" in 2009 and anticipated an additional \$600 million in 2010. $^{\! 70}$

We conclude by reiterating our primary conclusion. From the perspective of consumer welfare in this industry, to evaluate potential airline mergers, alliances, slot swaps or other transactions, one should not focus solely on the effect of concentration on nominal fares, rather, one should account for the welfare-enhancing effects of larger airline networks.

Appendix – Consumer Surplus

Given estimated demand parameters, we calculate the change in consumer surplus resulting from a merger following Small and Rosen (1981):

$$CV_{i} = -\frac{ln\left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{post}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{A} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right)\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \left[1 + \left[\sum_{j'} exp\left(\frac{\delta_{j'}^{pre}}{\rho_{A}}\right]^{\frac{\rho_{A}}{\rho_{0}}} \right]^{\frac{\rho_{A}}{\rho_{0}}}$$

To compute the consumer surplus generated by a merger, we start with standalone schedules from a time period just prior to the merger (for example, 3Q2008 for the Delta-Northwest merger). We then simulate the merger's effects on nonprice characteristics by consolidating the merging carriers under a single code (that is, we change the NW code to DL). We recompute the network characteristics that change as a result of the merger, including scheduling convenience and network size. The post-merger schedule will therefore reflect the incremental benefits to consumers flying on each route as a result of the larger network created by the merger. Note that this approach does not take into account any changes in the schedule resulting from the merger. But to the extent such schedules are available or can be simulated, the methodology could use these schedules as the basis for the post-merger network.

As discussed above, Brueckner et al. (2013) provides estimates of the nominal fare effects that arise from changing the number of non-stop legacy carriers on a route. Their analysis is based on airport pairs (though they also consider "adjacent" competition and generally find no significant effects). Therefore, in considering the net consumer welfare effects of a merger of legacy carriers, we first

⁷⁰ Delta Air Lines, Inc., Form 10-K For the fiscal year ended December 31, 2009 at 29.

identify the non-stop overlaps based on airport pairs and then apply the appropriate adjustment to the average fare for *all* itineraries operating on that airport pair. Although we allow the price of non-merging carriers to change based on the Brueckner et al. (2013) estimates, we do not allow the quality characteristics of those carriers to change, nor do we allow the carrier to reoptimize prices in response to improvements in quality from the merging carrier. To the extent that those carriers would respond to the increased quality of the merging carriers by also improving quality or reducing nominal fare, our model underestimates the benefits of mergers.

Note that we define routes based on city-pairs. Our model allows switching across airport pairs within a city pair in response to changes in quality and/ or prices as a result of a merger.⁷¹ In addition, the model allows for switching across carriers (in response to changes in quality characteristics) and switching to or from the outside good (in response to changes in the relative attractiveness of flying). The consumer surplus calculation takes such switching into account.

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⁷¹ However, we conservatively assume that convenience and network breadth are measured only on the basis of airports.

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