Airline Code-share Alliances and their Competitive Effects

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Abstract

Code-share alliances have become a prominent feature in the competitive landscape of the airline industry. However, policy makers are extremely hesitant to approve proposed code-share alliances when the potential partners' route networks have significant overlap. The main concern is that the alliance may facilitate price collusion on partners' overlapping routes. The main contribution of this paper is to show how policy makers can use a structural econometric framework developed by Nevo (2000b) to quantify the competitive effects of *proposed* code-share alliances, where potential alliance partners compete on overlapping routes in the pre-alliance industry. As an example, I apply the econometric model to the recently implemented Delta/Continental/Northwest alliance. This proposed alliance was initially greeted with skepticism by the U.S. Department of Transportation due to the potential partners' unprecedented level of route network overlap. For the markets considered in my analyses, it appears as though the ultimate approval of the alliance by policy makers was justified.

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1 Introduction

One of the most significant developments in the airline industry in recent years is the formation of alliances among airlines. Alliances vary from a limited marketing arrangement, such as reciprocal frequent flyer programs,[1] to more complex agreements such as code-sharing.[2] A code-sharing agreement allows an airline to sell seats on its partner's plane as if they were its own. In many cases, code-sharing effectively expands the route network of each partner airline without the need to add planes. Some code-share alliances may benefit consumers more than others, depending on the extent to which alliance partners' existing route networks are complementary rather than overlapping. In fact, policy makers are often concerned that code-share alliances may facilitate price collusion among partners on their overlapping routes. Using a structural econometric framework developed by Nevo (2000b), the main objective of this paper is to show how policy makers can quantify the extent to which collusive prices may depart from their pre-alliance competitive levels on partners' overlapping routes.

Together, the following hypothetical examples describe and distinguish between complementary versus overlapping route networks. Suppose prior to code-sharing neither Delta nor American Airlines offered service (direct or indirect) from Atlanta to Kansas City, but Delta offered service from Atlanta to Dallas (and American does not), while American offered service from Dallas to Kansas City (and Delta does not). The routes in the example above are complementary because together, they allow travel between two cities (Atlanta to Kansas City) that is not possible on any one of the airlines in the example. A code-sharing agreement between the two airlines allows each to sell tickets on each other's airline in the Atlanta to Kansas City market

[1] An airline's frequent flyer program normally allows passengers to accumulate miles flown over multiple trips on the airline. A passenger that accumulates miles beyond some threshold level can redeem the miles for a free or discounted trip. When alliance partners make their frequent flyer programs reciprocal, passengers are allowed to accumulate and redeem miles across airlines within the alliance. See Suzuki (2003) for a detailed discussion of various types of frequent flyer programs and their attractiveness to passengers.

[2] See "Aviation Competition: Effects on Consumers From Domestic Airline Alliances Vary," *United States General Accounting Office Report, GAO/RCED-99-37*, January 1999.

as if each were offering "online" service[3] in this market.

The current literature generally agrees that complementarity in route networks among alliance partners ought to benefit consumers both through reduced fares and expanded networks.[4] However, suppose prior to the code-share alliance both airlines in the example above offered competing online service in the Atlanta to Los Angeles market, then this portion of the airlines' route networks are overlapping, and the alliance could facilitate price collusion. To the extent that collusion occurs on overlapping routes, fares on these routes may increase, causing consumers' welfare to fall. This paper's main focus is on the *potential* collusive effect on products that traditionally competed prior to the alliance, rather than code-sharing per se.

In August 2002, Delta, Continental, and Northwest submitted code-sharing and frequent-flyer program reciprocity agreements to the U.S. Department of Transportation (DOT) for review.[5] The DOT expressed concerns about the potential competitive effects of the proposed Delta/Continental/Northwest code-sharing alliance. The DOT's main concern lies in the significant extent to which the three airlines' route networks overlapped, which is unlike any other existing domestic alliance. The DOT's analysis revealed that the three airlines offered overlapping services in 3,214 markets accounting for approximately 58 million annual passengers.[6] Given the broad nature of discussions that is required to implement the alliance, the DOT is concerned that such communications among the carriers may result in collusion, either tacit or explicit, on fares and service levels.[7]

[3] Online service refers to the case where a connecting passenger does not change airline throughout their round-trip travel.

[4] See Brueckner (2003), Brueckner (2001), Brueckner and Whalen (2000), Park, Zhang, and Zhang (2001).

[5] In 1998, Congress granted the Department of Transportation the authority to delay alliances that the Department believes may have an anticompetitive impact on consumers [see Bamberger, Carlton, and Neumann (2001)].

[6] See "Termination of review under 49U.S.C. § 41720 of Delta/Northwest/Continental Agreements," published by *Office of the Secretary, Department of Transportation*, January 2003.

[7] In addition to the significant route network overlap, the DOT was also concerned that the combined size of the three airlines is significantly greater than any other existing domestic alliance. According to the DOT, "Northwest and Continental together have a national market share of 18 percent as measured by domestic revenue passenger miles, and Delta has 17 percent of the national market. The proposed three-airline alliance would therefore have a national market share of 35 percent. In contrast, the largest of previous alliances, United/US Airways, resulted in a combined

While the existing literature has largely employed reduced-form econometric estimation to quantify the price effects of *existing* airline code-share agreements,[8] such an approach may not be sufficient for policy makers who must make decisions on whether to approve *proposed* code-share alliances. Before approving a code-share alliance, policy makers would like to have a reasonable answer to the following question: Given the existing level of competition between the potential alliance partners in a particular market, what is the maximum amount by which prices will increase if they collude on prices? Note that the question is posed in the context of a worst case scenario, since a code-share alliance does not automatically imply that partners will collude on prices for overlapping routes. An answer to this question effectively provides an estimate of the potential cost to consumers of the alliance. To the extent that policy makers can estimate the potential cost, then they can compare them to the potential benefits that the alliance partners will no doubt emphasize. As such, we need a structural econometric model designed to quantify the potential competitive effects of a proposed alliance on potential partners' overlapping routes.

A structural econometric model of the demand and supply for air travel is presented in section 2. Since the airline industry is a differentiated products industry, air travel demand is derived from a discrete choice model where each consumer chooses the product with the bundle of characteristics that maximizes her utility. The discrete choice approach to modeling consumer demand has been used extensively in differentiated products industries.[9] This approach has the advantage of allowing the researcher to explicitly model consumers' heterogeneity, which is crucial in differentiated products industries.[10]

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market share of 23 percent."

[8] See Bamberger, Carlton, and Neumann (2001) for an example of using reduced-form econometric models to evaluate competitive effects of domestic airline alliances. In the case of international airline alliances, see Brueckner (2003), and Brueckner and Whalen (2000) for a reduced-form econometric approach.

[9] See Gayle(2006a and 2006b), Armantier and Richard (2003), Berry, Carnal, and Spiller(1997), Berry(1990) for examples in the airline industry. For examples in other industries, see Berry, Levinsohn, and Pakes (1995), Berry(1994), Nevo(2000a), and Villas-Boas (2003).

[10] For example, the mixed logit (or random coefficients logit) model has recently become a popular discrete choice model of demand [see McFadden and Train (2000)]. In the mixed logit model, consumers are allowed to have different tastes for each product characteristic. In addition, the

For the supply side of the model, I assume that Nash equilibrium in a simultaneous-move price setting game can approximate price setting in the airline industry. Following Nevo (2000b), this assumption is used along with demand parameter estimates to recover marginal costs non-parametrically. With the marginal cost estimates in hand, the post-alliance collusive equilibrium can be simulated. The pre-alliance and predicted post-alliance prices can then be compared to quantify the extent to which prices may increase in the post-alliance industry. To the best of my knowledge, no one has used this structural approach to analyze the potential collusive effect of airline alliances.[11, 12] The proposed Delta/ Continental/ Northwest alliance provides an ideal setting in which to apply the econometric model since the partner airlines had significant overlap in their route networks in the pre-alliance industry.

The rest of the paper is organized as follows. The empirical model is presented in section 2. Section 3 discusses the estimation strategy. I discuss characteristics of the data in section 4, and results are presented and discussed in section 5. Even though the analysis in this paper focuses on a sample of U.S. domestic air travel markets, the research methodology can easily be extended to international air travel. Concluding remarks are made in section 6.

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mixed logit model is flexible enough to allow the researcher to use demographic information to partly explain taste heterogeneity [see Nevo(2000a)].

[11] To the best of my knowledge, Oum, Park, and Zhang (1996) are among the first set of researchers to use a structural econometric model to estimate the price effect of code-share alliances. However, in contrast to my model, their model only focused on the effect of an alliance among non-leader airlines on the price of the market leader.

[12] Armantier and Richard (2003) present an interesting consumer welfare analysis of domestic airline alliances using a discrete choice model. One crucial difference between their model and the model I present in the next section of this paper, is that their model did not have a supply side. As such, they did not explicitly model pre- and post-alliance firm conduct. Gayle (2006b) presents a structural econometric model of airline codesharing within a discrete choice framework but uses the model to evaluate the pricing efficiency of codeshare partners on complementary routes rather than investigating potential collusive behavior on overlapping routes. Park and Zhang (2000) also present an interesting econometric model of international airline alliances. The main difference between my model and the model in Park and Zhang, is that I allow products to be differentiated and explicitly model consumers' heterogeneity and choice behavior.

2 The Model

A model of demand and supply for air travel is presented in this section. This model is then used in subsequent sections to analyze the competitive effects of airlines jointly pricing their products in markets where they have traditionally competed. As pointed out by the U.S. Department of Transportation, such collusive behavior may be facilitated by code-share agreements between airlines. Following a technique developed by Nevo (2000b), I first use pre-alliance data to estimate demand parameters and use these parameter estimates together with a Bertrand-Nash assumption to recover marginal costs non-parametrically and simulate the collusive code-sharing equilibrium. In what follows, I first outline the demand side of the model, after which I outline the supply side.

2.1 Demand

A market is defined as a directional round-trip air travel between an origin and a destination city. The assumption that markets are directional implies that a round-trip air travel from Atlanta to Dallas is a distinct market than round-trip air travel from Dallas to Atlanta. This allows characteristics of origin city to affect demand [see Berry, Carnal, and Spiller(1997), Gayle (2006a and 2006b)]. In what follows, markets are indexed by t.

A flight itinerary is defined as a specific sequence of airport stops in traveling from the origin to destination city. Products are defined as a unique combination of airline and flight itinerary.[13] The products explicitly included in the model are "online" products. An online product means that passengers use the same airline throughout the trip even if they change planes at connecting airports. For example, three separate online products are (1) a non-stop round-trip from Atlanta to Dallas on Delta Airlines, (2) a round-trip from Atlanta to Dallas with one stop in Albuquerque

[13] Even though it is possible to further distinguish products by using a unique combination of price, airline, and flight itinerary as in Berry, Carnal, and Spiller(1997), I chose to use only airline and flight itinerary. The reason is that observed product market shares, which I define subsequently, will be extremely small if products are defined too narrowly. The empirical model becomes difficult to fit when product market shares are extremely small.

on Delta Airlines, and (3) a non-stop round-trip from Atlanta to Dallas on American Airlines. Note that all three products are in the same market.

Following the discrete choice random utility maximization framework [McFadden (1984)], let passenger i choose among J_t different products offered in market t by competing airlines. The passenger also has the option $(j = 0)$ not to choose one of the products explicitly included in the model. This is popularly referred to as the outside good/option. Since the model focuses on online products, the outside good includes air travel products that involve multiple airlines, and other means of getting from the origin to destination city and back besides air travel. Formally, a passenger chooses the alternative that gives them the highest utility, that is

$$\underset{j \in \{0,\ldots,J_t\}}{Max} \left\{ U_{ijt} = x_{jt}\beta_i - \alpha_i p_{jt} + a_j + \xi_{jt} + \varepsilon_{ijt} \right\}, \tag{1}$$

where U_{ijt} is the value of product j to passenger i, x_{jt} is a vector of observed product characteristics (a measure of itinerary convenience, whether or not the origin is a hub for the carrier, the number of intermediate stops used by an itinerary), β_i is a vector of individual-specific consumer taste parameters (assumed random) for different product characteristics, p_{jt} is the price of product j, α_i represents individual-specific marginal utility of price, a_j are product fixed effects (airline dummies) capturing characteristics of the products that are the same across markets, ξ_{jt} are unobserved (by the econometrician) product characteristics, and ε_{ijt} represents the random component of utility that is assumed independent and identically distributed across consumers, products, and markets.

I follow the mixed logit model specification outlined in Nevo (2000a) which results in the following predicted share function,[14]

[14] See McFadden and Train (2000) for a discussion of how the mixed logit model can approximate choice probabilities of any discrete choice model derived from random utility maximization. This feature makes the mixed logit model highly desirable for demand estimation, especially in the case of this paper where the demand parameter estimates are subsequently used to analyze supply behavior. I thank Sofia Villas-Boas for pointing this out.

$$s_{jt}(x_{jt},\ p_{jt};\ \alpha,\ \beta,\ \theta) = \int \frac{e^{\delta_{jt}+\mu_{ijt}}}{1+\sum_{l=1}^{J} e^{\delta_{lt}+\mu_{ilt}}} d\widehat{F}(D)dF(\nu), \tag{2}$$

where s_{jt} is the *predicted* market share of product j, $\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + a_j + \xi_{jt}$ is the mean utility obtained from product j, μ_{ijt} is an individual-specific deviation from the mean utility level which depends on individuals' taste for each product characteristic, θ is a vector of taste parameters that enters the share function nonlinearly through μ_{ijt}, $\widehat{F}(D)$ is the empirical distribution of demographic variables (income and age), and $F(\nu)$ is the standard normal distribution function which is the assumed parametric distribution for random taste parameters. As is well known in the empirical industrial organization literature, there is no closed form solution for equation (2) and thus it must be approximated numerically using random draws from $\widehat{F}(D)$ and $F(\nu)$ [see Nevo (2000a) for details].

Note that $s_{jt}(x_{jt},\ p_{jt};\ \alpha,\ \beta,\ \theta)$ in equation (2) is the *predicted* market share of product j and therefore is not observed. Given a market size of measure M, which I assume to be the size of the population in the origin city, *observed* market share of product j in market t is $S_{jt}{=}\frac{q_j}{M}$, where q_j is the actual number of travel tickets sold for a particular itinerary-airline combination called product j. The observed market share for each product is computed analogously.

2.2 Supply

The supply side of the model draws heavily from the exposition in Nevo (2000b). Based on the demand side of the model presented above, the market demand for product j in market t is given by

$$d_{jt} = M \cdot s_{jt}(x_{jt},\ p_{jt};\ \alpha,\ \beta,\ \theta).$$

To avoid a clutter of subscripts, I subsequently drop the market index t. However, all equations that follow are to be treated as if they were indexed by t. For example, when I specify an airline's profit function, it represents the airline's profit only in market t.

Let $f = 1, ..., F$ index airlines that compete in a particular market, and $\mathcal{F}_f$ be a subset of the J products that are produced by airline f. The profit of airline f is given by

$$\begin{aligned} \Pi_f &= \sum_{j \in \mathcal{F}_f} (p_j - c_j) d_j - K_f \\ &= \sum_{j \in \mathcal{F}_f} (p_j - c_j) M \cdot s_j(\mathbf{p}) - K_f, \end{aligned} \tag{3}$$

where $s_j(\mathbf{p})$ is predicted market share of product j, $\mathbf{p}$ represents a vector of prices, c_j is the constant marginal cost of product j, and K_f is the fixed cost of production. Note that $s_j(\cdot)$ is a function of all the product prices in the market [see equation (2)].

Following many papers in the empirical industrial organization literature, I assume that the Nash equilibrium in a simultaneous-move price setting game can approximate price setting in the airline industry. It is not inconceivable, however, that airlines' actual price setting mechanisms may be considerably more complicated than my simplifying static Nash assumption, but I leave such supply side modelling for future research. A pure strategy Nash equilibrium in prices implies that,

$$\mathbf{s}(\mathbf{p}) + (\Omega * \Delta)(\mathbf{p} - \mathbf{c}) = 0, \tag{4}$$

where $\mathbf{s}(\cdot)$, $\mathbf{p}$, and $\mathbf{c}$ are $J \times 1$ vectors of market shares, prices, and marginal costs respectively, while $\Omega * \Delta$ is an element by element multiplication of two matrices. Ω is a $J \times J$ product ownership matrix which has elements equal to 1 if products j and r are offered by the same airline and zero otherwise. Δ is a $J \times J$ matrix of first-order derivatives of product market shares with respect to prices.

As shown in Nevo (2000b), equation (4) can be used to measure the impact of collusion or joint pricing simply by appropriately changing Ω and solving for the new set of prices that satisfy equation (4). For example, using pre-alliance data and product ownership structure Ω^{pre}, product marginal costs, $\mathbf{c}$, can be recovered using equation (4). With these marginal costs in hand, but changing the product ownership structure matrix to Ω^{post} which reflects the extreme case of alliance partners jointly pricing their products, equation (4) can then be used to solve for the new set of equilibrium prices. The actual prices in the pre-alliance industry can then be compared to the predicted post-alliance equilibrium prices to see how the alliance could affect equilibrium prices. An alternative, but equally interesting experiment that quantifies the potential effect of the alliance is to compute the extent to which marginal cost must fall in order for prices to remain at their pre-alliance level in a collusive post-alliance equilibrium. In this case we are simply using Ω^{post} in equation (4) to solve for $\mathbf{c}$, given that $\mathbf{p}$ is unchanged.

3 Estimation

The estimation technique used is Generalized Methods of Moments (GMM). The estimation strategy follows Berry (1994), Berry, Levinsohn, and Pakes (1995), and Nevo(2000a). Basically the GMM estimates of the demand parameters are obtained by solving the following optimization problem,

$$\underset{\alpha,\beta,\theta}{Min}\ \xi' Z\Phi^{-1}Z'\xi, \tag{5}$$

where the structural demand error term is given by $\xi_{jt} = \delta_{jt} - (x_{jt}\beta - \alpha p_{jt} + a_j)$, Z is the matrix of instruments assumed orthogonal to the error vector ξ, and Φ^{-1} is the weight matrix.[15] Note however that we first need to obtain δ_{jt} before ξ_{jt} is computed. δ_{jt} is the mean level of utility that makes the *observed* product shares, S_{jt}, equal to the *predicted* product shares, s_{jt}. That is, δ_{jt} must be such that $S_{jt} = s_{jt}(\delta_{jt};\theta)$.[16] The system, $S_{jt} = s_{jt}(\delta_{jt};\theta)$, is non-linear and has to be solved numerically for δ_{jt}.[17]

[15] Fortunately, as detailed in Nevo(2000a), the computational burden of the optimization problem in (5) can be reduced substantially since α and β enter the objective function linearly. By taking the first order condition of the objective function with respect to α and β we can show that, $\begin{pmatrix} \beta \\ \alpha \end{pmatrix} = (X'Z\Phi^{-1}Z'X)^{-1}X'Z\Phi^{-1}Z'\delta(\theta)$ where X is the matrix of regressors containing x_{jt} and p_{jt}. We can then substitute the expression for $\begin{pmatrix} \beta \\ \alpha \end{pmatrix}$ in the objective function. This offers the advantage of performing the minimization in (5) just over θ.

[16] The predicted shares are numerically approximated using $ns = 1000$ random draws from $\widehat{F}(D)$ and $F(\nu)$, where $\widehat{F}(D)$ is the empirical distribution of demographic variables (income and age) in the origin city, and $F(\nu)$ is the multivariate standard normal distribution. As such, the simulated product shares are given by $s_{jt}(\delta_{jt};\theta) = \frac{1}{ns}\sum_{i=1}^{ns} \frac{e^{\delta_{jt}+[-p_{jt},\ x_{jt}](\Gamma D_i+\Sigma\nu_i)}}{1+\sum_{l=1}^{J} e^{\delta_{lt}+[-p_{lt},\ x_{lt}](\Gamma D_i+\Sigma\nu_i)}}$, where $\theta = (\Gamma, \Sigma)$.

[17] See Berry, Levinsohn, and Pakes (1995) and Nevo(2000a) for details on numerical methods used to solve $S_{jt} = s_{jt}(\delta_{jt};\theta)$ for δ_{jt} in the case of the random coefficients logit model. I used their

3.1 Instruments

If we assume that airlines take into account all the non-price characteristics (x_{jt} and ξ_{jt}) of their products before setting prices, then prices will depend on ξ_{jt}. In other words, components of ξ_{jt}, such as various marketing and promotional activities, all of which are market-specific and unobservable to me (but observable to consumers and airlines), are likely to influence prices. As such, the estimated coefficient on price will be inconsistent if appropriate instruments are not found for prices.

As is well known in econometrics, valid instruments must satisfy two requirements. First, instruments must be uncorrelated with the residual, and second, they must be correlated with the endogenous variable. In other words, valid instruments must be uncorrelated with ξ_{jt} but correlated with p_{jt}. I employ three sets of instruments in estimation, (1) average prices charged by an airline in other markets to instrument for its prices in each market; (2) measures of the level of competition in a market; (3) the number of other products offered by an airline in a market. In the case of the first set of instruments, the idea is that the prices charged by an airline across different markets may contain a common cost component.[18] The second set of instruments include, the number of competitor products in the market, the number of competing products offered by other airlines with equivalent number of intermediate stops, and the squared deviation of a product's itinerary distance from the average itinerary distance of competing products offered by other airlines. These instruments are motivated by supply theory which predicts that a product's price is affected by the number and closeness of competing products in the market. Finally, the third set of instruments recognizes the fact that an airline that offers multiple products in a market will jointly set the prices for these products. For example, if the airline increases the price on its direct flight in a market, consumers may substitute towards the said airline's connecting flights, rather than to a rivals product [see Lederman (2003)].

contraction mapping method in this paper.

[18] See Nevo(2000a) for more on the justification of instruments of this nature.

4 Data

Data on the airline industry are drawn from the U.S. Bureau of Transportation Statistics Origin and Destination Survey (DB1B), which is a 10% sample of airline tickets from reporting carriers. The DB1B database includes such items as number of passengers that chose a given flight itinerary, fares of these itineraries, the specific sequence of airport stops each itinerary uses in getting passengers from the origin to destination city, and distance flown on each itinerary in a directional market. The distance associated with each itinerary in a market may differ since each itinerary may use different connecting airports in transporting passengers from the origin to destination city. The data I use link each product to a directional market rather than a mere non-stop route or segment of a market. For this research, I focus on the U.S. domestic market in the first quarter of 2002, which is before the proposed code-share alliance of Continental, Delta, and Northwest (pre-alliance).

Variables that I gathered and constructed from the database are, "Price", "Stops", "Hub", and "Convenient". These variables are the observable product characteristics used in estimation. Recall that I define a product as a unique itinerary-airline combination. As such, "Price" is the average price paid by passengers who chose the specific itinerary-airline combination.[19] Vector x_{jt} in equation (1) contains "Stops", "Hub", "Hub×Stops", and "Convenient". "Stops" is a variable that counts the number of intermediate stops associated with each product. For example, in the case of products that use non-stop flight itineraries, "Stops" takes the value zero. "Hub" is a dummy variable taking the value one if the origin airport is a hub for the airline offering the product and zero otherwise. "Hub×Stops" is the interaction between "Hub" and "Stops", while "Convenient" is the ratio of itinerary distance to the non-stop distance between the origin and destination airports. An itinerary is presumed to be less convenient the further its "Convenient" measure is from 1. I

[19] Based on how products are defined in this paper, the demand model is only intended to explain choices between itinerary-airline combinations rather than more narrowly defined products that may differ within a given itinerary-airline combination.

leave discussing the rationale for using each of these variables until the results section, since the main task now is to provide descriptive information on the data.

One of the fifteen round-trip markets considered is the Minneapolis to Atlanta market.[20] Three products in this market are, (1) a non-stop flight on Northwest Airlines, (2) a non-stop flight on Delta Airlines, and (3) an itinerary with one stop in Chicago on American Airlines. Over the review period, 2,375 passengers bought product (1) at an average price of \$188.87. However, for the said review period, 24 passengers bought product (2) at an average price of \$162.10. For product (3), 12 passengers bought this product over the review period at an average price of \$144. Minneapolis is a hub for Northwest but not for Delta or American. There are two points worthy of mention here, (1) the hub product (product 1) seems to be the most popular among passengers even though it is relatively more expensive than the other two products; (2) the product with one stop is significantly cheaper than the non-stop products.

Table 1 provides a list of the airlines in the sample, while summary statistics for the entire sample of air travel data are presented in table 2. The sample contains 209 online products spread across fifteen markets. The first column in table 2 lists the fifteen markets considered, while the second column gives the number of products in each market. Columns three to six gives the number of products in each market that have zero, one, two, or three intermediate stops. These data suggest that there are more products with one intermediate stop compared to number of products in any other intermediate stops category. Products with three intermediate stops are the least common.

[20] The fifteen markets were chosen based on the hub airports for Delta, Continental, and Northwest. Specifically, the origin or destination airport in each market is a hub for at least one of the three airlines.

Table 1
List of Airlines

Name of Airline	Airline Code
American Airlines	AA
Continental Airlines	CO
Delta Airlines	DL
Frontier Airlines	F9
AirTran Airways	FL
American West	HP
Vanguard Airlines	NJ
Northwest Airlines	NW
ATA Airlines	TZ
United Airlines	UA
US Airways	US
Midwest Airlines	YX

Table 2
Summary Statistics

Markets	Sample of online Products [a] N=209	Number of online products with intermediate stops: 0	1	2	3	Hub [b] (%)	Itinerary Distance (Miles): Mean	Min	Max
Atlanta – Dallas	11	4	7	0	0	45.45	1014.18	732	1581
Atlanta - Newark	9	3	5	1	0	33.33	1085.56	745	1651
Atlanta - Los Angeles	31	5	19	5	2	6.45	2297.45	1946	3199
Atlanta - Salt Lake City	10	2	8	0	0	20	1741.90	1589	2094
Cincinnati - Atlanta	7	1	5	1	0	85.71	705.71	373	977
Cincinnati - Los Angeles	4	1	2	1	0	25	1992.5	1900	2047
Cincinnati - Salt Lake City	5	2	3	0	0	20	1645.4	1449	2066
Dallas - Atlanta	18	3	7	7	1	55.55	1210.5	732	2190
Dallas - Cincinnati	4	2	2	0	0	75	948.75	812	1105
Dallas - Newark	25	5	14	6	0	48	1641.72	1372	2956
Houston - Cleveland	12	1	9	2	0	50	1401.33	1091	2062
Houston - Newark	21	3	16	2	0	33.33	1598.86	1400	2466
Minneapolis - Atlanta	32	4	8	19	1	43.75	1365.13	906	2111
Salt Lake City - Atlanta	16	2	10	3	1	25	1874.31	1589	2510
Salt Lake City - Cincinnati	4	1	3	0	0	75	1813	1449	2490

[a] Number of distinct itinerary-airline combinations in the particular market, where passengers do not change airlines when the itinerary involves connecting flights.
[b] The percentage of the sample of products for which the origin airport is a hub.

In the seventh column of table 2, I report the percentage of products in each market for which the origin airport is a hub. For example, the table shows that of the 32 products in our sample for the Minneapolis to Atlanta market, Minneapolis is a hub for 43.75% of them (hub products).[21] Hub products may offer more convenient flight schedules since airlines normally fly to a wider range of destinations from their hub airport. As such, the empirical model should capture this non-price component

[21] Products offered by Northwest Airlines would be part of this 43.75% since Minneapolis is a major hub for Northwest. However, products offered by Delta or American Airlines in this market would not be included in the 43.75% since Minneapolis is not a hub for them.

of products as this is likely to influence passengers' choice behavior among alternative products. The last three columns in the table summarizes data on distances flown in each market.

Table 3 provides descriptive information on the "Convenient" variable. The data reveal that the "Convenient" measure does vary across itineraries that have the same number of intermediate stops. For example, "Convenient" ranges from 1.0006 to 2.28 for itineraries with one intermediate stop. This suggests that the number of intermediate stops contained in an itinerary can only capture a portion of the inherent convenience of the itinerary. In other words, even though two distinct itineraries may each have a single intermediate stop, one itinerary may use a significantly longer and presumably less desirable route.

Table 3
Summary Statistics for the "Convenient" variable

	Convenient			
Stops	**Mean**	**Standard Deviation**	**Min**	**Max**
1	1.32	0.32	1.0006	2.28
2	1.52	0.40	1.06	2.26
3	1.80	0.83	1.09	2.99

Since I am particularly interested in using this data set to analyze competition between Continental, Delta, and Northwest, it might be useful to break down the descriptive statistics, making these three airlines the focus. Table 4 shows how the distinct products in each market are distributed across airlines. For example, over the review period in the Minneapolis to Atlanta market, we see that Delta offered 1 route, Northwest offered 14 distinct routes, and Continental did not offer any product. In other words, if a passenger decided to fly on Northwest in the Minneapolis to Atlanta market, they had multiple routes to choose from, one of which is a non-stop route also offered by Delta. There are 17 other distinct products in this market, which are distinguished by either airlines, routing, or both.

Table 4
Disaggregated Sample of Products

Market	Total Sample of Online Products	Sample of online products distributed by Airlines: Continental	Delta	Northwest	Others
Atlanta – Dallas	11	0	4	1	6
Atlanta – Newark	9	1	2	2	4
Atlanta - Los Angeles	31	0	2	3	26
Atlanta - Salt Lake City	10	1	2	2	5
Cincinnati - Atlanta	7	0	6	1	0
Cincinnati - Los Angeles	4	0	1	0	3
Cincinnati - Salt Lake City	5	1	1	0	3
Dallas – Atlanta	18	0	3	0	15
Dallas – Cincinnati	4	0	2	0	2
Dallas – Newark	25	1	0	4	20
Houston - Cleveland	12	6	0	2	4
Houston – Newark	21	7	1	4	9
Minneapolis – Atlanta	32	0	1	14	17
Salt Lake City – Atlanta	16	1	4	1	10
Salt Lake City - Cincinnati	4	0	3	0	1

Even if we observe the three airlines offering a disproportionate number of products in a particular market, this information is not sufficient to draw inferences about the degree of competition that exists between them. For example, even though we observe Northwest offering 14 distinct products in the Minneapolis to Atlanta market, the information in table 4 does not allow us to say whether a significant number of passengers would rather choose Delta's single product or one of the other 17 products if Northwest increases its prices by 10%. The empirical model is design to explore such competition issues. In fact, we ultimately want to use the empirical model to predict the extent to which their prices will increase if the three airlines were to jointly, rather than competitively, price their products.

Continental, Delta, and Northwest's mean prices when they are independently pricing their products are reported in table 5. For comparative purposes, market means are also reported in the table. Interestingly, for the markets where at least two of the three airlines offer products, their mean prices are rarely uniformly above the market mean. For example, in the Atlanta to Los Angeles market where both Delta and Northwest offer products, Delta's mean fare is substantially above the market mean, while Northwest's mean fare is substantially below the market mean. This general pattern suggests that the three airlines may not have been colluding in the pre-alliance industry.

Table 5
Mean Prices

		Mean Price of Partner Airlines before alliance		
Market	**Mean Price (Market)**	**Continental**	**Delta**	**Northwest**
Atlanta – Dallas	183.77	-	232.54	239.00
Atlanta – Newark	215.67	191.68	360.18	109.75
Atlanta - Los Angeles	240.87	-	547.92	181.88
Atlanta - Salt Lake City	160.16	124.50	170.33	123.39
Cincinnati - Atlanta	327.05	-	363.06	111.00
Cincinnati - Los Angeles	315.27	-	604.50	-
Cincinnati - Salt Lake City	197.09	150.00	400.20	-
Dallas – Atlanta	280.17	-	222.59	-
Dallas – Cincinnati	271.26	-	307.17	-
Dallas – Newark	294.97	689.58	-	347.77
Houston - Cleveland	208.29	280.70	-	106.38
Houston – Newark	224.27	321.07	517.00	119.55
Minneapolis – Atlanta	287.46	-	162.10	293.95
Salt Lake City – Atlanta	178.14	157.67	238.94	115.78
Salt Lake City - Cincinnati	121.53	-	126.35	-

Given that the ticket purchase data discussed above do not have passenger-specific information, such as income or age, I use information on the distribution of demographic data in the origin city to account for taste heterogeneity in travel demand. As such, estimating equation (2) requires supplementing the ticket purchase data with demographic data drawn from the origin city's population in each market.[22] These demographic data are drawn from the 2001 and 2002 Current Population Survey (CPS) published by the U.S. Bureau of Labor Statistics. Tables 6A and 6B summarize the demographic data in each origin city.

A random sample of one thousand individuals is drawn from each origin city's

[22] This non-parametric approach to model consumer heterogeneity is explained in more detail in Nevo(2000a).

population. From the samples drawn, we can see that there is some diversity within each city. For example, while the majority of the sample between ages 21 and 40 have weekly income below $1,200, quite a few individuals in this age group earn above $1,200 per week. Further, most individuals above the age of 60 have income below $1,200 per week. When faced with the same set of options, it is likely that these distinct groups of potential passengers may make different product choices. One reason is that they may have different tastes over prices and flight schedule convenience. The empirical model is designed to account for such passenger heterogeneity.

Table 6A
Summary of Demographic Data

		Age								
Atlanta		**<21**	**21 to 30**	**31 to 40**	**41 to 50**	**51 to 60**	**61 to 70**	**71 to 80**	**>80**	Total
	Income < $300	27	37	25	21	10	5	2	0	127
	$300 to $599	9	112	95	71	40	9	0	1	337
	$600 to $899	2	79	64	65	43	6	1	0	260
	$900 to $1199	0	34	50	31	22	1	1	0	139
	$1200 to $1499	0	8	23	13	8	0	0	0	52
	$1500 to $1799	0	7	11	10	8	0	0	0	36
	$1800 or more	0	4	19	18	8	0	0	0	49
	Total	38	281	287	229	139	21	4	1	1,000
Cincinnati										
	Income < $300	26	51	26	21	23	10	8	1	166
	$300 to $599	16	108	85	76	58	18	3	0	364
	$600 to $899	3	35	71	70	48	6	1	0	234
	$900 to $1199	0	10	36	43	23	5	0	0	117
	$1200 to $1499	0	7	12	19	9	0	0	0	47
	$1500 to $1799	0	2	9	10	9	0	0	0	30
	$1800 or more	0	4	13	15	10	0	0	0	42
	Total	45	217	252	254	180	39	12	1	1,000
Dallas										
	Income < $300	36	49	39	27	6	5	1	1	164
	$300 to $599	17	101	99	71	36	7	1	0	332
	$600 to $899	3	66	69	50	31	4	0	0	223
	$900 to $1199	0	22	42	21	20	5	1	0	111
	$1200 to $1499	0	7	24	20	8	1	0	0	60
	$1500 to $1799	0	4	11	16	5	0	0	0	36
	$1800 or more	0	9	29	23	11	2	0	0	74
	Total	56	258	313	228	117	24	3	1	1,000

Notes: The income variable is weekly income. Numbers in matrix refer to number of individuals in the income-age category.

Table 6B
Summary of Demographic Data

		Age								
Hous-ton		**<21**	**21 to 30**	**31 to 40**	**41 to 50**	**51 to 60**	**61 to 70**	**71to 80**	**>80**	Total
	Income < $300	33	50	38	29	14	10	2	0	176
	$300 to $599	17	122	103	83	42	13	1	0	381
	$600 to $899	2	44	77	65	27	3	0	0	218
	$900 to $1199	1	22	19	21	22	1	1	1	88
	$1200 to $1499	0	13	22	25	4	0	0	1	65
	$1500 to $1799	0	2	8	14	4	1	0	0	29
	$1800 or more	0	4	3	23	10	3	0	0	43
	Total	53	257	270	260	123	31	4	2	1,000
Minne-apolis										
	Income < $300	38	29	21	19	10	12	6	0	135
	$300 to $599	13	87	63	69	22	8	5	1	268
	$600 to $899	5	58	76	67	38	9	0	0	253
	$900 to $1199	0	20	57	50	36	2	0	0	165
	$1200 to $1499	0	11	25	24	14	4	0	0	78
	$1500 to $1799	0	3	10	13	12	1	0	0	39
	$1800 or more	0	1	19	27	13	2	0	0	62
	Total	56	209	271	269	145	38	11	1	1,000
Salt Lake City										
	Income < $300	66	56	32	27	17	12	1	0	211
	$300 to $599	25	116	81	61	42	18	1	2	346
	$600 to $899	0	56	77	73	22	7	1	0	236
	$900 to $1199	0	17	31	29	25	8	1	0	111
	$1200 to $1499	0	3	18	12	11	2	0	0	46
	$1500 to $1799	0	3	6	7	3	3	0	0	22
	$1800 or more	0	3	7	7	5	6	0	0	28
	Total	91	254	252	216	125	56	4	2	1,000

Notes: The income variable is weekly income. Numbers in matrix refer to number of individuals in the income-age category.

5 Results

In this section, I first interpret and discuss the estimates of the demand parameters. I then use these estimates to compute own and cross price elasticities, and proceed to discuss these elasticities with a particular focus on competition between Continental, Delta, and Northwest in each market. The discussion on the elasticities serves as an introduction to analyzing the supply side of the model, where I simulate the collusive post-alliance equilibrium and quantify the extent to which these prices may differ from their pre-alliance levels.

5.1 Parameter Estimates

I found that two sets of demand parameter estimates are consistent with utility maximization in the data set. However, only one set is consistent with both utility and profit maximization (optimal static pricing). I report both sets of estimates in table 7 but only the set consistent with both utility and profit maximization are used in subsequent analyses.[23] The demand estimates that are not consistent with profit maximization imply that some products have negative marginal cost. However, all products have strictly positive marginal cost for the demand estimates that are consistent with both utility and profit maximization.

Table 7
Model Estimates

		Consistent with Utility and Profit Maximization		Consistent only with Utility Maximization	
	Variables	**Coefficients**	**Standard Errors**	**Coefficients**	**Standard Errors**
Mean	Price	-108.04*	16.56	-60.04*	4.11
	Hub	0.64*	0.05	0.52*	0.04
	Hub $\times$ Stops	-0.63*	0.04	-0.38*	0.03
	Stops	-2.51*	0.26	-1.60*	0.16
	Convenient	-3.83*	0.68	-1.44*	0.31
Standard Deviations	Constant	1.39*	0.08	-2.12*	0.09
	Price	2.60	4.67	-1.69	2.84
	Stops	0.38*	0.09	-0.47*	0.04
	Convenient	0.68*	0.05	-0.54*	0.10
Interactions with Age	Constant	-1.19	1.26	9.38*	1.22
	Stops	1.52*	0.65	0.38	0.99
	Convenient	3.20*	0.72	2.40*	1.21
Interactions with Income	Constant	-2.30	1.56	0.51	0.73
	Price	-1.47	30.27	0.24	19.40
	Stops	-2.43*	0.53	0.13	0.30
	Convenient	-4.29*	1.24	0.01	0.44
GMM Obj.		0.0051		0.0046	
Overidentification Test		$n = 209$ $n \times$ GMM Obj.= 1.06 $\chi^2(0.95,19)$=30.14		$n = 209$ $n \times$ GMM Obj.= 0.96 $\chi^2(0.95,19)$=30.14	

Notes: * indicates statistical significance at the 5% level. Each model is estimated with a full set of airline dummies even though the coefficient estimates on the dummies are not reported. The overidentification tests suggest that the overidentifying restrictions are valid.

To identify the set of parameters that are consistent with both utility and profit maximization, I imposed the constraint that implied marginal cost must be equal

[23] Table A1.1 in appendix 1 reports standard logit estimates, and non-linear least squares estimates for the demand model. There you will also find a price exogeneity test.

to or greater than zero when minimizing the GMM objective function.[24] In this constrained minimization, the constraint is not binding at the solution parameters. This therefore suggests that these solution parameters describe equilibrium consumer behavior irrespective of the non-negative marginal cost constraint. As such, rather than being a constraint, the non-negative marginal cost requirement serves more to identify optimizing consumer behavior that is consistent with market equilibrium.

As expected, the coefficient on "Price" is negative, indicating that an airline can increase the probability that potential passengers will choose it's flight itinerary by lowering the airfare on the said itinerary, *ceteris paribus*. It does not appear that there is significant taste heterogeneity with respect to price since the standard deviation of the price effect and the coefficient on the interaction of price with income are not statistically different from zero at conventional levels of significance.

Two possible reasons why passengers are more likely to choose itineraries offered by hub airlines are: (1) flight schedules offered by hub airlines may be more convenient, (2) it is more likely that passengers have frequent flyer membership with a hub airline.[25] The variable "Hub" is a dummy variable taking the value one if the product is offered by an airline that has a hub at the origin airport and zero otherwise. The coefficient on "Hub" is positive, indicating that potential passengers are more likely to choose itineraries where the origin airport is a hub for the airline offering the itinerary. In other words, airlines have a strategic advantage at their hub airports compared to their non-hub competitors.

Another product characteristic that influences passengers' choice of products is the convenience of flight schedule embodied in the itinerary. I use number of intermediate stops on an itinerary to capture a portion of this convenience effect. The coefficient on this variable has a negative sign as expected and is statistically significant at conventional levels of significance. This indicates that consumers are more likely to choose flight itineraries with less intermediate stops, *ceteris paribus*. The

[24] The inequality constraint is formulated as $\mathbf{p} - \left[-(\Omega * \triangle)^{-1}\,\mathbf{s}(\mathbf{p})\right] \geq 0$, where $\left[-(\Omega * \triangle)^{-1}\,\mathbf{s}(\mathbf{p})\right]$ is the markup function that is nonlinear in the demand parameters.

[25] See Proussaloglou and Koppelman (1995), Berry (1990), Schumann (1986).

coefficient on the interaction between number of intermediate stops and "Hub" is negative as expected, and statistically significant at conventional levels of significance. The negative coefficient on this interaction variable suggests that the attractiveness of hub products over their non-hub counterparts is lessened as the number of intermediate stops in hub products' itinerary increases, *ceteris paribus*. In addition, the marginal disutility of an intermediate stop is greater for hub products compared to non-hub products. This could be suggesting that passengers expect hub products to have convenient schedules and thus they are more heavily penalized relative to non-hub products for not having convenient schedules.

It appears that passengers' have heterogenous taste with respect to the number of intermediate stops as evidenced by the statistical significance of the standard deviation parameter for "Stops". Further, a negative coefficient when "Stops" is interacted with income suggests that higher income passengers are more likely to choose itineraries with less intermediate stops compared to lower income passengers. The positive coefficient when "Stops" is interacted with age suggests older passengers are more likely to choose itineraries with more intermediate stops compared to younger passengers. It could be that older passengers tend to be more leisure travelers and therefore care less about itinerary convenience relative to younger passengers. In summary, young high-income passengers seem to care more about number of intermediate stops relative to old low-income passengers.

Recognizing that number of intermediate stops may only capture a portion of the inherent convenience of an itinerary, I also included the "Convenient" variable. Recall that "Convenient" is the ratio of itinerary distance to the non-stop distance between the origin and destination cities. This variable is able to distinguish between various routes that have the same number of intermediate stops but differ with respect to distance flown in getting the passenger from the origin to destination city. As expected, the coefficient on "Convenient" has a negative sign and is statistically different from zero. In other words, passengers prefer to use a less circuitous route in traveling from the origin to destination city.

The statistical significance of the standard deviation parameter for "Convenient" suggests that passengers are heterogenous with respect to their taste for the distance of the route used in traveling from the origin to destination city. Further, the sign pattern of the coefficients when "Convenient" is interacted with income and age suggests that younger, higher income passengers are relatively more concerned with itinerary convenience. This qualitative result coincides with these young high-income passengers' taste for number of intermediate stops discussed above.

5.1.1 Elasticities

In analyzing the degree of competition that exists between Continental, Delta, and Northwest in each market, I first use the demand parameter estimates to construct matrices of own and cross prices elasticities of demand.[26] Each market has its own elasticity matrix associated with it. The entries on the main diagonal of each matrix are estimates of the airlines' average own price elasticity of demand, while off diagonal elements are estimates of the airlines' average cross price elasticities of demand. An element in the matrix is interpreted as the percentage by which a row airline's demand changes as a result of a change in the price of a column airline.

The elasticity matrix for the Atlanta-Dallas market is presented in table 8 while, the matrices for the other markets are located in appendix 2. The estimates in table 8 suggest that a 1% increase in Delta's price will reduce quantity demand for Delta's products by 2.48%. Similarly, a 1% increase in Northwest's price will reduce quantity demand for Northwest's products by 2.54%. However, cross elasticity estimates suggest that a 1% increase in Delta's price will increase Northwest's demand by 0.0027%, while a 1% increase in Northwest's price will increase Delta's demand by 0.0004%.

[26] See Nevo (2000a) for details on how own and cross price elasticities are computed in the case of the random coefficients logit model.

Table 8
Price Elasticity of Demand Matrix

	Market: Atlanta – Dallas					
	TZ	DL	FL	NJ	NW	UA
TZ	-1.4949	0.0018	0.0592	0.0013	0.0004	0.0088
DL	0.0270	-2.4809	0.0642	0.0016	0.0004	0.0109
FL	0.0194	0.0014	-1.3605	0.0008	0.0002	0.0045
NJ	0.0256	0.0019	0.0611	-1.2764	0.0004	0.0099
NW	0.0354	0.0027	0.0831	0.0029	-2.5437	0.0229
UA	0.0344	0.0026	0.0812	0.0026	0.0009	-2.0903
Outside	0.0011	0.0001	0.0027	0.00003	0.00001	0.0001

Recall that the outside good represents travel options in the given market that are not explicitly included in the model. For example, the outside good includes air travel products that involve multiple airlines, and other means of getting from the origin to destination city besides air travel. An element in the last row of the matrix tells us by how much the demand for the outside good changes as a result of a change in the price of the column airline. For example, a 1% increase in Delta's price increases demand for the outside good by 0.0001%, while a 1% increase in Northwest's price increase the demand for the outside good by 0.00001%.

While interpretation of the own and cross price elasticities of demand is a useful exercise to see how sensitive the demand is for an airline's products to changes in its own or other airlines' prices, we ultimately want to derive a comparative measure of the degree of competition between competing airlines. Such a measure is obtained by weighting the elasticities by their respective quantities and dividing an airline's quantity-weighted cross price elasticity by its quantity-weighted own price elasticity. This ratio tells us the proportion of an airline's lost sales that is captured by a competitor. For example, suppose airlines A, B, and C compete in a market. Let η_{aa}, η_{ba}, and η_{ca} be the own, and cross price elasticities for airline A, where $\eta_{aa} = \frac{\partial Q_a}{\partial P_a}\frac{P_a}{Q_a}$, $\eta_{ba} = \frac{\partial Q_b}{\partial P_a}\frac{P_a}{Q_b}$, and $\eta_{ca} = \frac{\partial Q_c}{\partial P_a}\frac{P_a}{Q_c}$ respectively. That is, η_{aa}, η_{ba}, and η_{ca} tell us how airline A, B, and C, sales are affected by a change in airline A's price. However, the ratio $\frac{\eta_{ba} \times Q_b}{\eta_{aa} \times Q_a}$ tells us the proportion of airline A's *lost* sales that is captured by airline B if airline A increases its price marginally. Likewise, $\frac{\eta_{ca} \times Q_c}{\eta_{aa} \times Q_a}$ tells us the proportion of airline A's lost sales that is captured by airline C if airline A increases its price marginally. Therefore, if $\frac{\eta_{ba} \times Q_b}{\eta_{aa} \times Q_a} > \frac{\eta_{ca} \times Q_c}{\eta_{aa} \times Q_a}$, we can infer that airline B is a closer competitor to airline A than is airline C to airline A.

These comparative measures of the closeness of competitors are computed and presented in tables 9A, 9B, and 9C. An entry in these tables tells us, on average,[27] the percentage of the column airline's lost sales that is captured by the row airline given a marginal increase in the column airline's price. Each column gives a complete break down of how the column airline's lost sales are distributed and therefore sums to 100. The tables are constructed with a focus on competition between Delta, Continental, and Northwest in each market. As such, entries in the row labeled "Inside" is an aggregate across the products of the other airlines included in the model. As before, the row labeled "Outside" represents the composite outside option.

Table 9A
Percentage of lost sales going to competing products

	Atlanta – Dallas		**Atlanta – Newark**			**Atlanta - Los Angeles**		**Atlanta - Salt Lake City**		
Airlines	DL	NW	CO	DL	NW	DL	NW	CO	DL	NW
CO	-	-	-	0.29	0.31	-	-	-	0.02	0.02
DL	0.35	0.58	0.13	0.04	0.12	0.03	0.05	0.01	0.01	0.01
NW	0.02	-	0.09	0.11	0.06	0.42	0.26	0.91	0.64	0.26
Inside	8.37	11.48	5.38	4.54	4.92	15.55	14.74	1.64	1.13	1.25
Outside	91.27	87.94	94.41	95.03	94.59	84.01	84.94	97.43	98.21	98.46
Total	100	100	100	100	100	100	100	100	100	100

[27] Since some airlines may offer multiple products within a market, for these airlines, an entry in the table is an average across the products offered by the airline.

Table 9B
Percentage of lost sales going to competing products

	Cincinnati – Atlanta		Cincinnati - Los Angeles	Cincinnati - Salt Lake City		Dallas – Atlanta	Dallas – Cincinnati	Dallas – Newark	
Airlines	DL	NW	DL	CO	DL	DL	DL	CO	NW
CO	-	-	-	-	0.01	-	-	-	0.03
DL	0.29	0.37	-	0.05	-	0.02	0.05	-	-
NW	0.04	-	-	-	-	-	-	0.05	0.05
Inside	-	-	0.98	0.07	0.05	1.31	0.05	2.97	3.78
Outside	99.67	99.63	99.02	99.88	99.94	98.66	99.91	96.98	96.14
Total	100	100	100	100	100	100	100	100	100

Table 9C
Percentage of lost sales going to competing products

	Houston – Cleveland		Houston – Newark			Minneapolis – Atlanta		Salt Lake City – Atlanta			Salt Lake City – Cincinnati
Airlines	CO	NW	CO	DL	NW	DL	NW	CO	DL	NW	DL
CO	0.03	0.04	0.04	0.05	0.04	-	-	-	0.10	0.08	-
DL	-	-	0.001	-	0.001	-	0.13	0.29	0.27	0.30	0.09
NW	0.02	0.01	0.06	0.06	0.04	7.72	13.30	3.33	4.28	-	-
Inside	0.06	0.07	0.34	0.33	0.32	1.60	3.42	9.11	11.66	9.47	0.46
Outside	99.89	99.88	99.57	99.57	99.59	90.68	83.14	87.27	83.70	90.15	99.45
Total	100	100	100	100	100	100	100	100	100	100	100

In the Atlanta to Dallas market we see that Northwest only captures 0.02% of Delta's lost sales when Delta increases its price marginally. In contrast, online products offered by other airlines in this market manage to capture 8.37% of Delta's lost sales, while 91.27% goes to the outside option. For completeness in describing the entries in the column, I ought to describe Delta's ability to recapture some of its lost sales. That is, since Delta is a multiproduct firm in this market, whenever it increases its price marginally on one of its products, on average, its other substitute products recapture 0.35% of the lost sales from the product whose price increased marginally.

The second column in the Atlanta to Dallas market tells us that Delta is only able to capture 0.58% of Northwest's lost sales if Northwest increases its price marginally, while the other inside products and the outside option capture 11.48% and 87.94% of Northwest's lost sales respectively. The data therefore suggest that competition between Delta and Northwest is relatively weak in the Atlanta to Dallas market. In fact, the only market where competition seems meaningful between Delta and Northwest is the Minneapolis to Atlanta market. In this market we see that Northwest has the ability to capture 7.72% of Delta's *lost* sales if Delta increases its price marginally.

In summary, competition between the three airlines seems weak. This suggests that equilibrium prices for these airlines should not be expected to change much if they jointly, as oppose to noncooperatively, price their products. In other words, passengers seem to have sufficiently attractive travel alternatives in these markets that would effectively constrain collusive behavior between Delta, Continental, and Northwest. However, without incorporating the supply side of the model in the analysis, we cannot predict by how much equilibrium prices may change in moving from a noncooperative to a collusive equilibrium.

5.1.2 Sensitivity Analysis

Before moving on to discuss the supply side results, it is prudent to analyze how sensitive the previous results are to changes in the definition of market size.[28] As a reminder, market size (M) is assume to be equal to the size of the population in the origin city. To perform the sensitivity analysis, I re-estimate the model under two different market size definitions: (1) market size equal to 15% of origin city population; (2) market size equal to twice the size of origin city population. I then re-compute the matrices in tables 9A, 9B, and 9C under each market size definition. These new matrices, 9A-1, 9B-1, 9C-1, 9A-2, 9B-2, and 9C-2, are located in appendix 2.

The outside option becomes a closer substitute to all products included in the model, the larger the potential market. In other words, by defining the market size as twice the origin city population instead of 15% of or equal to the origin city

[28] I thank an anonymous referee for suggesting that I do this.

population, we make the potential market larger and effectively make the outside option a closer substitute for all included products. Therefore, as expected, the matrices in tables 9A-1, 9B-1, and 9C-1 reveal that when market size is defined as 15% of origin city population, the amount of the airlines' lost sales going to the outside option is lower in most cases. The converse holds when the market size is defined as twice the origin city population. However, as is the case in tables 9A, 9B, and 9C, a relatively large proportion of lost sales still goes to the outside option irrespective of substantial variation in the definition of market size. Since we would not expect a substantial number of people to choose not to fly if the concerned airlines increase their price marginally, then the outside option is likely picking up air travel products not captured in the data. These excluded air travel products will likely further thwart effective collusive behavior by the three airlines. This inference is supported by the fact that substitutability between the three airlines remains relatively low irrespective of the market size definition as evidenced in the recomputed matrices.

Subsequent analyses are based on market size being equal to origin city population. However, qualitative results are robust to wide variations in market definition.

5.2 Supply and Equilibrium

Table 10 reports the predicted effects of Delta, Continental, and Northwest jointly as oppose to noncooperatively pricing their products. Tables A 3.1 and A 3.2, located in appendix 3, present similar price comparisons for other competing airlines in each market. The first data column in the table shows the three airlines' median pre-alliance prices in each market. The second data column shows the median percent by which each of the three airlines' price will increase if they jointly price their products in the post-alliance industry, *ceteris paribus*. Consistent with our analyses of the demand elasticities in the previous section, the only market where prices are expected to increase is the Minneapolis to Atlanta market. Furthermore, the largest median price increase is only 4.44%. These findings further confirm that passengers seem to have sufficiently attractive travel alternatives in these markets that would effectively constrain collusive behavior between the three airlines.

Table 10
Predicted Effects of Joint Pricing

Market	Airline	Median Price	Median Percent Price Increase	Median Marginal Cost	Median Marginal Cost Reduction
Atlanta – Dallas	Delta	219.00	0	124.81	0
	Northwest	239.00	0	145.04	0
Atlanta – Newark	Continental	191.68	0	97.91	0
	Delta	360.18	0	266.62	0
	Northwest	109.75	0	16.31	0
Atlanta - Los Angeles	Delta	547.92	0	453.86	0
	Northwest	180.60	0	86.24	0
Atlanta - Salt Lake City	Continental	124.50	0	31.66	0
	Delta	170.33	0	77.19	0
	Northwest	123.39	0	29.70	0
Cincinnati – Atlanta	Delta	276.69	0	182.69	0
	Northwest	111.00	0	17.04	0
Cincinnati - Salt Lake City	Continental	150.00	0	56.90	0
	Delta	400.20	0	306.95	0
Dallas – Newark	Continental	689.58	0	596.27	0
	Northwest	226.89	0	133.72	0
Houston – Cleveland	Continental	232.59	0	139.73	0
	Northwest	106.38	0	13.02	0
Houston – Newark	Continental	224.60	0	130.97	0
	Delta	517.00	0	423.25	0
	Northwest	120.60	0	26.93	0
Minneapolis – Atlanta	Delta	162.10	4.447	68.83	11.359
	Northwest	191.44	0.063	86.58	0.163
Salt Lake City – Atlanta	Continental	157.67	0	64.06	0
	Delta	209.39	0	115.68	0
	Northwest	115.78	0	19.02	0

Notes: The second data column shows the median percentage by which Delta, Continental, and Northwest's predicted collusive prices exceed their actual prices. The third data column shows the median implied marginal cost for each of the three airlines in respective markets. The last data column shows the median percent by which marginal cost must fall to prevent price from increasing if the three airlines practice price collusion.

Since alliance partners often jointly use each others facilities (lounges, gates, check-in counters etc.), and may also practice joint purchase of fuel, it is likely that alliances generate cost saving. As such, an interesting question to pose is: How much does marginal cost have to fall (extent of cost savings) in order to ensure that prices do not change in the event that the three airlines jointly price their products?[29] It is important that policy makers have an impartial assessment of such cost savings before making a decision on whether to approve a propose alliance. The policy makers can then compare their impartial assessment of required cost savings with the cost savings and other benefits that the airlines will present to persuade approval. The last column in table 10 provides these required cost savings estimates. Not surprisingly, the only market where a reduction in marginal cost is necessary is the Minneapolis to Atlanta market. The largest median marginal cost reduction required is only 11.36%.

5.2.1 The Bertrand-Nash Assumption

A legitimate concern with the supply side analysis above is whether the Bertrand-Nash assumption is reasonable in the case of the airline industry.[30] To explore this concern, I parameterize marginal cost using a popular functional form for marginal cost in the empirical industrial organization literature,[31]

$$c_{jt} = \exp(W_{jt}\gamma + b_j + \psi_{jt}), \tag{6}$$

where γ is a vector of parameters to be estimated, W_{jt} is a vector of variables that shift marginal cost, b_j are product fixed effects (airline dummies) capturing the components of an airline's products' marginal cost that are the same across markets, and ψ_{jt} is a mean zero, random error term that captures unobserved determinants of marginal cost.

The Bertrand-Nash assumption results in the following supply equation,

$$p_{jt} = \exp(W_{jt}\gamma + b_j + \psi_{jt}) + m_{jt}, \tag{7}$$

[29] I thank an anonymous referee for pointing out this important policy relevant cost analysis.

[30] I thank the editor, Dennis Carlton, for suggesting that I explore the appropriateness of the Bertrand-Nash assumption.

[31] For example, see Goldberg and Verboven (2001), and Ivaldi and Verboven (2004).

where m_{jt} is a markup variable that is computed prior to econometrically estimating the supply equation.[32] By transforming equation (7) as follows,

$$\ln(p_{jt} - m_{jt}) = W_{jt}\gamma + b_j + \psi_{jt}, \tag{8}$$

we can use simple linear estimation techniques to estimate the parameters of the marginal cost function. These parameter estimates are reported in table 11.[33]

Table 11
Marginal Cost Function Parameter Estimates

Variables	Coefficient Estimates	Standard Error
Hub	0.26	0.19
Itinerary Distance	2.44*	0.75
(Itinerary Distance)^2	-0.56*	0.20
R^2	0.97	

Notes: * indicates statistical significance at the 5% level. The coefficients are estimated using ordinary least squares. A full set of airline and market dummies are included when estimating the model, even though these parameter estimates are not reported.

While the coefficient on "Hub" is not statistically different from zero at conventional levels of significance, the other coefficients suggest that marginal cost has an inverted U-relationship with itinerary distance. This finding is consistent with an argument made in Berry, Carnal, and Spiller (1997) which says that at relatively short distances the superior cruising efficiency of larger planes may not dominate their larger takeoff and landing cost and therefore marginal cost is increasing in distance at relatively short distances. However, at relatively long distances it becomes

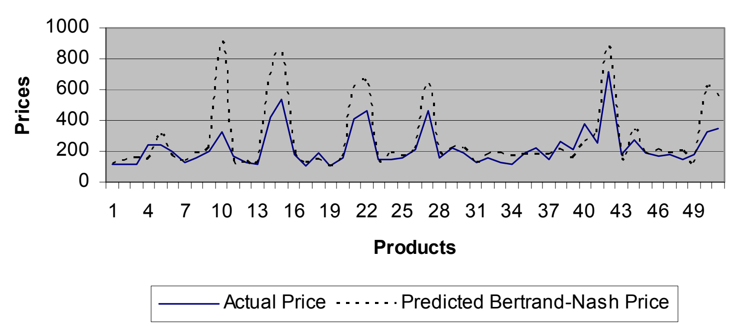
[32] With estimates of the demand parameters in hand, the markup variable is computed using $-(\Omega * \triangle)^{-1}\mathbf{s}(\mathbf{p})$.

[33] Technically, the standard errors of the supply parameters should be corrected to reflect the fact that m_{jt} is a function of previously estimated demand parameters [see Newey and McFadden (1994)]. However, this correction is complicated to implement because m_{jt} is highly nonlinear in the demand parameters. Since the method used below to evaluate the appropriateness of the Bertrand-Nash assumption, which is the main objective of this subsection, does not require corrected standard errors, I just report the uncorrected standard errors in table 11. As such, we must exercise caution when drawing conclusions from table 11 about the determinants of marginal cost.

optimal to use larger planes since their cruising efficiency may dominate their higher takeoff and landing cost which eventually cause marginal cost to decline in distance.

With estimates of the marginal cost parameters in hand, we can first compute estimates of marginal cost, $\widehat{c}_{jt} = \exp(W_{jt}\widehat{\gamma} + \widehat{b}_j)$, and then use these estimates to solve for the prices that satisfy equation (4), $\mathbf{s}(\mathbf{p}) + (\Omega * \Delta)(\mathbf{p} - \widehat{\mathbf{c}}) = 0$. If these predicted Bertrand-Nash prices are not highly correlated with actual prices, then either the functional form assumption for marginal cost is inappropriate or the Bertrand-Nash assumption is inappropriate, or both.[34] However, I found that predicted Bertrand-Nash and actual prices are highly correlated (correlation of 0.90) which suggests that the Bertrand-Nash assumption may be reasonable. This is also illustrated graphically in figures 1 to 4 where I plot the actual and predicted Bertrand-Nash price series. We can see that the model does a good job at predicting actual prices.

Figure 1: Products in Markets 1 - 3



[34] I thank an anonymous referee for pointing out that a comparison between actual prices and the predicted Bertrand-Nash prices is basically a joint test of the marginal cost specification and the Bertrand-Nash assumption.

Figure 2: Products in Markets 4 - 9

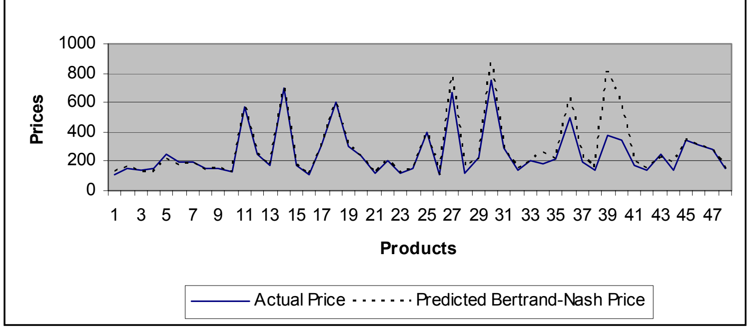


Figure 3: Products in Markets 10 - 12

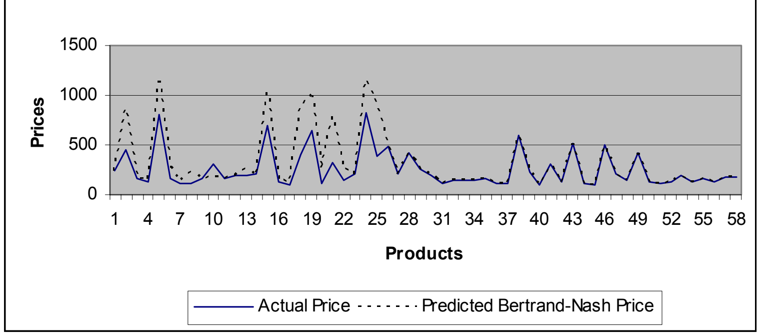
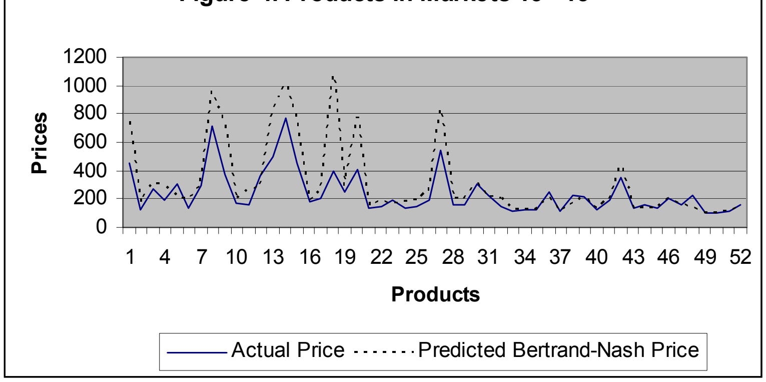


Figure 4: Products in Markets 13 - 15



5.2.2 Reconciling Predictions with Reality

In June 2003, Continental, Delta, and Northwest, launched their alliance after satisfying policy makers that they would remain competitive on overlapping routes rather than practice collusion. Recall that any predicted price increase in table 10, is based on the assumptions that, (1) alliance partners' collude on prices, (2) there were no cost efficiencies generated by the alliance. In other words, if alliance partners continue to compete as in the pre-alliance industry, and if the alliance generated cost efficiencies, then prices may even fall on overlapping routes in the post-alliance industry.

An extremely crude check of how prices actually changed is presented in table 12. The data in table 12 represent percent change in median prices by airline between the first quarter of 2002 (pre-alliance and sample period), and the first quarter of 2004 (post-alliance period). The reason these percentages are extremely crude checks of how prices actually changed is that the Origin and Destination Survey data is a 10% sample of tickets sold in respective quarters. As such, there is no guarantee that sampled products will correspond across quarters and therefore I am left with little choice but to compare each airlines' median prices across quarters. For example, the data for one quarter may contain an itinerary which has a passenger flying on Delta, from Atlanta to Newark with an intermediate stop in Chicago, but this itinerary may not be present in subsequent quarters.

Table 12
Actual Percentage Change in Median Price

Market	Continental	Delta	Northwest
Atlanta – Dallas		-12.3	-54.2
Atlanta – Newark	-8.2	-45.0	6.6
Atlanta - Los Angeles		-55.1	36.9
Atlanta - Salt Lake City	-8.0	46.3	5.3
Dallas – Newark	-35.1		-55.1
Houston – Cleveland	-19.9		26.7
Houston – Newark	-12.5	-45.0	-4.9
Minneapolis – Atlanta		19.8	-37.4
Salt Lake City – Atlanta	-24.1	18.0	0.4

Notes: The numbers in the table refer to percentage change in median price between the first quarter of 2002 and the first quarter of 2004. The subset of markets shown above are markets in which at least two of the partners competed in the pre-alliance market (first quarter of 2002) and continue to offer products in the post-alliance market (first quarter of 2004).

Notwithstanding the limitations of the data, the actual percent change in prices shown in table 12 reveal an interesting result. In the majority of cases, the alliance partners median prices actually fell in the post-alliance period.[35] This suggests that either the alliance partners kept their promise not to collude on prices, or the alliance generated sufficient cost savings[36] which resulted in lower prices, or both. In summary, both the post-alliance data and the results from the model seem to suggest that policy makers' ultimate approval of the alliance appeared justified.

6 Conclusion

The main contribution of this paper is to show how policy makers can use a structural econometric framework developed by Nevo (2000b) to quantify the competitive effects of *proposed* code-share alliances, where potential alliance partners compete on overlapping routes in the pre-alliance industry. Specifically, the framework can be used to quantify the extent to which collusive prices may depart from their pre-alliance levels in the worst case scenario where there is no commensurate generation of cost efficiency by the alliance. Furthermore, it can also be used to compute the extent to which marginal cost must fall in order for prices to remain unchanged in the event that partners do collude on prices in the post-alliance industry. In seeking approval from policy makers, potential alliance partners have an incentive to emphasize the benefits of the proposed alliance. Using this structural framework, policy makers can reconcile the alleged benefits with potential price increases, allowing them to make an informed decision regarding approval.

As an example, I applied the structural model to the proposed Continental/ Delta/ Northwest alliance. In reviewing the proposed alliance, the DOT raised con-

[35] Had the percentages in the table been adjusted for inflation, then the price increases would be even smaller.

[36] Chua, Kew, and Yong(2003) present an interesting empirical analysis of the effect of code-share alliances on partners' cost. They found that code-share alliances reduce airlines' cost, albeit small in magnitude.

cerns regarding the significant overlap in the potential partners' route network. In the sample of markets that were examined, I did not find any significant departure between collusive and pre-alliance prices. This suggests that passengers have sufficiently attractive travel alternatives in these markets that would effectively constrain collusive behavior between the three airlines.

With the potential partners' representation that they would not collude on prices along with satisfying other conditions,[37] the DOT ultimately allowed the alliance to go through. A crude comparison of the airlines' prices before and after formation of the alliance revealed that their prices actually fell in most of the markets considered in the analysis. Thus, both the model's predictions and the actual post-alliance prices suggest that policy makers' approval appears justified.

[37] See "Termination of Review Under 49 U.S.C § 41720 of Delta/Northwest/Continental Agreements," *Department of Transportation, Office of The Secretary*, January 2003.

A Appendix 1.

Table A1.1
Demand Estimates

	Variables	**(3) OLS**	**(4) 2SLS**	**(5) NNLS**
Mean	Price	-21.68**	-72.34**	-29.72
		(7.31)	(18.87)	(67.75)
	Hub	0.31	0.64	0.10
		(0.49)	(0.56)	(0.50)
	Hub $\times$ Stops	-0.41	-0.44	-0.60*
		(0.34)	(0.38)	(0.36)
	Stops	-1.28**	-1.19**	-2.68*
		(0.23)	(0.26)	(1.51)
	Convenient	-1.03**	-0.71*	-4.25
		(0.36)	(0.42)	(4.23)
Standard Deviations	Constant			1.42*
				(0.75)
	Price			2.23
				(29.07)
	Stops			0.36
				(0.74)
	Convenient			0.60
				(0.48)
Interactions with Age	Constant			-1.01
				(8.78)
	Stops			1.52
				(3.82)
	Convenient			2.92
				(5.36)
Interactions with Income	Constant			-2.43
				(7.97)
	Price			-1.95
				(116.58)
	Stops			-2.44
				(2.95)
	Convenient			-4.43
				(7.10)
Model Diagnostics	R2	0.98		
	Price Exogeneity Test Statistic		8.48	
	$\chi^2(0.95,1)$		3.84	

Notes: ** indicates statistical significance at the 5% level. * indicates statistical significance at the 10% level. Standard errors are in parentheses. All models are estimated with a full set of airline dummies even though the coefficient estimates on the dummies are not reported. The dependent variable for columns (3) and (4) is $\ln(s_{jt}) - \ln(s_{0t})$. The Nonlinear Least Squares (NLLS) estimates in column (5) are obtained without using any instrument for price. The price exogeneity test suggests that price is endogenous and needs to be instrumented for.

B Appendix 2.

Price Elasticity of Demand Matrix

	Market: Atlanta – Newark					
	AA	CO	DL	FL	NW	US
AA	-3.1079	0.0059	0.0013	0.0565	0.0007	0.0030
CO	0.0005	-2.0440	0.0013	0.0671	0.0005	0.0026
DL	0.0007	0.0059	-3.8526	0.0556	0.0007	0.0028
FL	0.0005	0.0071	0.0013	-1.2530	0.0005	0.0026
NW	0.0008	0.0063	0.0013	0.0603	-1.1752	0.0031
US	0.0007	0.0071	0.0014	0.0671	0.0007	-1.1291
Outside	0.00002	0.0003	0.0001	0.0026	0.00002	0.0001

Price Elasticity of Demand Matrix

	Market: Atlanta - Los Angeles								
	AA	DL	F9	HP	NJ	NW	UA	US	YX
AA	-2.556	0.0015	0.0122	0.0127	0.0361	0.0025	0.0076	0.0106	0.0002
DL	0.0060	-5.8369	0.0133	0.0136	0.0388	0.0028	0.0082	0.0119	0.0003
F9	0.0046	0.0013	-2.8234	0.0108	0.0299	0.0020	0.0061	0.0083	0.0002
HP	0.0058	0.0015	0.0123	-2.0621	0.0373	0.0027	0.0079	0.0112	0.0002
NJ	0.0045	0.0013	0.0106	0.0108	-2.1468	0.0020	0.0060	0.0082	0.0002
NW	0.0057	0.0015	0.0127	0.0131	0.0371	-1.9375	0.0078	0.0110	0.0002
UA	0.0061	0.0016	0.0131	0.0137	0.0392	0.0028	-2.8997	0.0119	0.0003
US	0.0066	0.0018	0.0142	0.0148	0.0423	0.0030	0.0090	-1.5570	0.0003
YX	0.0059	0.0016	0.0130	0.0135	0.0382	0.0027	0.0081	0.0114	-1.3590
Outside	0.0002	0.0001	0.0004	0.0004	0.0011	0.0001	0.0002	0.0002	0.00001

Price Elasticity of Demand Matrix

	Market: Atlanta - Salt Lake City						
	AA	CO	DL	F9	HP	NW	UA
AA	-1.8467	0.0003	0.0001	0.0042	0.0133	0.0053	0.0075
CO	0.0009	-1.3411	0.0001	0.0044	0.0141	0.0056	0.0079
DL	0.0006	0.0002	-1.8291	0.0031	0.0094	0.0039	0.0056
F9	0.0008	0.0003	0.0001	-2.6554	0.0117	0.0048	0.0068
HP	0.0010	0.0004	0.0001	0.0047	-1.5960	0.0061	0.0085
NW	0.0007	0.0003	0.0001	0.0034	0.0105	-1.3205	0.0061
UA	0.0008	0.0003	0.0001	0.0039	0.0121	0.0049	-1.6008
Outside	0.00004	0.00001	0.00001	0.0002	0.0005	0.0002	0.0003

Price Elasticity of Demand Matrix

Market: Cincinnati – Atlanta		
	DL	NW
DL	-3.86105	0.000463
NW	0.00209	-1.18139
Outside	0.00003	0.000004

Price Elasticity of Demand Matrix

Market: Cincinnati - Los Angeles			
	AA	DL	UA
AA	-1.3054	0.0096	0.0157
DL	0.0010	-6.3843	0.0142
UA	0.0011	0.0089	-2.8329
Outside	0.00002	0.0002	0.0002

Price Elasticity of Demand Matrix

	Market: Cincinnati - Salt Lake City		
	AA	CO	DL	UA
AA	-1.7516	0.0002	0.0021	0.0003
CO	0.0003	-1.6112	0.0023	0.0004
DL	0.0002	0.0001	-4.2916	0.0003
UA	0.0002	0.0001	0.0020	-1.1738
Outside	0.00001	0.000005	0.0001	0.00001

Price Elasticity of Demand Matrix

	Market: Dallas – Atlanta					
	AA	DL	FL	NJ	UA	YX
AA	-2.9999	0.0002	0.0024	0.0005	0.0006	0.0001
DL	0.0009	-2.3814	0.0031	0.0004	0.0006	0.0001
FL	0.0008	0.0002	-3.1621	0.0006	0.0009	0.0002
NJ	0.0009	0.0003	0.0026	-1.5361	0.0006	0.0001
UA	0.0009	0.0003	0.0027	0.0005	-1.3083	0.0001
YX	0.0009	0.0003	0.0026	0.0005	0.0007	-7.1524
Outside	0.00005	0.00001	0.0001	0.00002	0.00002	0.000004

Price Elasticity of Demand Matrix

Market: Dallas – Cincinnati			
	AA	DL	UA
AA	-3.3954	0.0013	0.0004
DL	0.0004	-3.2986	0.0006
UA	0.0004	0.0017	-1.6600
Outside	0.00002	0.0001	0.00002

Price Elasticity of Demand Matrix

	Market: Dallas – Newark							
	AA	CO	FL	NW	UA	US	TZ	YX
AA	-3.5423	0.0021	0.0093	0.0007	0.0019	0.0028	0.0082	0.0002
CO	0.0058	-7.3901	0.0055	0.0004	0.0011	0.0017	0.0051	0.0001
FL	0.0076	0.0020	-2.1114	0.0006	0.0016	0.0024	0.0072	0.0001
NW	0.0071	0.0019	0.0075	-3.7282	0.0015	0.0023	0.0067	0.0001
UA	0.0067	0.0018	0.0068	0.0005	-2.0160	0.0021	0.0062	0.0001
US	0.0075	0.0020	0.0078	0.0005	0.0016	-1.1747	0.0071	0.0001
TZ	0.0067	0.0018	0.0068	0.0005	0.0014	0.0021	-1.7261	0.0001
YX	0.0076	0.0020	0.0081	0.0006	0.0016	0.0024	0.0073	-2.2169
Outside	0.0002	0.00005	0.0001	0.00001	0.00003	0.00004	0.0001	0.000002

Price Elasticity of Demand Matrix

	Market: Houston – Cleveland				
	AA	CO	NW	UA	US
AA	-1.7962	0.0002	0.0001	0.0003	0.0004
CO	0.0001	-3.0171	0.0001	0.0003	0.0004
NW	0.0001	0.0002	-1.1396	0.0003	0.0004
UA	0.0001	0.0002	0.0001	-1.5825	0.0004
US	0.0001	0.0002	0.0001	0.0003	-1.2868
Outside	0.00001	0.00001	0.000004	0.00001	0.00002

Price Elasticity of Demand Matrix

	Market: Houston – Newark					
	AA	CO	DL	NW	UA	US
AA	-2.2286	0.0003	0.0001	0.0002	0.0005	0.0008
CO	0.0005	-3.4254	0.0001	0.0002	0.0005	0.0008
DL	0.0005	0.0003	-5.5149	0.0002	0.0005	0.0008
NW	0.0005	0.0003	0.0001	-1.2779	0.0004	0.0007
UA	0.0005	0.0003	0.0001	0.0002	-1.6216	0.0008
US	0.0005	0.0003	0.0001	0.0002	0.0005	-1.3687
Outside	0.00002	0.00001	0.000003	0.00001	0.00002	0.00003

Price Elasticity of Demand Matrix

	Market: Minneapolis – Atlanta					
	AA	DL	FL	NW	UA	US
AA	-3.1100	0.0019	0.0029	0.0169	0.0032	0.0022
DL	0.0011	-1.7381	0.0017	0.0112	0.0016	0.0010
FL	0.0031	0.0025	-3.2433	0.0215	0.0045	0.0033
NW	0.0029	0.0023	0.0036	-3.1441	0.0042	0.0029
UA	0.0015	0.0016	0.0022	0.0137	-3.2128	0.0015
US	0.0026	0.0022	0.0033	0.0191	0.0037	-1.4185
Outside	0.0001	0.0001	0.0001	0.0008	0.0001	0.00004

Price Elasticity of Demand Matrix

	Market: Salt Lake City – Atlanta						
	AA	CO	DL	F9	HP	NW	UA
AA	-1.7025	0.0012	0.0016	0.0133	0.0280	0.0366	0.0108
CO	0.0073	-1.6843	0.0017	0.0146	0.0319	0.0412	0.0120
DL	0.0092	0.0017	-2.5442	0.0181	0.0416	0.0527	0.0150
F9	0.0059	0.0010	0.0014	-2.6226	0.0245	0.0325	0.0098
HP	0.0114	0.0021	0.0027	0.0222	-1.3957	0.0663	0.0184
NW	0.0074	0.0013	0.0018	0.0147	0.0321	-1.1965	0.0121
UA	0.0070	0.0013	0.0017	0.0141	0.0303	0.0393	-1.6580
Outside	0.0002	0.00002	0.00004	0.0004	0.0005	0.0008	0.0003

Price Elasticity of Demand Matrix

Market: Salt Lake City – Cincinnati		
	DL	UA
DL	-1.3590	0.0053
UA	0.0007	-1.1465
Outside	0.0001	0.0004

Table 9A - 1
Percentage of lost sales going to competing products
(Market size equal to 15% of the origin city population)

	Atlanta – Dallas		**Atlanta – Newark**			**Atlanta - Los Angeles**		**Atlanta - Salt Lake City**		
Airlines	DL	NW	CO	DL	NW	DL	NW	CO	DL	NW
CO	-	-	-	0.51	0.51	-	-	-	0.04	0.05
DL	0.52	0.67	0.22	0.09	0.22	0.03	0.06	0.04	0.02	0.04
NW	0.02	-	0.14	0.28	0.13	0.51	0.33	1.87	1.78	0.84
Inside	13.39	14.10	8.86	8.19	8.28	19.86	20.03	3.18	3.03	3.02
Outside	86.06	85.22	90.78	90.94	90.86	79.60	79.58	94.90	95.13	96.06
Total	100	100	100	100	100	100	100	100	100	100

Table 9B - 1
Percentage of lost sales going to competing products
(Market size equal to 15% of the origin city population)

	Cincinnati – Atlanta		**Cincinnati - Los Angeles**	**Cincinnati – Salt Lake City**		**Dallas – Atlanta**	**Dallas – Cincinnati**	**Dallas – Newark**	
Airlines	DL	NW	DL	CO	DL	DL	DL	CO	NW
CO	-	-	-	-	0.01	-	-	-	0.03
DL	0.43	0.60	-	0.07	-	0.05	0.08	-	-
NW	0.08	-	-	-	-	-	-	0.06	0.04
Inside	-	-	0.68	0.08	0.08	2.70	0.06	3.45	3.45
Outside	99.49	99.40	99.32	99.85	99.91	97.26	99.86	96.49	96.48
Total	100	100	100	100	100	100	100	100	100

Table 9C - 1
Percentage of lost sales going to competing products
(Market size equal to 15% of the origin city population)

	Houston – Cleveland		**Houston – Newark**			**Minneapolis – Atlanta**		**Salt Lake City – Atlanta**			**Salt Lake City – Cincinnati**
Airlines	CO	NW	CO	DL	NW	DL	NW	CO	DL	NW	DL
CO	0.08	0.09	0.07	0.09	0.08	-	-	-	0.06	0.06	-
DL	-	-	0.002	-	0.002	-	0.23	0.26	0.20	0.26	0.21
NW	0.03	0.02	0.10	0.10	0.07	21.75	21.89	2.31	2.46	-	-
Inside	0.12	0.11	0.57	0.59	0.55	4.13	4.99	6.58	6.98	6.69	1.00
Outside	99.77	99.78	99.26	99.22	99.29	74.12	72.88	90.85	90.31	92.99	98.79
Total	100	100	100	100	100	100	100	100	100	100	100

Table 9A - 2
Percentage of lost sales going to competing products
(Market size equal to twice the origin city population)

	Atlanta – Dallas		Atlanta – Newark			Atlanta - Los Angeles		Atlanta - Salt Lake City		
Airlines	DL	NW	CO	DL	NW	DL	NW	CO	DL	NW
CO	-	-	-	0.14	0.14	-	-	-	0.01	0.02
DL	0.33	0.56	0.06	0.02	0.06	0.03	0.06	0.01	0.00	0.01
NW	0.02	-	0.04	0.06	0.03	0.49	0.31	0.80	0.54	0.22
Inside	7.81	11.01	2.53	2.20	2.26	18.08	16.72	1.41	0.94	1.07
Outside	91.84	88.43	97.37	97.58	97.51	81.40	82.91	97.78	98.50	98.69
Total	100	100	100	100	100	100	100	100	100	100

Table 9B - 2
Percentage of lost sales going to competing products
(Market size equal to twice the origin city population)

	Cincinnati – Atlanta		Cincinnati - Los Angeles	Cincinnati – Salt Lake City		Dallas – Atlanta	Dallas – Cincinnati	Dallas – Newark	
Airlines	DL	NW	DL	CO	DL	DL	DL	CO	NW
CO	-	-	-	-	0.01	-	-	-	0.02
DL	0.30	0.40	-	0.05	-	0.01	0.04	-	-
NW	0.05	-	-	-	-	-	-	0.04	0.05
Inside	-	-	0.63	0.06	0.04	0.69	0.05	2.06	3.13
Outside	99.66	99.60	99.37	99.89	99.96	99.29	99.91	97.90	96.81
Total	100	100	100	100	100	100	100	100	100

Table 9C - 2
Percentage of lost sales going to competing products
(Market size equal to twice the origin city population)

	Houston – Cleveland		Houston – Newark			Minneapolis – Atlanta		Salt Lake City – Atlanta			Salt Lake City – Cincinnati
Airlines	CO	NW	CO	DL	NW	DL	NW	CO	DL	NW	DL
CO	0.02	0.03	0.03	0.04	0.03	-	-	-	0.13	0.12	-
DL	-	-	0.001	-	0.001	-	0.11	0.39	0.35	0.41	0.09
NW	0.01	0.01	0.04	0.04	0.03	6.07	10.66	4.85	5.62	-	-
Inside	0.05	0.04	0.25	0.24	0.23	1.27	2.55	13.04	15.08	13.75	0.43
Outside	99.91	99.92	99.68	99.68	99.71	92.66	86.69	81.72	78.82	85.72	99.48
Total	100	100	100	100	100	100	100	100	100	100	100

C Appendix 3.

Table A 3.1
Predicted Effects of Joint Pricing

Market	Airline	Median Price	Median Percent Price Increase	Median Marginal Cost	Median Marginal Cost Reduction
Atlanta – Dallas	American	141.73	0	45.51	0
	AirTran	131.55	0	34.85	0
	Vanguard	119.64	0	25.84	0
	United	198.00	0	103.28	0
Atlanta – Newark	American	290.19	0	196.79	0
	AirTran	123.32	0	24.90	0
	US Airways	105.79	0	12.09	0
Atlanta - Los Angeles	American	178.62	0	84.07	0
	Frontier	264.79	0	170.66	0
	American West	169.42	0	71.09	0
	Vanguard	203.57	0	107.67	0
	United	244.75	0	148.06	0
	US Airways	142.24	0	46.54	0
	Midwest	127.50	0	33.68	0
Atlanta - Salt Lake City	American	171.64	0	78.65	0
	Frontier	247.46	0	154.27	0
	American West	149.44	0	55.81	0
	United	149.48	0	56.10	0
Cincinnati - Los Angeles	American	122.50	0	28.66	0
	United	267.05	0	172.36	0
Cincinnati - Salt Lake City	American	163.00	0	69.93	0
	United	109.25	0	16.18	0
Dallas – Atlanta	American	201.06	0	107.22	0
	AirTran	242.50	0	148.68	0
	Vanguard	143.45	0	50.06	0
	United	122.00	0	28.75	0
	Midwest	669.00	0	575.46	0

Notes: The second data column shows the median percentage by which each airline's prices are predicted to increase if Delta, Continental, and Northwest's practice price collusion. The third data column shows the median implied marginal cost for each airline in respective markets. The last data column shows the median percent by which marginal cost must fall to prevent price from increasing if Delta, Continental, and Northwest's practice price collusion.

Table A 3.2
Predicted Effects of Joint Pricing

Market	Airline	Median Price	Median Percent Price Increase	Median Marginal Cost	Median Marginal Cost Reductio
Dallas – Cincinnati	American	316.33	0	223.17	0
	United	154.36	0	61.37	0
Dallas – Newark	American	270.18	0	174.73	0
	AirTran	197.36	0	103.88	0
	United	187.84	0	94.63	0
	US Airways	109.57	0	16.11	0
	ATA	161.30	0	67.56	0
	Midwest	206.50	0	113.35	0
Houston – Cleveland	American	167.56	0	74.28	0
	United	147.53	0	54.30	0
	US Airways	119.83	0	26.71	0
Houston – Newark	American	181.06	0	87.38	0
	United	162.27	0	68.55	0
	US Airways	127.42	0	33.74	0
Minneapolis – Atlanta	American	185.39	0.000030	91.98	0
	AirTran	294.33	0.000304	198.99	0
	United	299.98	0.000037	206.50	0
	US Airways	132.00	0	38.94	0
Salt Lake City – Atlanta	American	130.84	0	36.34	0
	Frontier	246.36	0	152.42	0
	American West	134.74	0	33.82	0
	United	142.57	0	46.54	0
Salt Lake City – Cincinnati	United	107.05	0	13.68	0

Notes: The second data column shows the median percentage by which each airline's prices are predicted to increase if Delta, Continental, and Northwest's practice price collusion. The third data column shows the median implied marginal cost for each airline in respective markets. The last data column shows the median percent by which marginal cost must fall to prevent price from increasing if Delta, Continental, and Northwest's practice price collusion.

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