

ESSAYS IN EMPIRICAL INDUSTRIAL ORGANIZATION

by

CHI-YIN (JENNY) WU

B.A., Fu Jen Catholic University, 2001

M.B.A., Kansas State University, 2003

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Economics
College of Arts and Sciences

KANSAS STATE UNIVERSITY

Manhattan, Kansas

2012

Abstract

This dissertation is composed of two essays in the field of Industrial Organization. Specifically, the empirical studies are conducted by focusing on the market structure and competition issues in the airline industry.

The first essay investigates entry deterrence through incumbents' pricing strategies in the airline industry. Recent research finds evidence that incumbent airlines tend to cut fares in response to the "threat" of entry by Southwest Airlines. Instead of focusing on the entry threat by a single carrier, this essay re-examines this issue by looking at incumbent airlines' price response when entry is threatened by a wider variety of potential entrant airlines. Results show that incumbents' response vary by the identity of the firm making the threat. As expected, incumbents cut fares in response to the threat of entry by some potential entrants; however, a new result is also found that incumbents may respond by raising their fare depending on who is making the threat.

The second essay looks into an antitrust-relevant issue in the airline industry. Proper antitrust analysis often focuses on whether the concerned differentiated products are truly competing with each other. This essay uses a structural econometric model to investigate whether nonstop and connecting air travel products effectively compete with each other. Estimate results suggest that connecting products may be an attractive alternative to nonstop products for leisure travelers but less so for business travelers. If connecting products are counterfactually eliminated, the empirical model predicts small price changes for nonstop products. This suggests that the two product types only weakly compete with each other and can be treated as being in separate product markets for antitrust purposes.

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Dedication

To my mom, a true economist.

Essay One - A Re-examination of Incumbents' Response to the Threat of Entry: Evidence from the Airline Industry

1. INTRODUCTION

Goolsbee and Syverson (2008) and Morrison (2001) find evidence that incumbent airlines tend to cut fares in response to actual entry as well as the “threat” of entry by Southwest Airlines, while Brueckner, Lee and Singer (2011) investigate the impact of potential competition from low cost carriers (LCC) and find similar results. Rather than solely focusing on potential LCC competition, our present study re-examines this issue by looking at incumbent airlines’ price response when entry is threatened by a wider variety of potential entrant airlines, and documents that incumbents’ response vary by the identity of the firm making the threat. In particular, while incumbents cut fares in response to the threat of entry by some potential entrants like Southwest Airlines, importantly, this paper also finds that incumbents may respond by raising their fare when some potential entrants like US Airways threaten to enter the relevant market. This new evidence that incumbents may raise fare in response to the threat of entry constitutes an important extension to previous findings.

Why might incumbents respond to the threat of entry by raising their price? Klemperer (1987) has suggested that high consumer switching costs allow incumbents to charge a higher price to their loyal customers. Hollander (1987) also suggests that an incumbent could respond to entry by raising price to its inelastic-demand customers. While these previous studies are helpful in suggesting situations in which incumbents may raise their price in response to actual

entry,¹ this paper investigates the period that entry is threatened but does not actually occur. Broadening previous theoretical arguments, this paper argues that an incumbent might have an added incentive to take advantage of its loyal customers in order to deter potential entry. Specifically, when threatened by market entry, an incumbent may raise its price in order to signal to the potential entrant that the incumbent currently holds a large loyal customer base. Since the incumbent's loyal customers are likely to have high switching cost, possibly because these customers are heavily invested in the incumbent's frequent-flyer program, potential entrants may be deterred from entering such a market given that significant fare discounting will be required to entice a critical mass of customers to switch.

The analysis in this paper also constitutes a methodological extension to the analysis in Goolsbee and Syverson (2008). In particular, when analyzing incumbents' response to the threat of entry, the empirical framework accounts for the fact that market structure is endogenous, and therefore is able to mitigate potential biases in estimating incumbents' responses. For example, shocks to demand or costs that are unobserved by researchers, but observed by firms can jointly influence existing firm's pricing decisions and potential entrants' decisions to enter the market [Evans, Froeb, and Werden (1993)]. As such, the estimate of incumbents' pricing response to entry may either be biased upwards or downwards if we do not account for endogenous entry decisions associated with these demand and cost shocks. The empirical methodology in this paper is closest to Berry (1992) and Singh and Zhu (2008).

Given that the empirical analysis in this paper focuses on incumbents' response to the "threat" of entry, this paper should be placed as part of the entry deterrence literature. The

¹ Also see Chen and Riordan (2008).

question of entry deterrence has been examined extensively from a theoretical perspective,² but with the exception of our paper, Goolsbee and Syverson (2008), Huse and Oliveira (2010), Brueckner, Lee and Singer (2011), and Morrison (2001), formal empirical analysis of this issue is scarce. In addition to the entry deterrence literature, a distinct but related strand of literature studies the issue of how actual entry or competition, instead of the threat of entry, affects prices. Notable contributions to this literature include, Berry (1990, 1992); Borenstein (1989, 1990, 1991, 1992); Brueckner, Dyer and Spiller (1992); Brueckner and Spiller (1994); Chen and Savage (forthcoming); Evans and Kessides (1993, 1994); Evans, Froeb, and Werden (1993); and Ito and Lee (2004) among others. The empirical model in this paper also measures incumbents' price response to actual entry, and therefore is able to contribute to this literature as well.

Along with the key finding that incumbents may raise fare in response to the threat of entry, the econometric estimates in this paper yield other interesting results. First, as expected, an increase in the number of actual entrants reduces profitability, which coincides with results in Berry (1992). Second, incumbents' price response is different when faced with increased actual competitors compared to increased entry threat. In particular, incumbents seem to cut price more in response to an increase in actual number of competitors, as compared to an increase in the number of firms that threaten to enter. Third, when the endogeneity of market structure is taken into account, we find that the average price effect of actual entry is marginally smaller compared to when endogeneity is not taken into consideration. Conversely, when the endogeneity of market structure is taken into account, the average price effect of an entry threat is marginally larger compared to when endogeneity is not taken into account.

² See for example, Dixit (1979), Spence (1981), Milgrom and Roberts (1982), Aghion and Bolton (1987), Klemperer (1987), Farrell and Klemperer (2004), and Kwoka (2008).

The rest of the paper is organized as follows: Important definitions used throughout the paper are collected in section 2. Section 3 outlines the econometric model. Estimation techniques are discussed in section 4. Section 5 describes the data used in estimation. We discuss results in section 6, and offer concluding remarks in section 7.

2. DEFINITIONS

A market is defined as directional round-trip air travel between an origin city and a destination city. For example, round-trip air travel from Atlanta to Denver is a distinct market from round-trip air travel from Denver to Atlanta.

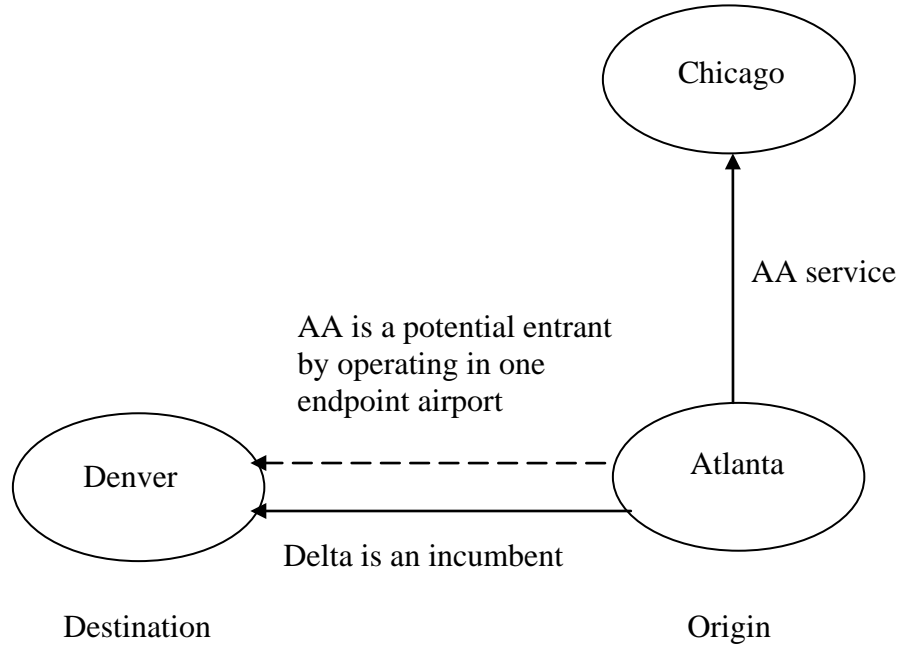
A flight itinerary is defined as a specific route of airport stops while traveling from the origin to destination city. A product is defined as a unique combination of airline and flight itinerary. The model in this study focuses on online products in which a passenger does not transfer to another airline during a round-trip in a market. Consider the market from Atlanta to Denver for example. Possible online products are: (1) a nonstop trip from Atlanta to Denver operated by Delta Air Lines; (2) a nonstop trip from Atlanta to Denver operated by United Airlines; and (3) a trip from Atlanta to Denver with one stop in Chicago operated by United Airlines. Note that all three products are in the same market.

An airline is defined as being an incumbent in a market during the time period that the airline offers air travel product(s) in the market. In this study, incumbents explicitly refer to the existing carriers which are offering nonstop online itineraries in each origin-destination market. On the other hand, a carrier is considered as a potential entrant to a nonstop market when this carrier operates in at least one endpoint city of the market in the period preceding the entry period under consideration. For example, suppose that an incumbent, Delta Air Lines, currently

operates a flight from Atlanta (ATL) to Denver (DEN). Any airline that flies between Atlanta and cities other than Denver in the preceding period, are considered potential entrants to the ATL-DEN market. Similarly, any airline that flies between Denver and cities other than Atlanta in the preceding period, are also considered potential entrants to the ATL-DEN market.

Figure 1-1 shows three cities and two airlines' operations between these cities. Solid arrows mean that the airline is actually offering flights between the cities, while dashed arrows means that the airline is a potential entrant to the market and therefore has presence in at least one of the relevant market's endpoint cities in the period preceding the entry period under consideration. As illustrated in Figure 1-1, American Airlines (AA) operates a route from Atlanta to Chicago (ORD) but not to Denver. Since this airline has been offering service from Atlanta to cities other than Denver, it is likely that AA can more easily start flying the ATL-DEN route in the near future compared to another airline that does not have a presence in Atlanta.

Figure 1-1 Identification of a Potential Entrant

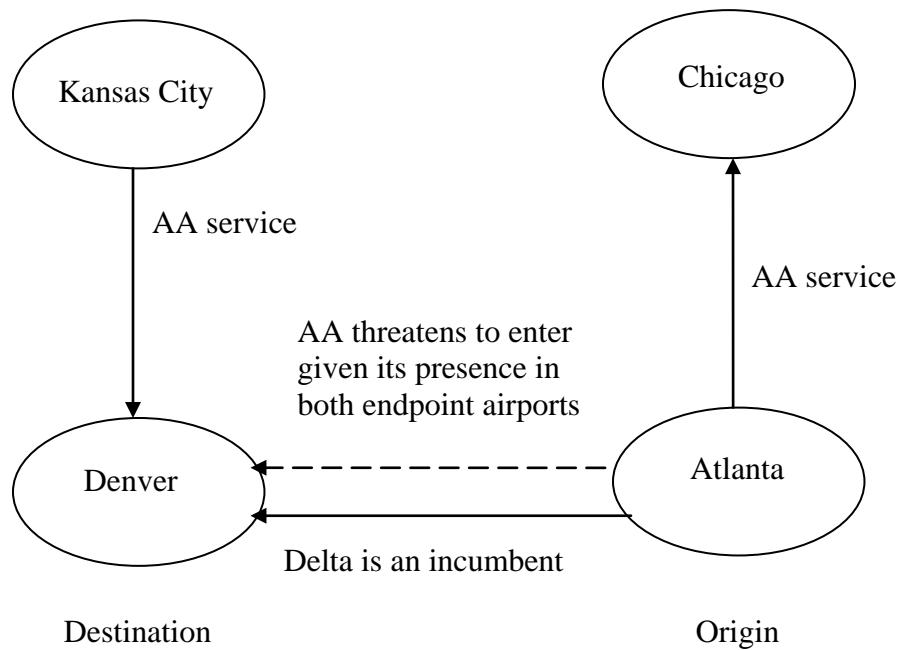


As illustrated in Figure 1-2, it is also possible that in the period preceding the entry period under consideration, American Airlines may operate service in both endpoint cities (ATL and DEN) without actually offering service between these two cities. Here, American Airlines provides service from Atlanta to cities other than Denver, such as a route from Atlanta to Chicago. In addition, American Airlines also provides service from Kansas City to Denver.

Comparing the scenarios in Figures 1-1 and 1-2, we might expect that American Airlines is even more likely to offer service from ATL-DEN when the airline has presence at both endpoint cities compared to just one endpoint city. Goolsbee and Syverson (2008) document that a carrier is 70 times more likely to enter a market when it already has operations at both endpoint cities. As such, throughout this paper we define an “entry threat” as a situation in which an airline has presence at both endpoint cities without offering service between the two cities. Figure 1-2 describes a situation in which American Airlines poses the greatest entry threat

to incumbents in the ATL-DEN market. Incumbents, like Delta in our example, may take actions in response to entry threats before American Airlines actually starts flying the ATL-DEN route. For example, as documented by Goolsbee and Syverson (2008), we can expect to see changes in incumbents' price when facing such heightened entry threat.

Figure 1-2 High Probability of Entry



3. MODEL

Applying methodologies from Singh and Zhu (2008) and Berry (1992),³ this paper investigates how incumbents respond to the threat of entry. Our model provides an empirical framework to examine strategic interactions in an oligopolistic market, which allows us to study the relationship between prices and market structure in the airline industry.

³ Also see Dunn (2008) for a similar methodology.

A discrete choice framework is used to make inferences about firm profits. In the structure of a strategic game, behavior in the market reflects the interaction of multiple agents' decisions. Therefore, econometric estimation is based on an oligopolistic equilibrium concept in this study. Similar in spirit to Berry (1992), firm k 's latent profit in market m with N_m^a competitors can be expressed as follows:

$$\pi_{mk}(N_m^a) = X_m\beta + \delta^\pi \ln(N_m^a) + \lambda^\pi \ln(N_m^{et}) + \alpha Z_{mk} + \varepsilon_{mk}, \quad (1)$$

where $\varepsilon_{mk} = \eta u_{m0} + \omega u_{mk}$. (2)

The vector X_m represents observed profit-shifting variables that vary only by market, and β is a vector of parameters associated with these profit-shifting variables. In our empirical application, the measured market characteristics included in X_m are: *Population*; *Nonstop Flight Distance*; and *Nonstop Flight Distance Squared*. Similar to Berry (1992), *Population* is measured by the product of population from the origin and destination cities. N_m^a is the equilibrium number of firms that actually enters market m . As such, the characteristics of rival firms affect firm k via the equilibrium number of firms in a given market. N_m^{et} is the number of potential entrants that poses a real entry threat to market m in terms of having a presence at both endpoint airports in the period preceding the entry period under consideration, but does not actually enter the relevant market during the entry period. δ^π and λ^π are parameters that capture marginal effects of actual entry and the threat of entry respectively on firm k 's latent profit.

Z_{mk} is an observed firm-specific profit-shifting variable based on information in the period preceding the entry period under consideration. Specifically, Z_{mk} is a zero-one dummy variable which takes a value of one only if the firm operates in both endpoint cities in the period preceding the entry period under consideration. Based on our previous discussion in the definitions section, we expect the parameter, α , to be positive.

ε_{mk} is a component of profit that is observed by all firms, but unobserved to researchers. This unobserved profit component is decomposed into two terms according to equation (2). u_{m0} represents unobserved market characteristics that are common across firms, while u_{mk} captures firm-specific unobservables. Both u_{m0} and u_{mk} are unobserved by the econometricians, but observed by all firms. We further assume that u_{m0} and u_{mk} are independent and identically standard normally distributed across firms and markets. For identification, we impose the traditional constraint that the variance of the unobservable (ε_{mk}) equals one, via the restriction $\omega = \sqrt{1 - \eta^2}$. Here η is the correlation of the unobservable ε_{mk} across firms in a given market.

The issue of interest is the pricing behavior of incumbents given the presence of numbers of actual competitors and potential competitors that are threatening to enter. Similar in spirit to Singh and Zhu (2008), a market level pricing regression intended to examine this issue can be expressed as follows:

$$\ln(p_m) = X_m \phi + \delta^p N_m^a + \lambda^p N_m^{et} + \varepsilon_m^p, \quad (3)$$

where p_m is a market descriptive statistic (median, 25th or 75th percentile) of price charged in market m ; X_m are observed market structure variables which can affect price; N_m^a is the number of actual competitors in market m ; δ^p is a parameter that captures the marginal effect of actual entry on price; N_m^{et} is the number of potential entrants that poses a real entry threat to market m ; and λ^p is a parameter that captures the pricing effect of the “threat” of entry. ε_m^p is a random error term.

There are two things worth noting at this point. First, note that the unit of analysis for the pricing regression is at the market level, which is different from the firm-level unit of analysis for the profit equation. Second, we have referred to N_m^a as the number of “actual competitors” as well as the number of “actual entrants”. This is because, in the context of our static entry model

that is used to draw inference from a cross-section of sample markets, “actual competitors” and “actual entrants” are equivalent and will simply be measured by the number of competing firms observed in each sample market in our data.

The concern in equation (3) is the potential correlation between unobservable ε_m^p and N_m^a , which will result in biased and inconsistent estimate of δ^p . Particularly, demand shocks that are unobserved to researchers but observed by firms can influence not only firms’ pricing, but also alter firms’ decision to operate in the market. For example, a positive unobserved demand shock will increase prices in a market, and attract more entrants as well. If this positive demand shock is not controlled for when estimating the relationship between N_m^a and p_m for instance, then an estimated negative effect between N_m^a and p_m will likely be understated since the observed data will contain situations in which relatively large N_m^a is associated with relatively high prices due to positive demand shocks that are not accounted for in the regression [see Manuszak and Moul (2008)]. In general, shocks to demand or cost that are unobserved by researchers, but observed by firms are likely to yield a problem of underestimation or overestimation of parameters in equation (3).

In order to correct for endogenous market structure in the pricing regression, we impose the following restriction on error terms in the price and profit equations:⁴

$$\begin{pmatrix} u_{m0} \\ \varepsilon_m^p \end{pmatrix} \sim BVN \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & \sigma_p^2 \end{pmatrix} \right] \quad (4)$$

where ε_m^p and u_{m0} are error terms from the price and profit equations, and ρ is the covariance between the two. The conditional mean of ε_m^p given u_{m0} is equal to ρu_{m0} , with the assumption of normally distributed error terms. Thus, we can construct the conditional expectation of the

⁴ See Singh and Zhu (2008) for a similar restriction.

error term in the price regression by using iterated expectation as follows:

$$E[\varepsilon_m^p | X_m, Z_{mk}, N_m^a, N_m^{et}] = \rho E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}]$$

We can then consider the following modified pricing regression equation:

$$\ln(p_m) = X_m \phi + \delta^p N_m^a + \lambda^p N_m^{et} + \rho E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}] + v_m^p, \quad (5)$$

where the error term $v_m^p = \varepsilon_m^p - E[\varepsilon_m^p | X_m, Z_{mk}, N_m^a, N_m^{et}]$ is now the pure idiosyncratic error

term, and ρ is simply an additional parameter to be estimated in equation (5), which is the

coefficient on the regressor, $E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}]$. The distinction between equations (3)

and (5) is the conditional expectation of the error term, which capture the potential correlation

between unobserved shocks and the market structure in market m . Note that Goolsbee and

Syverson (2008) did not take into account that N_m^a is endogenous in their pricing equation. Our

specification of pricing regression (5) is a key methodological extension to their work.

4. ESTIMATION

Generalized method of moments (GMM) is used to estimate parameters in the profit equation, while ordinary least squares is used to estimate parameters in the pricing equation. We first describe how the profit equation is estimated, and then describe how the price equation is estimated.

4.1 Estimating the Profit Equation

To begin, it is necessary to use equation (1) to predict the equilibrium number of firms, N_m^a , that will enter market m based on the following:

$$\tilde{N}_m^a = \max_n (\#\{k: \pi_{mk}(n, \varepsilon_{mk}) \geq 0\}) \quad (6)$$

\tilde{N}_m^a is the largest integer among $1, 2, \dots, K_m$ such that all firms that choose to enter have non-negative profits in a given market m ; and K_m is the total number of potential entrants to market m .

Following Berry (1992), we use two periods (periods 1 and 2) of data to determine K_m for a given market.⁵ Period 2 is the relevant period for analyzing strategic entry and competitive effects, while period 1 is only used to help identify the set of potential entrants that may enter in period 2. As such, in period 1 we identify airlines that have a presence in at least one endpoint airport of the market. In addition, we identify airlines that are actually serving the market in period 2. For purposes of the static entry model, the set of potential entrants, K_m , includes the airlines with endpoint airport presence in period 1 plus the airlines that are actually serving the market in period 2.

As discussed in Berry (1992), due to firm heterogeneity, captured by Z_{mk} and ε_{mk} in equation (1), equation (6) does not have a closed-form solution. Berry (1992) proposes using simulation, along with a sequential order-of-entry assumption,⁶ to approximate the expected number of firms that will enter a market and the identity of the entering firms. Specifically, we first take R_m independent random draws of the random portion of firms' profit,

$(u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r)$, from a standard normal probability distribution, where draws are indexed by r .⁷ With $(u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r)$ in hand, along with the variables, X_m and Z_{mk} , and guesses of α , β , δ^π , λ^π , and η , we can solve the system of K_m profit equations for the equilibrium number of firms, $\widehat{n}_{mr}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta, u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r)$, that is expected to enter

⁵ As we discuss further in the data section, a period in the data set is one quarter. Period 1 is quarter 1 in the data, while period 2 is quarter 3. As explained in Berry (1992), it will take approximately six months for an airline to implement operations in a market they have chosen to enter.

⁶ We assume most profitable firms enter first.

⁷ In this study we use 300 independent random draws of the random portion of firms' profit, i.e., $R_m = 300$.

market m on each r^{th} draw. In addition, we can construct a firm-specific zero-one indicator variable, $\widehat{a}_{mkr}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta, u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r)$, that takes the value 1 only if firm k is predicted to enter market m on the r^{th} draw of the random portion of profit. In order to reduce simulation error, \widehat{n}_{mr} and \widehat{a}_{mkr} are averaged across simulation draws to obtain:

$$\widehat{N}_m^a(X_m, Z_{km}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) = \frac{1}{R_m} \sum_{r=1}^{R_m} \widehat{n}_{mr}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta, u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r) \quad (7)$$

$$\begin{aligned} \widehat{Prob}_{mk}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) = \\ \frac{1}{R_m} \sum_{r=1}^{R_m} \widehat{a}_{mkr}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta, u_{m0}^r, u_{m1}^r, \dots, u_{mK_m}^r), \end{aligned} \quad (8)$$

where \widehat{N}_m^a and \widehat{Prob}_{mk} are the expected number of firms to enter market m and the probability that firm k enters market m respectively.

Note that $\frac{1}{R_m} \sum_{r=1}^{R_m} \widehat{a}_{mkr}(\cdot)$ is an accept-reject frequency simulator of the firm entry probability. As such, firm entry probabilities are not smooth and continuous functions of the parameters, which can make estimation challenging since the entry probabilities are not differentiable in parameter space. To achieve differentiability of the entry probability functions in parameter space, we replace the accept-reject frequency simulator with a ‘‘smooth’’ simulator,

$\frac{1}{R_m} \sum_{r=1}^{R_m} \widehat{s}_{mkr}(\cdot)$, where

$$\widehat{s}_{mkr}(\cdot) = \frac{\exp(rank_{mkr} - \widehat{n}_{mr})}{1 + \exp(rank_{mkr} - \widehat{n}_{mr})} \quad (9)$$

$rank_{mkr}$ is firm k simulated profit rank among the K_m potential entrants on the r^{th} draw, and \widehat{n}_{mr} is the predicted number of firms that will enter market m on the r^{th} draw. Since our sequential order-of-entry assumption is that the most profitable firms enter first on a given draw of the random portion of profit, then firm k is predicted to enter market m on the r^{th} draw if

$rank_{mkr} \geq \hat{n}_{mr}$, otherwise firm k is not predicted to enter. Therefore, $(rank_{mkr} - \hat{n}_{mr})$ is correlated with the probability of entry and is reasonable to use in our smooth simulator.

From the data, we observe the actual number of airlines serving a market, N_m^a . In addition, we can construct from the data a zero-one indicator variable for each potential entrant, I_{mk} , that takes the value 1 only if firm k actually serves market m . The following two equations therefore form the basis for our estimation strategy:

$$N_m^a = \widehat{N}_m^a(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) + v_m \quad (10)$$

$$I_{mk} = \widehat{Prob}_{mk}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) + \mu_{mk} \quad (11)$$

The prediction errors, v_m and μ_{mk} , are then used to form moment conditions in order to estimate the parameters via GMM.

Our assumption that v_m and μ_{mk} are mean independent of the exogenous data, yield the following moment conditions:

$$m_1(\theta) = \frac{1}{T_1} H' \left(N_m^a - \widehat{N}_m^a(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) \right) = 0 \quad (12)$$

$$m_2(\theta) = \frac{1}{T_2} H' \left(I_{mk} - \widehat{Prob}_{mk}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) \right) = 0 \quad (13)$$

where θ is simply a parameter vector containing $\beta, \alpha, \delta^\pi, \lambda^\pi$, and η ; T_1 is the number of markets; T_2 is the number of firm-level observations across the sample markets; and H is a matrix of instruments that include the interactions of *Population* with *Nonstop Flight Distance* and *Nonstop Flight Distance Squared*.

We obtain the GMM estimates for the profit equation by solving:⁸

⁸ Our MATLAB computer code uses the simplex search method (fminsearch command) to minimize the GMM objective function. The fminsearch routine iterates with successive tries at values for the profit function parameter vector, $(\hat{\theta}_{(1)}, \hat{\theta}_{(2)}, \hat{\theta}_{(3)}, \dots)$, until the associated value of the GMM objective function converges to a minimum value.

$$\text{Min}_{\hat{\theta}} [m(\hat{\theta})' W m(\hat{\theta})] \quad (14)$$

where $m(\hat{\theta}) = \begin{pmatrix} m_1(\hat{\theta}) \\ m_2(\hat{\theta}) \end{pmatrix}$ and W is the following block diagonal positive definite weight matrix:⁹

$$W = \begin{pmatrix} \left[\frac{1}{T_1} H' \tilde{e}_1 \tilde{e}_1' H \right]^{-1} & \mathbf{0} \\ \mathbf{0} & \left[\frac{1}{T_2} H' \tilde{e}_2 \tilde{e}_2' H \right]^{-1} \end{pmatrix}$$

where \tilde{e}_1 and \tilde{e}_2 are the residual vectors from moment conditions, $m_1(\cdot)$ and $m_2(\cdot)$ respectively.

4.2 Estimating the Price Equation

As mentioned in the model section, the main methodological contribution in this study is to construct a correction term to account for potential correlation between price errors and market structure variables. In particular, we showed in the model section that the appropriate correction term is to include the conditional mean, $E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}]$, as a regressor in the price equation. However, there is no closed-form solution for $E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}]$ with firm heterogeneity, so in the spirit of Singh and Zhu (2008) we use simulation technique to approximate this conditional mean as follows:

$$\hat{E}[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}] = \frac{1}{R_m} \sum_{r=1}^{R_m} u_{m0}^r \left[\prod_{k=1}^{K_m} (\hat{s}_{mkr})^{I_{mk}} (1 - \hat{s}_{mkr})^{1-I_{mk}} \right] \quad (15)$$

where the term in square brackets is the simulated probability of observing the actual market structure in the data for market m on the r^{th} draw, and \hat{s}_{mkr} is based on the smooth firm entry probability function in equation (9).¹⁰

⁹ The optimal W is given by the inverse of the asymptotic variance-covariance matrix of $m(\hat{\theta})$.

¹⁰ Instead of using a smooth simulator, as we did, to approximate the conditional mean of u_{m0} , Singh and Zhu (2008) uses an accept-reject frequency simulator.

In summary, we use a two-stage estimation procedure. At the first stage we estimate the profit equation using GMM as described above. We then use the estimated profit equation parameters along with equation (15) to compute the endogeneity correction term, $\hat{E}[u_{m0}|X_m, Z_{mk}, N_m^a, N_m^{et}]$. In the second stage we use ordinary least squares to estimate the linear pricing equation, in which $\hat{E}[u_{m0}|X_m, Z_{mk}, N_m^a, N_m^{et}]$ is a regressor. This procedure is similar to the two-step estimation used in Singh and Zhu (2008) to study the relationship between prices and market structure for auto rental industry.

5. DATA

Data are obtained from the Airline Origin and Destination Survey (DB1B), which are collected by the US Bureau of Transportation Statistics. DB1B is a 10% random sample of airline tickets from reporting carriers. The data include information such as: (i) origin and destination airports on each ticket itinerary; (ii) the nonstop flight distance between the origin and destination airports; (iii) the airline that transports the passengers on a given ticket itinerary; (iv) the price of the ticket; and (v) the number of passengers that purchase a ticket with given itinerary characteristics. We are most interested in the DB1BMarket file in the database, which contains directional market characteristics of each itinerary. Similar in spirit to Berry (1992), this paper focuses on U.S. domestic flights offered and operated by U.S. carriers in a single year, which is 2007 in this study. To identify potential entrants in each market, we treat the first quarter of 2007 as the first period and the third quarter of 2007 as the second period. The idea is to construct a single dataset that uses information from these two periods. As previously discussed in the estimation section, period 2 is the relevant period for analyzing strategic entry

and competitive effects, while period 1 is only used to help identify the set of potential entrants that may enter in period 2.

Some data restrictions are enforced in each period. First, only itineraries in the 48 states are included and foreign operating carriers are eliminated. Second, observations are dropped when market fares are less than \$30, which helps to rule out heavily discounted fares that could be associated with passengers using their accumulated frequent-flyer miles to partially offset cost of trip. Third, as defined before, only pure online¹¹ nonstop itineraries are considered in each origin-destination market.

We create a “*quantity*” variable by aggregating passengers by airline in each origin-destination market. Even though our discussion thus far focuses on incumbents price response to actual entry and the threat of entry, in what follows we also analyze incumbents quantity response, hence our need to create this quantity variable. Moreover, we follow Berry (1992) and use this quantity variable to help define a “valid” incumbent. In particular, a firm is considered as a “valid” incumbent in a market during the quarter when the quantity of passengers that travel on the airline in this market is larger or equal to 90. The *price* variable is the mean ticket fare by airline in each market. The 3rd quarter/second period data are then collapsed so that a given airline only appears once in each market.

Unlike the 3rd quarter data, the 1st quarter data are less restricted by not solely focusing on nonstop itineraries. For purposes of the static entry model, the set of potential entrants to a market refers to airlines that have some airport presence in at least one endpoint city of the market in the 1st quarter plus airlines that actually serve the market in the 3rd quarter. The final

¹¹ A pure online air travel product means that the passenger remains on a single carrier’s plane(s) for the entire round trip. In addition, the carrier that transports the passenger for this type of product is the same carrier that markets and sold the product to the passenger. Pure online products are the most popular type of products in US domestic air travel markets. For more discussion on various types of air travel products in US domestic markets see Ito and Lee (2007) and Gayle (2008).

dataset has sample size of 12,401 observations spread across 777 origin-destination markets, and a total of 22 U.S. domestic airlines.

Table 1-1 provides a list of all airlines that are involved in the sample dataset in the 3rd quarter of 2007. The table gives an idea how relatively active an airline is based on the number of markets served.

Table 1-1 Airlines represented in the dataset in the 3rd Quarter of 2007

Code	Airline	Number of markets served by each carrier
AA	American Airlines Inc.	190
AS	Alaska Airlines Inc.	63
B6	JetBlue Airways	95
CO	Continental Air Lines Inc.	64
DL	Delta Air Lines Inc.	227
F9	Frontier Airlines	80
FL	AirTran Airways	176
HP	America West Airlines	2
NK	Spirit Air Lines	52
NW	Northwest Airlines Inc.	116
SX	Skybus Airlines, Inc.	3
SY	Sun Country Airlines	22
TZ	ATA Airlines	7
U5	USA 3000 Airlines	20
UA	United Air Lines Inc.	216
US	US Airways Inc.	149
WN	Southwest Airlines	304
YX	Midwest Airlines	23
Other**	GQ/ OO/ QX/ RD/ XE	0

**Other includes GQ(Big Sky Airlines), OO(Skywest Airlines), QX(Horizon Air), RD(Ryan International Airlines), and XE(Expressjet Airlines). These airlines in the “Other” category did not actually serve any of our sample markets, but they were potential entrants in some markets.

Table 1-2 reports the number of potential entrants that serve 0 (City 0), 1 (City 1), or 2 (City 2) endpoint cities of the markets in our sample during period 1.¹² The table also shows the number and percent of these potential entrants that actually serve the market in period 2. Among the potential entrants, only three firms do not have presence at endpoint cities in the first period. These three firms all enter markets in the second period, and are considered as incumbents in that period. Among the 4,400 potential entrants that only serve one city of a pair in the first period, 0.84% of them decide to enter the market in the second period. On the other hand, among the 7,998 potential entrants that serve both endpoint cities of the market in the first period, 22.1% of them decide to enter the market in the second period. This evidence suggests that firms who serve both endpoints in a city pair more easily enter the market in the subsequent period. These firms can easily take advantage of their access to both airports in that market, so that the cost of entry will likely be lower for them compared to other firms that do not yet have access to both airports. As such, we treat City2 as an observed firm-specific measure of heterogeneity that shifts firms' profit and therefore influences entry decisions.

Table 1-2 Number of Potential Entrants by Number of Cities Served

No. of Cities Served	Total No. of Potential Entrants	No. of entry in the 2 nd Period	% of Entry
City 0	3	3	-
City 1	4,400	37	0.84
City 2	7,998	1,770	22.13
Total	12,401	1,810	-

¹² The reason why it is possible to have a subset of our defined potential entrants that do not serve an endpoint airport in the relevant market is because, on rare occasions, these airlines enter a market in the same period they establish presence at both endpoint airports.

In addition, we construct variables such as “*Population*”, “*Nonstop Flight Distance*”, and “*Nonstop Flight Distance Squared*” that are defined previously. Table 1-3 reports descriptive statistics of the sample data.

Table 1-3 Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
Population	Product of population from the origin and destination cities, in one hundred trillions.	0.0154	0.054	2.1E-05	0.7078
Distance	Nonstop flight distance, in thousands of miles.	0.1108	0.063	0.0177	0.2704
Distance ²	Nonstop flight distance squared.	0.0162	0.017	0.00031	0.0731
City1	Equals 1 if carrier operates in only one endpoint city of the market in the 1 st quarter.	0.3548	0.479	0	1
City2	Equals 1 if carrier operates in both endpoint cities of the market in the 1 st quarter.	0.6449	0.479	0	1
<i>I</i>	Equals 1 if the potential entrant actually enters the market.	0.1460	0.353	0	1
<i>K</i>	Number of potential entrants for each market.	16.2541	2.141	10	21
<i>N^a</i>	Number of actual entrants to a market	2.3505	0.623	2	6
No. of entry threats (<i>N^{et}</i>)	Number of potential entrants that poses a real entry threat, but did not actually enter the relevant market.	8.1097	1.881	1	14
Log(P_50th)	Log of the 50 th percentile of market prices.	5.2068	0.316	4.3641	6.3933
Log(P_25th)	Log of the 25th percentile of market prices	5.0691	0.321	4.0958	5.9388
Log(P_75th)	Log of the 75th percentile of market prices	5.3273	0.319	4.4678	6.5380
Log(Q_50th)	Log of the 50th percentile of passengers	7.2829	0.7607	4.9273	9.1942
Log(Q_25th)	Log of the 25th percentile of passengers	6.5371	0.9925	4.4998	8.8926
Log(Q_75th)	Log of the 75th percentile of passengers	7.6764	0.7644	5.2523	9.4256

Note that N^a is the sum of the dummy I in a given market. K is the total number of possible entrants in a market. Following up on a previous example we discussed in the definitions section, the route of ATL-DEN contains 4 actual entrants out of 19 possible entrants (i.e. $N^a=4$ and $K=19$). “*No. of entry threats (N^{et})*” is the subset of potential entrants that have a presence at both endpoint airports of a market in period 1, but did not actually enter the relevant market in period 2. In other words, “*No. of entry threats (N^{et})*” is the total number of potential entrants that poses a real and credible entry threat. Note that the mean of “*No. of entry threats (N^{et})*” is much smaller than the mean of K .

6. RESULTS

This section presents the results from estimating the empirical model discussed above. Table 1-4 presents results from the entry model. The entry model estimates suggest that the profitability of firm entry in a market is increasing in the size of the market as measured by population, which is consistent with results in Berry (1992). Profitability of firm entry also seems to be increasing in distance between the origin and destination.

Table 1-4 Parameter Estimates for Entry Model

Variable	Parameter est.	Std. error
Constant	-5.2957*	2.4959
Population	3.2815*	0.4670
Distance	6.7193*	3.1277
(Distance) ²	-4.4358	3.5719
City2	5.1432*	2.3159
Number of competing firms (δ^π)	-0.7065*	0.0704
Number of entry threats (λ^π)	-0.0500	0.0343
Correlation (η)	-0.9587*	0.1384
Number of obs.	12401	
GMM objective	0.0424	

*significant at the 0.05 level.

The positive coefficient on City2 suggests that a firm is likely to find entry more profitable if it has presence in both endpoint cities in the period prior to the entry period under consideration. The effect is statistically significant, and therefore implies that we should allow for firm heterogeneity in the entry model, as suggested by Berry (1992).

As expected, δ^π is negative and statistically significant, which indicates that actual entry reduces profitability. This result is consistent with standard oligopoly theory, which predicts that profitability should decline with increased competition. Similarly, λ^π is negative, suggesting that the profitability of entry decreases with increased entry threat. However, the marginal profit effect of entry threat is relatively small and statistically insignificant at conventional levels of significance in the entry model.

Recall that the parameter, η , measures the correlation of profit components that are unobserved to the researcher but observed by firms. This parameter is statistically different from zero at conventional levels of significance, and its point estimate (-0.9587) suggests a strong

correlation of unobserved profit components across firms in a market. This effect suggests that market-wide shocks are strong relative to firm-level shocks.¹³

As mentioned previously, the main purpose in this paper is to re-examine the issue of how incumbents respond to the threat of entry in the airlines industry. Our methodology explicitly accounts for the endogeneity of market structure. In particular, the estimates of the entry model allow us to correct for this problem of potential endogeneity in incumbents' price and quantity regressions. Results for these price and quantity regressions are shown in Table 1-5. Recall that the unit of analysis for these regressions is at the market level. As such, the dependent variable for a price or quantity equation is either the market 50th percentile value, 25th percentile value, or 75th percentile value. This table only reports results for the 50th percentiles, while results of the 25th and 75th percentiles are shown in the appendix A.2 and A.3.

¹³ We also estimate the entry model using data samples drawn from different time periods. For example, we use the third quarter of 2007 as the first period and the first quarter of 2008 as the second period. We find that results, as shown in the appendix A.1, are qualitatively similar to those reported above.

**Table 1-5 Parameter Estimates for Price/Quantity Regressions
that Capture the Average Effect of Entry Threats**

Variable	<i>Estimates without Correction</i>		<i>Estimates with Correction</i>	
	<u><i>ln(P 50th)</i></u>	<u><i>ln(Q 50th)</i></u>	<u><i>ln(P 50th)</i></u>	<u><i>ln(Q 50th)</i></u>
	Parameter Est.	Parameter Est.	Parameter Est.	Parameter Est.
Constant	4.9243* (0.0517)	6.6367* (0.1709)	4.9178* (0.0517)	6.6445* (0.1712)
Population	0.7813* (0.1544)	3.3131* (0.5104)	0.7843* (0.1538)	3.3049* (0.5098)
Distance	5.2078* (0.5198)	-0.1436 (1.7186)	5.3047* (0.5198)	-0.3080 (1.7228)
Distance ²	-6.5103* (1.9290)	-8.4158 (6.3783)	-6.8158* (1.9275)	-7.8788 (6.3883)
No. of competing firms (N_m^a)	-0.0444* (0.0132)	0.0549 (0.0435)	-0.0434* (0.0131)	0.0534 (0.0435)
No. of entry threats (N_m^{et})	-0.0119* (0.0043)	0.0754* (0.0140)	-0.0122* (0.0042)	0.0762* (0.0140)
Endogeneity correction	NA	NA	248.52* (101.93)	-470.81 (337.85)
R-squared	0.5207	0.0944	0.5243	0.0961

*represents significant at the 0.05 level. Recall that the “Endogeneity correction” variable is, $\hat{E}[u_{m0}|X_m, Z_{mk}, N_m^a, N_m^{et}]$. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample.

The left panel in Table 1-5 shows the results from models without the endogeneity correction variable.¹⁴ These estimates suggest that airfare is increasing in market size, as measured by population. Second, airfare increases with distance between the origin and destination cities up to some threshold distance, but declines in distance thereafter.

Consistent with the findings in Goolsbee and Syverson (2008), the negative signs of actual entry and entry threat coefficients suggest that incumbents cut prices when faced with

¹⁴ Recall that the “Endogeneity correction” variable is, $\hat{E}[u_{m0}|X_m, Z_{mk}, N_m^a, N_m^{et}]$.

increased actual competitors or entry threat. While Goolsbee and Syverson's incumbent price and quantity regressions measure these effects based on time dummy coefficients surrounding the period of the event, our study looks at incumbents' price and quantity responses to changes in the numbers of actual competitors, and threatening potential competitors. The results here indicate that prices fall by an average 4.44% when the actual number of competitors increases by one firm. On the other hand, prices only drop by an average 1.19% when incumbents face an additional entry threat. Therefore, the degree of incumbent price cutting is different in response to actual entry compared to the threat of entry. Specifically, incumbent firms seem to cut price more in response to an increase in actual number of competitors as compared to an increase in the number of firms that threaten to enter. This evidence is consistent with findings in Morrison (2001) and Kwoka and Shumilkina (2010).

In the case of the quantity regression, a positive coefficient for population suggests that a larger market size will stimulate the actual number of airplane passengers. We are surprised to find that, on average, the number of passengers tends to be smaller for long-distance trips based on the negative coefficients on distance and distance squared in the quantity regressions. However, these distance coefficients are not statistically significant at conventional levels of significance in the quantity regressions.

The right panel in Table 1-5 shows results when the endogeneity correction variable is included as a regressor. This endogeneity correction variable accounts for the fact that "No. of competing firms" variable is endogenous in the price and quantity regressions. The results show that the coefficients are roughly similar in magnitude compare to the case without endogeneity correction. However, for the price regression at conventional levels of statistical significance, a

Hausman test rejects that “No. of competing firms” is an exogenous variable.¹⁵ We find that the average effect of actual entry is marginally smaller when endogeneity of market structure is taken into account. An increase in number of actual entry is associated with a price drop of 4.34% and quantity increase of 5.34% in case of the endogeneity-corrected specifications, as compared to a price drop of 4.44% and a quantity increase of 5.49% in case of specifications without endogeneity correction. Therefore, the measured average price and quantity effects from actual entry could be slightly overestimated if we ignore the endogeneity of market structure.

When it comes to the average effects due to the threat of entry, the market median price drops 1.22% with an additional threat of entry in the case of the endogeneity-corrected specification. This average price effect is marginally larger than the 1.19% average price drop in the case of the specification without endogeneity correction. The market median number of passengers increases by 7.62% with the threat of entry by a firm in the case of the endogeneity-corrected specification. This average quantity response to the threat of entry is marginally larger compared to the 7.54% average quantity increase in the case of the specification without endogeneity correction. Therefore, the measured average price and quantity effects from the threat of entry could be slightly underestimated if we ignore the endogeneity of market structure.

Note that the result of endogeneity correction implies a positive relationship between price shocks and profit shocks due to the positive coefficient on the “Endogeneity correction” variable in the price regression. This positive coefficient implies that, on average, the unobserved factors affect both observed prices and probability of firm entry in the same direction. However, the coefficient on the “Endogeneity correction” variable is statistically insignificant in

¹⁵ The Hausman computed statistic is 10.689, while the critical Chi-square statistic at 5% level of significance with one degree of freedom is 3.84.

quantity regression.¹⁶ Even though controlling for potential endogeneity only marginally affects the estimated parameters in this data sample, we still recommend reinforcing the model with the endogeneity correction term so as to mitigate the potential biases in estimating incumbents' responses that could be present in other data samples.

Next, we decompose the effect of the threat of entry based on the identity of the carrier that is threatening to enter the market. This is an important extension to previous research which focuses solely on potential threat from low cost carriers. The pricing regression specification in equation (5) uses variable N_m^{et} to capture the average effect of entry threats. However, the following modified specification of the pricing equation allows for a decomposition of the average entry threat effect based on the identity of carriers threatening to enter the market:

$$\begin{aligned} \ln(p_m) = & X_m\phi + \delta^p N_m^a + \sum_{l \in L_m} \beta_l I_{ml}^{NOT} + \sum_{l \in L_m} \gamma_l I_{ml}^{NOT} \times D_{ml} \\ & + \rho E[u_{m0} | X_m, Z_{mk}, N_m^a, N_m^{et}] + v_m^p, \end{aligned} \quad (16)$$

where I_{ml}^{NOT} is a zero-one dummy that equals one only if firm l is not an incumbent firm in market m during the entry period; D_{ml} is a zero-one dummy that equals one only if firm l has presence at both endpoint airports of market m during the period preceding the entry period under consideration. A value of one for the interaction term $I_{ml}^{NOT} \times D_{ml}$ indicates that firm l poses a credible entry threat in market m , and γ_l is a parameter that captures incumbents' average pricing response across markets that firm l is not an incumbent but threatens to enter. Therefore, γ_l for each potential entrant are our key parameters of interest that capture the effects of entry threats. Note however, that inclusion of the stand-alone regressor, I_{ml}^{NOT} , is important to control

¹⁶ The estimation results are qualitative similar when we use nonlinear specifications of “No. of competing firms” and “No. of entry threats” in the price and quantity regression. Results are shown in the appendix A.4 and A.5.

for potential differences in pricing across markets in which firm l is an incumbent versus markets in which firm l is not an incumbent. If there are differences in pricing behavior depending on whether firm l is an incumbent or not, then we do not want these general pricing differences to confound measuring pricing behavior that is purely due to the entry threat of firm l .

The estimation results from the modified price and quantity equations at the market 50th percentile value for respective dependent variables are shown in Table 6, while results for the 25th and 75th percentiles of the dependent variables are shown in the appendix A.6 and A.7. The marginal price and quantity effects of population, distance, and distance squared are similar to the results in Table 5. When the endogeneity correction variable is included as a regressor in the price and quantity regressions, the result shows that the coefficients are roughly similar in magnitude compared to the case without endogeneity correction.

Recall that AA is American Airline's two-letter identifying code. Therefore, the coefficient on the entry threat interaction dummy $I_{AA}^{NOT} \times D_{AA}$ measures, on average, how incumbents price differ across markets that AA threatens to enter compared to similar markets that AA does not threaten to enter. The other airline entry threat market-level interaction dummies and their associated coefficients are similarly defined and interpreted. In other words, the comparison category for each entry threat interaction dummy is the set of markets that the relevant airline is not an incumbent and does not threaten to enter.

The evidence in Tables 1-6 shows that some potential entrants that threaten to enter relevant markets do have significant impact on the average market price and quantity. As we expect, incumbents are likely to lower their price in response to the entry threat of many potential carriers. In particular, the threat of market entry by Southwest Airline (WN) reduces

market fare significantly, by an average of 5.04 percent,¹⁷ compared to the case that the threat by WN does not occur to an otherwise similar market. This substantial price-dropping evidence is consistent with the finding in Goolsbee and Syverson (2008).

The crucial new result that is revealed in Table 1-6 is that incumbents may respond to the threat of entry by raising their price, or lowering their quantity, depending on the identity of the firm making the entry threat. For example, the coefficient of the entry threat by US Airways (US) is positive and statistically significant. When incumbents face US's entry threat, the responding market fare could increase significantly (approximately 25.35 percent) compared to an otherwise similar market with no entry threat by US. A potential explanation is that some incumbents may charge a higher price when threatened by entry in order to signal to the potential entrant that the incumbent has a relatively large loyal customer base. An incumbent's large loyal customer base serves to discourage entry since entrants would need to significantly discount fares to entice a critical mass of customers to switch. In the case of airline markets, consumers may be loyal to an airline if these consumers are heavily invested in the airline's frequent-flyer program.

Klemperer (1987) has used a theoretical switching-cost model to argue that entry can be deterred by high consumer switching costs. Rational consumers would display brand loyalty due to high switching costs and product searching time. Hollander (1987) argues that entry can cause incumbents to increase their price if they choose to concentrate on consumers with inelastic demand for the incumbent's own brand. Our study adds to this literature by empirically examining incumbents' price response in the period that entry is threatened but has not actually

¹⁷ Given that the dependent variable of the regression equation is in logarithm, the following transformation of the dummy coefficient, $\exp(\text{coefficient}) - 1$, yields percentage change. So the entry threat coefficient of -0.0517 for Southwest Airlines (WN) corresponds to a 5.04% fall in incumbent's price.

occurred and documents evidence that incumbents may respond by either lowering or raising their price.

**Table 1-6 Estimation Results for Price/ Quantity Regressions
with Identity of the Entry Threat Carriers**

Variable	<i>Estimates without Correction</i>				<i>Estimates with Correction</i>			
	<i>ln(P 50th)</i>		<i>ln(Q 50th)</i>		<i>ln(P 50th)</i>		<i>ln(Q 50th)</i>	
	Parameter Est.	Std. Error	Parameter Est.	Std. error	Parameter Est.	Std. error	Parameter Est.	Std. error
Constant	6.6148*	0.1595	5.0677*	0.6492	6.5860*	0.1591	5.1110*	0.6505
Population	0.7671*	0.1385	1.2821*	0.5637	0.7633*	0.1378	1.2880*	0.5637
Distance	5.6680*	0.439	-2.4018	1.7872	5.7890*	0.4392	-2.5830	1.7960
Distance2	-7.9929*	1.6044	-8.7655	6.5319	-8.3830*	1.6030	-8.1810	6.5570
No. of firms	-0.1930*	0.0132	0.1303*	0.0539	-0.1913*	0.0132	0.1277*	0.0540
Endogeneity correction	NA	NA	NA	NA	215.50*	77.62	-322.80	317.50
$I_{AA}^{Not} \times D_{AA}$	0.0045	0.0494	0.1923	0.2009	0.0042	0.0491	0.1927	0.2009
$I_{AS}^{Not} \times D_{AS}$	0.0037	0.0158	0.3331*	0.0642	0.0017	0.0157	0.3361*	0.0643
$I_{B6}^{Not} \times D_{B6}$	-0.0340*	0.0165	0.0407	0.067	-0.0351*	0.0164	0.0424	0.0670
$I_{CO}^{Not} \times D_{CO}$	0.0883 ⁺	0.0525	0.2823	0.2137	0.0838	0.0523	0.2890	0.2138
$I_{DL}^{Not} \times D_{DL}$	0.0941	0.139	-0.1653	0.5659	0.0987	0.1384	-0.1723	0.5659
$I_{F9}^{Not} \times D_{F9}$	0.0247	0.0183	0.1218	0.0746	0.0234	0.0183	0.1238 ⁺	0.0747
$I_{FL}^{Not} \times D_{FL}$	-0.0095	0.0163	0.1527*	0.0662	-0.0123	0.0162	0.1570*	0.0664
$I_{GQ}^{Not} \times D_{GQ}$	0.1241	0.084	-0.0473	0.3421	0.1209	0.0837	-0.0427	0.3422
$I_{HP}^{Not} \times D_{HP}$	-0.0252	0.0339	0.3531*	0.1378	-0.0248	0.0337	0.3525*	0.1378
$I_{NK}^{Not} \times D_{NK}$	0.0021	0.0237	0.3819*	0.0964	0.0001	0.0236	0.3850*	0.0965
$I_{NW}^{Not} \times D_{NW}$	0.0022	0.0349	-0.0096	0.142	0.0026	0.0347	-0.0102	0.1420
$I_{OO}^{Not} \times D_{OO}$	-0.0915*	0.0334	-0.4021*	0.1359	-0.0868*	0.0333	-0.4091*	0.1360
$I_{QX}^{Not} \times D_{QX}$	0.1833	0.1649	0.9022	0.6711	0.1841	0.1641	0.9009	0.6711
$I_{RD}^{Not} \times D_{RD}$	-0.0662	0.1644	0.0517	0.6694	-0.0660	0.1637	0.0514	0.6694
$I_{SY}^{Not} \times D_{SY}$	0.025	0.0192	0.013	0.0783	0.0185	0.0193	0.0228	0.0789
$I_{TZ}^{Not} \times D_{TZ}$	0.0415*	0.018	0.3230*	0.0732	0.0446*	0.0179	0.3182*	0.0733
$I_{U5}^{Not} \times D_{U5}$	0.0354	0.0289	-0.0016	0.1175	0.0372	0.0287	-0.0044	0.1175
$I_{UA}^{Not} \times D_{UA}$	-0.0206	0.0566	-0.3521	0.2305	-0.0204	0.0564	-0.3524	0.2305
$I_{US}^{Not} \times D_{US}$	0.2259*	0.039	-0.6748*	0.1587	0.2209*	0.0388	-0.6673*	0.1589
$I_{WN}^{Not} \times D_{WN}$	-0.0517*	0.0252	-0.3487*	0.1026	-0.0531*	0.0251	-0.3466*	0.1027
$I_{XE}^{Not} \times D_{XE}$	0.0304	0.0787	-0.3433	0.3202	0.0356	0.0783	-0.3510	0.3203
$I_{YX}^{Not} \times D_{YX}$	-0.0165	0.0154	0.1270*	0.0625	-0.0179	0.0153	0.1290*	0.0626
R-squared	0.7623		0.3190		0.7648		0.3199	

* significant at the 0.05 level and ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample. All regressions contain dummy non-incumbent effects ($\sum_{l \in L_m} \beta_l I_{ml}^{NOT}$) that are suppressed for brevity.

7. CONCLUSION

This paper re-examines incumbents' response to the threat of entry in the airline industry. Our key finding is that, while incumbents cut fares in response to the threat of entry by some potential entrants as documented in the existing literature, importantly, we also find a new result that incumbents may respond by raising their fare depending on who is making the threat. We believe that incumbents may respond to an entry threat in this way in order to deter entry. In particular, raising price may be an effective signal to potential entrants that the incumbent has a large loyal customer base. As such, an entrant will need to heavily discount fares in order to entice a critical mass of customers to switch, and therefore market entry will be unattractive in this case.

The analysis in this paper also constitutes a methodological extension to the analysis in Goolsbee and Syverson (2008). In particular, when analyzing incumbents' response to the threat of entry, our empirical framework accounts for the fact that market structure is endogenous, and therefore is able to mitigate potential biases in estimating incumbents' responses.

Apart from our key finding, the econometric estimates in this paper yield other interesting results. First, an increase in the number of actual entrants reduces profitability, which coincides with results in Berry (1992). Second, incumbents' price response is different when faced with increased actual competitors compared to increased entry threat. In particular, incumbents seem to cut price more in response to an increase in actual number of competitors, as compared to an increase in the number of firms that threaten to enter. This finding is consistent with Morrison (2001), which studies the effect of various forms of actual, adjacent, and potential competition from Southwest Airline. Third, when the endogeneity of market structure is taken into account, we find that the average price effect of actual entry is marginally smaller compared to when

endogeneity is not taken into account. Conversely, when the endogeneity of market structure is taken into account, the average price effect of an entry threat is marginally larger compared to when endogeneity is not taken into account.

The structural econometric model we use in this paper is static in nature. As such, our model is not ideal to capture dynamics in incumbents' response to actual entry and the threat of entry. For example, we did not attempt to analyze if incumbents initially respond aggressively but dampen their response overtime. Goolsbee and Syverson (2008) attempt to answer issues of this nature within their reduced-form econometric framework. However, a structural econometric framework that explicitly incorporates optimal dynamic behavior might improve our understanding of the issues. Of course a dynamic entry model is more challenging to implement and estimate, but may be rewarding in terms of the type of questions that can be answered, and therefore deserves an attempt by future research.

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Appendix A - Additional Tables

**Table A-1 Parameter Estimates for Entry Model
using 2007:Q3 as the first period and 2008:Q1 as the second period**

Variable	Parameter est.	Std. error
Constant	-3.3022*	0.1367
Population	1.2236*	0.0212
Distance	0.4978*	0.0399
(Distance) ²	-0.7877*	0.2360
City2	4.2844*	0.1413
Number of competing firms (δ^π)	-1.1140*	0.0193
Number of entry threats (λ^π)	-0.0191*	0.0036
Correlation (η)	-0.9979*	0.0021
Number of obs.	13962	
GMM objective	0.0420	

*significant at the 0.05 level.

**Table A-2 Estimation Results for Price/ Quantity Regressions
at the 25th Percentile**

Variable	<i>Estimates without Correction</i>		<i>Estimates with Correction</i>	
	<u><i>ln(P 25th)</i></u>	<u><i>ln(Q 25th)</i></u>	<u><i>ln(P 25th)</i></u>	<u><i>ln(Q 25th)</i></u>
	Parameter Est.	Parameter Est.	Parameter Est.	Parameter Est.
Constant	4.7595* (0.0541)	6.3834* (0.2307)	4.7503* (0.0540)	6.3951* (0.2310)
Population	0.5443* (0.1616)	2.0339* (0.6889)	0.5482* (0.1607)	2.0322 (0.6877)
Distance	6.4318* (0.5441)	1.9208 (2.3197)	6.5614* (0.5429)	1.6062 (2.3239)
Distance2	-11.156* (2.0195)	-13.918 (8.6091)	-11.562* (2.0133)	-12.936 (8.6173)
No. of firms (N_m^a)	-0.0605* (0.0138)	-0.0466 (0.0587)	-0.0593* (0.0137)	-0.0496 (0.0587)
No. of entry threats (N_m^{et})	-0.0111* (0.0044)	0.0296 (0.0189)	-0.0114* (0.0044)	0.0317 ⁺ (0.0189)
Endogeneity correction	NA	NA	328.06* (106.48)	-768.81 ⁺ (455.72)
R-squared	0.4971	0.0235	0.5031	0.0273

*represents significant at the 0.05 level. ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample.

**Table A-3 Estimation Results for Price/ Quantity Regressions
at the 75th Percentile**

Variable	<i>Estimates without Correction</i>		<i>Estimates with Correction</i>	
	<i>ln(P 75th)</i>	<i>ln(Q 75th)</i>	<i>ln(P 75th)</i>	<i>ln(Q 75th)</i>
	Parameter Est.	Parameter Est.	Parameter Est.	Parameter Est.
Constant	5.0143* (0.0534)	6.6267* (0.1696)	5.0099* (0.0535)	6.6341* (0.1701)
Population	0.7631* (0.1594)	3.5619* (0.5065)	0.7653* (0.1591)	3.5520* (0.5064)
Distance	4.5860* (0.5368)	-0.2914 (1.7057)	4.6576* (0.5377)	-0.3947 (1.7113)
Distance2	-4.3337* (1.9921)	-7.2269 (6.3306)	-4.5601* (1.9939)	-6.8770 (6.3457)
No. of firms (N_m^a)	-0.0173 (0.0136)	0.2225* (0.0419)	-0.0166 (0.0136)	0.2217* (0.0432)
No. of entry threats (N_m^{et})	-0.0117* (0.0044)	0.0755* (0.0139)	-0.0120* (0.0044)	0.0756* (0.0139)
Endogeneity correction	NA	NA	185.50 ⁺ (105.45)	-332.97 (335.59)
R-squared	0.4962	0.1242	0.4981	0.1251

*represents significant at the 0.05 level. ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample.

**Table A-4 Estimation Results for Price/ Quantity Regressions
when Number of Actual Competitors and Number of Entry Threats
enter Equations in Logarithm**

Variable	<i>Estimates without Correction</i>		<i>Estimates with Correction</i>	
	<u><i>ln(P 50th)</i></u>	<u><i>ln(Q 50th)</i></u>	<u><i>ln(P 50th)</i></u>	<u><i>ln(Q 50th)</i></u>
	Parameter Est.	Parameter Est.	Parameter Est.	Parameter Est.
Constant	4.9185* (0.0677)	6.2480* (0.2233)	4.9157* (0.0675)	6.2535* (0.2233)
Population	0.8187* (0.1546)	3.2413* (0.5098)	0.8199* (0.1541)	3.2391* (0.5095)
Distance	5.2015* (0.5221)	-0.2672 (1.7222)	5.3033* (0.5223)	-0.4621 (1.7270)
Distance ²	-6.5383* (1.9361)	-8.0192 (6.3861)	-6.8528* (1.9349)	-7.4169 (6.3974)
$ln(N_m^a)$	-0.1229* (0.0364)	0.1772 (0.1201)	-0.1203* (0.0363)	0.1721 (0.1201)
$ln(N_m^{et})$	-0.0449 (0.0285)	0.4803* (0.0940)	-0.0481 ⁺ (0.0285)	0.4863* (0.0941)
Endogeneity correction	NA	NA	243.00* (102.32)	-465.32 (338.30)
R-squared	0.5172	0.0921	0.5207	0.0944

*represents significant at the 0.05 level. ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample.

**Table A-5 Estimation Results for Price/ Quantity Regressions
when Number of Actual Competitors and Number of Entry Threats
enter Equations as Quadratic Variables**

Variable	<i>Estimates without Correction</i>		<i>Estimates with Correction</i>	
	<u><i>ln(P_50th)</i></u>	<u><i>ln(Q_50th)</i></u>	<u><i>ln(P_50th)</i></u>	<u><i>ln(Q_50th)</i></u>
	Parameter Est.	Parameter Est.	Parameter Est.	Parameter Est.
Constant	4.6886* (0.1332)	5.7909* (0.4416)	4.6877* (0.1328)	5.7930* (0.4413)
Population	0.8028* (0.1535)	3.2578* (0.5089)	0.8035* (0.1530)	3.2560* (0.5086)
Distance	4.9802* (0.5254)	-0.7049 (1.7423)	5.0842* (0.5257)	-0.9090 (1.7470)
Distance2	-5.8436* (1.9417)	-6.4467 (6.4390)	-6.1651* (1.9407)	-5.8160 (6.4510)
No. of firms (N_m^a)	-0.0603 (0.0786)	0.7570* (0.2607)	-0.0594 (0.0784)	0.7552* (0.2605)
$(N_m^a)^2$	0.0022 (0.0132)	-0.1194* (0.0438)	0.0022 (0.0132)	-0.1194* (0.0438)
No. of entry threats	0.0626* (0.0215)	0.0546 (0.0714)	0.0608* (0.0215)	0.0581 (0.0714)
$(N_m^{et})^2$	-0.0048* (0.0014)	0.0014 (0.0045)	-0.0047* (0.0013)	0.0013 (0.0045)
Endogeneity correction	NA	NA	239.15* (101.31)	-469.20 (336.80)
R-squared	0.5282	0.1032	0.5316	0.1054

*represents significant at the 0.05 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample.

**Table A-6 Estimation Results for Price/ Quantity Regressions (at the 25th Percentile)
with Identity of the Entry Threat Carriers**

Variable	<i>Estimates without Correction</i>				<i>Estimates with Correction</i>			
	<i>ln(P 25th)</i>		<i>ln(Q 25th)</i>		<i>ln(P 25th)</i>		<i>ln(Q 25th)</i>	
	Parameter Est.	Std. Error	Parameter Est.	Std. error	Parameter Est.	Std. Error	Parameter Est.	Std. error
Constant	6.6430*	0.1671	4.3587*	0.886	6.6038*	0.1661	4.4600*	0.8867
Population	0.3067*	0.1451	0.8899	0.7693	0.3015*	0.1439	0.9032	0.7683
Distance	6.6398*	0.4601	-1.2853	2.4394	6.8045*	0.4586	-1.7110	2.4480
Distance ²	-11.694*	1.682	-7.769	8.915	-12.225*	1.674	-6.397	8.937
No. of firms	-0.2136*	0.0139	-0.0043	0.0736	-0.2113*	0.0138	-0.0103	0.0735
Endogeneity correction	NA	NA	NA	NA	293.28*	81.06	-757.80 ⁺	432.70
$I_{AA}^{Not} \times D_{AA}$	0.0219	0.0517	0.2418	0.2742	0.0216	0.0513	0.2426	0.2738
$I_{AS}^{Not} \times D_{AS}$	-0.027	0.0165	0.2793*	0.0877	-0.0297 ⁺	0.0164	0.2863*	0.0876
$I_{B6}^{Not} \times D_{B6}$	-0.0259	0.0173	0.0029	0.0915	-0.0274	0.0171	0.0068	0.0914
$I_{CO}^{Not} \times D_{CO}$	0.0753	0.055	0.9766*	0.2916	0.0692	0.0546	0.9924*	0.2914
$I_{DL}^{Not} \times D_{DL}$	0.0029	0.1457	-0.855	0.7724	0.0092	0.1445	-0.8712	0.7713
$I_{F9}^{Not} \times D_{F9}$	-0.0036	0.0192	-0.0237	0.1019	-0.0053	0.0191	-0.0191	0.1017
$I_{FL}^{Not} \times D_{FL}$	-0.0253	0.0171	0.1667 ⁺	0.0904	-0.0292 ⁺	0.0169	0.1768 ⁺	0.0905
$I_{GQ}^{Not} \times D_{GQ}$	0.0735	0.0881	0.1934	0.467	0.0693	0.0874	0.2044	0.4664
$I_{HP}^{Not} \times D_{HP}$	-0.0279	0.0355	0.3111 ⁺	0.1881	-0.0274	0.0352	0.3098 ⁺	0.1879
$I_{NK}^{Not} \times D_{NK}$	0.0299	0.0248	0.5549*	0.1316	0.0271	0.0246	0.5620*	0.1315
$I_{NW}^{Not} \times D_{NW}$	0.0093	0.0366	0.2191	0.1938	0.0098	0.0363	0.2177	0.1935
$I_{OO}^{Not} \times D_{OO}$	-0.0680 ⁺	0.035	-0.5383*	0.1854	-0.0616 ⁺	0.0347	-0.5548*	0.1854
$I_{QX}^{Not} \times D_{QX}$	0.0599	0.1728	1.3247	0.916	0.0611	0.1714	1.3220	0.9147
$I_{RD}^{Not} \times D_{RD}$	-0.0683	0.1723	-0.2917	0.9137	-0.0681	0.1709	-0.2924	0.9124
$I_{SY}^{Not} \times D_{SY}$	0.0422*	0.0202	-0.0946	0.1069	0.0334 ⁺	0.0201	-0.0718	0.1076
$I_{TZ}^{Not} \times D_{TZ}$	0.0464*	0.0188	0.1838 ⁺	0.0999	0.0506*	0.0187	0.1728 ⁺	0.0999
$I_{U5}^{Not} \times D_{U5}$	0.0276	0.0303	0.1874	0.1604	0.0301	0.0300	0.1809	0.1602
$I_{UA}^{Not} \times D_{UA}$	0.0171	0.0593	-0.4477	0.3146	0.0174	0.0589	-0.4484	0.3142
$I_{US}^{Not} \times D_{US}$	0.1469*	0.0409	-0.4629*	0.2166	0.1400*	0.0406	-0.4452*	0.2165
$I_{WN}^{Not} \times D_{WN}$	-0.0510 ⁺	0.0264	-0.4725*	0.1401	-0.0529*	0.0262	-0.4674*	0.1399
$I_{XE}^{Not} \times D_{XE}$	0.0391	0.0824	-0.2511	0.4371	0.0461	0.0818	-0.2693*	0.4366
$I_{YX}^{Not} \times D_{YX}$	-0.0157	0.0161	0.2357*	0.0854	-0.0176	0.0160	0.2404	0.0853
R-squared	0.7500		0.2491		0.7544		0.2522	

* significant at the 0.05 level and ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample. All regressions contain dummy non-incumbent effects ($\sum_{l \in L_m} \beta_l I_{ml}^{NOT}$) that are suppressed for brevity.

**Table A-7 Estimation Results for Price/ Quantity Regressions (at the 75th Percentile)
with Identity of the Entry Threat Carriers**

Variable	<i>Estimates without Correction</i>				<i>Estimates with Correction</i>			
	<i>ln(P_75th)</i>		<i>ln(Q_75th)</i>		<i>ln(P_75th)</i>		<i>ln(Q_75th)</i>	
	Parameter Est.	Std. Error	Parameter Est.	Std. error	Parameter Est.	Std. error	Parameter Est.	Std. error
Constant	6.3435*	0.1772	5.3931*	0.6378	6.3219*	0.1772	5.4100*	0.6396
Population	0.8882*	0.1538	1.4392*	0.5538	0.8853*	0.1536	1.4410*	0.5542
Distance	5.1836*	0.4878	-3.1418 ⁺	1.7561	5.2744*	0.4894	-3.2110 ⁺	1.7660
Distance2	-6.5511*	1.7827	-6.1324	6.4181	-6.8439*	1.7865	-5.9100	6.4470
No. of firms	-0.1467*	0.0147	0.3068*	0.0530	-0.1455*	0.0147	0.3058*	0.0530
Endogeneity correction	NA	NA	NA	NA	161.78 ⁺	86.49	-123.00	312.10
$I_{AA}^{Not} \times D_{AA}$	-0.0056	0.0548	0.1660	0.1974	-0.0058	0.0547	0.1661	0.1975
$I_{AS}^{Not} \times D_{AS}$	0.0383*	0.0175	0.3234*	0.0631	0.0368*	0.0175	0.3245*	0.0632
$I_{B6}^{Not} \times D_{B6}$	-0.0552*	0.0183	0.0249	0.0659	-0.0560*	0.0183	0.0255	0.0659
$I_{CO}^{Not} \times D_{CO}$	0.0786	0.0583	0.1531	0.2099	0.0753	0.0582	0.1557	0.2102
$I_{DL}^{Not} \times D_{DL}$	0.1860	0.1544	-0.1452	0.5560	0.1894	0.1542	-0.1479	0.5564
$I_{F9}^{Not} \times D_{F9}$	0.0384 ⁺	0.0204	0.1531*	0.0733	0.0375 ⁺	0.0203	0.1539*	0.0734
$I_{FL}^{Not} \times D_{FL}$	-0.0037	0.0181	0.1174 ⁺	0.0651	-0.0058	0.0181	0.1190 ⁺	0.0653
$I_{GQ}^{Not} \times D_{GQ}$	0.1336	0.0934	-0.2038	0.3362	0.1313	0.0932	-0.2020	0.3364
$I_{HP}^{Not} \times D_{HP}$	-0.0220	0.0376	0.3533*	0.1354	-0.0218	0.0376	0.3531*	0.1355
$I_{NK}^{Not} \times D_{NK}$	-0.0166	0.0263	0.3268*	0.0948	-0.0182	0.0263	0.3279*	0.0949
$I_{NW}^{Not} \times D_{NW}$	0.0111	0.0387	-0.0935	0.1395	0.0114	0.0387	-0.0937	0.1396
$I_{OO}^{Not} \times D_{OO}$	-0.1346*	0.0371	-0.4008*	0.1335	-0.1311*	0.0371	-0.4035*	0.1337
$I_{QX}^{Not} \times D_{QX}$	0.2634	0.1832	0.7117	0.6594	0.2641	0.1829	0.7112	0.6598
$I_{RD}^{Not} \times D_{RD}$	-0.0630	0.1827	0.2175	0.6577	-0.0628	0.1824	0.2174	0.6581
$I_{SY}^{Not} \times D_{SY}$	0.0206	0.0214	-0.0065	0.0770	0.0157	0.0215	-0.0028	0.0776
$I_{TZ}^{Not} \times D_{TZ}$	0.0219	0.0200	0.3479*	0.0719	0.0242	0.0200	0.3461*	0.0721
$I_{U5}^{Not} \times D_{U5}$	0.0353	0.0321	-0.0605	0.1155	0.0366	0.0320	-0.0616	0.1156
$I_{UA}^{Not} \times D_{UA}$	-0.0429	0.0629	-0.2921	0.2265	-0.0427	0.0628	-0.2922	0.2266
$I_{US}^{Not} \times D_{US}$	0.2569*	0.0433	-0.7525*	0.1559	0.2531*	0.0433	-0.7496*	0.1562
$I_{WN}^{Not} \times D_{WN}$	-0.0625*	0.0280	-0.3401*	0.1009	-0.0636*	0.0280	-0.3393*	0.1009
$I_{XE}^{Not} \times D_{XE}$	0.0105	0.0874	-0.4252	0.3146	0.0144	0.0873	-0.4282	0.3149
$I_{YX}^{Not} \times D_{YX}$	-0.0138	0.0171	0.1250*	0.0615	-0.0148	0.0170	0.1258*	0.0615
R-squared	0.7107		0.3546		0.7121		0.3547	

* significant at the 0.05 level and ⁺ significant at the 0.10 level. The number of observations for these regressions is 777, which corresponds to the number of origin-destination markets in our sample. All regressions contain dummy non-incumbent effects ($\sum_{l \in L_m} \beta_l I_{ml}^{NOT}$) that are suppressed for brevity.

Essay Two - Are Air Travel Markets Segmented Along the Lines of Nonstop versus Intermediate-stop(s) Products?

1. INTRODUCTION

In evaluating a proposed merger, the U.S. Department of Justice (DOJ) normally identifies relevant product markets in which the merger may “substantially lessen competition”.¹⁸ Regarding the merger enforcement standards in the airline industry, the DOJ has published a document stating the following:¹⁹

“...there are many city pairs that are served by some carriers on a nonstop basis and others on a connecting basis, which poses the following question: is a passenger having the ability to take a nonstop flight likely to regard connecting service as a reasonable alternative, such that he or she would switch from nonstop service offered by one carrier to connecting service offered by another carrier if the first carrier raised its fare?”

This statement indicates that at the heart of conducting proper antitrust analysis in the airline industry is the question of whether nonstop and intermediate-stop(s)/connecting air travel products are truly competing with each other, or put another way: Can these two types of air travel products be treated as being in the same market segment? This paper intends to shed light on this very important antitrust-relevant question. To the best of our knowledge, there is no formal empirical analysis of this issue in the literature, even though some researchers have separately analyzed competition between nonstop products from competition between intermediate-stop(s) products [e.g. see Brueckner et al. (2011)].

¹⁸ See the Horizontal Merger Guidelines published by U.S. Department of Justice and Federal Trade Commission (2010). <http://www.justice.gov/atr/public/guidelines/hmg-2010.html>.

¹⁹ U.S. Department of Justice (2000), “Statement of John M. Nannes, Deputy Assistant Attorney General, Antitrust division, Before the Committee on Transportation & Infrastructure, U.S. House of Representatives, Concerning Antitrust analysis of Airline Mergers.” <http://www.justice.gov/atr/public/testimony/4955.htm>.

A typical air travel origin-destination market contains a menu of nonstop and intermediate-stop(s) products from which potential consumers choose. If these two differentiated products are considered being in the same market segment, then consumers should be willing to substitute between these products in response to relative changes in price. Under such circumstance, the intermediate-stop(s) products can have significant competitive impact on nonstop products. On the other hand, if the market is segmented along the lines of nonstop versus intermediate-stop(s) products, there is likely to be low consequential competitive effect between these two product types.

Berry and Jia (2010) provides evidence suggesting that in recent time consumers have an increasingly strong preference for nonstop products compared to intermediate-stop(s) products in the airline industry. Gillen et al. (2003) conduct a report of air travel demand elasticities for Canada. They suggest that the demand for air travel should be distinguished by types of consumers (leisure vs. business travelers), length of haul (short-haul vs. long-haul distance), and types of markets (domestic vs. international destinations). So in addition to a general investigation of market segmentation along the lines of these product types, it might be useful to see if the result of the investigation depends on length of market haul or types of consumers. The following quote from a DOJ published document further motivates breaking down the analysis by consumer types:²⁰

“...Chances are that passengers traveling for leisure -- on vacation perhaps -- are more likely to consider switching; their demand is said to be more elastic. However, passengers making

²⁰ U.S. Department of Justice (2000), “Statement of John M. Nannes, Deputy Assistant Attorney General, Antitrust division, Before the Committee on Transportation & Infrastructure, U.S. House of Representatives, Concerning Antitrust analysis of Airline Mergers.” <http://www.justice.gov/atr/public/testimony/4955.htm>.

business trips are significantly less likely to regard connecting service as a reasonable alternative...”

The challenge we face in breaking down the analysis by consumer type is that publicly available data, like the Airline Origin and Destination Survey (DB1B) which we use, do not provide information about consumers' purpose of travel (e.g. business versus leisure). As such, in the spirit of recent literature on differentiated products demand, we use a structural econometric model to capture consumers' heterogeneity in tastes.²¹ Modeling consumers' heterogeneity is important for more accurate estimation of demand elasticity and the corresponding product markups and marginal cost.

Our econometric estimates suggest that consumers' ideal air travel product is a cheap nonstop flight between their origin and destination. When we decompose consumers' choice behavior according to leisure versus business travelers, the result suggests that these two types of consumers view a product differently with respect to their marginal utilities of price. Leisure travelers are much more price-sensitive compared to business travelers irrespective of whether the market is short-haul, mid-haul, or long-haul distance travel.

The statistically significant cross-price elasticity of demand estimates suggest that, on average, consumers perceive intermediate-stop(s) products substitutable for nonstop products. Furthermore, when facing an increase in price of nonstop products, we find that leisure travelers are more willing than business travelers to switch to intermediate-stop(s) products, suggesting that leisure travelers are more willing to tolerate intermediate stops compared to business travelers.

²¹ We follow Berry and Jia (2010) approach, but for more flexible consumer heterogeneity specifications see Nevo (2000) and Petrin (2002).

We use the estimated econometric model of air travel demand and supply to perform an equilibrium counterfactual analysis, which helps us better evaluate whether nonstop and intermediate-stop(s) products can be treated as being in separate market segments. Essentially the counterfactual experiment is done by removing intermediate-stop(s) products from each sample market, then assuming the previously estimated product marginal costs and preference parameters are unchanged, we use the supply-side of the model to solve for new equilibrium prices for nonstop products. A comparison of the actual nonstop products' prices with their model predicted equilibrium prices when intermediate-stop(s) products are counterfactually removed reveals the extent to which the presence of intermediate-stop(s) products influences the pricing of nonstop products. The counterfactual analysis reveals the existence of three effects that might simultaneously influence the predicted equilibrium price change of nonstop products if competing substitute products are removed from the market counterfactually: (1) a market power effect; (2) a multi-product firm effect; and (3) a price-sensitivity effect.

The market power effect is the most straightforward of the three effects to understand. The idea is that carriers who remain in the market with nonstop products may raise the price of these products owing to increased demand and market power which stem from fewer competing substitute products in the market. On the other hand, if the product that is removed from the market is one of several substitute products offered by a firm, this firm has an incentive to marginally reduce the price on its remaining products. We call this downward price pressure the multi-product firm effect. The other downward pressure on the price of nonstop product occurs when the average price-sensitivity of the set of potential consumers of these products increases. By eliminating intermediate-stop(s) products, we in effect force carriers to optimally adjust the price of nonstop products for those consumers who are more price-sensitive and do not have any

other product options. We call this effect on the price of nonstop products the price-sensitivity effect. In summary, the net effect on the price of nonstop products if intermediate-stop(s) products are removed from the market depends on which of the three effects dominate.

The result from our counterfactual exercise shows that most markets are predicted to have either no price change or price decreases, and among the markets with predicted price increases, these price increases are typically smaller than 1%. Overall, the predicted price changes for nonstop products typically lie between -1% and 1%. The evidence therefore suggests that the market power effect is often offset by the multi-product firm effect and price-sensitivity effect. Furthermore, the small net price changes suggest that nonstop and intermediate-stop(s) air travel products can be treated as being in separate product markets for antitrust purposes.

The rest of the paper is organized as follows: Important definitions used throughout the paper are collected in Section 2. Section 3 describes the data used in estimation. Sections 4 and 5 outline the econometric model and the estimation technique respectively. We discuss results in Section 6, and offer concluding remarks in Section 7.

2. DEFINITIONS

We now define some key concepts that are used throughout the paper. A market is directional air travel between origin and destination airports, independent of any intermediate stops. Thus, a trip from Kansas City to Atlanta is considered a different market than a trip from Atlanta to Kansas City. This direction-specific approach of defining air travel markets allows origin city characteristics to influence demand. For example, origin cities that differ in

population density and proportion of business versus leisure travelers are likely to have different demands for air travel.

A trip itinerary refers to a specific sequence of airport stops in traveling from the origin to destination airport. An air travel product is defined as the combination of a trip itinerary and airline. In a given market, airlines often compete with each other by offering a variety of products. For example, varied products in the Atlanta to Kansas City market are: (1) a nonstop trip operated by American Airlines; (2) a nonstop trip operated by Delta Airlines; and (3) a trip that requires an intermediate stop in Chicago operated by American Airlines. In other words, an air travel carrier can offer several distinct products in a given market, as in the example above in which American Airlines offer both a nonstop product along with a product that requires an intermediate stop in Chicago.

For any given product, the responsibilities of a “ticketing” carrier are different from those of an “operating” carrier. A ticketing carrier is an air travel carrier that markets and sells the flight ticket for a product to consumers, while an operating carrier is the one that actually transports the passengers. For most products, typically labeled in the literature as pure online products, a single carrier is the ticketing and operating carrier, while for other products, some of which are referred to as codeshare products, the ticketing and operating carriers differ.²² In this research we treat the ticketing carrier as the “owner” of the product since this is the carrier that offers the product for sale to the consumer.²³

²² See Ito and Lee (2007), Gayle (2011, 2008, 2007a and 2007b) for discussions of the various types of air travel products and their relative popularity in US domestic air travel markets.

²³ In relatively rare occasions products with intermediate stops may have different ticketing carriers for each trip segment, but we do not consider such products in our analysis. The products considered in our analysis have a single ticketing carrier for all trip segments.

3. DATA

Data are obtained from the Airline Origin and Destination Survey (DB1B), published by the U.S. Bureau of Transportation Statistics. DB1B is a 10% random sample of airline tickets from reporting carriers in the U.S. The database includes identifying information for ticketing and operating carriers associated with each ticket, the ticket fare and the number of passengers that purchase each ticket, the origin and destination airports as well as the sequence of any intermediate airport stop(s) that each itinerary may use, total itinerary flight distance, and the nonstop flight distance between the origin and destination airports. The data do not contain any passenger-specific information such as whether the passenger holds frequent-flyer membership with an airline, whether the purpose of the trip is for business or leisure, date of ticket purchase, how long in advance of travel date ticket was purchased, etc. Data in our study are focused on U.S. domestic flights offered and operated by U.S. carriers in the 1st quarter in 2010.

Some data restrictions are imposed in our study. Observations are dropped with missing market fares and market fares less than \$100 due to the high probability that these may be data entry coding errors or discounted fares that may be related to passengers using accumulated frequent-flyer miles to offset the full cost of travel. Only products between the 48 main land U.S. states are included. In addition, flight itineraries with a change in the ticketing carrier or the operating carrier are eliminated. In order for a product to remain in our sample we require that at least 5 passengers purchase it during the quarter. In addition, we drop the relatively rare occasions when products have 3 or more intermediate stops since in these instances the intermediate stops may themselves be destinations of importance for the passenger rather than a mere route to get the passenger to their final destination. In other words, consumers that purchase products with 3 or more intermediate stops are unlikely to perceive products with

fewer, or no, intermediate stop as substitutable with the chosen product since the final destination may not have been the only destination of importance for the passenger. Given that the main objective of our analysis is to investigate the extent to which nonstop products are substitutable with intermediate-stop(s) products, including products with 3 or more intermediate stops may unduly bias our results towards finding weak substitutability. Last, consistent with our main objective, an origin-destination market remains in our sample only if it has both nonstop and intermediate-stop(s) products.

In order to collapse the data based on our definition of air travel product, we compute the mean price for each distinct itinerary-carrier combination. Thus, a product's "*price*" is the mean ticket fare for its unique itinerary-carrier combination. Also, a "*quantity*" variable is created based on the sum of passengers that purchase the product. This variable is used to construct observed product shares, which is defined as product "*quantity*" divided by the potential market size²⁴. The final dataset has sample size of 10,883 products spread across 741 origin-destination markets.

We then construct some product characteristics variables. An "*Interstop*" variable is the number of intermediate stops in each product. A measure of product "*Inconvenience*" is created as the ratio of the total itinerary flight distance to the nonstop flight distance between origin and destination. The minimum possible value of the *Inconvenience* variable is 1, indicating the least inconvenient itinerary distance in the market. An airline "*HUB_Origin*" zero-one dummy variable equals 1 if the origin airport is a HUB for the ticketing carrier of the product.

Following Berry and Jia (2010), in order to capture potential product characteristics that are unobservable to us due to the relatively high traffic congestion in Florida and Las Vegas, we

²⁴ The origin city population is used as the potential market size.

create a “*Tour*” zero-one dummy variable that equals 1 if the airport is in Florida or Las Vegas. A “*Slot_control*” variable counts the number of slot-controlled airports in a product, which captures the inconvenience of possible longer handling time of air traffic control due to limited airport capacity.²⁵ In the subsequent sections of the paper we posit that air travel demand is affected by the following variables: *Price* (in thousand dollars), *Interstop*, *Inconvenience*, *HUB_Origin* dummy, *Tour* dummy, *Slot_control*, and ticketing carrier fixed effects.

We posit that air travel supply is affected by the following cost-shifting variables: Itinerary *Distance* (in thousand miles), Itinerary *Distance Squared* (noted as *Distance*²), *HUB_MC* dummy, *Slot_MC* dummy and operating carrier dummies. “*HUB_MC*” is a zero-one dummy variable that equals 1 if the origin, intermediate stop(s), or destination airport is a HUB for the carrier. “*Slot_MC*” is a zero-one dummy variable that equals 1 if the *Slot_control* variable is greater than zero. Descriptive statistics of the sample data are reported in Table 2-1.

²⁵ The slot-controlled airports are New York LaGuardia, New York Kennedy, Washington National, and Chicago O'Hare.

Table 2-1 Descriptive Statistics

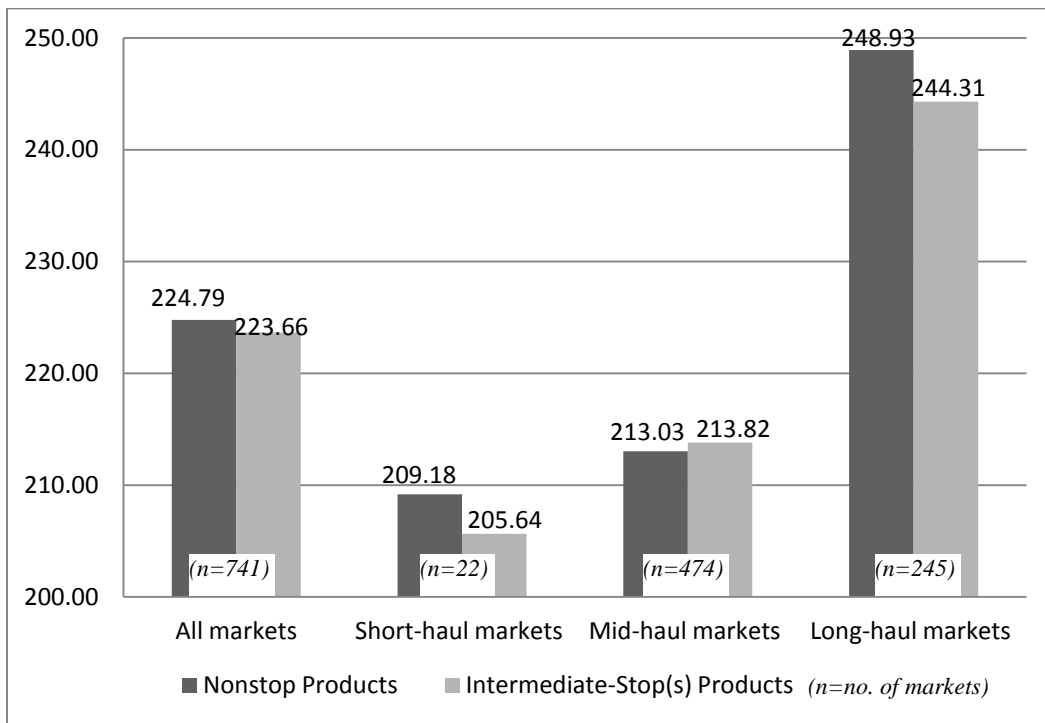
Variable	Description	Mean	Std. Dev.	Min	Max
Price	Mean ticket fare for each product, in thousand dollars	0.2245	0.1067	0.1033	4.553
Quantity	Number of passengers for each product	187.149	542.09	5	7796
Interstop	Number of intermediate stops	0.7488	0.4587	0	2
Inconvenience	The ratio of the total itinerary distance to the nonstop flight distance	1.1465	0.2218	1	2.875
HUB_Origin	Dummy equals 1 if the origin airport is a HUB for the ticketing carrier	0.1267	0.3327	0	1
Tour	Dummy equals 1 if the airport is in Florida or Las Vegas	0.1963	0.3972	0	1
Slot_control	Number of slot-controlled airports	0.2300	0.4555	0	2
Distance	Itinerary flying distance covered on the route used by product, in thousands of miles	1.6852	0.6670	0.337	3.843
Distance ²	Itinerary flying distance squared	3.2848	2.4164	0.114	14.769
HUB_MC	Dummy equals 1 if either the origin, the intermediate stop(s), or the destination airport is a HUB for the carrier	0.4723	0.4993	0	1
Slot_MC	Dummy equals 1 if the Slot_control variable is greater than zero	0.2148	0.4107	0	1
Observations	10,883				

Overall, across the 741 markets in our sample, the average market fare is about \$224.50. Figure 2-1 illustrates average market fare of nonstop products compared to intermediate-stop(s) products based on flight distance of markets. A short-haul market refers to the nonstop flight distance in a market shorter than 500 miles. The other two market distance categories are the mid-haul market, with the distance between 500 miles and 1,500 miles, and the long-haul market, with the distance longer than 1,500 miles, according to definitions in Gillen et al. (2003).

The average market fare is increasing in distance for both types of products. A comparison of nonstop and intermediate-stop(s) products' prices reveal that a pricing gap between the two product types varies depending on the length of the trip. The average market

fare of nonstop products is greater than that of intermediate-stop(s) products in short-haul and long-haul markets. However, in mid-haul markets, the average price ranking is reversed between these two product types. This suggests that competition between these differentiated products may depend on the market nonstop flight distance.

**Figure 2-1 Average Market Fares
for Nonstop vs. Intermediate-Stop(s) Products in 2010:Q1**



4. MODEL

4.1 Demand

Following Berry and Jia (2010) and Berry, Carnal and Spiller (2006),²⁶ we use a random coefficients discrete choice approach, which allows us to estimate with aggregate market-level data while still being able to identify average choice behavior of different types of consumers. Assume air travel markets are populated with two types of consumers; type 1 consumers which on average is relatively more price-sensitive and have a higher tolerance for less convenient travel itineraries compared to type 2 consumers. Therefore, we may reasonably interpret type 1 consumers to be leisure travelers (subsequently denoted by L) and type 2 consumers to be business travelers (subsequently denoted by B). But this interpretation of the two consumer types is not “cast in stone”.

The indirect utility consumer i , who is type $t \in \{L, B\}$, obtain from purchasing product j in market m is given by:

$$u_{ijm} = x_{jm}\beta_t + \alpha_t p_{jm} + \xi_{jm} + \sigma \zeta_{igm} + (1 - \sigma)\varepsilon_{ijm} , \quad (1)$$

where x_{jm} is a vector of non-price observable product characteristics,²⁷ β_t is a vector of taste coefficients for x_{jm} for consumers of type t , p_{jm} is the product price, α_t is the marginal utility from a change in price for consumers of type t , ξ_{jm} captures components of product characteristics that are observed by consumers but unobserved to researchers, ζ_{igm} is a random component of utility that is common to all products in group g , whereas the random term ε_{ijm} is specific to product j . Note that $g = 0, 1, 2, \dots, G$ index product groups within a market, and one

²⁶ Also see Berry (1990).

²⁷ Based on our previous discussion in the data section, variables in x_{jm} includes: *Interstop*, *Inconvenience*, *HUB_Origin* dummy, *Tour* dummy, *Slot_control*, and ticketing carrier fixed effects.

outside alternative ($g=0$). The outside alternative is the option not to purchase one of the air travel products considered in the model.

Some passengers may view the set of products offered by a given airline to be closer substitutes for each other compared to the substitutability of these products with products offered by other airlines, since a given airline's set of products may share a common desirable characteristic. A passenger may therefore choose to have frequent-flyer membership with a given airline, which serves to reinforce the passenger's loyalty to the set of products offered by that airline. Since we do not have passenger-specific information in the data, such as frequent-flyer membership, one attempt to capture airline brand-loyal choice behavior of consumers is to group products by airline in the demand model. This type of product grouping allows preferences to be correlated across products offered by a given airline. Therefore, product groups that are indexed by g in equation (1) are based on airlines.

The parameter σ , lying between 0 and 1, measures the correlation of the consumers' utility across products belonging to the same group/airline. If $\sigma = 1$, there is perfect correlation of preferences for products within the same group. On the other hand, there is no correlation of preferences if $\sigma = 0$. Consumer choice behavior is consistent with utility maximization when $\sigma \in (0,1)$ and product shares have the traditional nested logit form.

Let there be G_g products in group g . If product j is in group g , the formula for the within group share of product j among type t consumers in market m is:

$$s_{j|g,m}^t(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta) = \frac{\exp [(x_{jm}\beta_t + \alpha_t p_{jm} + \xi_{jm}) / (1 - \sigma)]}{D_{gtm}}, \quad (2)$$

where the denominator in equation (2) is given by:

$$D_{gtm} = \sum_{j \in G_g} \exp [(x_{jm}\beta_t + \alpha_t p_{jm} + \xi_{jm}) / (1 - \sigma)]. \quad (3)$$

The share of group g among type t consumers in market m is:

$$s_{gm}^t(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta) = \frac{D_{g|tm}^{1-\sigma}}{1 + \sum_{g=1}^G D_{g|tm}^{1-\sigma}}. \quad (4)$$

Let λ_t be the percentage of type t consumers in the population, where $t \in \{L, B\}$. The overall market share of product j in market m is:

$$s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta) = \lambda_L \times s_{j|g,m}^L \times s_{gm}^L + \lambda_B \times s_{j|g,m}^B \times s_{gm}^B, \quad (5)$$

where $\lambda_L + \lambda_B = 1$. Note that θ is the vector of demand parameters to be estimated, which consists of the taste for product characteristics of both consumer types (β_L and β_B), the marginal utility of price of both consumer types (α_L and α_B), the correlation of consumers' utility across products belonging to the same group σ , and the probability of type L consumer λ_L . λ_B is obtained by $\lambda_B = 1 - \lambda_L$.

The demand for product j is given by:

$$d_{jm} = M \times s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta), \quad (6)$$

where M is a measure of the market size, which is assumed to be the origin city population in our study.

For comparative purposes we also estimate two more restrictive discrete choice models of demand: (1) the standard logit model; and (2) the simple nested logit model. The simple nested logit model allows consumers' tastes to be correlated across products in the same group but consumers do not differ in their marginal utilities for product characteristics, i.e., consumers are all the same type. The most restrictive of the alternate demand models we consider is the standard logit model, which does not allow consumer taste to be correlated across product groups, nor does the model allow consumers to differ in their marginal utilities for product characteristics.

4.2 Markups and Marginal Cost

We assume that carriers simultaneously choose prices as in a static Bertrand-Nash model of differentiated products. Let each carrier f offer for sale a set F_{fm} of products in market m .

Firm f 's variable profit in market m is given by:

$$\pi_{fm} = \sum_{j \in F_{fm}} (p_{jm} - mc_{jm}) q_{jm} , \quad (7)$$

where $q_{jm} = d_{jm}(\mathbf{p})$ in equilibrium, q_{jm} is the quantity of travel tickets for product j sold in market m , $d_{jm}(\mathbf{p})$ is the market demand for product j in equation (6), \mathbf{p} is a vector of prices for the J products in market m , and mc_{jm} is the marginal cost of product j in market m .

The corresponding first-order conditions are:

$$\sum_{r \in F_{fm}} (p_{rm} - mc_{rm}) \frac{\partial s_r}{\partial p_j} + s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta) = 0 \quad \text{for all } j = 1, \dots, J \quad (8)$$

which can be rewritten in matrix notation as:

$$(\mathbf{p} - \mathbf{mc}) \times (\Omega * \Delta) + \mathbf{s}(\mathbf{p}) = 0 , \quad (9)$$

where \mathbf{p} , \mathbf{mc} , and $\mathbf{s}(\cdot)$ are $J \times 1$ vectors of product prices, marginal costs, and predicted product shares respectively, while $\Omega * \Delta$ is an element-by-element multiplication of two matrices. Δ is a $J \times J$ matrix of first-order derivatives of model predicted product market shares with respect to prices, where element $\Delta_{jr} = \frac{\partial s_r(\cdot)}{\partial p_j}$. Ω is a $J \times J$ matrix which describes carriers' ownership

structure of the J products. For example, let Ω_{jr} denote an element in Ω , where

$$\Omega_{jr} = \begin{cases} 1 & \text{if there exist } f: \{j, r\} \subset F_f \\ 0 & \text{otherwise} \end{cases}$$

That is, $\Omega_{jr} = 1$ if products j and r are offered for sale by the same carrier, otherwise $\Omega_{jr} = 0$.

Based on equation (9), the markup equation can be obtained as:

$$\text{Markup} = \mathbf{p} - \mathbf{mc} = -(\Omega * \Delta)^{-1} \times \mathbf{s}(\mathbf{p}) . \quad (10)$$

Finally, the marginal cost equation is specified as:

$$\ln(\mathbf{mc}) = \mathbf{w}\gamma + \boldsymbol{\eta} , \quad (11)$$

where \mathbf{w} is a matrix of observed marginal cost-shifting variables,²⁸ γ is a vector of cost parameters to be estimated, and $\boldsymbol{\eta}$ is a vector of cost shocks that is unobserved by researchers.

The supply equation implied by equations (10) and (11) is therefore,

$$\ln[\mathbf{p} - Markup(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta)] = \mathbf{w}\gamma + \boldsymbol{\eta} . \quad (12)$$

5. ESTIMATION

Generalized Method of Moments (GMM) is used to estimate the demand and marginal cost parameters jointly. First we describe how moment conditions are constructed from the demand side of the model, and then describe how other moment conditions are constructed from the supply side of the model.

In case of the demand model, the estimation strategy involves searching for parameter values satisfying the equality between observed product shares ($S_{jm} = \frac{q_{jm}}{M}$) and product shares predicted by the model, $s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta)$, that is,

$$S_{jm} = s_{jm}(\mathbf{x}, \mathbf{p}, \boldsymbol{\xi}, \theta), \quad (13)$$

where the right-hand-side of equation (13) is based on the predicted share function in equation (5). To construct moment conditions, we first invert equation (13) to solve for the vector of unobserved product characteristics, $\boldsymbol{\xi}$, as a function of the observed non-price product characteristics, prices, the observed product shares, and parameters, that is:

$$\boldsymbol{\xi} = s^{-1}(\mathbf{x}, \mathbf{p}, \mathbf{S}, \theta). \quad (14)$$

²⁸ Based on our previous discussion in the data section, w_{jm} includes: Itinerary *Distance* (in thousand miles), Itinerary *Distance Squared* (noted as *Distance*²), *HUB_MC* dummy, *Slot_MC* dummy and operating carrier dummies.

Following Berry and Jia (2010), this inversion is done numerically via the following contraction mapping technique:²⁹

$$\xi_{jm}^k = \xi_{jm}^{k-1} + (1 - \sigma)[\ln(\mathbf{S}_{jm}) - \ln(s_{jm}(\mathbf{x}, \mathbf{p}, \xi^{k-1}, \theta))], \quad (15)$$

where k indexes iterations, \mathbf{S}_{jm} is the observed product share, and $s_{jm}(\mathbf{x}, \mathbf{p}, \xi, \theta)$ is the predicted product share function defined by equation (5).

For the simple nested logit model, the unobservable ξ_{jm} is computed analytically using:

$$\xi_{jm} = y_{jm} - [x_{jm}\beta_t + \alpha_t p_{jm} + \sigma \ln(\mathbf{S}_{j/g})], \quad (16)$$

where $y_{jm} = \ln(\mathbf{S}_{jm}) - \ln(\mathbf{S}_{0m})$, \mathbf{S}_{0m} is the observed share of the outside good ($g=0$), and $\mathbf{S}_{j/g}$ is the observed within group share of product j . If we set $\sigma = 0$, equation (16) yields the unobservable for the standard logit model.

Therefore, the demand error term ξ_{jm} from either equation (15) or (16), depending on which demand model is used, yields the following moment conditions:

$$m_d = \frac{1}{n} Z_d' \xi(\mathbf{x}, \mathbf{p}, \mathbf{S}, \theta) = 0, \quad (17)$$

where n is the number of observations in the sample, and Z_d is a $n \times L_d$ matrix of instruments.

The marginal cost error term η is obtained from equation (12) as follows:

$$\eta = \ln[\mathbf{p} - Markup(\mathbf{x}, \mathbf{p}, \xi, \theta)] - w\gamma, \quad (18)$$

which is then used to generate the supply-side moment conditions:

$$m_s = \frac{1}{n} Z_s' \eta(\mathbf{w}, \mathbf{p}, Markup, \gamma) = 0. \quad (19)$$

We combine moment conditions from equations (17) and (19) into a single GMM objective function and jointly estimate parameters in the demand and marginal cost equations.

The GMM optimization problem is:

²⁹ The iteration continues until the maximum difference between ξ_{jm}^k and ξ_{jm}^{k-1} is smaller than 10^{-8} .

$$\text{Min}_{\hat{\theta}, \hat{\gamma}} \left[m(\hat{\theta}, \hat{\gamma})' W m(\hat{\theta}, \hat{\gamma}) \right] \quad (20)$$

where $m(\hat{\theta}, \hat{\gamma}) = \begin{bmatrix} m_d \\ m_s \end{bmatrix}$, and W is the following block diagonal positive definite weight matrix:

$$W = \begin{pmatrix} \left[\frac{1}{n} Z_d' \xi \xi' Z_d \right]^{-1} & \mathbf{0} \\ \mathbf{0} & \left[\frac{1}{n} Z_s' \eta \eta' Z_s \right]^{-1} \end{pmatrix}.$$

Due to the fact that prices and "within" group product shares are endogenous, we need instruments that are associated with these endogenous variables but not with the error terms. Following much of the literature on discrete choice models of demand, we make the admittedly strong identifying assumption that observed non-price product characteristics are uncorrelated with unobserved product quality, ξ , or unobserved marginal cost, η .³⁰ Similar to Gayle (2011, 2007a, 2007b) and Brown and Gayle (2010), we create the following instruments: (1) the number of substitute products offered by an airline in a market; (2) the number of competitor products in the market; (3) the number of competing products with equivalent number of intermediate stops offered by other carriers; (4) the squared deviation of a product's itinerary distance from the average itinerary distance of competing products offered by other carriers; (5) the sums and averages of the *Inconvenience* and *Interstop* variables;³¹ and (6) interactions of these instrument variables.

The instruments are motivated by standard supply theory, which predicts that equilibrium price is affected by the size of markup. In other words, the instruments are assumed to influence the size of an airline's markup on each of its products. For example, a product's markup is constrained by the "closeness" of competing products in characteristics space, which is the rationale for instruments (3) and (4). A product's markup is constrained by the number of

³⁰ For example, see Berry and Jia (2010) and Peters (2006) for similar identifying assumptions.

³¹ See the data section for definition and explanation of the *Inconvenience* and *Interstop* variables.

competing products in the market, which is the rationale for instrument (2). A firm typically can achieve a marginally higher markup on a given product the more substitute products it owns in the market, which is the rationale for instrument (1). Instrument (5) is based on the idea that the average markup that a firm is able to charge is related to the characteristics of its products.

6. RESULTS

6.1 *Parameter Estimates*

Table 2-2 reports parameter estimates of the demand and marginal cost equations for three alternate demand specifications - standard logit, nested logit and random coefficients logit. We first discuss the demand parameter estimates.

The demand coefficients are consistent in signs and roughly similar in magnitudes across the standard logit and nested logit specifications. These two model estimates essentially capture aggregate choice behavior across consumer types. All coefficients are statistically significant at conventional levels of statistical significance. The negative coefficients for the *Price* and *Interstop* variables suggest that a consumer's utility tends to decrease when the market fare or the number of intermediate stops increase. In other words, consumers most prefer cheap nonstop flights between their origin and destination.³²

An airline may offer several different single-intermediate stop products in a given market that differ in the location of the intermediate stop and therefore the flying distance required to get to the destination. However, the negative *Inconvenience* coefficient suggests that, for any given

³² A Hausman test confirms that price and within group product share variables are indeed endogenous at conventional levels of statistical significance. The computed Hausman test statistic, which is chi-square distributed, has a value of 174.51. When the demand model is estimated without instruments the price coefficient is positive and σ is almost twice as large, which suggest bias due to endogeneity. As such, we believe that our instruments do a reasonable job in mitigating endogeneity problems.

number of intermediate stops, consumers prefer to take the shortest possible route to get to their destination.

Consistent with documented evidence in the existing literature, the *HUB_Origin* coefficient is positive, which indicates that a carrier is more likely to be chosen by consumers if the origin airport is the carrier's HUB. As such, consumers can exploit the carrier's convenient gate access and superior menu of departure options.³³ As suggested in Berry and Jia (2010), the positive *Tour* dummy coefficient captures the relatively high traffic volume in Florida and Las Vegas that cannot be explained by the observed product attributes. A consumer's utility is likely to decrease if he/she chooses a product passing through a slot-controlled airport, probably owing to longer wait time due to congestion in a slot-controlled airport.

³³ See discussions in Berry, Carnall and Spiller (2006), Berry (1990), Borenstein (1989) and Borenstein (1991).

Table 2-2 Joint Estimation of Demand and Marginal Cost Equations

<i>Demand Equation</i>						
Variable	<u>Standard Logit</u>		<u>Nested Logit</u>		<u>Random Coefficients Logit</u>	
	coeff.	Se	coeff.	se	coeff.	se
Both Types of Consumers						
Price	-9.707*	(0.717)	-9.690*	(0.768)		
Interstop	-1.625*	(0.050)	-1.393*	(0.055)		
Constant	-7.047*	(0.182)	-7.206*	(0.190)		
Type L Consumers						
Price					-11.562*	(1.132)
Interstop					-1.304*	(0.129)
Constant					-5.861*	(0.170)
Type B Consumers						
Price					-1.456*	(0.211)
Interstop					-1.404*	(0.145)
Constant					-9.055*	(0.186)
Inconvenience	-0.914*	(0.075)	-0.774*	(0.076)	-0.997*	(0.019)
HUB_Origin	0.807*	(0.068)	1.063*	(0.071)	0.961*	(0.097)
Tour	1.435*	(0.040)	1.480*	(0.039)	1.580*	(0.104)
Slot-control	-0.590*	(0.043)	-0.556*	(0.042)	-0.583*	(0.058)
AirTran	1.440*	(0.148)	1.379*	(0.144)	1.376*	(0.255)
Alaska	3.685*	(0.709)	3.701*	(0.719)	1.930*	(0.267)
Allegiant	2.454*	(0.466)	2.449*	(0.481)	3.291*	(1.650)
American	1.559*	(0.156)	1.566*	(0.153)	1.329*	(0.144)
JetBlue	2.158*	(0.175)	2.241*	(0.171)	2.104*	(0.681)
Continental	1.186*	(0.159)	1.127*	(0.157)	0.877*	(0.072)
Delta	1.401*	(0.149)	1.502*	(0.146)	1.309*	(0.072)
Frontier	1.274*	(0.164)	1.107*	(0.163)	1.055 ⁺	(0.550)
Northwest	0.583*	(0.154)	0.558*	(0.152)	0.432 ⁺	(0.241)
Southwest	1.265*	(0.141)	1.481*	(0.139)	1.432*	(0.135)
Spirit	1.348*	(0.249)	1.223*	(0.249)	0.164 ⁺	(0.085)
Sun Country	1.710*	(0.417)	1.589*	(0.416)	1.463*	(0.215)
United	1.390*	(0.152)	1.448*	(0.149)	1.218*	(0.111)
US Airways	1.606*	(0.156)	1.645*	(0.153)	1.395*	(0.222)
USA 3000	1.415*	(0.493)	1.401*	(0.485)	1.154*	(0.403)
Virgin America	2.219*	(0.246)	2.280*	(0.242)	2.034*	(0.848)
σ			0.170*	(0.020)	0.209*	(0.008)
λ_L					0.318*	(0.034)

* represents significant at the 0.05 level. ⁺ represents significant at the 0.10 level. Standard errors are in parentheses. Midwest Airlines is the excluded ticketing carrier dummy.

Table 2-2 Joint Estimation of Demand and Marginal Cost Equations (Continued)

<i>Marginal Cost Eq.</i>	<u>Standard Logit</u>		<u>Nested Logit</u>		<u>Random Coefficients Logit</u>	
	coeff.	Se	coeff.	se	coeff.	se
Constant	-2.772*	(0.102)	-2.774*	(0.102)	-3.099*	(0.082)
Distance	0.273*	(0.045)	0.274*	(0.046)	0.376*	(0.046)
Distance ²	-0.009	(0.013)	-0.009	(0.013)	-0.063*	(0.011)
HUB_MC	0.129*	(0.016)	0.129*	(0.016)	0.117*	(0.023)
Slot_MC	0.090*	(0.014)	0.090*	(0.014)	0.037*	(0.014)
GMM objective	2.78E+03		2.52E+03		2.47E+04	
Number of obs.	10883		10883		10883	

* represents significance at the 0.05 level. + represents significance at the 0.10 level. Standard errors are in parentheses. The marginal cost equation includes operating carrier dummies even though these are not reported in the table.

As expected, the parameter σ lies between 0 and 1, which measures the correlation of the consumers' utility across products belonging to the same airline. The value of σ is 0.17 and suggests that there is correlation of preferences for products belonging to a given airline, but this correlation does not seem to be economically strong since the correlation value is substantially less than 1.

Recall that the random coefficients logit model allows us to disentangle choice behavior for two types of consumers. Parameter estimates for the random coefficients logit demand model are reported in the rightmost panel of Table 2-2. The coefficients are all statistically significant at conventional levels of significance. The price coefficients suggest that type L consumers (leisure travelers) are much more sensitive to price changes compared to type B consumers (business travelers). Therefore, the evidence suggests that the two types of consumers view a product differently with respect to their marginal utilities of price.

The value of σ still shows some correlation of preferences for products belonging to a given airline. The estimate of λ_L is 0.318, indicating 32 percent of type L consumers in the population.

As to the marginal cost equation in Table 2-2, the coefficients are consistent in signs and roughly similar in magnitudes irrespective of the demand model specification. The sign pattern of the coefficients on *Distance* and *Distance*² suggests that marginal cost increases with distance up to some threshold distance, but declines in distance thereafter. The positive *HUB_MC* and *Slot_MC* coefficients suggest that an increase in the marginal cost occurs if an airport on the product itinerary is the carrier's HUB or a slot-controlled airport. When a carrier passes through the slot-controlled airport, the cost is higher possibly due to higher landing fees. Channeling passengers through the airline's hub normally allows the airline to better exploit economies of density since passengers from different origins and with different destinations can eventually be put on a single large plane for a segment of the trip. This should have a downward pressure on marginal cost.³⁴ However, as suggested by arguments in Borenstein and Rose (2007) and Mayer and Sinai (2003), often time hub airports are congested, which could cause flight delays and ultimately puts an upward pressure on cost for the airline.³⁵ Therefore, the coefficient on *HUB_MC* captures the net effect of these opposing forces, and possibly others.

6.2 Own Price Elasticity of Demand

Using the parameter estimates in Table 2-2, we compute average own- and cross-price elasticities of demand, but first we discuss the own-price elasticity estimates. Own-price elasticity measures the percentage change in demand for an air travel product in response to a percentage change in price of that product. Table 2-3 reports summary statistics for own-price elasticity estimates for the three alternate demand model specifications.

³⁴ See Berry, Carnall and Spiller (2006) and Brueckner and Spiller (1994).

³⁵ For a detailed analysis of the theory of congestion and delays, see Brueckner (2002) and Morrison and Winston (2008).

The upper panel of Table 2-3 shows results for all products in 741 markets, and also the results for nonstop and intermediate-stop(s) products separately. The own-price elasticity estimates across the three demand models are statistically different from zero at conventional levels of significance. Our own-price elasticity estimates for the average consumer range from -1.67 to -2.39 depending on the discrete choice demand model used. Oum, Gillen and Noble (1986), and Brander and Zhang (1990) argue that a reasonable range for own price elasticity in the airline industry is from -1.2 to -2.0. Peters (2006) study of the airline industry produces own-price elasticity estimates ranging from -3.2 to -3.6, while Berry and Jia (2010) find own-price elasticity estimates ranging from -1.89 to -2.10 in their 2006 sample. Therefore, we are comfortable that the elasticity estimates generated from our model are reasonable and accord with evidence in the existing literature.

**Table 2-3 Summary Statistics for Own-Price Elasticity Estimates
across all Markets in our Sample**

Demand Model	<u>All Products</u>		<u>Nonstop Products</u>		<u>Intermediate-stop(s) Products</u>	
	Mean	se	Mean	se	Mean	se
Standard Logit	-2.169*	(0.018)	-2.175*	(0.022)	-2.171*	(0.025)
Nested Logit	-2.390*	(0.021)	-2.291*	(0.023)	-2.443*	(0.030)
Random Coefficients Logit						
Both Types	-1.675*	(0.004)	-1.554*	(0.004)	-1.731*	(0.005)
Type L Consumer	-2.929*	(0.025)	-2.779*	(0.028)	-3.010*	(0.037)
Type B Consumer	-0.368*	(0.003)	-0.349*	(0.003)	-0.379*	(0.005)
No. of markets	741		741		741	

Demand Model	<u>Short-haul markets (less than 500 miles)</u>		<u>Mid-haul markets (between 500 and 1,500 miles)</u>		<u>Long-haul markets (greater than 1,500 miles)</u>	
	Mean	se	Mean	se	Mean	se
Standard Logit	-1.994*	(0.128)	-2.067*	(0.023)	-2.381*	(0.028)
Nested Logit	-2.154*	(0.133)	-2.260*	(0.025)	-2.662*	(0.031)
Random Coefficients Logit						
Both Types	-1.571*	(0.018)	-1.648*	(0.004)	-1.735*	(0.005)
Type L Consumer	-2.625*	(0.161)	-2.764*	(0.030)	-3.277*	(0.039)
Type B Consumer	-0.330*	(0.020)	-0.348*	(0.004)	-0.412*	(0.005)
No. of markets	22		474		245	

* represents significant at the 0.05 level. Standard errors are in parentheses.

The elasticity estimates in the upper panel of Table 2-3 indicate that consumers are sensitive to a price change, irrespective of whether the product is nonstop or requires intermediate stop(s). However, in the case of the nested logit and random coefficients logit models, the average consumer responds differently when facing a price change of a nonstop product compared to an equivalent percent price change of an intermediate-stop(s) product. Specifically, it is noticeable that the average consumer is more price-sensitive in the case of intermediate-stop(s) products compared to nonstop products.

Elasticity estimates from the random coefficients logit model indicate that leisure travelers (Type L) are much more price-sensitive compared to business travelers (Type B). Overall, a 1% increase in price causes leisure travelers to decrease their demand for the product by 2.93%, while business travelers would only decrease their demand by 0.37%. Leisure travelers are likely more sensitive to price changes because they have more flexibility in their travel schedule and usually have a more restrictive travel budget. The price-sensitivity gap between leisure and business travelers is even wider in the case of intermediate-stop(s) products (-3.01 versus -0.379) compared to the price-sensitivity gap for nonstop products (-2.779 versus -0.349).

In the bottom panel of the table we decompose the own-price elasticity estimates according to market nonstop flight distance categories. The average own-price elasticity seems to be increasing in distance, which is consistent with findings in Bhadra (2003). In other words, consumers are less price-sensitive in short-haul markets compared to long-haul markets. It is possible that many of the passengers who travel short distance are business travelers. They likely purchase flight tickets at the last moment and have little or no chance to respond to price changes.

6.3 Cross Price Elasticity of Demand

Cross price elasticity measures the percentage change in demand for intermediate-stop(s) products in response to a percentage change in price of nonstop products. Summary statistics for cross-price elasticity estimates across all markets are reported in Table 2-4.

Table 2-4 Summary Statistics for Cross-Price Elasticity Estimates across all Markets in our Sample

Demand Model	Mean	Se
Standard Logit	0.00018*	(1.05E-05)
Nested Logit	0.01321*	(0.0004)
Random Coefficients Logit		
Both Types	0.01258*	(0.0004)
Type L Consumer	0.02023*	(0.0007)
Type B Consumer	0.00257*	(8.93E-05)
No. of markets	741	

* represents significant at the 0.05 level. Standard errors are in parentheses.

Overall, across the 741 markets in our sample, the positive and statistically significant cross-price elasticity of demand estimates indicate that intermediate-stop(s) products and nonstop products are substitutes. The result from each demand model shows that the mean cross-elasticity ranges from 0.00018 to 0.0202, and they are statistically different from zero at conventional levels of significance.

Compared to business travelers, leisure travelers perceive intermediate-stop(s) products and nonstop products as closer substitutes. A 1% increase in the price of nonstop products causes leisure travelers to increase their demand for intermediate-stop(s) products by 0.0202%, but only causes business travelers to increase their demand for intermediate-stop(s) products by 0.0026%.³⁶ In other words, leisure travelers are more willing than business travelers to switch to intermediate-stop(s) products when facing an increase in price of nonstop products, suggesting that leisure travelers are more willing to tolerate intermediate stops compared to business travelers.

³⁶ A t-test is used here to confirm that at conventional levels of statistical significance there is a statistically significant difference in mean cross-price elasticity between leisure travelers and business travelers. The difference in mean cross-price elasticities (0.0202 - 0.0026) is 0.0176 and the standard error of the difference is 0.000686, which implies a t-statistic of 25.65.

Table 2-5 breaks down the cross-price elasticity estimates by market nonstop flight distance. Within each distance category, the results show that the mean cross-price elasticities are statistically different from zero at conventional levels of significance. These results suggest that consumers perceive intermediate-stop(s) products and nonstop products as substitutable in all distance categories of air travel markets.

**Table 2-5 Summary Statistics for Cross-Price Elasticity Estimates
Broken Down by Market Nonstop Flight Distance**

Demand Model	<u>Short-haul markets</u> (less than 500 miles)		<u>Mid-haul markets</u> (between 500 and 1,500 miles)		<u>Long-haul markets</u> (greater than 1,500 miles)	
	Mean	se	Mean	se	Mean	se
Standard Logit	0.00008*	(1.67E-05)	0.00021*	(1.52E-05)	0.00015*	(1.13E-05)
Nested Logit	0.00787*	(0.0019)	0.01375*	(0.0006)	0.01263*	(0.0007)
Random Coefficients Logit						
Both Types	0.00851*	(0.0021)	0.01366*	(0.0006)	0.01085*	(0.0005)
Type L Consumer	0.01144*	(0.0028)	0.02108*	(0.0009)	0.01937*	(0.0010)
Type B Consumer	0.00167*	(0.0004)	0.00267*	(0.0001)	0.00246*	(0.0001)
No. of markets	22		474		245	

* represents significant at the 0.05 level. Standard errors are in parentheses.

Irrespective of whether the market is short-haul, mid-haul, or long-haul, leisure travelers are more willing to switch to intermediate-stop(s) products compared to business travelers in response to an increasing price of nonstop products. Again, it is evident that leisure travelers are more flexible to change their travel schedule in response to price changes.

It is notable that consumers in the short-haul markets are less willing to switch to an intermediate-stop(s) product in response to an increase in price of a nonstop product. In addition, the average cross-price elasticity increases from short-haul market to mid-haul market, but decrease a bit from mid-haul market to long-haul market.

Table 2-6 reports statistical comparisons of mean cross-price elasticity estimates across different market distances. The results suggest that there is a statistically significant difference in mean cross-price elasticity between short-haul and mid-haul markets. However, when separate consumer types are accounted for, there is not a significant mean difference between mid-haul and long-haul markets.

Table 2-6 Statistical Comparison of Mean Difference in Cross-price Elasticity between Distance Markets

Distance Market Comparison	Standard <u>Logit</u>	Nested <u>Logit</u>	<u>Random Coefficients Logit</u>		
			Both types	Type L Consumers	Type B Consumers
Mid- vs. Short-haul	0.00013* (2.3E-05)	0.00589* (0.0020)	0.00515* (0.0022)	0.00965* (0.0030)	0.00100* (0.0004)
Long- vs. Mid-haul	-0.00006* (1.9E-05)	-0.00112 (0.0009)	-0.00281* (0.0008)	-0.00172 (0.0014)	-0.00021 (0.0002)
Long- vs. Short-haul	0.00007* (2.0E-05)	0.00476* (0.0020)	0.00234 (0.0022)	0.00793* (0.0030)	0.00079+ (0.0004)

* represents significant at the 0.05 level. + represents significant at the 0.10 level. Standard errors are in parentheses.

It may be argued that the distance categories used in the previous tables are arbitrary. As such, using an approach that is more flexible than the distance categories, we investigate a potential relationship between computed elasticities and the nonstop market distance. In particular, we estimate the following regression via ordinary least squares (OLS):

$$Y_i = \alpha_0 + \alpha_1 Dist_i + \alpha_2 Dist_i^2 + \varepsilon_i,$$

where Y_i is the cross-price elasticity in market i , which is regressed on the market nonstop flight distance ($Dist$) and distance squared ($Dist^2$). Table 2-7 shows the results of the OLS regression.

**Table 2-7 Parameter Estimates for the Relationship
Between Cross-price Elasticities and Market Nonstop Distance**

	Random Coefficients Logit				
	Standard Logit	Nested Logit	Both type Consumers	Type L Consumers	Type B Consumers
Dist	3.23E-07* (9.41E-08)	7.54E-06+ (4.05E-06)	5.34E-06 (3.76E-06)	1.24E-05* (6.13E-06)	1.23E-06 (8.06E-07)
Dist ²	-1.13E-10* (3.08E-11)	-2.62E-09* (1.33E-09)	-2.38E-09+ (1.23E-09)	-4.25E-09* (2.01E-09)	-4.35E-10+ (2.64E-10)
Constant	-9.61E-06 (6.31E-05)	8.72E-03* (2.72E-03)	1.05E-02* (2.52E-03)	1.27E-02* (4.11E-03)	1.85E-03* (5.40E-04)
Threshold point	1434	1438	1122	1456	1417
R-squared	0.0186	0.0055	0.0133	0.0061	0.0039

* represents significant at the 0.05 level. + represents significant at the 0.10 level. Standard errors are in parentheses. The distance threshold point is computed by, $Dist\ threshold = -\frac{\alpha_1}{2\alpha_2}$.

The parameter estimates suggest that cross-price elasticity is increasing with distance between the origin and destination cities up to some threshold distance, but decline in distance thereafter. The range of the estimated distance threshold point is between 1122 and 1456 miles, depending on the demand model used to generate the cross-price elasticity estimates. These results are roughly consistent with the arbitrary distance category analysis done previously.

6.4 Markup and Marginal Cost Analysis

The parameter estimates in the demand equation allows us to compute markups and marginal costs, which are summarized in Table 2-8.

Table 2-8 Summary Statistics for Markup and Marginal Cost (in Dollars)

	<u>Standard Logit</u>		<u>Nested Logit</u>		<u>RC Logit</u>	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Markup						
All products	103.215	0.321	103.336	0.230	151.867	32.249
Nonstop products	103.345	0.602	103.365	0.304	155.581	40.775
Intermediate-stop(s) products	103.162	0.226	103.324	0.211	150.450	34.051
Marginal Cost						
All products	120.476	51.883	120.356	51.875	71.825	28.370
Nonstop products	121.441	62.280	121.422	62.257	69.205	33.639
Intermediate-stop(s) products	120.494	69.975	120.331	69.972	73.205	50.084

Based on the standard logit and nested logit models, on average, nonstop and intermediate-stop(s) products have markups that are roughly similar in size. However, the random coefficients logit model suggests that, on average, a nonstop product enjoys larger markup (about 5 dollars more) than an intermediate-stop(s) product, which is more consistent with our expectations. Based on our previous results on own-price elasticity of demand, we believe that price-sensitive consumers are more likely to buy intermediate-stop(s) products compared to nonstop products. In addition, standard static oligopoly theory tells us that the more price-sensitive consumers are, the lower the markup firms are able to charge. Thus, the markups under the random coefficient logit model better reflect the differing choice behavior of dissimilar consumer types across nonstop and intermediate-stop(s) products.

As we previously discussed in the subsection on own-price elasticities, our own-price elasticity estimates are within the range of those obtained by other researchers [see for example Berry and Jia (2010), Brander and Zhang (1990), Oum, Gillen and Noble (1986), and Peters (2006)]. Since standard static oligopoly theory predicts that product markups are determined by

price elasticity of demand, then product markups generated by our model will be similar to product markups implied by the elasticity estimates of other researchers.

Recall that observed prices minus estimated markups yield estimates of marginal costs. Therefore it is not surprising that the larger average markup from the random coefficients logit model results in smaller average marginal cost, compared to results from the other two models. In addition, the random coefficients logit model yields the result that average marginal cost of nonstop products is less than that of intermediate-stop(s) products.

The mean itinerary distance for products in our sample is 1685 miles, while the mean marginal cost estimates from the standard, nested, and random coefficients logit models are \$120.48, 120.36 and \$71.82 respectively. Therefore, the implied marginal cost per mile is about 7 cents in case of the standard and nested logit models, and about 4 cents in case of the random coefficients logit model. Berry and Jia (2010) estimate their econometric model on data in the year 2006 and find a marginal cost per mile estimate of 6 cents, which they argue is plausible based on carriers' reported costs. As such, we believe our marginal cost estimates are within the "ballpark" of what is expected.

6.5 Counterfactual Analysis

The goal of the counterfactual analysis is to assess the extent to which the presence of intermediate-stop(s) products influences the pricing of nonstop products. In other words, do intermediate-stop(s) products effectively compete with nonstop products, or can they be treated as being in separate market segments?

Essentially the counterfactual experiment is done by removing intermediate-stop(s) products from each sample market, then assuming the previously estimated product marginal

costs and preference parameters are unchanged,³⁷ we use the supply-side of the model to solve for new equilibrium prices for nonstop products. A comparison of the actual nonstop products' prices with their model predicted equilibrium prices when intermediate-stop(s) products are counterfactually removed reveals the extent to which the presence of intermediate-stop(s) products influences the pricing of nonstop products.

Formally, in the spirit of Petrin (2002), Nevo (2000) and others, we first use estimated markups, actual prices and equation (10) to recover product marginal costs as follows:

$$\widehat{\mathbf{mc}} = \mathbf{p} + (\mathbf{\Omega} * \mathbf{\Delta})^{-1} \times \mathbf{s}(\mathbf{p}), \quad (21)$$

where $\widehat{\mathbf{mc}}$ is the estimated marginal cost vector. Second, we eliminate intermediate-stop(s) products, and holding recovered marginal cost constant for the remaining products, we numerically solve for the new nonstop product price vector, \mathbf{p}_{ns}^* , that satisfies:

$$\mathbf{p}_{\text{ns}}^* = \widehat{\mathbf{mc}}_{\text{ns}} - [\mathbf{\Omega}_{\text{ns}} * \mathbf{\Delta}_{\text{ns}}(\mathbf{p}_{\text{ns}}^*)]^{-1} \times \mathbf{s}_{\text{ns}}(\mathbf{p}_{\text{ns}}^*), \quad (22)$$

where equation (22) is only for nonstop products. Finally, we compare the counterfactual equilibrium price vector \mathbf{p}_{ns}^* to actual nonstop product prices in vector \mathbf{p} to see the influence that intermediate-stop(s) products may have on the equilibrium prices of nonstop products.

Before we examine the results of the counterfactual exercise, it is useful to discuss what forces are at play in the market equilibrium analysis. In other words, do we expect equilibrium prices of nonstop products to fall, rise, or remain the same when intermediate-stop(s) products are counterfactually removed, and what does the predicted price change depend on? We argue that there are potentially three effects simultaneously at work that may influence the predicted

³⁷ We concede that marginal cost and preferences may be different in a world that does not have intermediate-stop(s) products. However, such *ceteris paribus* assumptions are necessary and typical in the literature when using structural models to perform counterfactual analyses. For example, see Nevo (2000) and Petrin (2002).

equilibrium price change of nonstop products: (1) the market power effect; (2) the multi-product firm effect; and (3) the price-sensitivity effect.

The most intuitive of the three effects is the market power effect. This effect simply refers to the increased ability and incentive of carriers to raise the price of the remaining products if competing substitute products are removed from the market.

The multi-product firm effect refers to the situation in which, if the product that is removed from the market is one of several substitute products offered by a firm, then this firm has an incentive to marginally reduce the price on its remaining products. In the appendix B we use a linear demand example to illustrate this effect. The intuition is that a multi-product firm selling substitute products tends to price these products marginal higher than if it were a single-product firm because a marginal increase in the price of one product raises the demand for the substitute products.

The price-sensitivity effect refers to the situation in which there is downward pressure on the price of a product when the price-sensitivity of consumers increases. This effect is likely to exist in our counterfactual exercise since our previous results show that intermediate-stop(s) products tend to be consumed by more price-sensitive consumers compared to the consumers of nonstop products. Therefore, by removing the intermediate-stop(s) products from the market, we in effect force carriers to optimally adjust the price of nonstop products for a more price-sensitive set of consumers that do not have any other air travel product options. This will put a downward pressure on the price of nonstop products.

In summary, by counterfactually removing intermediate-stop(s) products from the market, the market power effect puts an upward pressure on the price of nonstop products, while

the multi-product firm and price-sensitivity effects cause downward pressure on price. Thus, what ultimately happens to the price of nonstop products depends on which effects dominate.

Table 2-9 summarizes one way of examining the counterfactual results. In particular, among the nonstop products in the sample, the table reports the number and proportion of these products with positive predicted percentage change in their equilibrium price. These results are broken down by whether or not the nonstop products were offered by carriers that also offered substitute intermediate-stop(s) products in the same market, i.e., single-product versus multi-product carriers.

First, we focus our discussion on results in the table for the standard logit and nested logit models. Interestingly, for these two models, there is a predicted increase in price for all 777 nonstop products offered by carriers that only offer a single product in the market before and after intermediate-stop(s) products are removed. The multi-product firm effect is not present for these 777 nonstop products since they are offered by single-product carriers. However, we cannot rule out the presence of both the market power and price-sensitivity effects. If both effects are present, then we must conclude that the market power effect dominates the price-sensitivity effect for these products. On the other hand, among the 2078 nonstop products that are offered by carriers that also offered intermediate-stop(s) products, few nonstop product prices are predicted to increase. The majority of these nonstop product prices are predicted to either remain the same or fall. The market power effect is obviously dominated by either or both of the other two effects for the majority of these products.

Table 2-9 Number and Proportion of Nonstop-products with Positive Predicted Percentage change in Equilibrium Price for Single-product and Multi-product carriers in a Market

	No. of Products	Standard Logit		Nested Logit		RC Logit	
		No. of Products with Positive % Change	Proportion of Products with Positive % Change	No. of Products with Positive % Change	Proportion of Products with Positive % Change	No. of Products with Positive % Change	Proportion of Products with Positive % Change
Single-product carrier	777	777	1.00	777	1.00	52	0.0669
Multi-product carrier	2078	13	0.0063	4	0.0019	202	0.0972

Now turning to results from the random coefficients model in Table 2-9, we see that even in the case of single-product carriers in a market, only 52 of the 777 nonstop products offered by single-product carriers are predicted to experience an increase in price. Since the multi-product firm effect is not present for these products, we know that the lack of many predicted price increases is owing to the domination of the price-sensitivity effect over the market power effect. The evidence suggests that the random coefficients model does a better job of picking up the price-sensitivity effect compared to the standard logit and nested logit models. In addition, among the 2078 nonstop products offered by multi-product carriers, the random coefficients logit model predicts that only a few (202) are predicted to have price increases. Again, the market power effect is clearly dominated by either or both of the other two effects for the majority of these products.

We now examine results of the counterfactual exercise in terms of actual predicted percent price changes for nonstop products, rather than mere direction of the predicted price changes previously discussed. Results for actual predicted price changes are reported in Table 2-10. The results reveal that for the vast majority of markets, there is a mean percent decline in the prices of nonstop products, with overall predicted mean percent declines of -0.0009%, -0.0083%

and -0.125%, from the standard, nested, and random coefficients logit models respectively. The predicted declines seem to be largest in mid-haul distance markets.

The bottom right-hand-side panel of the table shows that only 2 of the 741 markets have mean predicted percent price increase greater than 5%, and only 1 market has mean predicted percent price decrease less than -5%. In addition, the 2 markets that have mean predicted percent price increases are long-haul distance markets. In summary, with the exception of 2 long-haul distance markets, all markets have mean predicted price changes for nonstop products being less than 5%.

In defining relevant product markets for antitrust purposes, 5% predicted change in price is typically used as an economically important threshold.³⁸ Since the counterfactual results suggest that the presence of intermediate-stop(s) products typically have a less than 5%, and in most cases less than 1%, impact on the price of nonstop products, then we may conclude that for antitrust purposes nonstop and intermediate-stop(s) air travel products can be treated as being in separate product markets.

³⁸ For example, see Section 4.1 in U.S. Department of Justice and Federal Trade Commission (2010), “Horizontal Merger Guidelines”.

**Table 2-10 Nonstop-products Predicted Percent Price Change
for Different Market Distance Categories**

<u>Standard Logit Model</u>						
Distance Type	No. of Markets	Mean	Std. Dev	Min	Max	No. of Markets with Positive % Change
All markets	741	-0.0091	0.0172	-0.2083	0.0006	13
Short-haul markets	22	-0.0030	0.0045	-0.0160	3.63E-08	1
mid-haul markets	474	-0.0101	0.0197	-0.2083	0.0006	12
long-haul markets	245	-0.0076	0.0113	-0.0795	-4.80E-06	0

<u>Nested Logit Model</u>						
Distance Type	No. of Markets	Mean	Std. Dev	Min	Max	No. of Markets with Positive % Change
All markets	741	-0.0083	0.0162	-0.1954	0.0002	13
Short-haul markets	22	-0.0026	0.0040	-0.0135	1.82E-08	1
mid-haul markets	474	-0.0093	0.0187	-0.1954	0.0002	12
long-haul markets	245	-0.0069	0.0106	-0.0781	-3.99E-06	0

<u>Random Coefficients Logit Model</u>								
Distance Type	No. of Markets	Mean	Std. Dev	Min	Max	No. of Markets that lie within the Percent Change category		
						>0%	>5%	<-5%
All markets	741	-0.1254	0.8464	-6.8557	5.2747	76	2	1
Short-haul markets	22	-0.0628	0.1212	-0.5521	0.0014	2	0	0
mid-haul markets	474	-0.1926	0.5898	-6.8557	4.6205	21	0	1
long-haul markets	245	-0.0011	1.2135	-2.7893	5.2747	53	2	0

7. CONCLUSION

The main objective of this paper is to investigate the extent to which nonstop products are substitutable with intermediate-stop(s) products. Cross-price elasticity of demand estimates suggest that, on average, consumers perceive intermediate-stop(s) products substitutable for nonstop products. In addition, the average cross-price elasticity increases from short-haul

distance to mid-haul distance markets, but decreases a bit from mid-haul distance to long-haul distance markets. Consumers in short-haul distance markets are less willing to switch to an intermediate-stop(s) product in response to an increase in price of a nonstop product. The results also suggest that intermediate-stop(s) products may be an attractive alternative for leisure travelers but less so for business travelers, regardless of the length of market distance.

We then conduct a counterfactual exercise to better understand the extent to which the presence of intermediate-stop(s) products influences the pricing of nonstop products. By removing intermediate-stop(s) products from each market, we identified three effects that may simultaneously influence the pricing of nonstop products: (1) a market power effect; (2) a multi-product firm effect; and (3) a price-sensitivity effect. The market power effect puts an upward pressure on the price of nonstop products, while the multi-product firm and price-sensitivity effects cause downward pressure on price. Therefore, the net change in price of nonstop products that results from eliminating intermediate-stop(s) products depends on which of the three effects dominate. We find that in the vast majority of markets the prices of nonstop products are predicted to either remain the same or fall, which suggest that the market power effect is often offset by the multi-product firm and price-sensitivity effects. Furthermore, the vast majority of the predicted price changes lie between -1% and 1%. The evidence therefore suggests that the presence of intermediate-stop(s) products in most markets have little net impact on the price of nonstop products. As such, for antitrust purposes, these two products can be treated as being in separate product markets.

The findings in this paper have important implications for analyzing proposed mergers. For example, a merger between one carrier that serves a market exclusively with nonstop products and one that serves the market exclusively with intermediate-stop(s) products is not

likely to enhance market power substantially. By the same token, two carriers that currently serve a market using nonstop service and are seeking approval to merge will be hard pressed to make a convincing argument that the existence of intermediate-stop(s) service offered by competing carriers will effectively constrain the newly merged firm from exercising market power.

The focus of our analysis is on domestic air travel markets. However, antitrust analysis and approval of international airline alliances often requires answering the very question we tackle in this paper. Since consumers may display different choice behavior in international air travel markets than they do in domestic markets, future research may want to investigate if our findings extend to international air travel markets.

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Appendix B - Multi-product Firm Effect Illustration

The following example is used to illustrate the multi-product firm effect assuming linear demand and constant marginal cost.

Assume an airline is a multi-product monopolist who offers differentiated products 1 and 2 in an origin-destination market, where product 1 is a nonstop product while product 2 is an intermediate-stop(s) product. The products' linear demand equations are:

$$q_1 = 1 + \beta p_2 - p_1 ; q_2 = 1 + \beta p_1 - p_2$$

where $0 < \beta < 1$. For simplicity, assume each product has the same constant marginal cost, c .

The variable profit for the airline is:

$$\pi = (p_1 - c)[1 + \beta p_2 - p_1] + (p_2 - c)[1 + \beta p_1 - p_2]$$

The corresponding first-order conditions are:

$$c(1 - \beta) - 2p_1 + 2\beta p_2 + 1 = 0 ;$$

$$c(1 - \beta) - 2p_2 + 2\beta p_1 + 1 = 0$$

Thus, the equilibrium prices for products 1 and 2 are:

$$p_1^* = p_2^* = \frac{1}{2(1 - \beta)} + \frac{c}{2}$$

Now suppose we counterfactually eliminate the intermediate-stop(s) product, which is product 2. In other words, the airline becomes a single-product monopolist who only offers nonstop products 1 in the market. The product's linear demand equation is:

$$q_1 = 1 - p_1.$$

With the assumption of constant marginal cost, c , the variable profit is:

$$\pi = (p_1 - c)[1 - p_1]$$

The corresponding first-order condition is:

$$c - 2p_1 + 1 = 0$$

Thus, the monopoly price is:

$$p_1^M = \frac{1}{2} + \frac{c}{2}$$

Comparing the price of product 1 before and after the counterfactual exercise, we can see that $p_1^M < p_1^*$, which indicates that the price of product 1 decreases if product 2 is removed.

Therefore, this example illustrates that, *ceteris paribus*, there exists a downward pressure on price for the remaining products of a multi-product firm when one of the firm's substitute products is removed from the market.