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

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Abstract

Much of the literature on the airline industry identifies a potential entrant to a market based on whether the relevant carrier has presence in at least one of the endpoint airports of the market without actually operating between the endpoints. Furthermore, a potential entrant is often defined as a credible "entry threat" to market incumbents once the potential entrant establishes presence at the second endpoint airport of the market. This paper provides evidence that even when a potential entrant has presence at both endpoint airports of a market, incumbents may not respond to this as an effective "entry threat". Specifically, we find that: (1) incumbents lower price by more when the potential entrant has a hub at one or both market endpoints; and (2) incumbents increase rather than lower their price if they have an alliance partnership with the "potential entrant".

K*eywords:* Empirical Entry Model; Airline Competition

JEL Classification codes: L13, L93, C1, C25

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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 (2013) investigate the impact of potential competition from low cost carriers (LCC) and find similar results. Much of this literature identifies a potential entrant based on whether the relevant carrier has presence in at least one of the endpoint airports of the market without actually operating between the endpoints. Furthermore, Goolsbee and Syverson (2008) among others elevate the status of a potential entrant to a credible "entry threat" to market incumbents once the potential entrant establishes presence at the second endpoint airport of the market. However, a key point we make in this paper is that even when potential entrants have presence at both endpoint airports of a market, these "potential entrants" may not all be effective "competitive threats" to incumbents in the market.

First, some potential entrants will be better able to exploit economies of passenger-traffic density than others. A carrier enjoys economies of passenger-traffic density when its marginal cost of transporting a passenger falls as the volume of passengers it transports increases [Brueckner and Spiller (1994)]. The carriers that can better exploit economies of passenger-traffic density will have lower marginal cost upon actual entry, and therefore provide more of a competitive threat to incumbents. We capture potential entrants' ability to exploit economies of passenger-traffic density based on whether the potential entrant uses at least one of the market endpoint airports as a hub. The argument is that if a market endpoint is a hub for a potential entrant, then upon actual entry in this market, this hub airport will enable the carrier to transport a larger volume of passengers on flights between the endpoints since many of these passengers may just be connecting through the endpoint hub. Therefore, an endpoint hub airport can enable the carrier to have lower marginal cost in the market due to the relatively high volume of passengers it will transport between the endpoints of the market.

Second, we argue that some carriers that have presence at the market endpoint airports without operating between these endpoints may incentivize market incumbents to increase rather than decrease price. Specifically, we posit that if the carrier present at the endpoint airports has an alliance partnership with an incumbent, this alliance partnership can enable the incumbent to charge a higher price due to consumers' increased preference for alliance partners' products. An alliance may increase consumers' preference for partner carriers' products since passengers have greater opportunities to accumulate and redeem frequent-flyer miles across partner carriers [Lederman (2007)], especially when partner carriers' networks are complementary rather than overlapping.

We draw inference on our hypotheses from a reduced-form price regression in which market-level price charged by incumbents is regressed on various market characteristic controls as well as measures of the characteristics of the set of potential entrants to a market. Following the literature we identify potential entrants to a market based on the set of airlines that have presence in at least one endpoint airport of the market. However, we go a step further to distinguish between potential entrants that have presence at both market endpoints based on: (1) whether a market endpoint airport is a hub for a potential entrant; and (2) whether a potential entrant has an alliance partnership with any of the market incumbents.

Consistent with our arguments above, the econometric estimates suggest that incumbents lower price by more when potential entrants have a hub at one or both market endpoints. That is, potential entrants that have a hub at the market endpoint seem to pose a greater competitive threat to incumbents in the market. Perhaps due to this type of potential entrant's unique ability to better exploit economies of passenger-traffic density upon actual entry. Also consistent with our arguments above, the econometric estimates suggest that incumbents increase rather than lower their price if they have an alliance partnership with the "potential entrant". In sum, incumbents seem to be most threatened by potential entrants that they are not allied with and when these potential entrants use the market endpoint airports as their hub.

The analysis in our 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. 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 we use to account for endogenous market structure is closest to Singh and Zhu (2008) and Berry (1992).

Given that our empirical analysis focuses on incumbents' response to the "threat" of entry, we believe this focus places the paper as part of the entry deterrence literature. The question of entry deterrence has been examined extensively from a theoretical perspective,[1] but with the exception of our paper, Goolsbee and Syverson (2008), Huse and Oliveira (2012), Brueckner, Lee and Singer (2013), Gayle and Xie (2013) 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

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

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 (2011); Evans and Kessides (1993, 1994); Evans, Froeb, and Werden (1993); and Ito and Lee (2004) among others. Our empirical model also measures incumbents' price response to actual entry, and therefore is able to contribute to this literature as well.

Along with our two key findings previously described, our econometric estimates 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 larger 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 smaller compared to when endogeneity is not taken into account.

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 product is defined as a unique combination of airline and flight itinerary. Consider the market from Atlanta to Denver for example. Possible products are: (1) a nonstop trip from Atlanta to Denver operated by Delta Air Lines; and (2) a nonstop trip from Atlanta to Denver operated by United Airlines. Note that both 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 our study, incumbents are the existing carriers that offer 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, is considered a potential entrant to the ATL-DEN market. Similarly, any airline that flies between Denver and cities other than Atlanta in the preceding period, is also considered a potential entrant to the ATL-DEN market.

Figure 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, 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.

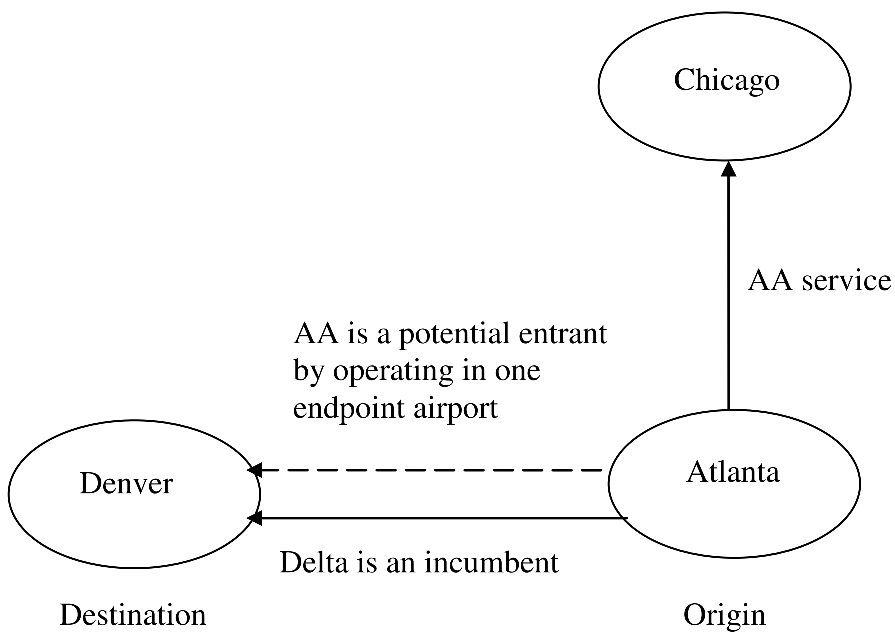

Figure 1
Identification of a Potential Entrant

As illustrated in Figure 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 and 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. Based on Goolsbee and Syverson (2008) among others, Figure 2 describes a situation in which American Airlines poses a credible 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.

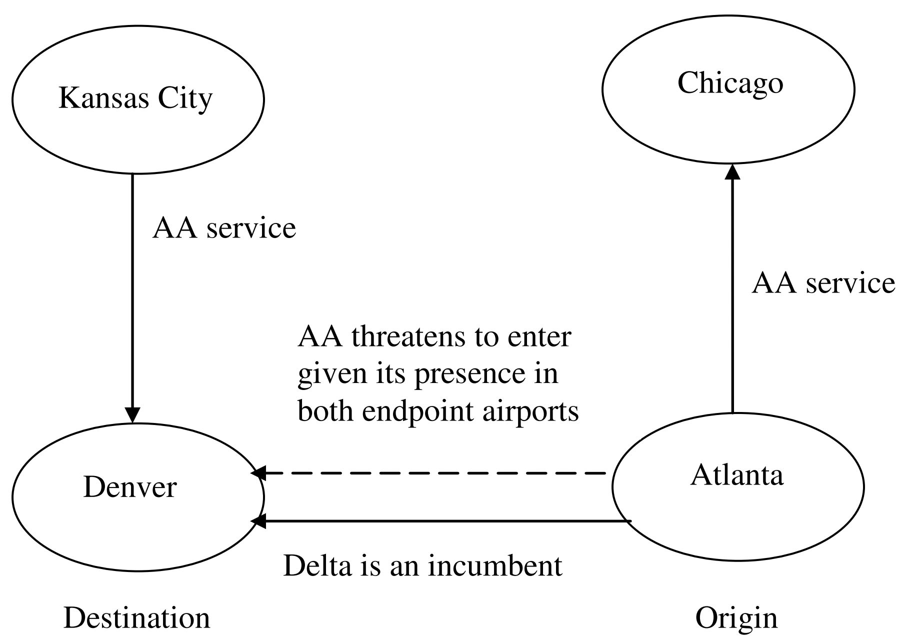

Figure 2
High Probability of Entry

3. The Model

Applying methodologies from Singh and Zhu (2008) and Berry (1992),[2] we investigate 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.

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

A unit of observation for the profit equation above is at the firm-level. For each market in the data, any carrier serving the market becomes an observation for that market along with any carrier serving at least one of the market endpoints. 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*;[3] *Income*;[4] *Nonstop Flight Distance*; *Nonstop Flight Distance*

[2] Also see Dunn (2008) for a similar methodology.
[3] Similar to Berry (1992), *Population* is measured by the product of population from the origin and destination cities.
[4] As we describe in the data section of the paper, the variable *Income* is measured by the product of median incomes at the origin and destination cities.

Squared; and *Slot_dummy*.[5] 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 a vector of observed firm-specific profit-shifting variables based on information in the period preceding the entry period under consideration. Three firm-specific variables included in our empirical application are: *City2*; *Hub_dummy*; and *City2*Alliance_dummy*. *City2* is a zero-one dummy variable that 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 its parameter to be positive. *Hub_dummy* equals to 1 if either one or both market endpoints is a hub for the carrier. *City2*Alliance_dummy* equals to 1 if the carrier operates at both market endpoints in the period preceding the entry period under consideration, and has an alliance partner present at one or both market endpoints.

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

[5] *Slot_dummy* equals to 1 if any of the airports are slot-controlled, which are New York LaGuardia, New York Kennedy, Washington National, and Chicago O'Hare.

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:[6]

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

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

$$E\left[\varepsilon_m^p \middle| X_m, Z_m, N_m^a, N_m^{et}\right] = \rho E[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}],$$

where Z_m represents the market-level collection of Z_{mk} vectors for carrier *k* in market *m*. We can then consider the following modified pricing regression equation:

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

[6] See Singh and Zhu (2008) for a similar restriction.

where the error term $\upsilon_m^p = \varepsilon_m^p - E\left[\varepsilon_m^p \middle| X_m, Z_m, N_m^a, N_m^{et}\right]$ 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, $E[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$. The distinction between equations (3) and (5) is the conditional expectation of the error term, which captures 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:

$$\widetilde{N}_m^a = \max_n (n\colon \#\{k\colon \pi_{mk}(n, \varepsilon_{mk}) \geq 0\}) \qquad (6)$$

$\widetilde{N}_m^a$ is the largest integer among *1,2,…,*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.[7]

[7] Looking at the profit function in equations (1) and (6) might leave the reader curious as to why we use N_m^a to denote number of firms in equation (1), but n to denote number of firms in equation (6). To understand the need for differing notations, it is key to note that equation (1) is an empirical specification of the profit function, while

Following Berry (1992), we use two periods (periods 1 and 2) of data to determine K_m for a given market.[8] 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. So for some airlines included in K_m, "entry" is equivalent to a decision "not to exit" 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,[9] 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, $(u_{m0}^r, u_{m1}^r, \ldots, u_{mK_m}^r)$, from a standard normal probability distribution, where draws are indexed by r.[10] With $(u_{m0}^r, u_{m1}^r, \ldots, u_{mK_m}^r)$ 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, $\widehat{n_{mr}}(X_m, Z_{mk}, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta, u_{m0}^r, u_{m1}^r, \ldots, u_{mK_m}^r)$, that is expected to enter

equation (6) describes a mathematical problem. In equation (1), N_m^a is representing the number of actual firms observed in a market from the data. However, equation (6) is positing that N_m^a can be thought of as a solution to a mathematical problem, where the choice variable in the mathematical problem is n, and the optimal choice of n, i.e., the solution to the mathematical problem is N_m^a. So n in equation (6) is mathematically referring to a more general variable that can take on a range of integer values.

[8] 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.

[9] We assume most profitable firms enter first.

[10] 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, $\widehat{a_{mkr}}(X_m, Z_{mk}, \beta, \alpha, \delta^{\pi}, \lambda^{\pi}, \eta, u^r_{m0}, u^r_{m1}, \dots, u^r_{mK_m})$, 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:

$$\widehat{N^a_m}(X_m, Z_m, \beta, \alpha, \delta^{\pi}, \lambda^{\pi}, \eta) = \frac{1}{R_m}\sum_{r=1}^{R_m} \widehat{n_{mr}}(X_m, Z_{mk}, \beta, \alpha, \delta^{\pi}, \lambda^{\pi}, \eta, u^r_{m0}, u^r_{m1}, \dots, u^r_{mK_m}) \qquad (7)$$

$$\widehat{Prob_{mk}}(X_m, Z_{mk}, \beta, \alpha, \delta^{\pi}, \lambda^{\pi}, \eta) = \qquad (8)$$
$$\frac{1}{R_m}\sum_{r=1}^{R_m} \widehat{a_{mkr}}(X_m, Z_{mk}, \beta, \alpha, \delta^{\pi}, \lambda^{\pi}, \eta, u^r_{m0}, u^r_{m1}, \dots, u^r_{mK_m}),$$

where $\widehat{N^a_m}$ 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. The reason why $\frac{1}{R_m}\sum_{r=1}^{R_m} \widehat{a_{mkr}}(\cdot)$ is not smooth and continuous in parameter space is owing to $\widehat{a_{mkr}(\cdot)}$ being only able to take two possible values - zero or one. So for different parameter values, $\widehat{a_{mkr}(\cdot)}$ can only switch between zero and one making it a step-like function 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, $\frac{1}{R_m}\sum_{r=1}^{R_m} \hat{s}_{mkr}(\cdot)$, where

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

$rank_{mkr}$ is firm k simulated profit rank among the K_m potential entrants on the r^{th} draw, and $\hat{n}_{mr}$ 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.

Note that unlike the right-hand-side of equation (8), the right-hand-side of equation (9) can take any real number between 0 and 1, and the specific real number taken by the right-hand-side of equation (9) depends on the parameter values. Therefore, the right-hand-side of equation (9) is continuous in the parameters, and the logit functional form makes it smooth in parameter space.

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:

$$N_m^a = \widehat{N_m^a}(X_m, Z_m, \beta, \alpha, \delta^\pi, \lambda^\pi, \eta) + v_m \tag{10}$$

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

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:

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

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

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: [11]

$$\underset{\hat{\theta}}{Min} \left[m(\hat{\theta})' W m(\hat{\theta}) \right] \quad (14)$$

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:[12]

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

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

[11] 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, $(\hat{\theta}_{(1)}, \hat{\theta}_{(2)}, \hat{\theta}_{(3)}, \ldots)$, until the associated value of the GMM objective function converges to a minimum value.

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

correction term is to include the conditional mean, $E[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$, as a regressor in the price equation. However, there is no closed-form solution for $E[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$ with firm heterogeneity, so in the spirit of Singh and Zhu (2008) we use a simulation technique to approximate this conditional mean as follows:

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

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).[13]

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, $\hat{E}[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$. In the second stage we use ordinary least squares to estimate the linear pricing equation, in which $\hat{E}[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$ 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 the 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

[13] 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.

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), we focus on U.S. domestic flights offered and operated by U.S. carriers in a single year, which is 2007 in our 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.

We enforce some data restrictions 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 online[14] nonstop itineraries are considered in each origin-destination market.

In our opinion, much is not lost by focusing on nonstop products instead of considering both nonstop and connecting products. First, Gayle and Wu (2013) provide structural econometric evidence revealing that in most markets nonstop and connecting products have sufficiently weak cross-price elasticity of demand such that if connecting products were

[14] 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).

artificially removed from markets containing both product types, the remaining nonstop product prices typically will not increase by more than 1%. As such, they argue that these two product types can be treated as being in separate product markets. Second, Brueckner, Lee and Singer (2013) also provide evidence that the competitive impact of connecting products on nonstop products is relatively weaker than the competitive impact of nonstop products on other nonstop products.

We create a "*quantity*" variable by aggregating passengers by airline in each origin-destination market. This quantity variable is used to help define a "valid" incumbent. Following Berry (1992), a firm is considered a "valid" incumbent in a market during the quarter when the quantity of passengers appearing in the DB1B survey for 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 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 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
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 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.[15] The table also shows the number and percent of these potential entrants that actually serve the market in period 2. Among

[15] 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.

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.

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

Table 2
Number of Potential Entrants by Number of Cities Served

No. of Cities Served	Total No. of Potential Entrants	No. of entry in the 2nd 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	-

Table 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	0.0536	2.09E-05	0.7078
Distance	Nonstop flight distance, in ten thousands of miles	0.1108	0.0627	0.0177	0.2704
Income	Product of median incomes at the origin and destination cities, measured in ten billion dollars	0.2181	0.0788	0.0817	0.5869
Slot_dummy	Equals to 1 if any of the airports are slot-controlled. The slot-controlled airports are New York LaGuardia, New York Kennedy, Washington National, and Chicago O'Hare	0.1743	0.3793	0	1
City1	Equals 1 if carrier operates in only one endpoint airport of the market in 1st quarter	0.3548	0.4785	0	1
City2	Equals 1 if carrier operates in both endpoint airports of the market in 1st quarter	0.6449	0.4785	0	1
I	Equals 1 if the potential entrant actually enters the market	0.1460	0.3531	0	1
K	Number of potential entrants for each market	16.2541	2.1414	10	21
HUB_dummy	Equal to 1 if carrier has a Hub at one or both market endpoints	0.1500	0.3571	0	1
City2*Alliance_dummy	Equal to 1 if carrier operates at both market endpoints in the 1st quarter and has an alliance partner present at one or both market endpoints.	0.5579	0.4967	0	1

Table 3 continues
Descriptive Statistics

Variable	Description	Mean	Std. Dev.	Min	Max
N	Number of actual entrants to a market	2.3505	0.6230	2	6
No. of entry threats	Number of potential entrants that have presence at both market endpoints in period 1, but did not enter the market in period 2.	8.1244	1.8852	1	14
No. of entry threats (no HUB at market endpoints)	Number of entry threats that do not use any of the market endpoints as a Hub	7.5254	1.7888	1	13
No. of entry threats (with HUB at one or both market endpoints)	Number of entry threats that use one or both market endpoints as a Hub	0.5990	0.7572	0	5
No. of entry threats allied with at least one incumbent	Number of entry threats to the market who are allied with at least one incumbent in the market	1.5396	0.9303	0	4
Price_50th	Market 50th percentile of price levels	192.05	64.62	78.58	597.83
Price_25th	Market 25th percentile of price levels	167.53	55.86	60.09	379.48
Price_75th	Market 75th percentile of price levels	216.90	74.37	87.17	690.93

Note that N^a is the sum of the dummy variable "*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, according to much of the literature *"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 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). As expected, an increase in consumers' income also increases the profitability of entry. Profitability of firm entry seems to be increasing in distance up to some distance threshold, then decrease in distance thereafter. The negative coefficient on *Slot_dummy* indicates that a firm is likely to find entry less profitable if any of the airports is slot-controlled, which are: New York LaGuardia; New York Kennedy; Washington National; and Chicago O'Hare airports.

Table 4
Parameter Estimates for Entry Model

Variable	Parameter est.	std. error
Constant	-3.2518 *	0.2821
Population	4.7134 *	0.0761
Distance	2.2734 *	0.1620
$(\text{Distance})^2$	-8.9535 *	0.3909
Income	6.6341 *	0.1699
Slot_dummy	-0.4221 *	0.0199
City2	3.3342 *	0.2816
HUB_dummy	0.0011	0.6330
City2*Alliance_dummy	-0.4112 *	0.0102
Number of competing firms (δ^{π})	-1.5068 *	0.0284
Number of entry threats(λ^{π})	-0.0526 *	0.0084
Correlation(η)	-0.9998 *	0.0012
Number of obs.	12401	
GMM objective	0.1700	

*represents statistical significance 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). The positive coefficient estimate on *Hub_dummy* suggests that carriers that use one or both market endpoint airports as a hub may find market entry profitable, however, this coefficient is statistically insignificant. The negative coefficient on *City2*Alliance_dummy* suggests that a firm finds it less profitable to enter a market if it has presence at both market endpoints, and also has an alliance partner present at both market endpoints.

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. In addition, the marginal profit effect of entry threat is relatively small compared to the marginal profit effect of actual entry.

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 (-0.9998) 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. [16]

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

[16] 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 are qualitatively similar to those reported above.

entry model allow us to correct for this problem of potential endogeneity in incumbents' price regression. Results for price regressions are shown in Table 5. Specification (1) in the table captures the average effect of entry threats. In Specification (2), we decompose the effect of entry threats based on: (1) whether a market endpoint airport is a hub for a potential entrant; and (2) whether a potential entrant has an alliance partnership with any of the market incumbents.

Recall that the unit of analysis for these regressions is at the market level. As such, the dependent variable for a price 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.

The left column in Specification (1) shows the results from model without the endogeneity correction variable.[17] These estimates suggest that airfare is increasing in market size, as measured by population. Second, the positive coefficient estimate on the *Slot_dummy* variable suggests that airfare is higher in markets that include a slot-controlled airport. Third, the sign pattern of the coefficient estimates on *Distance* and *(Distance)*^{2} suggests that airfare increases with distance between the origin and destination cities up to some threshold distance, but declines in distance thereafter.[18]

[17] Recall that the "Endogeneity correction" variable is, $\hat{E}[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$.

[18] The coefficient estimates on *Distance* and *(Distance)*^{2} imply a distance threshold of 4,413 miles [= 10,000 * 4.9999/(2*5.664)], which is outside the range of distances in our data sample. Therefore, the airfare is continuously increasing with distance in our data sample.

Table 5 Parameter Estimates for Price Regressions
that Capture the Effect of Entry Threats on Median Market Price

	Specification (1)		Specification (2)	
	Without Endog. Corr.	With Endog. Corr.	Without Endog. Corr.	With Endog. Corr.
Population	0.5365 *	0.5376 *	0.5737 *	0.5769 *
	(0.1667)	(0.1663)	(0.1604)	(0.1601)
Income	-0.0584	-0.0351	-0.0052	0.0137
	(0.1056)	(0.1059)	(0.1022)	(0.1024)
Distance	4.9999 *	4.9989 *	5.4705 *	5.4616 *
	(0.5238)	(0.5226)	(0.5050)	(0.5040)
$(\text{Distance})^2$	-5.6640 *	-5.7132 *	-7.6680 *	-7.6747 *
	(1.9547)	(1.9501)	(1.8923)	(1.8883)
Slot_dummy	0.0878 *	0.0882 *	0.0570 *	0.0573 *
	(0.0234)	(0.0234)	(0.0227)	(0.0227)
No. of competing firms	-0.0456 *	-0.0473 *	-0.0774 *	-0.0787 *
	(0.0131)	(0.0131)	(0.0130)	(0.0130)
No. of entry threats	-0.0084 $^{+}$	-0.0077 $^{+}$		
	(0.0044)	(0.0044)		
No. of entry threats (no HUB at market endpoints)			-0.0019	-0.0011
			(0.0045)	(0.0045)
No. of entry threats (with HUB at one or both market endpoints)			-0.0211 *	-0.0216 *
			(0.0103)	(0.0103)
No. of entry threats (allied with at least one incumbent)			0.0758 *	0.0752 *
			(0.0088)	(0.0088)
Endogeneity Correction Variable		-16401 *		-14870 *
		(7534)		(7219)
Constant	4.9093 *	4.9050 *	4.7990 *	4.7956 *
	(0.0543)	(0.0542)	(0.0534)	(0.0533)
N=777				
R-squared	0.5292	0.5321	0.5712	0.5735

*represents statistical significance at the 0.05 level. $^{+}$represents statistical significance at the 0.10 level. Standard errors are in parentheses. Recall that the "Endogeneity correction" variable is, $\widehat{E}[u_{m0}|X_m, Z_m, N_m^a, N_m^{et}]$.

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 increased actual competitors or entry threats. While Goolsbee and Syverson's incumbent price regression measures these effects based on time dummy coefficients surrounding the period of the event, our study looks at incumbents' price response to changes in the numbers of actual competitors, and threatening potential competitors. The results here indicate that prices fall by an average 4.56% when the actual number of competitors increases by one firm. On the other hand, prices only drop by an average 0.84% 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).

The right column in Specification (1) shows estimation 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 regression. The results show that the coefficients are roughly similar in magnitude compared to the case without endogeneity correction. We find that the average effect of actual entry is marginally larger when endogeneity of market structure is taken into account. An increase in number of actual entry is associated with a price drop of 4.73% in case of the endogeneity-corrected specification, as compared to a price drop of 4.56% in case of specifications without endogeneity correction. Therefore, the measured average price effect from actual entry could be slightly underestimated 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 0.77% with an additional threat of entry in the case of the endogeneity-corrected specification. This average price effect is marginally smaller than the 0.84% average price drop in case of the specification without endogeneity correction. Therefore, the measured average price effect from the threat of entry could be slightly overestimated if we ignore the endogeneity of market structure.

Note that the significantly negative coefficient on the "Endogeneity correction" variable implies a negative relationship between price shocks and profit shocks. This negative coefficient implies that, on average, the unobserved factors affect both observed prices and probability of firm entry in the opposite direction. 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.

Now focusing on the econometric estimates from Specification (2) in Table 5, we see that incumbents lower price by more when entry threats have a hub at one or both market endpoints. In other words, potential entrants that have a hub at the market endpoint seem to pose a greater competitive threat to incumbents in the market. In case of the endogeneity corrected coefficient estimates, we see that incumbents cut airfares by 2.16% when face with an entry threat from a potential entrant who has a hub at one or both of the market endpoints. On the other hand, incumbents have small and statistically insignificant response (0.11%) to an entry threat when the potential entrant does not use any of the market endpoints as a hub. We argue that this asymmetric response from incumbents is likely driven by the fact that potential entrants with hub airports at the market endpoints can better exploit economies of passenger-traffic density and therefore will have lower marginal cost upon actual entry.

A second key result in Specification (2) is that incumbents seem to increase rather than lower their price if they have an alliance partnership with the "potential entrant".[19] The coefficient estimate suggests that incumbents raise price approximately 7% when the potential entrant present at both market endpoints is an alliance partner. We argue that if the carrier present at the endpoint airports has an alliance partnership with an incumbent, this alliance partnership can enable the incumbent to charge a higher price due to consumers' increased preference for alliance partners' products. An alliance may increase consumers' preference for partner carriers' products since passengers have greater opportunities to accumulate and redeem frequent-flyer miles across partner carriers [Lederman (2007)], especially when partner carriers' networks are complementary rather than overlapping.

Last, as a robustness check on whether our qualitative results are sensitive to seasonality, we also estimate the entry model and pricing equation using data samples drawn from the same quarter in different years. Specifically, we use the third quarter of 2006 as the first period, and the third quarter of 2007 as the second period. We find that results, which are reported in Table A.3 and Table A.4 in the appendix, are qualitatively similar to those reported in Table 4 and Table 5 above.

7. Conclusion

Much of the airline industry literature identifies a potential entrant to a market based on whether the relevant carrier has presence in at least one of the endpoint airports of the market

[19] This result is consistent with some of the findings in Armantier and Richard (2006). Also see Zhang and Czerny (2012).

without actually operating between the endpoints. Furthermore, several studies elevate the status of a potential entrant to a credible "entry threat" to market incumbents once the potential entrant establishes presence at the second endpoint airport of the market. However, a key point we make in this paper is that even when potential entrants have presence at both endpoint airports of a market, these "potential entrants" may not all be effective "competitive threats" to incumbents in the market. Our paper provides evidence of two situations in which potential entrants that have presence at both endpoint airports of a market are not effective "competitive threats" to incumbents in the market.

First, we find evidence that incumbents lower price by more when entry threats have a hub at one or both market endpoints. In other words, potential entrants that have a hub at the market endpoint seem to pose a greater competitive threat to incumbents in the market. In fact, our estimates suggest that incumbents cut airfares by 2.16% when face with an entry threat from a potential entrant who has a hub at one or both of the market endpoints, but incumbents have small and statistically insignificant response (0.11%) to an entry threat when the potential entrant does not use any of the market endpoints as a hub. We argue that this asymmetric response from incumbents is likely driven by the fact that potential entrants with hub airports at the market endpoints can better exploit economies of passenger-traffic density and therefore will have lower marginal cost upon actual entry.

Second, we find evidence that incumbents seem to increase rather than lower their price if they have an alliance partnership with the "potential entrant". Specifically, we estimate that incumbents raise price approximately 7% when the potential entrant present at both market endpoints is an alliance partner. We argue that if the carrier present at the endpoint airports has an alliance partnership with an incumbent, this alliance partnership can enable the incumbent to charge a higher price due to consumers' increased preference for products offered by alliance partners. As suggested in Lederman (2007), an alliance can increase the desirability for partner carriers' products since the alliance provides passengers with greater opportunities to accumulate and redeem frequent-flyer miles across partner carriers. This is especially true when partner carriers' networks are complementary rather than overlapping.

Apart from our two key findings described above, our econometric estimates 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 larger 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 smaller compared to when endogeneity is not taken into account.

The 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 these 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.

Appendix

Table A.1 Parameter Estimates for Price Regressions
using the log of Market 25th Percentile Price Levels as the Dependent Variable.

	Specification (1)		Specification (2)	
	Without Endog. Corr.	With Endog. Corr.	Without Endog. Corr.	With Endog. Corr.
Population	0.1852	0.1858	0.2288	0.2304
	(0.1730)	(0.1729)	(0.1684)	(0.1684)
Income	-0.0818	-0.0695	-0.0417	-0.0322
	(0.1096)	(0.1102)	(0.1073)	(0.1077)
Distance	6.1325 *	6.1320 *	6.5365 *	6.5320 *
	(0.5436)	(0.5435)	(0.5302)	(0.5302)
$(\text{Distance})^2$	-9.9334 *	-9.9593 *	-11.6372 *	-11.6406 *
	(2.0285)	(2.0283)	(1.9866)	(1.9866)
Slot_dummy	0.1286 *	0.1288 *	0.0999 *	0.1001 *
	(0.0243)	(0.0243)	(0.0239)	(0.0239)
No. of competing firms	-0.0622 *	-0.0632 *	-0.0905 *	-0.0911 *
	(0.0136)	(0.0136)	(0.0137)	(0.0137)
No. of entry threats	-0.0059	-0.0055		
	(0.0046)	(0.0046)		
No. of entry threats (no HUB at market endpoints)			0.0007	0.0011
			(0.0047)	(0.0047)
No. of entry threats (with HUB at one or both market endpoints)			-0.0225 *	-0.0227 *
			(0.0108)	(0.0108)
No. of entry threats (allied with at least one incumbent)			0.0679 *	0.0676 *
			(0.0093)	(0.0093)
Endogeneity Correction Variable		-8616		-7456
		(7836)		(7594)
Constant	4.7364 *	4.7342 *	4.6361 *	4.6344 *
	(0.0563)	(0.0564)	(0.0561)	(0.0561)
N=777				
R-squared	0.5146	0.5154	0.5476	0.5481

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

Table A.2 Parameter Estimates for Price Regressions
using the log of Market 75th Percentile Price Levels as the Dependent Variable.

	Specification (1)		Specification (2)	
	Without Endog. Corr.	With Endog. Corr.	Without Endog. Corr.	With Endog. Corr.
Population	0.5970 *	0.5985 *	0.6296 *	0.6343 *
	(0.1729)	(0.1720)	(0.1662)	(0.1654)
Income	0.0604	0.0941	0.1212	0.1492
	(0.1096)	(0.1096)	(0.1059)	(0.1058)
Distance	4.5171 *	4.5156 *	5.0241 *	5.0109 *
	(0.5435)	(0.5406)	(0.5234)	(0.5208)
$(\text{Distance})^2$	-4.0785 *	-4.1497 *	-6.2478 *	-6.2577 *
	(2.0281)	(2.0173)	(1.9611)	(1.9513)
Slot_dummy	0.0572 *	0.0578 *	0.0253	0.0259
	(0.0243)	(0.0242)	(0.0236)	(0.0234)
No. of competing firms	-0.0183	-0.0209	-0.0520 *	-0.0539 *
	(0.0136)	(0.0135)	(0.0135)	(0.0135)
No. of entry threats	-0.0103 *	-0.0093 *		
	(0.0046)	(0.0046)		
No. of entry threats (no HUB at market endpoints)			-0.0040	-0.0028
			(0.0047)	(0.0047)
No. of entry threats (with HUB at one or both market endpoints)			-0.0204 +	-0.0211 *
			(0.0107)	(0.0106)
No. of entry threats (allied with at least one incumbent)			0.0799 *	0.0790 *
			(0.0091)	(0.0091)
Endogeneity Correction Variable		-23753 *		-22017 *
		(7793)		(7459)
Constant	4.9884 *	4.9822 *	4.8731 *	4.8681 *
	(0.0563)	(0.0561)	(0.0554)	(0.0551)
N=777				
R-squared	0.5005	0.5064	0.546	0.5511

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

Table A.3 Parameter Estimates for Entry Model

Variable	Parameter est.	std. error
Constant	0.1688 *	0.0053
Population	13.0303 *	0.0149
Distance	1.7832 *	0.0219
$(\text{Distance})^2$	-1.0759 *	0.1004
Income	9.5743 *	0.0086
Slot_dummy	-1.8253 *	0.0002
City2	4.3901 *	0.0008
HUB_dummy	4.3831 *	0.0103
City2*Alliance_dummy	-0.5891 *	0.0027
Number of competing firms (δ^{π})	-6.3745 *	0.0085
Number of entry threats(λ^{π})	-0.8729 *	0.0037
Correlation(η)	-0.9999 *	0.0008
Number of obs.	12881	
GMM objective	0.1797	

*represents statistical significance at the 0.05 level.

Table A.4 Parameter Estimates for Price Regressions
that Capture the Effect of Entry Threats on Median Market Price

	Specification (1)		Specification (2)	
	Without Endog. Corr.	With Endog. Corr.	Without Endog. Corr.	With Endog. Corr.
Pop	0.5473 *	0.5477 *	0.5717 *	0.5724 *
	(0.1669)	(0.1668)	(0.1607)	(0.1606)
Income	-0.0816	-0.0723	-0.0055	0.0016
	(0.1059)	(0.1061)	(0.1024)	(0.1025)
Distance	4.9483 *	4.9810 *	5.4562 *	5.4810 *
	(0.5254)	(0.5258)	(0.5072)	(0.5076)
$(\text{Distance})^2$	-5.5106 *	-5.6300 *	-7.6362 *	-7.7220 *
	(1.9620)	(1.9630)	(1.9005)	(1.9020)
Slot_dummy	0.0927 *	0.0920 *	0.0548 *	0.0543 *
	(0.0234)	(0.0234)	(0.0229)	(0.0229)
No. of competing firms	-0.0461 *	-0.0462 *	-0.0799 *	-0.0798 *
	(0.0131)	(0.0131)	(0.0131)	(0.0131)
No. of entry threats	-0.0046	-0.0049		
	(0.0046)	(0.0046)		
No. of entry threats (no HUB at market endpoints)			-0.0003	-0.0005
			(0.0046)	(0.0046)
No. of entry threats (with HUB at one or both market endpoints)			-0.0122	-0.0127
			(0.0101)	(0.0101)
No. of entry threats (allied with at least one incumbent)			0.0751 *	0.0748 *
			(0.0088)	(0.0088)
Endogeneity Correction		-5.44E+10		-4.46E+10
		(4.11E+10)		(3.94E+10)
Constant	4.8876 *	4.8860 *	4.7883 *	4.7880 *
	(0.0550)	(0.0549)	(0.0539)	(0.0539)
N=777				
R-squared	0.5276	0.5287	0.5685	0.5693

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

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