Empirical Evidence of Airline Merger Waves Based on A Selective Entry Model

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Abstract

Ever since the Deregulation Act in 1978 in the U.S. airline industry, there have been series of major airline mergers and acquisitions, notably three major waves in the 1980's, 1990's, and late 2000's. These mergers, especially the more recent multi-billion mergers (e.g. Delta-Northwest, United-Continental) have shown a trend of substantial market consolidation that inevitably worries consumers as well as the U.S. Department of Justice (DoJ). Most academic literature to date have tried to study mergers in a static setting where these mergers are assumed to be exogenous. However, the clear pattern of merger waves in the airline industry, as well as many other industries, suggests strong correlation between mergers. A few studies that attempted at a dynamic merger model remain theoretical due to computational barriers. In this paper, I found empirical evidence of merger waves by investigating the change of airline carriers' incentive to merge after another merger between two other carriers. These results are based on a structural model of the U.S. airline industry, in which I estimate demand with a standard (for differentiated product markets) discrete-choice nested logit model, but allow for selection on entrants' costs and qualities, i.e. firms with lower costs and higher qualities would have been selected into the market before the merger, suggesting that post-merger entry is less likely than what non-selective entry models have predicted.[1]

JEL Classification Numbers: L13; L25; L93.

Keywords: Airline; Merger Wave; Selective Entry.

[1]I am extremely grateful to Professor Andrew Sweeting and Professor James Roberts for generously giving me the preliminary estimates of the current model from their Airline Selective Entry Model project, in which Ying Li, Joe Mazur and I are research assistants. I would like to thank Professor James Roberts individually for all his guidance and encouragement throughout the writing of this paper. I would also like to thank Professor Andrew Sweeting for his invaluable advice. I am also grateful to Ying Li and Joe Mazur from the Economics Department of Duke University for their help in the Matlab code and data set, respectively, as well as their comments on the paper. Finally, I would like to thank the Davies Fellowship from the Economics Department of Duke University for sponsoring my summer research with generous funding.

1 Introduction

Due to its comprehensive and publicly available data, the U.S. airline industry since deregulation has long been the focus of empirical studies, a lot of which dealt with merger simulations and antitrust merger policies. In most of these empirical studies, people tend to abstract away from the endogeneity of consecutive mergers to establish their models in a simple static setting. However, this might be too costly an assumption to make.

In the past five years (2008 - 2012), the U.S. airline industry has experienced tremendous market consolidation through two record multi-billion merger deals. Delta Air Lines (DL) and Northwest Airlines (NW) announced and closed their merger deal in 2008, setting a world airline merger record of $3.1 billion. Less than two years later, United Airlines (UA) and Continental Airlines (CO) almost tripled the size of the DL-NW deal in their merger in 2010. In 2011, AMR Corporation, American Airlines' (AA) holding company, filed for bankruptcy protection and was recently reported to seek for a possible merger with US Airways (US).[2] It is hard to believe that all six major network airline legacy carriers all paired up in five years without much correlation.

The industry also believes that series of mergers are inevitable. Morningstar analysts Basili Alukos and Adam Fleck, pointing out AA's comparative disadvantages in the market after DL-NW and UA-CO mergers, expected mergers from AA-JetBlue. Scott Rostan, founder of Training the Street and a former M&A banker at Merill Lynch, stressed that the importance of synergies from mergers is what incentivizes airlines to merge and that many other mergers would happen following the DL-NW, Southwest-AirTran (WN-FL), and UA-CO mergers, a common phenomenon known as the domino effect in M&A.[3] W. Douglas Parker, CEO of US Airways, when speaking to industry analysts in 2008, reiterated that consolidation is inevitable. "We believe that first and foremost, consolidation is going to

[2] *Source*: "Report: US Airways brings takeover plan to AA's creditors" USA Today (2012): http://travel.usatoday.com/flights/post/2012/03/us-airways-discussing-american-airlines-merger/654891/1

[3] *Source*: "With More Airline Mergers on the Runway, American Could Be Next," Forbes News (2010): www.forbes.com/sites/steveschaefer/2010/10/11/with-more-airline-mergers-on-the-runway-american-could-be-next/

happen. While there clearly is value in getting international route networks broader, the real value of consolidation is rationalization of the domestic industry, which is overly fragmented."[4]

To find out the evidence of merger waves, a survey of all U.S. airline merger incidents since deregulation is in place:

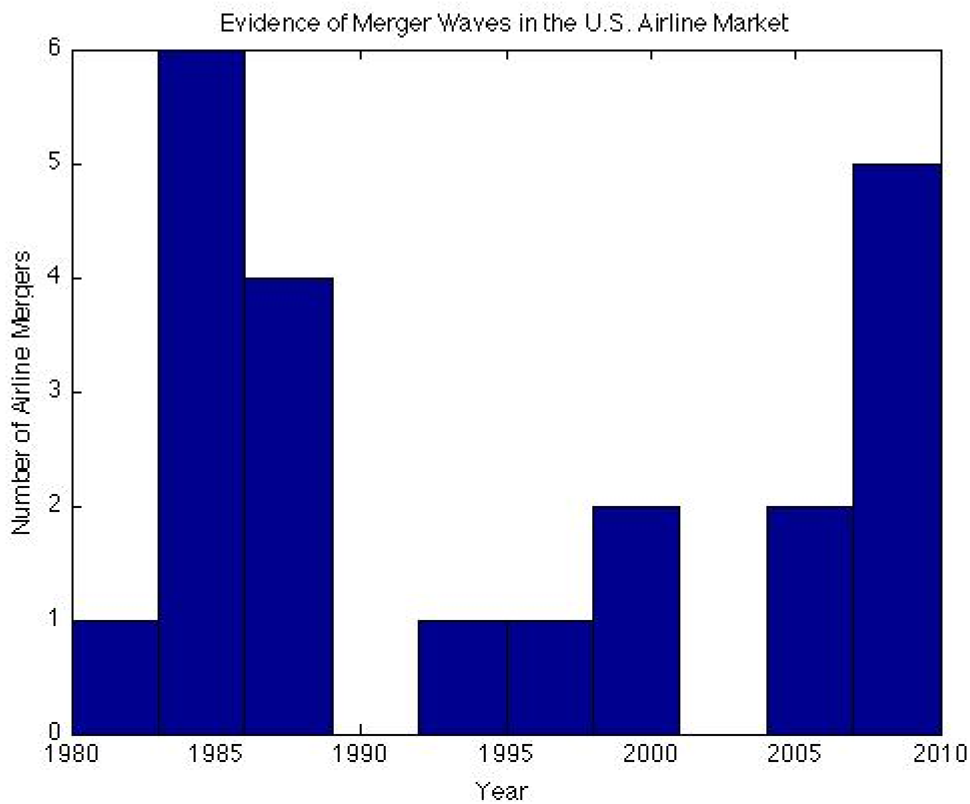

Figure 1: Airline Merger Frequency

In Figure 1, I collected all 22 major airline mergers in the U.S. and plotted them against time. It is quite clear that these mergers are divided into three major waves in time, which suggests certain degree of correlation between consecutive mergers.[5]

[4] *Source*: "The Domino Effect: Will Airlines Follow One Another in the Consolidation Game?" Knowledge@Wharton (2008): http://knowledge.wharton.upenn.edu/article.cfm?articleid=1898

[5] Figure 1 highly suggests a dynamic story where one merger would perturb the equilibrium and trigger a series of mergers. In about 17-18 years of time, after some dynamic interactions between firms (where antitrust policies also come into play, e.g. there were quite a few more mergers in the 1980's wave due to the exceptionally loose antitrust policy before 1990), the industry reaches some steady state until the next merger happens (in about 5 years). Due to technical and computational constraints, however, in this paper,

Another major theme of the story of the U.S. airline industry since deregulation is the expansion of low-cost carriers[6] through strategic entry into dense (in population and travel demand) city-pair markets. Notably, Southwest has become the largest airline in the U.S. based on domestic passengers carried and even maintained consistent profitability through the most difficult times for the airline industry (e.g. 2001, after the 9/11 incident). According to Ito and Lee (2006), LCCs expanded from 7% domestic passengers carried and limited geographic scope, to almost 25% domestic passengers carried in 2002 and the entire U.S. covered.

In fact, when a particular merger application is reviewed by DoJ, there are three major defenses to the anti-competitive argument: (i) synergies generated by the merger, (ii) the failing firm defense (where one of the merging firms is failing and its assets will exit the market without the merger), and (iii) potential entry defense (where potential post-merger entry would mitigate the anti-competitive effects from the merger). Historically, DoJ has approved many mergers partially based on the potential entry defense in the hope that if incumbent firms try to raise fares or reduce services to an anti-competitive extent, potential entries would happen to counter such behaviors. However, in reality, we observe persistent fare increase and few post-merger entries (Borenstein (1990), Kim and Singal (1993), Peters (2006)).

Thus, in order to quantify the extent to which potential entry plays into the dynamics of mergers, I adopt the selective entry model in Roberts and Sweeting (2011), in which potential entrants' costs and qualities are taken into account when entries are determined. I will elaborate on this in much more details when introducing the model, but the basic idea behind this model is that we divide the competition game into two stages. During the first stage, all potential entrants make their entry decisions through a sequential game, in which

I only intend to suggest some empirical evidence of such dynamics, instead of implementing a fully functional dynamic model, which is my next step in future research.

[6]Historically, the six major network carriers are called legacy carriers (LEG) including AA, UA, CO, US, DL, NW. Smaller carriers are called low-cost carriers (LCC) including Southwest, AirTran, JetBlue, and etc. Some other carriers are ambiguous on this front. In this version of the paper, I define Alaska Airlines as an additional legacy carrier and everyone else is LCC.

all the game outcomes are profits derived from their respective qualities and costs. This means that entry decisions are endogenous and firms with lower costs and higher qualities are more likely to enter. During the second stage, all firms that decided to enter in the first period compete in the market in a Bertrand fashion where firms compete in prices.

Traditionally, merger analysis has been mostly based on market concentration measures. Merger effects are primarily decided by calculating pre-merger and post-merger concentration in a given market. This approach is problematic when differentiated products are offered and thus oftentimes involves strong assumptions about the market. This paper follows the recent prevailing differentiated products market demand estimation methodology, e.g. Berry (1994), Berry, Levinsohn, and Pakes (1995), Nevo (2000), and Peters (2006). To estimate the structural model, I employed the Method of Simulated Moments (MSM) and an importance sampling estimator proposed by Ackerberg (2009). [7]

Finally, with the model estimates, I will conduct counterfactuals by proposing and simulating consecutive mergers in a particular market. Particularly, I will investigate the change of profitability of the second merger due to the first merger. I provide here a very simple example to illustrate merger incentives with potential selective entry in a Cournot setting.

Consider a market with four identical incumbent firms with constant marginal costs $c = 0.5$, demand $P(Q) = 2 - Q$, and Cournot competition. A potential entrant has marginal cost $c' \geq 0.5$ and does not enter with four incumbent firms present in the market. Furthermore, all firms have fixed cost $F = 0.1$. c' will then reflect the degree of selection. Now consider a first merger in the market between two incumbent firms. The merged firm will only have to pay fixed cost F and marginal cost $c - s$, with s representing the synergy created between the merging firms. I further assume the same synergy level across all mergers. Then I simulate another merger between the remaining two original incumbent firms conditional on the first merger. Entry could be induced after each merger.

Formally, let the four incumbent firms be A, B, C, and D. Let AB represent the merged

[7] In the current paper, I did not use more advanced identification methods, e.g. Andrews and Soares (2010), Ciliberto and Tamer (2009), which is another direction of my future research.

firm from A and B, and CD being the combination of C and D. Suppose we want to study firm C's incentive to merge (again, the four incumbents are identical), let

$$\pi_1 = \pi(C|AB, C, D) \tag{1}$$

$$\pi_2 = \pi(C|AB, CD) \tag{2}$$

$$\pi_3 = \pi(C|A, B, C, D) \tag{3}$$

$$\pi_4 = \pi(C|A, B, CD) \tag{4}$$

where $\pi(C|AB, C, D)$ is the profit of firm C given that A and B have merged (with possible entry of the potential entrant into the market), $\pi(C|AB, CD)$ is the profit of C given that both A, B and C, D have merged, and etc. I then define

$$I = (\pi_2 - \pi_1) - (\pi_4 - \pi_3) \tag{5}$$

as the additional merger incentive of C induced by the merger between A and B. For given levels of c', I will give below the level of I with different synergies.

Figure 2 shows how the incentive changes as the synergy level changes when the marginal cost of the potential entrant is at 0.58, whereas in Figure 3, $c' = 0.6$. In both cases, a profitable merger has led to positive incentive for other market participants to merge. Despite being a very naive model, it provides us some intuition as to the empirical evidence of merger endogeneity and how we study such evidence.

The rest of the paper is organized as follows. Section 2 gives a brief literature review on the related literature concerning the airline industry, differentiated products markets, merger simulations, and dynamic models. Section 3 presents my structural model of the airline industry that accounts for selective entry. Section 4 describes the way I connect my model with data and estimate the structural parameters that I am interested in. Section 5 talks about the source of my data and how I tailored it for my specific use as well as some summary statistics. Section 6 presents the estimates of the current specification of the model

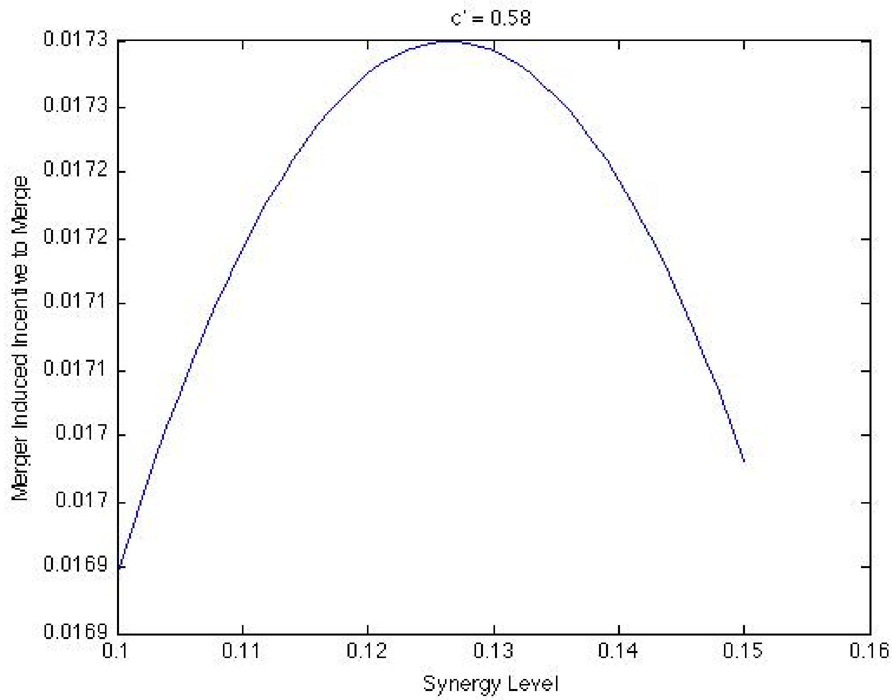

Figure 2: Merger Incentive with Potential Entrant Cost = 0.58

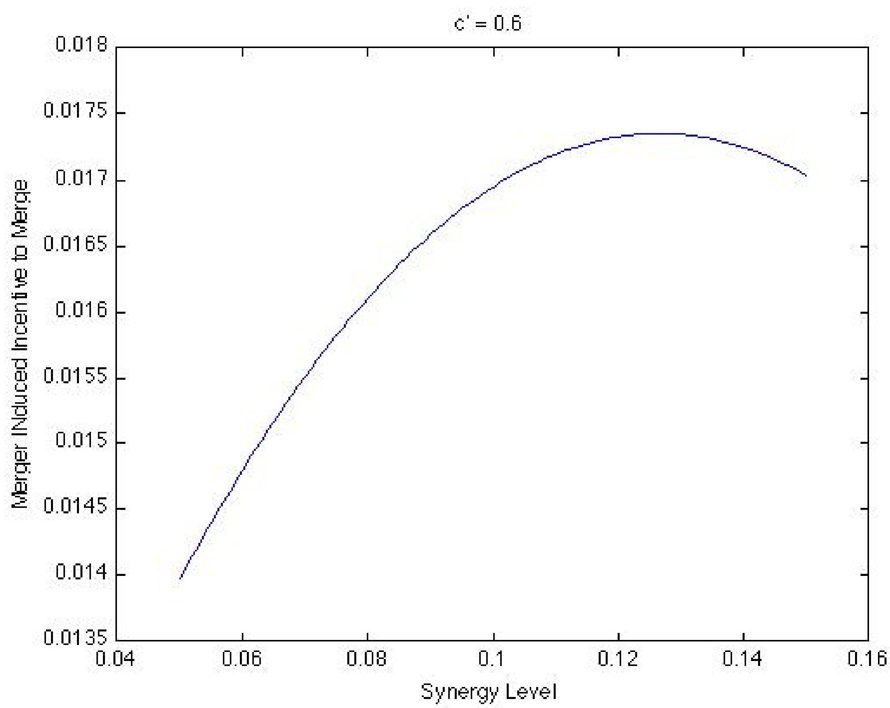

Figure 3: Merger Incentive with Potential Entrant Cost = 0.60

and how well they fit predicted moments to the data. In section 7, I conduct counterfactuals by simulating two consecutive mergers in chosen markets using estimates provided above. Section 8 finally concludes the paper with my findings about merger waves, implications of this study, and suggestions of future research.

2 Literature Review

In this very brief literature review, I will follow the literature on the U.S. airline industry (as well as some similar industries) in a chronological order, with specific focus on recent demand estimation methodology used in differentiated product markets, merger simulations and dynamic models.

In the early to mid-1980's, when the Deregulation Act just went into effect in the U.S. airline industry, there was an extensive theoretical discussion on the contestability[8] of the airline market and its transition from regulation to deregulation (Bailey and Panzar (1981), Bailey and Friedlaender (1982), Bailey and Baumol (1983), and Morrison and Winston (1987)).

From late 1980's to early 1990's, when air fares and airline profitability skyrocketed, the first huge wave of airline mergers went through unchallenged, and Legacy carriers started to build their "hub-and-spoke" network systems through mergers and acquisitions, research, especially empirical research, turned to the study of hub premium, concentrated market power, and barriers to entry. These studies have found that hub dominance and market consolidation gave rise to high fares, barriers to entry and less competition (Borenstein (1989), Borenstein (1990), Borenstein (1992), and Levine (1987)), but at the same time brought along economies of scale, i.e. reduction of cost by putting passengers with different destinations on the same plane (Brueckner, et al. (1992) and Brueckner and Spiller (1991)).

Since the early 1990's, a long list of literature have adopted the now standard differen-

[8]A perfectly contestable market is one that is served by a small number of firms, but is characterized as competitive with desirable welfare outcomes because of the existence of potential entrants.

tiated products market demand estimation methodology using a discrete-choice nested logit model. These papers include but not limited to, Berry (1992), Berry and Pakes (1993), Peters (2006), Berry, Carnall, and Spiller (2006), and Armantier and Richard (2008). Such literature is also not limited to the airline industry: there are studies with similar methodology on the beer industry (Baker and Bresnahan (1985), Hausman, Leonard and Zona (1994)), long-distance telecommunications industry (Werden and Froeb (1994)), ready-to-eat cereals industry (Nevo(2000)), soft drinks industry (Dube (2000)), and automobile industry (Berry, Levinsohn, and Pakes (BLP) (1995)).

With these structural models, merger simulations and counterfactuals are easily conducted because post-merger competition is fully specified bearing some assumption about the time-invariance of the firm conduct. For example, Craig Peters (2006) used a standard discrete-choice framework with underlying random utility model and pre-merger data to estimate demand and recover marginal costs. Then by comparing post-merger equilibrium prices of his model with actual post-merger data, he found significant effects of cost reduction and change in firm conduct on post-merger price changes.

However, the literature on entry models that explicitly address selection bias is quite limited, especially in the context of the airline industry (Reiss and Spiller (1989)). Our model, on the other hand, sets up an entry game as such with observed and unobserved heterogeneity that also incorporates the standard demand estimation mechanism. This model also has the full potential to be estimated with more advanced model identification methods and used to conduct counterfactuals about profitability, welfare changes, and entries induced by mergers.

At the same time, research in dynamic models stay behind and mostly remain in a theoretical framework due to computational complexity. Berry and Pakes (1993), Cheong and Judd (1992), and Ericson and Pakes (1995) all provide good theoretical guidance on this front. Gowrisankaran (1999) proposed a dynamic model that endogenizes mergers. In this model, firms rationally make decisions about merger, investment, entry, and exit to maximize their expected discounted future profits. Gowrisankaran tested the model with a base case vector that specifies an industry with some arbitrary (although sensible) parameters. Despite the intuitive results Gowrisankaran found with his toy example and the potential usefulness, this paper remains a methodological study that is yet to be used in practice. Moreover, it would need some adaptation if we want to apply it on the airline industry because of its original assumption of Cournot competition in a homogeneous goods market. Nevertheless, this would be a good start towards a fully functional dynamic model of airline mergers in the future.

Nocke and Whinston (2010) studies the interaction between mergers and the optimal antitrust policies associated with it in a purely theoretical setting. They found that, among other things, in a Cournot setting, if merger M_1 is CS-nondecreasing (CS stands for consumer surplus) in isolation, while M_2 is CS-decreasing in isolation but CS-nondecreasing conditional on M_1, then the joint profit of firms involved in M_1 is strictly larger if both mergers happen than if neither happens. Despite its touch on profitability of mergers and thus merger incentives, this paper, with its main purpose of optimal forward-looking antitrust policies, deal mostly with the welfare effects of mergers. Their main result is that the sign of a merger's CS effect is unchanged if another merger whose CS effect has the same sign happens. Therefore, antitrust authority can achieve the optimal forward-looking CS-maximizing goals by setting myopic policies such that all mergers are CS-nondecreasing. Another hurdle in applying similar analysis to the airline market is that, in order to get by their assumptions about Cournot competition and homogeneous product market, we have to make strong assumptions about the cost structure of all firms such that they all have identical marginal costs, both pre-merger and post-merger.

As a result, this paper will contribute to the existing literature as empirical evidence of the endogenous nature of mergers in the airline industry, when allowing for selective entry. And hopefully this will set the first step for future empirical studies with dynamic models. With these background in mind, I will proceed to present the current model.

3 Model

In this paper, I set up a structural model that intends to describe the competition in the U.S. airline industry. On the supply side, competition is divided into two stages. During the first (entry) stage, all market potential entrants make their entry decisions (direct flight, indirect flight, out) based on a sequential game, aiming to maximize their respective profits. During the second stage, all firms that decided to enter (either as direct or indirect) would compete (in price) in the market and clear market with equilibrium (prices), given our Bertrand assumption.

On the demand side, first of all, all firms are assumed to be single-product firms, i.e. a carrier can either fly direct or indirect but not both. I then estimate demand in the spirit of the recent literature on product differentiation by adopting a discrete-choice nested logit model where between the top two nests consumers choose between flying versus other transportations and conditional on flying, consumers choose between different carriers (since each carrier only produces one product).

In practice, I estimate demand first and recover supply from the demand estimation to set up the first order conditions for the equilibrium. Then for any possible outcome from the game tree, I solve for the equilibrium prices, from which I can derive profits of all firms. Finally, I solve the game tree with firms' profits in different outcomes. Now I will elaborate on the model in this order and use an example of three firms for illustrative purposes whenever necessary.

3.1 Demand Estimation

To illustrate demand estimation, I will follow Berry (1994) to review the basic discrete-choice nested logit model in differentiated products markets where competition is imperfect and some product characteristics are unobserved. Instead of using a random-coefficient model, we will make some distributional assumptions on such characteristics.

The nested logit model assumes that consumer tastes have a particular type of generalized extreme value (GEV) distribution. However, under this assumption, consumer tastes are correlated across products, which allows for more reasonable substitution patterns than simple logit models.

Suppose we have three carriers A, B, and C, that decided to enter the market either as direct flight or indirect flight after the sequential entry game (first stage), our nest structure would look like Figure 4.

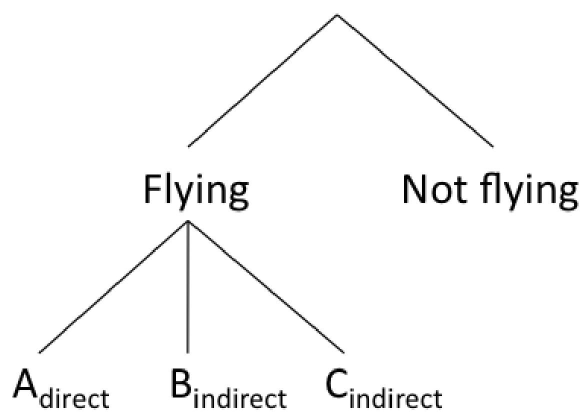

Figure 4: Nest Structure

where A_{direct}, $B_{indirect}$, and $C_{indirect}$ are the three products in group 1 (call it G_1) and the outside good ("Not flying") is the only one product in group 0 (call it G_0). Note that this is only one possible outcome of the sequential game in stage one, out of the $3^3 = 27$ possible outcomes. Then the utility of consumer i for product j is given by

$$u_{ij} = x_j\beta_i - \alpha p_j + \xi_j + (1-\sigma)\epsilon_{ij} \tag{6}$$

where x_j is a vector of observed product characteristics for product j, i.e., whether it is air travel, carrier specific qualities, whether it is direct, whether it is Legacy carrier or Low-Cost carrier, and travel distance. β_i is a vector of consumer i's perceived product qualities associated with the corresponding characteristics, or consumer i's tastes of such characteristics. These tastes are unobserved (to the econometrician) but are assumed to take on some a priori distributions. α is the price coefficient, which is also a measure of the average price elasticity. p_j is the price of product j. ξ_j is the unobserved product characteristics, which could be treated as the mean of consumers' tastes of an unobserved product characteristic, while ϵ_{ij} is the distribution of consumers' tastes around this mean. σ is the within group correlation of utility levels, which also means $\sigma \in (0, 1)$.

Now to compute market share of product j, let $\delta_j = x_j\beta_i - \alpha p_j + \xi_j$, and

$$D_g = \sum_{j \in G_g} e^{\delta_j/(1-\sigma)} \tag{7}$$

Then the market share of product j conditional on choosing its group is

$$\bar{s}_{j/g} = e^{\delta_j/(1-\sigma)}/D_g \tag{8}$$

And the group share is

$$\bar{s}_g = \frac{D_g^{(1-\sigma)}}{\sum_g D_g^{(1-\sigma)}} \tag{9}$$

Thus the unconditional market share of product j is given by

$$s_j = \bar{s}_{j/g}\bar{s}_g = \frac{e^{\delta_j/(1-\sigma)}}{D_g^{\sigma}[\sum_g D_g^{(1-\sigma)}]} \tag{10}$$

3.2 Supply and Equilibrium

We assume firms to be price setters in this model and thus profits for firm j are

$$\pi_j = p_j M s_j - C_j \tag{11}$$

where M is market size and C_j is the total cost for firm j. Taking partial derivative with respect to price, we obtain the usual first-order conditions:

$$p_j = c_j + s_j / |\partial s_j / \partial p_j| \tag{12}$$

or

$$p_j = c_j + \frac{1}{\alpha}[s_j / (\partial s_j / \partial \delta_j)] \tag{13}$$

since $\partial s_j / \partial p_j = -\alpha \partial s_j / \partial \delta_j$. Differentiating equation (5) with respect to δ_j, we get

$$\partial s_j / \partial \delta_j = \frac{1}{1-\sigma} s_j [1 - \sigma \bar{s}_{j/g} - (1-\sigma) s_j] \tag{14}$$

Substitute equation (9) back into equation (8), we get the first order conditions:

$$(p - c) + \frac{1-\sigma}{\alpha} \frac{1}{1 - \sigma \bar{s}_{j/g} - (1-\sigma) s_j} = 0 \tag{15}$$

For each possible market outcome, we can then solve for market equilibrium prices, from which we calculate firm profits using equation (6).

3.3 Solving Game Tree

With the potential profits earned by each firm in stage two obtained from the previous two sections, we can now go back to the first stage of the competition game and solve the sequential game tree. All potential entrants of the market participate in the entry game in the first stage. Firms observe each other's profits in each outcome but have to move (make a decision) in sequential order. Every time I solve this game, I randomize the order of all potential entrants to avoid any restriction a specific game order might have.[9] When it is certain firm's turn to move, it can make a decision from his choice set { serving direct flights, serving indirect flights, staying out }. If it stays out, it earns a profit of zero, while direct

[9] Although this practice seems somewhat unrealistic, an exercise of solving games with all possible orders shows that there is on average less than two equilibria in all game orders and thus any particular order does not matter.

and indirect flights' profits were obtained from last two sections.

Now, in our example of three potential entrants, the game tree looks like the one in Figure 5. With three firms, each with three choices, we have a total of $3^3 = 27$ possible outcomes, as shown in Figure 6, where 1 represents serving direct flights, 2 indirect flights, and 0 represents staying out.

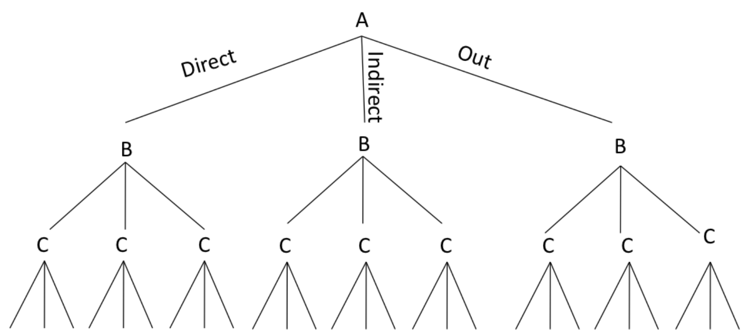

Figure 5: Game Tree

0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2
0	0	0	1	1	1	2	2	2	0	0	0	1	1	1	2	2	2	0	0	0	1	1	1	2	2	2
0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2	0	1	2

Figure 6: All Possible Outcomes

Accordingly, there is a profit matrix that has firms' profits corresponding to each possible outcome like Figure 7 (all numbers are made up for illustrative purposes).

0	0	0	0	0	0	0	0	0	.9	.6	.7	.5	.2	.3	.4	.3	.4	.5	.5	.3	.4	.4	.3	.3	.3	-.3
0	0	0	.8	.4	.6	.5	.4	.2	0	0	0	.3	-.1	-.2	.3	.1	.5	0	0	0	.7	.1	.5	-.5	.3	-.4
0	.6	.3	0	.2	.3	0	.7	.1	0	.5	.3	0	-.5	.3	0	.4	.1	0	.3	-.3	0	.2	.1	0	-.3	.1

Figure 7: Profit Matrix

To solve this game, we use backward induction on the profit matrix. First, let's consider firm C, who moves last. Given any possible combination of firm A and firm B's decisions, firm C would compare its profits associated with his three choices and make the decision that would give it the highest profit. Thus, we can safely eliminate outcomes where C's profit is not optimal given A and B's decisions, as shown in Figure 8. All outcomes that are eliminated in the first round are shaded in black. Now similarly, for any decision of A, there were nine possible outcomes, six of which were eliminated by C in the first round. Thus, B is only left with three possible outcomes associated with its three choices. Therefore, the game tree is effectively reduced to 2 layers (2 firms) and thus we could apply one more round of elimination, as shown in Figure 9. Red blocks are the outcomes eliminated in the second round. Now A is left with 3 choices and it would choose the one with the highest profit for itself, as shown in Figure 10. Comparing the result with the original outcome matrix, we know that the solution to this particular game is {A_indirect, B_direct, C_direct}.

0	0	0	0	0	0	0	0	0	.9	.6	.7	.5	.2	.3	.4	.3	.4	.5	.5	.3	.4	.4	.3	.3	.3	-.3
0	0	0	.8	.4	.6	.5	.4	.2	0	0	0	.3	-.1	-.2	.3	.1	.5	0	0	0	.7	.1	.5	-.5	.3	-.4
0	.6	.3	0	.2	.3	0	.7	.1	0	.5	.3	0	-.5	.3	0	.4	.1	0	.3	-.3	0	.2	.1	0	-.3	.1

Figure 8: Profit Matrix after First Round of Eliminations

0	0	0	0	0	0	0	0	0	.9	.6	.7	.5	.2	.3	.4	.3	.4	.5	.5	.3	.4	.4	.3	.3	.3	-.3
0	0	0	.8	.4	.6	.5	.4	.2	0	0	0	.3	-.1	-.2	.3	.1	.5	0	0	0	.7	.1	.5	-.5	.3	-.4
0	.6	.3	0	.2	.3	0	.7	.1	0	.5	.3	0	-.5	.3	0	.4	.1	0	.3	-.3	0	.2	.1	0	-.3	.1

Figure 9: Profit Matrix after Second Round of Eliminations

0	0	0	0	0	0	0	0	0	.9	.6	.7	.5	.2	.3	.4	.3	.4	.5	.5	.3	.4	.4	.3	.3	.3	-.3
0	0	0	.8	.4	.6	.5	.4	.2	0	0	0	.3	-.1	-.2	.3	.1	.5	0	0	0	.7	.1	.5	-.5	.3	-.4
0	.6	.3	0	.2	.3	0	.7	.1	0	.5	.3	0	-.5	.3	0	.4	.1	0	.3	-.3	0	.2	.1	0	-.3	.1

Figure 10: Game Solution

4 Estimation

In order to estimate the model, I want to explain the variations in the data using our model, and ultimately, how the observed and unobserved heterogeneity is explained by my structural parameters. Thus, I make distributional assumptions about the unobserved characteristics and estimate those distributions from which the key variables are drawn. In this paper, I use the method of simulated moments (MSM) with an importance sampling estimator proposed by Ackerberg (2009). Then I test the consistency of the estimator by Monte

Carlo simulations before I move to real world data, which is more noisy and unpredictable in general.

4.1 Parameters

In the current version of the estimation, I assume that the parameters are distributed as the following, where x_{jm} is a vector of observed product characteristics of product j in market m, and $TRN(\mu, \sigma^2, a, b)$ is a truncated normal distribution with mean μ, standard deviation σ, and truncated at a and b. $LogN(\mu, \sigma^2)$ is a log normal distribution with mean μ and standard deviation σ.

Direct Flight Quality: $\beta_{jm} \sim N(x_{jm}\beta^1, \sigma^2_{\lambda(D_m)})$, where $\beta^1 = \beta_{1,j} + D_m\beta_{2,\tau(j)} + \text{Hub}_{jm}\beta_{3,\tau(j)}$. $\beta_{1,j}$ is the mean carrier-specific quality. D_m is the distance of market m, and $\lambda(D_m)$ is a binary variable that is equal to 1 if $D_m >$ median(D) (long routes) and 0 otherwise. $\tau(j)$ is also a binary variable that is equal to 1 if firm j (since each firm only produces one product by assumption) is a Legacy carrier and 0 if it is a LCC carrier. This characterizes the different effects of distance and hub on Legacy and LCC carriers.

Indirect service quality is specified as direct flight quality minus an indirect quality penalty: $\beta_{jm} \sim N(x_{jm}\beta^2, \sigma_p^2)$, where $\beta^2 = \beta_4 + D_m\beta_5$.

Price coefficient: $\alpha_m \sim LogN(\beta_\alpha, \sigma_\alpha^2)$.

Nesting parameter (within-group correlation): $\sigma_m \sim TRN(\beta_\sigma, \sigma_\sigma^2, 0.2, 0.95)$.

Marginal costs: $C_{jm} \sim TRN(x_{jm}\gamma^1, \sigma_M^2, 0, \infty)$, where $\gamma^1 = \gamma_{1,\tau(j),\phi(j)} + D_m\gamma_{2,\tau(j),\phi(j)} + \text{Hub}\gamma_{3,\tau(j),\phi(j)}$ and $\sigma_M = \sigma_{1,\tau(j),\phi(j)}$. $\phi(j)$ is a binary variable that is equal to 1 if product j is providing direct service and 0 otherwise.

Fixed costs: $F_{jm} \sim TRN(x_{jm}\gamma^2, \sigma_F^2, 0, \infty)$, where $\gamma^2 = \gamma_{4,\tau(j),\phi(j)} + D_m\gamma_{5,\tau(j),\phi(j)} + \text{Hub}\gamma_{6,\tau(j),\phi(j)}$ and $\sigma_F = \sigma_{2,\tau(j),\phi(j)}$.

The set of structural parameters to be estimated is then

$\Gamma = \{\beta_1, \beta_2, \beta_3, \sigma_{\lambda(D_m)}, \beta_4, \beta_5, \sigma_p, \beta_\alpha, \sigma_\alpha, \beta_\sigma, \sigma_\sigma, \gamma_1, \gamma_2, \gamma_3, \sigma_1, \gamma_4, \gamma_5, \gamma_6, \sigma_2\}$.

And a draw of a set of parameters $\{\beta_{jm}^{Direct}, \beta_{jm}^{Indirect}, \alpha_m, \sigma_m, C_{jm}, F_{jm}\}$ is called θ_t.

4.2 Importance Sampling Estimator

In this section, I will follow Ackerberg (2009) and Roberts and Sweeting (2011) to illustrate my estimation approach based on MSM with importance sampling. But the basic idea is that I first generate a large number of simulations by solving my model described above with some pre-specified set of structural parameters Γ_0. Then I calculate moment functions from both the simulations and data observations. Then when I search over the parameter region of Γ for the optimal set of structural parameters, I re-weight my simulated moments by likelihood functions of the realized draws θ_t and compare them with the data moments to calculate my objective value (the value that I am minimizing throughout the estimation).

Formally, suppose we have n data observations. For each data observation, I take the market-specific parameters from the data, i.e. market size, number of potential entrants, number of LCC potential entrants, and market distance. Then together with a parameter draw θ_t, I am able to solve my model described in the previous section. Repeat this process and generate S simulations per data observation. All simulations are generated based on the same pre-specified underlying structural parameters Γ_0.

Let's then define our moments as the following. Suppose we have k moments. For the ith observation W_i in the data set, we define $d_{i,j}(W_i)$ as the jth moment calculated from that observation, e.g. AA market share given that AA has a hub.

In reality, I divide my moments into groups. In this version of the estimation, I first divide the moments into 7 groups by the number of potential entrants in the market (ranging from 3 to 9). Then I further divide each of these groups into a group with short distance (less than the median distance in the data sample), and one with long distance. Within each group, we calculate 8 moments for each of the nine carriers (more on this later in the data section), as shown in Table 1.

Thus I will end up with 14 groups with 72 moments in each group. Ultimately, moments in each group are weighted by the number of observations (out of 1000 we sampled) in that group when I construct the objective function.

Probability of AA entry as direct given hub status
Probability of AA entry as indirect given hub status
Average AA fare given hub status
Average AA market share given hub status
Probability of AA entry as direct given non-hub status
Probability of AA entry as indirect given non-hub status
Average AA fare given non-hub status
Average AA market share given non-hub status

Table 1: Sample Moments for AA

Let's denote the simulation results obtained from a particular draw θ_j by y_j, the likelihood function is given by

$$\int f_j(y_j|\theta)\phi(\theta|x_j,\Gamma)d\theta \approx \frac{1}{S}\sum_{s=1}^{S} f_j(y_j|\theta_s) \tag{16}$$

where ϕ is the probability density function of the realized parameters given their respective distributions and the structural parameters used at that time. This would be the obvious MSM estimator, but at the same time, it requires us to re-calculate f_j and thus re-solve the model every time the structural parameters change. Since we are searching for the optimal set of parameters on many dimensions (we have quite a few parameters to estimate) and the computation of f_j is quite costly, the computational cost of this estimator is prohibitively high.

What Ackerberg (2009) suggests is the following:

$$\int f_j(y_j|\theta)\phi(\theta|x_j,\Gamma)d\theta = \int f_j(y_j|\theta)\frac{\phi(\theta|x_j,\Gamma)}{g(\theta|x_j)}g(\theta|x_j)d\theta \tag{17}$$

where $g(\theta|x_j)$ is called the importance sampling density which does not depend on the structural parameters Γ. Easily we can see that our estimator becomes

$$E_s(W_i,\Gamma) = \int f_j(y_j|\theta)\frac{\phi(\theta|x_j,\Gamma)}{g(\theta|x_j)}g(\theta|x_j)d\theta \approx \frac{1}{S}\sum_{s=1}^{S} f_j(y_j|\theta_s)\frac{\phi(\theta_s|x_j,\Gamma)}{g(\theta_s|x_j)} \tag{18}$$

where θ_s is now a realized draw from the importance sampling density g. What this means is that, since g does not depend on the structural parameters, we can calculate $f_j(y_i|\theta_s)$ once and for all. During estimation, when the structural parameters change, all we have to do is to re-compute $\phi(\theta_s|x_j,\Gamma)$ and re-weight our estimator in equation (13).

My moment function would then be

$$\overline{m}_n(\Gamma) = (\overline{m}_{n,1}(\Gamma), ..., \overline{m}_{n,k}(\Gamma))' \tag{19}$$

where $\overline{m}_{n,j}(\Gamma) = n^{-1}\sum_{i=1}^{n}(d_{i,j}(W_i) - E_s(W_i,\Gamma))$. I assume that

$$E[d_{i,j}(W_i) - E_s(W_i,\Gamma^*)] = 0 \tag{20}$$

where Γ^* is the vector of true parameters. Thus, in practice, I search for Γ that minimizes the norm of the moment vector $\overline{m}_n(\theta)$, with each moment weighted by the number of observations in its moment group. Specifically, my objective function in the minimization process is

$$F = \sum_{j=1}^{k} w_j(\overline{m}_{n,j}(\Gamma))^2 \tag{21}$$

4.3 Monte Carlo Simulations

To test the consistency of this estimator before I am confident enough to move to data, I ran several sets of Monte Carlo simulations. I first generate "data observations" by simulating the above-mentioned games with parameters drawn from the specified a priori distributions Γ_0. In order to conduct the Monte Carlo simulations, I pretend that I know the "true distribution" and let the importance sampling density $g(\theta|x_j) = \phi(\theta_s|x_j,\Gamma_0)$. Then I estimate the model exactly as described above to see whether I can recover the known true parameters.

Table 2 presents the Monte Carlo results from a previous model where I had one more layer of nest and carriers only had two choices, i.e. entering and staying out.[10] Although the model is slightly different, I have developed the same estimator, and thus I show the results

[10] In the 3-level nested logit model, consumers first choose between flying versus other transportations. Conditional on flying, they choose between Legacy and LCC carriers. Within one category, they finally choose which carrier to fly with.

here to test its consistency.

Here I used 2000 "fake data" generated from the model with parameters labeled as True Value in the table. (Note that Table 2 only presents a selected sample of parameters.) For each observation, I used 1000 simulations with parameters from the same underlying distributions. In the "Predicted I" column, I started the search of optimal parameters with the initial guess the same as the true parameters to make sure it is an local minimum. Then in "Predicted II" column, I started it off with an initial guess that is up to 25% away from the true parameters to make sure it is indeed the global minimum. All standard errors are based on 100 bootstraps.

Monte Carlo Results for Selected Parameters							
Structural	Distn		True	Predicted I		Predicted II	
Parameter	Family	Parameter	Value	Mean	SD	Mean	SD
LEG Marginal Cost	Log Normal	Mean	0.4	0.4	0.01	0.4	0.02
		Variance	0.01	0.01	0.002	0.009	0.002
LEG Fixed Cost	Log Normal	Mean	3	3.02	0.12	2.89	0.03
		Variance	0.25	0.26	0.09	0.25	0.003
LEG Quality	Normal	Mean	1.5	1.52	0.07	1.47	0.03
		Std. Dev.	0.4	0.37	0.07	0.38	0.02
Price Sensitivity	Log Normal	Mean	3	3.03	0.11	3.05	0.03
		Variance	0.25	0.25	0.05	0.41	0.03
Nest Parameter	Truncated N.	Mean	0.8	0.8	0.02	0.75	0.01
		Std. Dev.	0.03	0.03	0.01	0.02	0.008

Table 2: Monte Carlo

5 Data

To estimate the current model, I use the publicly available and commonly used T100 flight data and the DB1B Origin and Destination database maintained by the Department of Transportation. The DB1B database is a 10% sample of all passenger itineraries updated quarterly that include operating carrier, origin and destination airports, type of service (direct vs. indirect), number of passengers, miles flown, airport presence, air fares, city population, and etc. I use the T100 flight data to mainly identify airline hub status.

In cleaning up the data set, I only included domestic round trips with Economy class tickets (fares ranging from \$50 to \$2000). A market is defined as a non-directional airport pair. Some small carriers are aggregated into one carrier for computational costs considerations: AA, CO, DL, NW, UA, US, other Legacy, WN, other LCC. I also want to exclude services that served less than 15 sampled passengers (150 in actuality) during a quarter. A potential entrant is then defined as a carrier who serves both endpoints of a particular market. Since I assume that each carrier only produces one product in a particular market, I choose the service of the carrier that has the most passengers.

For the current estimation, I restrict the data set to Q2 of 2008 to focus on the effects of Delta-Northwest merger. I then sampled the data set to 1000 airport-pair markets based on market sizes. The sampled relevant markets are relatively large markets, with endpoint cities having more than 500,000 population. Table 3 below shows some summary statistics for key variables of interests.

	Summary Statistics of the Current Sample				
Variable	# of Obs.	Mean	SD	10th Percentile	90th Percentile
Potential Entrant	1000	7.6	1.1	6	9
Legacy PE	1000	6.3	0.9	5	7
LCC PE	1000	1.3	0.6	1	2
Entrants	1000	4.0	1.7	2	6
Direct Entrants	1000	0.9	1.0	0	2
Indirect Entrants	1000	3.0	1.6	1	5
Hub Status	9000	0.19	0.15	0	1
Hub if direct	938	0.63	0.23	0	1
Fare	3978	390.21	92.53	283.98	510.65
Direct Fare	938	403.56	113.61	277.96	564.84
Indirect Fare	3040	386.09	84.58	285.64	497.63
Market Share	3978	0.060	0.089	0.008	0.155
Direct Share	938	0.156	0.138	0.016	0.359
Indirect Share	3040	0.030	0.026	0.008	0.064

Table 3: Summary Statistics

6 Results

For the current estimation, I used 250 simulations for each of the 1000 sampled markets and obtained the estimates for the structural parameters that describe the perceived qualities of product characteristics (demand side) as shown in Table 4. All standard errors are based on a random bootstrap of 100 repetitions. Table 5 presents other demand-side parameters including the price sensitivity coefficient α, nesting parameter σ that quantifies within-group correlation, and the indirect penalty which describes the difference between the perceived qualities of the same product (for both Legacy and LCC carriers) serving direct and indirect. In Table 6, we show estimates of marginal and fixed costs parameters for different types of services.

With these estimates, Table 7 presents a selected sample (to be consistent with the example above) of all the moments associated with AA in the group (out of the 14 moment groups) where there are 7 potential entrants and above-median distance. There are 139 observations out of the total 1000 observations that fall in this group, and thus the difference between the moments of simulations and data moments is weighted by 0.139 in the objective function in the optimization process.

Among these estimates, hub dominance (Table 4) gives carriers a big boost in their perceived quality among consumers. Price sensitivity (Table 5) is fairly sensible and increases in both magnitude and variance with distance. Penalty in perceived quality of product decreases with distance, which reflects the fact that people are more willing to take indirect flights when the travel distance is long. On the supply side (Table 6), hub status always reduces fixed costs, but increases marginal costs for LCC carriers and indirect marginal costs for Legacy carriers. This is probably the result of the strategic entry and selection of hubs of LCC carriers. Once we introduce some exogenous cost shifters into the model in future research, this might turn out differently. All marginal costs go up with longer distance, while most fixed costs go down with longer distance.

Qualities					
Legacy Carriers			LCC Carriers		
	Mean	Std. Dev.		Mean	Std. Dev.
AA	0.6579	(0.0453)	WN	1.5553	(0.1031)
CO	-0.0436	(0.0499)	Other LCC	0.4522	(0.0698)
DL	0.7842	(0.0431)	Distance	-0.0864	(0.0326)
NW	0.3447	(0.0444)	Hub	-0.0908	(0.1240)
UA	0.8104	(0.0468)	Short Std.	0.7815	(0.0318)
US	0.4408	(0.0457)	Long Std.	0.6526	(0.0485)
Other LEG	-0.1747	(0.0666)			
Distance	0.0127	(0.0177)			
Hub	0.9355	(0.0435)			
Short Std.	0.6945	(0.0129)			
Long Std.	0.8015	(0.0199)			

Table 4: Estimates of Quality Parameters

Other Demand Parameters								
Price Sensitivity α			Nesting Parameter σ			Indirect Penalty		
	Mean	Std. Dev.		Mean	Std. Dev.		Mean	Std. Dev.
Constant	0.3029	(0.0100)	Mean	0.5339	(0.0072)	Constant	1.0153	(0.0190)
Distance	0.0879	(0.0055)	Std.	0.1343	(0.0068)	Distance	-0.1653	(0.0084)
Short Var.	0.0062	(0.0008)				Std.	0.3132	(0.0047)
Long Var.	0.0255	(0.0030)						

Table 5: Estimates of Other Demand Parameters

Cost Parameters					
		Marginal Costs, Direct			
	Legacy Carriers			LCC Carriers	
	Mean	Std. Dev.		Mean	Std. Dev.
Constant	2.0966	(0.0508)	Constant	1.1289	(0.1109)
Distance	0.5566	(0.0246)	Distance	0.4708	(0.0428)
Hub	-0.2506	(0.0664)	Hub	0.3934	(0.1029)
Std.	0.9705	(0.0155)	Std.	0.7212	(0.0247)
		Marginal Costs, Indirect			
	Legacy Carriers			LCC Carriers	
	Mean	Std. Dev.		Mean	Std. Dev.
Constant	1.2205	(0.0403)	Constant	1.7031	(0.1374)
Distance	0.7669	(0.0180)	Distance	0.6847	(0.0505)
Hub	0.2004	(0.0458)	Hub	0.2162	(0.1553)
Std.	0.7963	(0.0170)	Std.	1.1068	(0.0448)
		Fixed Costs, Direct			
	Legacy Carriers			LCC Carriers	
	Mean	Std. Dev.		Mean	Std. Dev.
Constant	3.7276	(0.0378)	Constant	4.5748	(0.0932)
Distance	0.1223	(0.0158)	Distance	-0.1836	(0.0394)
Hub	-0.1168	(0.0394)	Hub	-0.477	(0.1125)
Std.	0.4848	(0.0210)	Std.	0.6946	(0.0600)
		Fixed Costs, Indirect			
	Legacy Carriers			LCC Carriers	
	Mean	Std. Dev.		Mean	Std. Dev.
Constant	0.6718	(0.0220)	Constant	0.4815	(0.0367)
Distance	-0.0714	(0.0063)	Distance	-0.0501	(0.0094)
Std.	0.525	(0.0543)	Std.	0.2362	(0.0626)

Table 6: Estimates of Quality Parameters

Sample Moments Fit			
7 Potential Entrants, Long Routes			
Moments	# of Obs.	Data	Predicted
AA_entry_direct_hub	139	0.0288	0.0143
AA_entry_indirect_hub	139	0.1655	0.1659
AA_price_hub	139	0.8994	0.9468
AA_share_hub	139	0.0095	0.0222
AA_entry_direct_non-hub	139	0.0072	0.0027
AA_entry_indirect_non-hub	139	0.5324	0.4121
AA_price_non-hub	139	2.1722	2.1692
AA_share_non-hub	139	0.0230	0.0421

Table 7: Sample Moments Fit

7 Counterfactuals

With the current estimated model, I will investigate the merger endogeneity much in a similar fashion as the Cournot model at the beginning of the paper by conducting the following counterfactuals.

Consider the route from Atlanta to Detroit (ATL-DTW market) in 2008 Q2. In this market, as shown in Table 8, there are 5 incumbents and 2 potential entrants. All 7 carriers participate in the entry game, in which we define a natural order: DL, NW, FL, US, UA, AA, CO, based on their hub status, type of service, and market share (again, I can make this assumption because the game order only matters to some extent - there are on average less than 2 equilibria among all possible orders). Given the five incumbents' observed prices and market shares, I can solve for their implied qualities and marginal costs associated with their type of service (e.g. I can only solve for direct qualities for DL because DL is flying direct on that route) by minimizing the difference between model-predicted and observed prices and market shares. I then draw the rest of the parameters from the estimated distributions. For now, I keep α and σ at their respective mean (so it is easier to collect useful games in the following steps). Then I first simulate 5000 games with the implied parameters and parameters drawn from estimated distributions. Out of the 5000 simulated games, I collected 1853 games that matched the actual outcome of the entry game, i.e. Northwest entered as direct, Delta entered as direct, AirTran entered as direct, United entered as indirect, US Airways entered as indirect, and American and Continental did not enter.

ATL-DTW Market in 2008 Q2				
Carrier	Hub	Service	Fare	Passengers
Delta (DL)	Y	Direct	334.42	15960
Northwest (NW)	Y	Direct	315.77	19210
AirTran (FL)	Y	Direct	263.49	9870
US Airways (US)	N	Indirect	399.41	330
United (UA)	N	Indirect	230.44	160
American (AA)	N	Potential	-	-
Continental (CO)	N	Potential	-	-

Table 8: Market Summary I

I consider these 1853 games as my base set (call it set A) of market simulations, out of which I can simulate mergers. To simulate a merger between Northwest and Delta, I take out Northwest, give Delta the mean marginal costs, qualities (both direct and indirect) of the two. Keeping everything else the same (same move orders and parameter draws), I re-simulate these 1853 games and store the results in set B. Then I simulate two mergers between FL and US: one conditional on set A and store the results in set C, the other conditional on set B and store in set D.

Similar to the motivating example in the introduction, I am interested in the incentive for firms to merge, which is measured in the profitability of the merger, i.e. the change of profits of the merging firms before and after the merger. Specifically, let

$$\pi_1 = \pi(\text{FL}|\text{DL, NW, FL, US, others}) + \pi(\text{US}|\text{DL, NW, FL, US, others}) \tag{22}$$

$$\pi_2 = \pi(\text{FL-US}|\text{DL, NW, FL-US, others}) \tag{23}$$

$$\pi_3 = \pi(\text{FL}|\text{DL-NW, FL, US, others}) + \pi(\text{US}|\text{DL-NW, FL, US, others}) \tag{24}$$

$$\pi_4 = \pi(\text{FL-US}|\text{DL-NW, FL-US, others}) \tag{25}$$

$$I = (\pi_4 - \pi_3) - (\pi_2 - \pi_1) \tag{26}$$

$(\pi_2 - \pi_1)$ is the incentive for AirTran and US Airways to merge in the current market.

$(\pi_4 - \pi_3)$ is the incentive for them to merge given that Delta and Northwest completed their merger in the market. Therefore, I is the extra incentive for AirTran and US Airways to merge provided by the DL-NW merger.

Counterfactual Results: ATL-DTW				
	Min	Max	Mean	% Positive
π_1	5.34	14.12	11.57	100%
π_2	5.33	31.78	12.88	100%
π_3	22.97	31.74	29.17	100%
π_4	23.41	54.10	31.48	100%
$(\pi_2 - \pi_1)$	-0.22	19.17	1.31	57%
$(\pi_4 - \pi_3)$	-5.50	27.00	2.31	89%
I	-5.55	8.38	1.00	98%

Table 9: Counterfactual Results I

Table 9 presents the counterfactual results, in which the last column means what percentage of the 1853 game results are positive. Out of 1853 games, only 57% of the FL-US mergers are profitable initially. After DL and NW merged, however, 89% of the FL-US mergers would be profitable. About 33% of the FL-US mergers changed from non-profitable to profitable after the DL-NW merger, while only 0.7% of the FL-US mergers changed from profitable to non-profitable. Overall, 98% of the extra incentive to merge for FL and US from the DL-NW merger are positive and thus, the DL-NW merger would at least to some extent increase the probability of a merger between FL and US.

I then perform the same counterfactual analysis on a different market with more relevant carriers in terms of current industry focus. Table 10 presents a market summary of the ABQ-CLT market just like Table 8. In simulating the market to match the market outcome this time, however, I was only able to collect 526 games out of 20,000 simulations. Then out of these 526 games, I again simulate a first merger between Delta and Northwest and a second merger between American and US Airways, and study how the DL-NW merger affects the potential AA-US merger, which is more in line with what is happening in the news. Table 11 shows the results I get with this counterfactual. Initially, only 21% of the

US-AA mergers are profitable, while after the DL-NW merger, there are 40% of them that are profitable. 19.2% of the US-AA mergers changed from non-profitable to profitable after the DL-NW merger, while only 1 out of 526 (0.2%) changed in the other direction. Finally, 89% of the extra incentive for US and AA to merge from the DL-NW merger are positive, suggesting the positive correlation between mergers.

ABQ-CLT Market in 2008 Q2				
Carrier	Hub	Service	Fare	Passengers
US Airways (US)	Y	Indirect	459.49	390
Northwest (NW)	Y	Indirect	328.89	160
American (AA)	N	Indirect	429.12	790
Dleta (DL)	N	Indirect	469.08	520
Continental (CO)	N	Potential	-	-
United (UA)	N	Potential	-	-

Table 10: Market Summary II

Counterfactual Results: ABQ-CLT				
	Min	Max	Mean	% Positive
π_1	0.25	1.28	0.90	100%
π_2	0.20	0.99	0.77	100%
π_3	0.05	1.49	1.10	100%
π_4	0.34	1.30	1.06	100%
$(\pi_2 - \pi_1)$	-0.71	0.53	-0.13	21%
$(\pi_4 - \pi_3)$	-0.77	0.72	-0.04	40%
I	-0.41	0.58	0.09	89%

Table 11: Counterfactual Results II

8 Conclusions

In this paper, I constructed and estimated a preliminary structural model of the U.S. airline industry that takes into account the entry selection bias based on firms' costs and qualities. In estimating demand, I incorporated a standard discrete-choice nested logit model for differentiated products market. The structural model is estimated with the method of simulated moments and an importance sampling estimator. Finally, I drew my conclusion upon this model by conducting counterfactual analysis of merger simulations and revealing some empirical evidence of positive correlation between consecutive mergers.

Specifically, from a firm's perspective, I found that a potential merger's profitability in a given market is usually substantially augmented by a previous merger. In spirit of recent news, what I found means that, given Delta and Northwest has completed their merger in many markets (airport-to-airport routes), there is now a much higher incentive for other carriers in the same markets to merge, e.g. United and Continental, and American and US Airways, which to some extent explains the recent series of airline mergers.

This paper contributes to the current existing literature in the following ways. Merger analysis has long been done in a static model based on the assumption that mergers are exogenous. Studies of dynamic models in differentiated product markets like the U.S. airline market have been extremely limited to only theoretical analysis. This paper presents empirical results from repeatedly solving a static model, suggesting the endogenous nature of airline mergers. Another interesting aspect of this paper is that it is based on a selective entry model, where the selection bias of entry is addressed and adjusted, which would in turn affect the post-entry competition in the market.

This paper also has important implications to the antitrust authorities. Traditional myopic antitrust policies only focus on the simulated welfare effects of the current merger under review. Nocke and Whinston (2010) suggests that, in a Cournot setting, myopic antitrust policies work as well as any forward-looking policies. However, in a differentiated product market with Bertrand competition, strong assumptions about firms' costs have to be made in order to reach the same conclusion. Thus, our exercise based on the selective entry model is in place to suggest that in a forward-looking antitrust policy, antitrust authorities have to be more cautious about approving airline mergers due to the entry selection bias and the potential domino effect induced by the current merger.

Going forward from the current paper, there are several directions that I would like to further explore. First and foremost, I am eager to attempt to develop a fully functional dynamic model of the U.S. airline industry that takes into account the dynamic interplay of merger, investment, entry and exit much similar to Gowrisankaran (1999). Second, the current model is fully capable of more advanced identification methods such as generalized method of moments proposed by Andrews and Soares (2010), by which I might obtain more accurate estimates. Third, several new model specifications will be introduced such as carrier aggregation, cost shifters, and etc. Fourth, a model will be estimated with a data set up to 2011 Q3 to investigate effects of Delta-Northwest merger, United-Continental merger, and potential effects of American-US Airways merger.

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