# Network Competition in the Airline Industry: A Framework for Empirical Policy Analysis*

Zhe Yuan†

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†Department of Economics, University of Toronto. 150 St. George Street, Toronto ON M5S 3G7, Canada. z.yuan@mail.utoronto.ca.

**Abstract**

This paper studies network competition in the US airline industry. I propose a structural model of oligopoly competition where the set of endogenous strategic decisions of an airline includes its network structure (i.e., the set of city-pairs where the airline operates nonstop flights), capacities (i.e., flight frequency and number of seats) for every city-pair where they are active, and prices for nonstop and one-stop routes. In this paper, I propose and implement simple methods for the estimation of the model and for the evaluation of counterfactual experiments that avoid the computation of an equilibrium. The estimation of the model shows that ignoring the endogenous network structure in this industry implies a substantial downward bias in the estimates of marginal revenues and marginal cost of capacity. The estimated model is used to evaluate the effects of the counterfactual entry of JetBlue into the segment between Atlanta and New York. I find that the JetBlue entry into this city-pair (segment) would have substantial competition effects in other city-pairs, even in those that that are not directly connected to Atlanta or New York.

**Key words**: Airline industry, Entry models, Network competition, Moment inequalities, Counterfactual experiments
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*An ideal model for the study of airline networks would involve an explicit model of firm profitability as a function of its entire network and the network of its competitors.*

*Steven Berry, Econometrica 1992*

# 1 Introduction

The U.S. airline industry helps drive nearly $1.5 trillion of the U.S. economic activity (close to 10% U.S. GDP) and relates to more than 11 million jobs. A relatively small number of airlines compete in this industry. One of the most important strategic choices for an airline is the decision of the city-pairs where to operate direct flights. This entry decision determines the set of routes[1] that the airline serves and whether these routes are operated with direct service or flights with connections. There are substantial interdependence and synergies between an airline's entry decisions at different city-pairs. Some of these synergies have to do with economies of scale and scope at the airline-airport level, e.g., the additional cost of operating flights between cities A and B can be smaller if the airline already operates other routes in airports A or B. However, the most obvious interdependence between the entry decisions at different city-pairs is that they determine the set of routes with connections (or stops) that the airline provides. For instance, consider an airline that operates direct flights between cities A and B, and has to decide whether to start operating flights either between cities B and C or between C and D. Suppose that the operating cost and the demand of these new routes are similar. We should expect the airline will choose to operate between B and C rather than between C and D simply because the first choice will also attract new clients who want to travel between A and C. This source of synergies is very important in the airline industry. It is well known that airlines concentrate their operations within a few airports, or hubs. As a result, in the US airline industry, one-stop service accounts for more than a quarter of total air travel in terms of both revenue and number of passengers.

This paper builds on an important literature on structural models in the airline industry pioneered by Berry (1992).[2] The papers in this literature have answered important questions in this industry related to demand, cost structures, strategic interactions and entry deterrence. However, most models of entry in this literature have taken into account these interconnections in service across city-pairs in a relatively simple way and they have treated them as

[1] A route is a directional trip from an origin city to a destination city.

[2] The growing literature includes Berry (1990), Berry (1992), Brueckner and Spiller (1994), Berry, Carnall, and Spiller (2006), Williams (2008), Ciliberto and Tamer (2009), Snider (2009), Berry and Jia (2010), Aguirregabiria and Ho (2012), Ciliberto and Williams (2014), Ciliberto and Zhang (2014), Gedge, Roberts, and Sweeting (2014), Kundu (2014), Onishi and Omori (2014), Blevins (2015) and Gayle and Yimga (2015).

exogenously given. Ignoring these interconnections has been an approach in the literature.[3] Other approaches have incorporated in the profit function variable(s) that represents airline presence in the origin-destination airports (e.g., number of connections) and have treated these variables as exogenously given.[4] Other papers have treated the entry decision in the same way regardless of whether it was "direct entry" (with non-stop flights) or indirect entry (with stop flights).[5]

I develop a model of network competition in the airline industry. Airline competition is represented as a three-stage game in which network structures, capacities, prices and quantities for every nonstop and stop route are endogenized. In the first stage, each airline chooses its network structure, i.e., the set of city-pairs for which it operates non-stop flights. Second, airlines decide their capacities (flight frequencies and number of seats) for every city-pair where they are active. In the third stage, airlines compete in prices taking their networks and capacities as given. Airlines receive revenues from both nonstop and connecting services. The model incorporates the network feature of airline competition in two ways: first, when airlines choose their network structures, they decide which cities to connect with using direct flights and which city-pairs to provide stopovers in. Second, airlines consider synergies across city-pairs when building capacity. If an airline increases its nonstop capacities in a city-pair, it may carry more passengers not only in nonstop service but also potentially in stop service with this city-pair as part of the journey. Ignoring the network structure in this industry can imply a substantial downward bias in the estimates of revenues and cost structure.

This network competition model can be used to investigate important questions on the airline industry that cannot be studied using previous models where network structure is ignored or is exogenously given. These research questions include but are not limited to (a) how entry into a city-pair (segment)[6] from a low cost carrier impacts the network structure and (b) how networks will evolve if two airlines merge. Entry into a segment from a low cost carrier will affect not only the segment where entry happens, but also other segments connected to this segment because the low cost carrier can now carry connecting passengers through this segment. On the other hand, incumbents may re-optimize their

[3] Berry (1992), Ciliberto and Tamer (2009), Ciliberto and Zhang (2014), Onishi and Omori (2014) and Blevins (2015) specify the game to be played in a single market: An entry decision in a market is independent of entry decisions in other markets.

[4] Aguirregabiria and Ho (2012) use the number of cities (or sum of population) that an airline serves from a city as measure of hub-size.

[5] Berry (1992) and Ciliberto and Tamer (2009) define market as origin and destination city-pair regardless of whether there is a connection.

[6] A city-pair is also referred to as a segment when I analyze nonstop service in a city-pair. Segment is commonly used in the airline industry.

network structures due to reduction in motivation to creating one-stop capacity and strategic interactions. Finally, network structure in the other part of the network may also be affected. However, these properties are not maintained in previous models. If all city-pairs are treated as isolated markets, the effect of entry into a city-pair is restricted to this city-pair and other city-pairs will not be affected. For merger analysis, suppose two airlines merge into a new airline. The optimal network of the new airline is not simply a combination of the two pre-merger networks. Changes will occur within the network such as capacity redistribution or even hub reallocation. However, if synergies across city-pairs are ignored, the new airline will build 'locally' optimal capacity in each city-pair but not 'globally' optimal hub-and-spoke network. Answers to these questions have important policy implications. The competition authorities are interested in the evolution of networks, for instance, how connecting service between two small cities is affected due to airline mergers or entry from an airline.

This paper contains four main contributions. First, I construct and estimate an equilibrium model of network competition where airlines compete in three-stages. The model endogenizes network structure, capacities, prices and quantities for every nonstop and stop route and is estimated without solving for an equilibrium even once. Second, this paper implements a moment inequality method to obtain consistent estimator of the fixed cost under mild conditions. The empirical framework is based upon the necessary conditions of pure strategy Nash equilibrium which avoids the solution of the model and is computationally feasible. In order to deal with the selection issue associated with the error term, I extend and implement the bound estimator proposed in Aguirregabiria, Clark, and Wang (2014). Third, I propose a novel algorithm to evaluate the impact of airline entry which can be used to analyze how airline entry into one segment affects the entire network. Fourth, I propose and construct measures of both nonstop and one-stop capacities in the airline service. These variables are incorporated as important endogenous choices in the model. The technological relationship between one-stop capacity and nonstop capacity is also estimated.

As far as I know, this is the first paper that estimates a game of network competition that endogenizes firms' prices, quantities, capacities, and of course, network structure. Estimation of a three-stage model of network competition is challenging. Previous literature simplified the network structure and network competition due to extremely high dimensionality in strategy space. The number of strategies of an airline increases exponentially with the number of city-pairs.[7] It is computationally infeasible to solve for an equilibrium of the model with such high-dimensional space. Methods in the estimation of complete

[7] In a world with 87 cities, the number of possible strategy profiles is $2^{87\times 86/2} \simeq 1.4\times 10^{1126}$. The number of feasible network configurations with 13 airlines is $2^{13\times 87\times 86/2} \simeq 10^{14640}$.

information game such as Berry (1992) and Ciliberto and Tamer (2009) require solving for an equilibrium of the model or solving for the upper and lower bounds of choice probabilities. However, computation of an equilibrium in the network competition game is infeasible for a simple entry game even with only a small number of players. Jia (2008) solves for a network competition equilibrium with two players. Her method, nonetheless, doesn't apply to the US airline industry where more than two major players compete with each other. Ellickson, Houghton, and Timmins (2013) estimate a network competition game among the retail chains without solving for an equilibrium. However, their approach to construct "swapping" pairs to eliminate common sources of unobserved heterogeneity is impractical for an airline industry with hub-and-spoke networks. Moreover, it is impossible to estimate conditional choice probabilities with high-dimensional strategy space. Assumptions have been proposed to reduce the dimensionality of strategies. Aguirregabiria and Ho (2012) assume in each city-pair there is a local manager for each airline who makes entry decision independently. Under their assumptions, each local manager chooses only 1 out of 2 strategies. Other papers such as Xu (2011) and Sheng (2012) divide the entire network into relatively uncorrelated sub-networks. However, these assumptions are not appropriate because I am interested in the synergies across entry decisions into different city-pairs and consider an endogenous network structure.

In the current paper, I propose and implement simple methods for the estimation of the model and for the evaluation of counterfactual experiments that avoid the computation of an equilibrium. I first estimate airlines' revenues and variable costs as functions of their capacities at every city-pair. The estimation of this part of the model is based on marginal conditions of optimality for capacity choices. Then, I estimate fixed costs of entry by exploiting the inequality restrictions implied by airlines' best response conditions in the entry game.

For the counterfactual experiments, I am interested in how entry into a segment from a low cost carrier impacts the network structure. Airline entry into one segment has an impact on not only the segment where entry happens[8] but also the other part of the network. There are three tiers of effects. For the first-tier effect, a new entrant will choose optimal capacity and incumbents will respond to the entry within the affected segment. For the second-tier effect, the low cost carrier increases its capacity in the segments connected to the affected segment.[9] On the other hand, other incumbents may re-optimize their capacities in the segments connected to the affected segment. For the third-tier effect, airlines re-optimize their capacities in the segments that are not connected to the affected segment. I propose

[8]Also referred to as affected segment.

[9]It can now carry one-stop passengers with the affected segment as part of the journey.

two different approaches to evaluate these three tiers of effects. In the first approach, I propose an order of all airline-segment pairs and evaluate a series of best responses of the airlines segment by segment. All airline-segment pairs are divided into three groups which correspond to the three tiers of effects. Within each group, responds in segments connected to a larger city will be evaluated first followed by segments connected to smaller cities. Within each segment, airlines with larger capacity respond first followed by smaller players. In the second counterfactual, I order all segments the same way as in the first counterfactual and compute an equilibrium in each local segment sequentially. Follow Berry (1992), I assume that firms can be ranked in order of profitability, which guarantees the existence of an equilibrium[10] in each city-pair. In each segment, I order incumbents by decreasing capacity and then potential entrants by decreasing potential profitability. The equilibrium in each segment is constructed by letting the firms enter in this order until the next firm would be unprofitable. In both counterfactuals, the network structures of all airlines in all other segments are treated as exogenous when I compute the best response or entry decision of an airline in a segment. Network structures are updated every time the network configuration of an airline changes. These two counterfactuals provide us frameworks to understand how change in one city-pair impacts the entire network.

In the empirical analysis, I find that airlines' marginal revenues and costs are underestimated by around a third without taking into account the network structures of the airlines. In the counterfactual experiment, I use the estimated model to evaluate the effects of the counterfactual entry of JetBlue on Atlanta-New York segment. I find that on a daily basis, JetBlue schedules 1028 seats[11], carries 414 nonstop passengers, and collects \$62105 from nonstop service between Atlanta and New York. I also find that JetBlue's entry into the Atlanta-New York segment will create substantial competition affecting other airlines' profit, both within this segment and at other city-pairs. For instance, Delta's capacity in Atlanta-New York will decrease by 666 seats. In those segments which have either Atlanta or New York as an endpoint, JetBlue will build more capacity because it can carry more connecting (stop) passengers. I estimate that revenue could increase by 21% if interconnections across city pairs are examined. There is significant competition effects on city-pairs that are not directly related to either Atlanta or New York. I find that these "third-tier" effects are heterogeneous across segments, with capacity increments in some city-pairs and capacity reductions in others. Explanations are provided for these heterogeneous effects.

This paper builds on and contributes to at least three streams of literature. The first is the research on the entry game and airline competition pioneered by Bresnahan and Reiss (1991)

[10]This is an equilibrium if the network structures in the other part of the network are treated as exogenous.
[11]1028 seats are equivalent to 10 flights on a daily basis.

and Berry (1992). Most entry models abstract from the interconnections across markets with several exceptions: Seim (2006) studies the spatial competition in the video rental industry. She endogenizes store locations and estimates an entry game of spatial competition. Zhu and Singh (2009) employ a more flexible model of spatial competition and allow for more general heterogeneity across firms. Jia (2008) analyzes the network entry game between Wal-Mart and Kmart over 2065 locations. She considers a specification of the profit function which implies the supermodularity of the game and facilitates the computation of an equilibrium. Her model allows for the economics of density but ignores cannibalization effects and spatial competition between stores of different chains at different locations. Nishida (2014) extends Jia's model by allowing multiple stores in the same location and incorporates spatial competition. Holmes (2011) analyzes the spatial structure of Wal-Marts' national network to infer the importance of economics density. Ellickson, Houghton, and Timmins (2013) and Aguirregabiria, Clark, and Wang (2014) estimate network economics in retail chains and banking industry, respectively.

For the research in the airline industry, previous studies have discussed the benefits of airline hubs, including cost efficiency (Berry (1990), Berry (1992), Brueckner and Spiller (1994), Berry, Carnall, and Spiller (2006), Ciliberto and Tamer (2009), Aguirregabiria and Ho (2012)), demand factors (Berry (1990), Berry (1992), Aguirregabiria and Ho (2012)), and strategic entry deterrence (Hendricks, Piccione, and Tan (1997), Hendricks, Piccione, and Tan (1999) , Aguirregabiria and Ho (2012)). However, very few structural models of entry in the airline industry incorporate synergies between an airline's entry decisions at different city-pairs. The importance of synergies in entry decisions and airline network in airline competition has been discussed in the theoretical work of Hendricks, Piccione and Tan (1995, 1997, 1999). Aguirregabiria and Ho (2012) is the first paper which empirically estimates network competition game and separates the contribution of demand, costs and strategic factors. Benkard, Bodoh-Creed, and Lazarev (2010) estimate the dynamic change in the airline industry after the merger. Ciliberto and Williams (2014) analyze the pricing competition and conduct of firms who have multimarket contact with their competitors. Gedge, Roberts, and Sweeting (2014), Lazarev (2013) and Williams (2013) analyze the pricing strategy of the airlines. The first paper develops a dynamic model with persistent asymmetric information, where an incumbent has incentives to signal its costs to a potential entrant and deter entry. The other papers two analyze the intertemporal price discrimination and welfare effect in the airline industry.

This paper also relates to other research in the network economics such as Xu (2011) and Leung (2014). Xu (2011) studies social interactions in a game theoretic model and considers a network stability property where the dependence between two players' decisions declines with their network distance. Leung (2014) establish a law of large numbers and central limit theorem for a large class of network moments. Uetake (2012) investigates the network structure of venture capitalists based on co-investments, and the effects of network structure on investment performance.

The rest of the paper is organized as follows: I first propose a model of airline competition in section 2. Section 3 describes the data sets and the construction of the working sample. Section 4 presents the empirical strategies and the assumptions. Section 5 presents the empirical results. Section 6 discusses the counterfactual analysis. I summarize and conclude in Section 7.

# 2 Model

From the point of view of airline operation and competition, a market is a non-directional city-pair in which airlines provide regular commercial aviation service. Different types of service may be provided in a city-pair. Service in a city-pair without a stop is referred as nonstop service and service between two cities with a stop in a third city is referred as one-stop service.[12] All nonstop and one-stop services form the network of an airline. In a world with $C$ cities[13], there are $M = \frac{C\times(C-1)}{2}$ non-directional city-pairs. City-pairs are indexed by $ij$ with $i$ and $j$ representing the two endpoints. A total of $N$ airlines make entry decisions into these $M$ segments simultaneously. Airlines are labeled with $n$.

My model is a game of network competition such as models of competition between retail networks in Jia (2008), Ellickson, Houghton, and Timmins (2013), and Aguirregabiria, Clark, and Wang (2014).[14] However, the game of competition between airline networks has some important distinguishing features with respect to previous models of retail networks. The possibility of stop service is an important feature of an airline network that does not appear in retail networks. One-stop service is a significant source of airline revenue and

[12] I restrict the model and analysis to nonstop and one-stop services because services with two or more stops consist of less than 3% of air travel. However, the model and estimation method can be easily extended to the cases with more than one-stop.

[13] I follow the approach in Berry (1992) and define markets as city-pairs instead of airport pairs.Berry, Carnall, and Spiller (2006) and Aguirregabiria and Ho (2012) also define markets as city-pairs. Borenstein (1989) and Ciliberto and Tamer (2009) define markets as airport pairs. The implicit assumption is that airports in the same city are perfect substitutes in both demand and supply. In this paper, competition between airports is ignored.

[14] I consider a static model rather than a dynamic model. If the profit function in the static game is treated as present value of the dynamic game under the assumption that there will not be changes in the network and the adjustment cost function, the static game is equivalent to a dynamic game. My paper is not the only paper that models a complicated dynamic game as a static game. Other papers include Jia (2008) and Ellickson, Houghton, and Timmins (2013) and Aguirregabiria, Clark, and Wang (2014).

it introduces an important interconnection between the decisions to operate at different city-pairs. I construct a game of airline network competition that endogenizes both nonstop and one-stop services.

## 2.1 Three-stage Model of Airline Competition

In this subsection, I propose a model of airline competition where airlines compete in three stages.[15] In the first stage, each airline chooses its network structure. Second, airlines decide their capacities for every city-pair where they are active. In the third stage, airlines compete in prices taking their networks and capacities as given.

### 2.1.1 First Stage

In the first stage, the entry or network game, each airline determines its network structure. Each airline makes entry decisions into all $M$ city-pairs. I denote $a_{nij} = 1$ if airline $n$ enters into segment $ij$, and $a_{nij} = 0$ otherwise. Let $FC_n$ be the total entry cost (or fixed cost) of airline $n$. If entry costs are additively separable across segments and $FC_{nij}$ denotes entry cost of airline $n$ into segment $ij$, then the total entry cost is $FC_n = \frac{1}{2} \sum_i \sum_{j \neq i} FC_{nij} \times 1 \left[ a_{nij} = 1 \right]$.

### 2.1.2 Second Stage

In the second stage, the capacity stage, airlines decide their capacities (flight frequencies and number of seats) for every city-pair where they are active. Specifically, airlines will determine the type of aircrafts and the time of departures and arrivals in all segments. The total variable cost of building capacity which airline $n$ incurs: $VC_n^S$ including costs of negotiating schedules with airports, setting up flights, counters and recruiting crews. If the total variable cost of building capacity in all city-pairs is additively separable across city-pairs, and $VC_{nij}^s$ denotes total variable cost of building capacity in city-pair $ij$, then total variable cost of building capacity in the network $VC_n^S = \frac{1}{2} \sum_i \sum_{j \neq i} VC_{nij}^S$.

Variable cost and revenue depend on the airline's capacity at every city-pair. I distinguish two different variables that represent capacity in a segment: nonstop capacity ($s_n^{NS}$), and one-stop capacity ($s_n^{OS}$). Airline $n$'s nonstop capacity in segment $ij$ ($s_{nij}^{NS}$) represents the

[15] Alternatively, I can aggregate stage 1 and stage 2 in a single stage. In this stage, an airline chooses capacity and it is possible to choose capacities equal to zero. However, the current three-stages has several advantages. Stage 1 is the extensive margin in the capacity choice, and stage 2 is the intensive margin in the capacity choice. Though I could describe these decisions in a single stage, it is very convenient to describe the model and methods to separate the extensive and intensive margins in two stages.

maximum number of passengers airline $n$ can carry with nonstop service in segment $ij$. This is a standard concept of capacity and it depends on the number of scheduled flights and the aircraft sizes used between the two cities. The concept of one-stop capacity is a little bit more subtle. It represents the airline's ability to connect passengers between two city-pairs. More specifically, airline $n$'s one-stop capacity in city-pair $ij$ through city $k$ ($s_{nij}^{OS(k)}$) represents the maximum number of passengers airline $n$ can carry between cities $i$ and $j$ with a connection at $k$. One-stop capacity depends on the number of flights and the aircraft sizes but also on the departure and arrival schedules such that connections are feasible. Airline $n$'s total one-stop capacity in city-pair $ij$ is $s_{nij}^{OS} = \sum_k s_{nij}^{OS(k)}$, and it measures the maximum number of passengers airline $n$ can carry between city $i$ and city $j$ with one stop or connection, whatever is the connecting city. The details how one-stop capacities are constructed are described in the Section 3.2.4.

The capacity of airline $n$ in city-pair $ij$: $\mathbf{s}_{nij}$ contains capacities in both nonstop and one-stop services, i.e. $\mathbf{s}_{nij} = \left\{s_{nij}^{NS}, s_{nij}^{OS}\right\}$. Airline $n$'s capacities can be represented as $\mathbf{s}_n = \left\{\mathbf{s}_{nij} : \forall i, \forall j \; and \; i \neq j\right\}$. Similarly, capacities of all competitors in segment $ij$ are denoted as $\mathbf{s}_{-nij} = \left\{s_{n'ij}^{NS}, s_{n'ij}^{OS} : n' \neq n\right\}$ and the capacities of all competitors in the network are denoted as $\mathbf{s}_{-n} = \left\{\mathbf{s}_{n'ij} : \forall i, \forall j, i \neq j \; and \; n' \neq n\right\}$.

### 2.1.3 Third Stage

In the third stage, the pricing game, given networks and capacities determined by the previous stages, airlines compete in prices and receive revenues from both nonstop and one-stop services. Specifically, in city-pair $ij$, given own capacity: $\mathbf{s}_{nij}$ and the capacity of the competitors $\mathbf{s}_{-nij}$, airline $n$ sets prices in nonstop service ($P_{nij}^{NS}$) and one-stop service ($P_{nij}^{OS}$) , respectively.[16] And equilibrium quantity in nonstop service ($Q_{nij}^{NS}$) and one-stop service ($Q_{nij}^{OS}$) will be realized afterwards. The demand model can be a standard model of discrete choice as described in Appendix A.

Indirect revenue functions $R_{nij}^{NS}\left(\mathbf{s}_{nij}, \mathbf{s}_{-nij}\right)$ and $R_{nij}^{OS}\left(\mathbf{s}_{nij}, \mathbf{s}_{-nij}\right)$ represent the revenues airline $n$ collects from nonstop and onestop services in city-pair $ij$, respectively. And $R_n^{NS}\left(\mathbf{s}_n, \mathbf{s}_{-n}\right)$ and $R_n^{OS}\left(\mathbf{s}_n, \mathbf{s}_{-n}\right)$ represent the total revenues airline $n$ collects from its nonstop and onestop services, respectively. Revenue will be the product of price[17] and quantity.

[16] Here I assume in each city-pair, airlines charge a uniform price for its nonstop service and another uniform price for its one-stop service, which is common in the literature.

[17] Following the literature, I suppose one airline charges one unique price for nonstop service and one unique price for one-stop service in a market.

For airline $n$, total revenue from nonstop service sums up revenue in all city-pairs.

$$R_n^{NS}(\mathbf{s}_n, \mathbf{s}_{-n}) = \frac{1}{2}\sum_i \sum_{j \neq i} R_{nij}^{NS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij})$$

where $R_{nij}^{NS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij}) = P_{nij}^{NS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij}) \times Q_{nij}^{NS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij})$. Total revenue from one-stop service is defined similarly.

Total revenue of airline $n$ equals the sum of revenues from both nonstop and one-stop services

$$R_n(\mathbf{s}_n, \mathbf{s}_{-n}) = R_n^{NS}(\mathbf{s}_n, \mathbf{s}_{-n}) + R_n^{OS}(\mathbf{s}_n, \mathbf{s}_{-n}).$$

An important feature of the model is that, revenues $R_{nij}^{NS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij})$ and $R_{nij}^{OS}(\mathbf{s}_{nij}, \mathbf{s}_{-nij})$ depend not only on nonstop capacity in the city-pair $ij$: $s_{nij}^{NS}$ and $s_{-nij}^{NS}$ but also one-stop capacity in the city-pair $ij$: $s_{nij}^{OS}$ and $s_{-nij}^{OS}$. More importantly, schedules and capacities of the direct flights in the other part of the network determine the one-stop capacity in the city-pair $ij$. Thus, revenue in one city-pair actually depends on capacity allocations in the other part of the network. This is one source of network effect.

To better understand this network effect, let's consider the following case: suppose (a) I can separate the services in city-pair $ij$ into two groups of products: non-stop service and one-stop service; (b) I assume that the demand systems for these groups of products are perfectly separable (i.e. these are two uncorrelated markets); (c) then, airlines compete separately on prices for each group of products; (d) under these conditions, equilibrium prices and quantities for non-stop service depend on nonstop capacities in city-pair $ij$ only, and equilibrium prices and quantities for one-stop service depend on one-stop capacities in city-pair $ij$; (e) in this simple model, the revenue function $R_{nij}^{NS}$ depends only on capacities $\left(s_{nij}^{NS}, s_{-nij}^{NS}\right)$, and the revenue function $R_{nij}^{OS}$ depends only on capacities $\left(s_{nij}^{OS}, s_{-nij}^{OS}\right)$. However, the demand system does not have the separable structure argued above, which means that condition (b) fails. Thus, equilibrium prices and quantities of non-stop service in city-pair $ij$ depend on both nonstop and one-stop capacities in city-pair $ij$.

It is worth noting that the network effect doesn't limit to the potential demand substitution between nonstop and one-stop flight. The network effect also includes at least economies of scale and scope at the hub city. Once airlines concentrate their services in the hub cities, airlines can carry passengers to the hub city and more effectively transfer them to other destinations which reduces cost.

The profit of airline $n$ can be specified as

$$\begin{aligned}\pi_n &= R_n^{NS} + R_n^{OS} - VC_n^{Q} - VC_n^{S} - FC_n \\ &= \frac{1}{2}\sum_i \sum_{j \neq i} \left( \underbrace{R_{nij}^{NS}\left(\mathbf{s}_{nij}, \mathbf{s}_{-nij}\right)}_{Revenue:Nonstop} + \underbrace{R_{nij}^{OS}\left(\mathbf{s}_{nij}, \mathbf{s}_{-nij}\right)}_{Revenue:Onestop} - \underbrace{VC_{nij}^{Q}}_{VC:Q} - \underbrace{VC_{nij}^{S}}_{VC:Capacity} - \underbrace{FC_{nij} \times 1\left[a_{nij} = 1\right]}_{Fixed\ Cost} \right).\end{aligned}$$

## 2.2 Best Responses and Equilibrium

An equilibrium of the three-stage complete information game can be described in terms of three Nash equilibria.

(a) In the pricing game, conditional on entry and capacities, a Nash Equilibrium is a $2NM$-tuple $\{P_{nij}^{NS*}, P_{nij}^{OS*} : \forall n, \forall i, \ and \ \forall j \neq i\}$ such that for every airline $n$ in any city-pair $ij$, the following best response condition is satisfied:

$$\left(P_{nij}^{NS*}, P_{nij}^{OS*}\right) = \underset{P_{nij}^{NS}, P_{nij}^{OS}}{argmax} \quad R_{nij}^{NS} + R_{nij}^{OS} - VC_n^{Q},$$

(b) In the capacity stage, conditional on entry decisions and given a particular equilibrium selection in the pricing game, a Nash Equilibrium is a $N$-tuple $\{\mathbf{s}_n^* : \forall n\}$ such that for every airline $n$, the following best response condition is satisfied:

$$\mathbf{s}_n^* = \underset{\mathbf{s}_n}{argmax} \quad R_n^{NS} + R_n^{OS} - VC_n^{Q} - VC_n^{S},$$

(c) In the entry or network game, given a particular equilibrium selection in the capacity game and in the pricing game, a Nash Equilibrium is a $N$-tuple $\{\mathbf{a}_n^* : \forall n\}$ such that for every airline $n$, the following best response condition is satisfied:

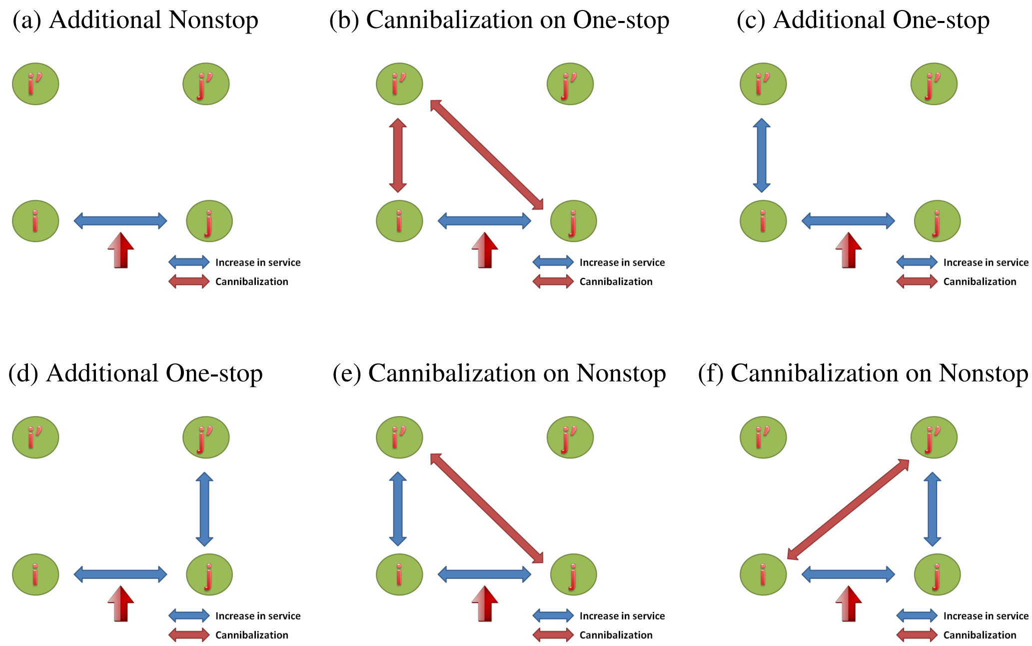
$$\mathbf{a}_n^* = \underset{\mathbf{a}_n}{argmax} \quad \pi_n.$$

## 2.3 Properties of the Model

### 2.3.1 Six Channels of Revenue

An airline may provide nonstop or one-stop services in a maximum of $\frac{C(C-1)}{2}$ city-pairs. A change in nonstop capacity in segment $ij$ ($s_{nij}^{NS}$) may affect capacities and revenues in not only city-pair $ij$ but also all city-pairs with city $i$ or $j$ as an endpoint, regardless of nonstop or one-stop. If nonstop capacity of airline $n$ increases in segment $ij$, it may have

Figure 1: Six Channels of Revenue




a cannibalization effect on one-stop service in city-pair $ij$. Moreover, airline $n$ may carry more one-stop passengers through segment $ij$ and the increments in one-stop service may affect airline $n$'s nonstop service.

To summarize, a change in nonstop capacity in segment $ij$ will affect the revenue of airline $n$ through 6 different channels:

1. Creating additional nonstop capacity in city-pair $ij$ (1 nonstop service)
2. Cannibalization effect on existing one-stop service in city-pair $ij$ (1 one-stop service)
3. Creating additional one-stop capacity from all other cities to $j$ with a connection at $i$ ($C-2$ one-stop services)
4. Creating additional one-stop capacity from all other cities to $i$ with a connection at $j$ ($C-2$ one-stop services)
5. Cannibalization effect on existing nonstop service from all other cities to city $j$ ($C-2$ nonstop services)
6. Cannibalization effect on existing nonstop service from all other cities to city $i$ ($C-2$ nonstop services)

The six subfigures in Figure 1 represent the six different channels.

$MR_{nij}$ measures the total effect of nonstop capacity change in segment $ij$ on the overall revenue of airline $n$, which is equal to

$$
\begin{aligned}
MR_{nij} &= \underbrace{\underbrace{\frac{\partial R^{NS}_{nij}}{\partial s^{NS}_{nij}}}_{\textit{Addtional service ij}} + \underbrace{\frac{\partial R^{OS}_{nij}}{\partial s^{NS}_{nij}}}_{\textit{Cannibalization ij}}}_{\textit{Revenue Change in Nonstop Service}} \\
&+ \underbrace{\underbrace{\sum_{i'\neq i}\frac{\partial R^{OS}_{ni'j}}{\partial s^{NS}_{nij}}}_{\textit{Addtional service .j}} + \underbrace{\sum_{j'\neq j}\frac{\partial R^{OS}_{nij'}}{\partial s^{NS}_{nij}}}_{\textit{Addtional service i.}} + \underbrace{\sum_{i'\neq i}\frac{\partial R^{NS}_{ni'j}}{\partial s^{NS}_{nij}}}_{\textit{Cannibalization .j}} + \underbrace{\sum_{j'\neq j}\frac{\partial R^{NS}_{nij'}}{\partial s^{NS}_{nij}}}_{\textit{Cannibalization i.}}}_{\textit{Revenue Change in Onestop Service}}.
\end{aligned}
$$

This is a property that appears only when there is an interconnection across markets. The models where firms compete in isolated markets, a decision in one market will affect the revenue only in the local market to the exclusion of the other markets.

Here I have made a simplifying assumption on capacity:

**Assumption 1** ***CO*** *Capacity, either nonstop or one-stop, is a continuous variable. The revenue and the variable cost functions are continuous differentiable with respect to this variable. Nonstop capacity is measured by the aggregate number of seats over all the flights during a certain period (quarter), regardless of the flight time or the type of aircrafts.*

Capacity is continuous in the sense that the airline can always change aircraft size or by scheduling or eliminating flights. The model can be extended to allow airlines to build their capacities at different times of the day or allow different aircraft models to have heterogeneous effects on equilibrium quantity and price.

### 2.3.2 Comparison of Network Model with Other Models

To compare the network competition model with other models, if the demand systems for nonstop and one-stop services are perfectly separable, the profit function can be specified as

$$
\pi_n = \frac{1}{2}\sum_i\sum_{j\neq i}\left(\underbrace{R^{NS}_{nij}\left(s^{NS}_{nij}, s^{NS}_{-nij}\right)}_{\textit{Revenue:Nonstop}} + \underbrace{R^{OS}_{nij}\left(s^{OS}_{nij}, s^{OS}_{-nij}\right)}_{\textit{Revenue:Onestop}} - \underbrace{VC^{Q}_{nij}}_{\textit{VC:Q}} - \underbrace{VC^{S}_{nij}}_{\textit{VC:Capacity}} - \underbrace{FC_{nij}\times 1\left[a_{nij}=1\right]}_{\textit{Fixed Cost}}\right),
$$

and in the case where travelers only demand nonstop services, airlines will not receive revenue from one-stop service $R^{OS}_{nij}\left(\mathbf{s}_n, \mathbf{s}_{-n}\right)$. The revenue in $ij$ depends only on the nonstop capacity in $ij$ segment. The profit function can be specified as

$$\pi_n = \frac{1}{2}\sum_i \sum_{j \neq i} \left( \underbrace{R^{NS}_{nij}\left(s^{NS}_{nij}, s^{NS}_{-nij}\right)}_{Revenue:Nonstop} - \underbrace{VC^{Q}_{nij}}_{VC:Q} - \underbrace{VC^{S}_{nij}}_{VC:Capacity} - \underbrace{FC_{nij} \times 1\left[a_{nij} = 1\right]}_{Fixed\ Cost} \right).$$

## 2.4 The Model and Literature

Most models in the structural empirical games of competition in the airline industry exemplify this model. Berry (1992), Ciliberto and Tamer (2009), Ciliberto and Zhang (2014), Onishi and Omori (2014) and Blevins (2015) provide entry models which fit into the first stage of the model. Berry (1992) propose and estimate one of the first entry games which allows for heterogeneity in profitability at different airports for different airlines. Ciliberto and Tamer (2009) extend Berry's model and allow for general forms of heterogeneity across players. Ciliberto and Zhang (2014) and Blevins (2015) allow firms to play sequential games instead of simultaneous games. Kundu (2014) allows airlines to first make entry decisions then compete on price. Williams (2008) and Snider (2009) construct dynamic games which incorporate all three stages into their model. They are interested in how capacity expansion (measured by the number of seats) and predatory behavior affects the equilibrium outcome. Multiple models have proposed price competition analysis. It can be standard price competition models as in Berry, Carnall, and Spiller (2006), Berry and Jia (2010) and Gayle and Yimga (2015) or as complex as models in Lazarev (2013) and Williams (2013) with dynamic pricing competition at the flight level for given capacity. The models in Lazarev (2013) and Williams (2013) are restricted to monopoly routes and require very high frequency data (i.e. daily data) which are not compatible with the research question in the current paper. Ciliberto and Williams (2014) analyze the pricing competition and conduct of the firms which have multimarket contact with their competitors. However, all these models are not games of network competition. They assume competition happens only at the city-pair (or airport-pair) level but ignore the synergies between airline entry decisions across city-pairs.

## 2.5 Computational Issues

In this subsection I discuss the computational issues in the computation of best response function and equilibrium.

Classic methods in the estimation of complete information game such as Berry (1992) and Ciliberto and Tamer (2009) usually involve solving for the equilibria of the model. Berry

(1992) allows for airline heterogeneity in profits at different airports. He considers order of entry, which guarantees the uniqueness of the number of entrants, solves for the entry game and matches the observed number of entrants with his model prediction. Ciliberto and Tamer (2009) allow for general forms of heterogeneity across players without making equilibrium selection assumptions. Given primitives of the model, they solve for the upper and lower bounds of the choice probabilities. The set of estimates is based on minimizing the distance between the solved choice probability set and the choice probabilities estimated from data. However, these methods are limited to solving for an equilibrium or equilibria in an isolated market.

Another closely related estimation method is the research on department chain store competition. Jia (2008) analyzes the network entry game between Wal-Mart and Kmart over 2065 locations. As an extension to Berry's model, the entry choices to the nearby locations will enter into the profit function of the local market, i.e., there are synergies in the entry decisions across markets. She considers a specification of the profit function which implies the supermodularity of the game and facilitates the computation of an equilibrium. The primitives of the model match the equilibrium outcome of the model and the observed network. However, a maximum of two players are allowed to utilize the supermodularity of the game.

Other estimation methods which analyze complex strategic games on high-dimensional space without solving for an equilibrium of the model include at least Ellickson, Houghton, and Timmins (2013) . They swap pairs of stores owned by rival firms between matched pairs of markets to eliminate common sources of unobserved market heterogeneity and construct a set of profit inequalities from revealed preference. Using their method to the airline industry is difficult because of the varied sets of airport connections, departures and destinations from any airport. Nonstop and one-stop services vary a lot for different airlines and it is not clear how to construct "swapping" pairs to eliminate all common sources of unobserved heterogeneity.

Alternatively, I model the game as a game of imperfect information. The equilibrium concept in imperfect information is Bayesian Nash Equilibrium. The two-step (or k-step) method is commonly used in the estimation of incomplete information game. For instance, Aguirregabiria and Mira (2007) and Bajari, Benkard, and Levin (2007). Although these estimation procedures are primarily developed for the estimation of dynamic games, they can also be used to estimate static game as in Yang (2012). The estimation procedures usually start with the estimation of conditional choice probabilities of all strategies.

Without imposing assumptions to reduce their dimensionality, the number of strategies for an airline equal to $2^M$; in each period (quarter), the entire network can be observed only once. It is not feasible to estimate conditional choice probabilities if there are more strategies than the number of observations. Functional forms of the conditional choice probabilities may be imposed but conditional choice probability estimates will be imprecise. More importantly, a large portion of the strategies do not appear in the sample.

I may make some simplifying assumptions and reduce the dimensionality of the strategy set. One possible alternative is to impose local manager assumption from Aguirregabiria and Ho (2012) and assume that in each city-pair there is a local manager who makes entry decision independently for each airline. However, there are several advantages if the local manager assumption is relaxed. First, the current paper studies the synergies in airline entry decisions into different segments and I don't want to impose the assumption that entry decisions are independent across segments. Second, the entire network structure is analyzed in the current research, which makes it possible to evaluate network change segment by segment. Lastly, network structure is assumed to be exogenous in their model but is endogenized in this paper. Alternatively, I can impose sub-network assumptions as in Xu (2011) and Sheng (2012). In order to validate these assumptions, it is required that the entire network be divided into several relatively isolated sub-networks. However, in the airline industry, nonstop services are provided between any two major cities and the sub-network assumption may not be valid. In summary, estimation of an entry game of network competition is difficult. The estimation process becomes more complicated when I estimate a three-stage model where airlines make not only entry but also capacity and pricing decisions.

## 2.6 My approach

In this subsection, I discuss the methods to estimate the model and implement counterfactual experiments.

### 2.6.1 Estimation Method

In this paper, I estimate the model without solving for an equilibrium and all estimation procedures are based on the observed network, which is assumed to be an equilibrium. The three-stage game is estimated sequentially. I first estimate airlines' revenues and variable costs as functions of their capacities at every city-pair. The estimation of this part of the model is based on marginal conditions of optimality for capacity choices. Then, I estimate the fixed costs of entry by exploiting the inequality restrictions implied by airlines' best response conditions in the entry game.

In the third stage, the pricing game, demand can be estimated from price and quantity information, given observed network and capacities. There are a couple of ways to estimate the demand. One method is to use a BLP type of model with airlines' capacity choices representing the quality of service or product characteristics. However, both the capacity choices and airline network structures are endogenous and additional exogenous variation is needed to estimate the model. Following Fan (2013)[18], I can estimate demand with endogenous product characteristics. However, it is not easy to find the type of exogenous variation in her paper within the airline industry and the estimation process will be computationally demanding. Alternatively, in this paper, I estimate hedonic models of equilibrium prices and quantities and attribute equilibrium price and quantity to capacity and market characteristics. This estimation procedure is relatively simple and it is easier to solve for the optimal capacity in any counterfactual network structures. The detailed specification and comparison will be discussed in Section 4.

In the second stage, the capacity stage, I estimate the variable cost of building capacities. Edlin and Farrell (2004) and Elzinga and Mills (2009) have discussed the difficulty in measuring airline costs using accounting data. In this paper, the variable cost of building capacity will be reinforced through economic analysis. Once equilibrium prices and quantities are estimated, a relationship between revenues and capacity allocations can be constructed. I proceed to estimate the marginal cost of building capacity by considering marginal deviation in capacity. If an airline allocates extra capacities in one segment, it can collect extra revenue from serving more nonstop passengers in this segment, while also collecting extra revenue from serving more one-stop passengers with this segment as part of the journey. Moreover, increments in nonstop and one-stop services may have a cannibalization effect on existing services. The details have been discussed in Section 2.3.1. Marginal revenue from additional capacity is measured as the increments in revenue with additional units of nonstop capacity within a segment. According to the marginal condition of optimality, the marginal cost of building capacity is equal to marginal revenue from additional capacity.

Lastly, the estimation of fixed cost structure is based on principle of revealed preference. If it is observed that an airline is active in a segment with nonstop service, the difference between observed variable profit of the airline[19] and the counterfactual variable profit if the airline exits from the segment, provides an upper bound of fixed cost. On the other hand, if it is observed that an airline is inactive in a segment, the difference between observed variable profit of the airline and the counterfactual variable profit of the network if the airline enters with optimal capacity into this segment, provides a lower bound of the fixed cost. Again, all changes in capacity will change not only capacity in nonstop service but also capacity

[18] Fan (2013) estimates a demand model where the product characteristics are endogenized in the newspaper market.

[19] The variable profit here is the variable profit of the entire network for an airline.

in one-stop service. The estimates minimize the penalty function which returns a positive value if fixed cost is greater than the upper bound or lower than the lower bound.

### 2.6.2 Approach for Conducting Counterfactuals

For the counterfactual experiments, I am interested in how entry into a segment from a low cost carrier impacts the network structure. As I have discussed in Section 2.3.1, airline entry into one segment impacts not only the segment where entry happens but also the city-pairs connected to the affected segment. However, this is not the end of the effects because the airline may want to reconstruct its network and other airlines will re-optimize their networks. Imagining the 'butterfly effect', a small change in a complicated system may change the state of the entire system. Similarly, entry into a segment may impact the entire network: the affected segment, the segments connected to the affected segment and the segments that are not connected to the affected segment. Airlines may not re-optimize the entire networks immediately after entry. It is expected that the airlines change capacities in the affected segment first, and then change capacities in those segments which can make connections with the affected segment, while finally changing capacities in those segments that are not directly connected to the affected segment.

Three tiers of effects are evaluated sequentially. For the first-tier effect, a new entrant will choose optimal capacity and incumbents will reduce their capacities within the affected segment. For the second-tier effect, the low cost carrier may want to increase its capacity in the segments connected to the affected segment because it can now carry one-stop passengers with the affected segment as part of the journey. On the other hand, incumbents may re-optimize their capacities in the segments connected to the affected segment. For the third-tier effect, airlines re-optimize their capacities in the segments that are not connected to the affected segment. The driving forces of network re-optimization include incentives to construct one-stop capacities, the cannibalization effect from their own services or strategic interactions from competitors' nonstop and one-stop services. I propose two algorithms to evaluate these three tiers of effects sequentially.

#### A Series of Best Responses

For the first counterfactual experiment, I order all airline-segment pairs according to their proximity to the city-pair where entry happens and evaluate a series of best responses of the airlines segment by segment. All airline-segment pairs are divided into three groups which correspond to the three tiers of effects. The first group includes only the segment where entry happens. The second group includes all segments connected to the segment where entry happens. The third group includes all other segments. Within each group, responds in segments connected to a larger city will be evaluated first followed by segments connected to smaller cities. Within each segment, airlines with larger capacity respond first followed by smaller players. I evaluate the best responses of an airline while taking as given the network structures of all airlines in the other part of the network. The network structure will be updated every time an airline changes its network configuration. Once all three tiers of effects are evaluated, I obtain the counterfactual network.

A nice property of this counterfactual study is that the best responses in each segment are the best responses of the airlines. So this reports the first order best reponses of the airlines. If we iterate this series of best responses, we may obtain a Nash Equilibrium of the network competition game. However, as I have discussed above, the existence of a Nash Equilibrium is not guaranteed and it may take an extremely long time before the best responses converge.

#### Equilibrium with Local Managers

For the second counterfactual, I order all segments the same way as in the first counterfactual and compute an equilibrium in each segment sequentially. The equilibrium concept here is not an equilibrium for the entire network but a set of equilibria in a series local city-pairs. Suppose that every airline has $M$ local managers[20], one for each segment. Entry and capacity decisions in a local market are made by the local manager, who cares about the "local" profit which involves (a) the nonstop revenue in this city-pair (b) all the one-stop revenues that have this city-pair as a segment and (c) the fixed cost and the capacity cost in this city-pair. These local managers can be treated as myopic airline decision makers. The dimensionality of strategy space is reduced significantly under the local manager assumption. Follow Berry (1992), I assume that firms can be ranked in order of profitability, which guarantees the existence of an equilibrium[21] in each city-pair. In each segment, I order incumbents by decreasing capacity and then potential entrants by decreasing potential profitability.[22] The equilibrium in each local segment is constructed by letting the local managers make entry decisions in this order until the next firm would be unprofitable while taking as given the network structures in the other part of the network. The counterfactual consists of the equilibria in all city-pairs.

A nice property of this approach is that the equilibrium conditions in these "local" games are necessary conditions of the equilibrium conditions in the network game. The estimation

[20] Follow Aguirregabiria and Ho (2012).

[21] This is an equilibrium if the network structures in the other part of the network are treated as exogenous.

[22] I assume that the incumbents enter with the observed capacity level and potential entrants enter with the optimal counterfactual capacity level.

procedures in Section 2.6.1 is based on equilibrium conditions in the "local" games. If the entry and capacity decisions observed in the data come from "local" game equilibrium, "local" equilibrium can be the equilibrium concept in the counterfactual.

In all counterfactuals, network change in one market may affect the best responses or local equilibrium in other markets. These two counterfactuals provide us with a framework to understand how change in one city-pair affects the entire network.

## 2.7 Model of Technological Relationship between One-stop and Nonstop Services

To estimate the model and answer the research question of this paper, it is not enough to know the observed one-stop capacity. I also need to know how one-stop capacity will change with any change in nonstop capacity, i.e. counterfactual one-stop capacity. I can always refer to the dataset and re-calculate the number of one-stop seats if one seat in any flight is eliminated or added. However, if there are multiple flights scheduled at different times of the day, it is not clear what impact capacity changing has. Moreover, it is troublesome to keep referring to the OAG database and evaluate the counterfactual one-stop capacity every time the network structure changes. I want to have a closed form expression for one-stop capacity as a function of nonstop capacity. Thus, in this subsection, I propose a model of the technological relationship between one-stop capacity and nonstop capacity.

Recall that $s_{nij}^{OS(k)}$ indicates one-stop capacity between $i$ and $j$ with a connection at $k$. The relationship between one-stop capacity $s_{nij}^{OS(k)}$ and the nonstop capacities in its two legs: $s_{nik}^{NS}$ and $s_{nkj}^{NS}$ is quite complex because it depends on the schedules of all flights and the size of the planes in each flight. For the sake of simplicity, I model $s_{nij}^{OS(k)}$ as a homothetic and symmetric function of $s_{nik}^{NS}$ and $s_{nkj}^{NS}$:

$$s_{nij}^{OS(k)} = H_{nij}^{(k)}\left(s_{nik}^{NS}, s_{nkj}^{NS}\right),$$

where $s_{nij}^{OS(k)}$ is a non-decreasing function in both $s_{nik}^{NS}$ and $s_{nkj}^{NS}$. This function is specific for each airline - city-pair - connection city combination because airlines may have different schedules or connection technologies in different city-pairs at different connection points. This function should be symmetric because the analysis is based on non-directional city-pairs and the nonstop capacity in one leg should impact the capacity of one-stop service the same as the nonstop capacity in the other leg. For instance, there is no reason to assume that the number of seats in segment AB impacts the one-stop capacity from A to C with a connection at B differently than the number of seats in segment BC. Moreover, the technology function is assumed to be homothetic because when the capacities in all flights double, one-stop capacity is expected to increase by the same proportion.

If airlines can expand the capacity of all flights without any constraints, then $H_{nij}^{(k)}(.)$ performs constant returns to scale property: if the capacity of all flights doubles, the capacity of the one-stop service will double. However, in reality, it is impossible to keep expanding the capacity of all flights and airlines have to schedule more flights instead of scheduling larger planes. However, some seats may not be used to construct one-stop capacity due to flight schedules or the full utilization of the seats on the other flights. Thus, it performs decreasing returns to scale property.

# 3 Data

My sample is restricted to the top 100 busiest airports in mainland U.S. which are grouped into 87 Metropolitan Statistic Areas (or cities). Thus, for each airline in each quarter, there will be a total of $M = \frac{C\times(C-1)}{2} = 3741$ entry decisions to be made.

The working dataset is based on a merger of two databases: Data Bank 1B (DB1B) and OAG databases. DB1B is part of TranStats, the Bureau of Transportation Statistics' (BTS) online collection of databases, which contains a 10% quarterly random sample of all US domestic ticket information. The Official Airline Guide (OAG) database provides complete flight schedules of all domestic airlines. It also reports for the detailed capacity for each flight. Complete flight schedules and capacities are needed to construct measure of one-stop capacity.[23] The working dataset ranges from the first quarter of 2006 to the second quarter of 2014 for a total of 34 quarters, with a total of 531952 observations.

## 3.1 Measure of Nonstop Capacity

The measure of non-stop capacity is the aggregate number of seats over all flights which an airline schedules in a quarter.

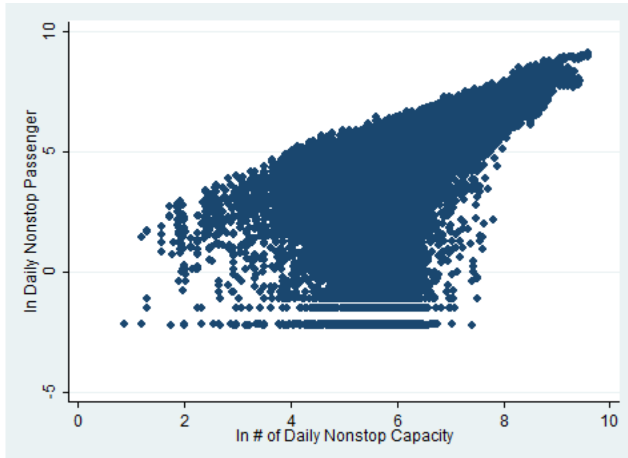
There are 56697 airline-segment-quarter observations with positive capacity in nonstop service. One average, an airline schedules 862 seats in a segment with a median value of 550. Southwest operates the busiest nonstop service between southern California and the Bay area with over 14000 seats daily.

Figure 2 shows the relationship between the number of nonstop passengers and nonstop capacity level. There is a clear positive relationship between the two.[24]

[23] Standard sample selection threshold applies. All coding-sharing tickets are dropped.

[24] Additional Summary Statistics can be found in Appendix D.

Figure 2: Relationship Between Number of Nonstop Passengers and Capacity




## 3.2 Measure of One-stop Capacity

As I have discussed, one-stop service is an important source of airline revenue and it introduces important interconnections between airlines' decisions regarding operations at different city-pairs. Previous literature measures one-stop service in a relatively simple way: it is assumed that an airline provides one-stop service in a city-pair if the number of one-stop passengers exceeds a threshold. However, this measure is based on the equilibrium outcome from a 10 percent sample and ignores the heterogeneity in one-stop service. In this paper, I propose a measure of one-stop service and capacity based on airline schedules, flight capacities and the technology of connecting service. The measure of one-stop capacity is as follows: for any flight, if there is another flight belonging to the same airline scheduled 45 minutes to 4 hours[25] after its arrival at the same airport, it is assumed that connecting service can be constructed between these two flights. One-stop capacity is measured as the minimum seats of these two flights, which represents the maximum number of passengers that can be served from one-stop service. If multiple flights can be matched with one flight or multiple flights can be matched with multiple flights, a novel algorithm is proposed to measure the one-stop capacity. This measures the maximum number of passengers which can be served from one-stop service. The details of the construction of one-stop capacity can be found in Appendix C.

With this measure, one physical seat is counted only once in one-stop service. However, it may be counted twice for both nonstop and one-stop services. In reality, it is not clear how airlines allocate the number of seats of one flight to nonstop and one-stop services.

[25] I use the same threshold as in Molnar (2013). The minimum connection times are usually 45 to 75 minutes. And a maximum of 4 hours are usually used on ticket reservation system.

Actually, whether a seat is reserved for nonstop or one-stop services may not be determined until demand is realized. I believe the current measure of one-stop capacity is the best that can be done given the data I have.

As far as I know, no measures of capacity or heterogeneity in one-stop service have been proposed in the literature. Without a measure of one-stop capacity, it is not clear whether one-stop service can be constructed between any two flights, or how many passengers can be served with one-stop service. This measure introduces a clear definition of airline entry with one-stop service (two flights with a gap of 45 minutes to 4 hours) as well as heterogeneity or quality in one-stop service (measured by the number of one-stop seats). The measure is economically important to understand the competition and profitability in this industry. Airlines face more intensive competition if their competitors can carry more passengers with one-stop service and they may collect more revenue from one-stop service if they schedule their flights strategically to create larger one-stop capacity. The measure of one-stop service is also consistent with the existence of airline hubs. Airlines concentrate their services in a small number of cities which makes it easier to construct one-stop capacities.

This measure of one-stop capacity captures the maximum number of one-stop seats or alternatively, the maximum number of passengers one airline can carry using its one-stop service. In the empirical analysis, I analyze how equilibrium prices and quantities depend upon the maximum number of one-stop seats while holding others constant.

There are 475255 airline-city-pair-quarter observations with positive capacity in one-stop service. On average, an airline can carry a maximum of 38 passengers between two cities with one-stop service and the median value is 12. The average is much higher than the median because some airlines concentrate most of their services within a few airports, which creates many one-stop seats.

Figure 3: Relationship Between Nonstop and One-stop Capacities

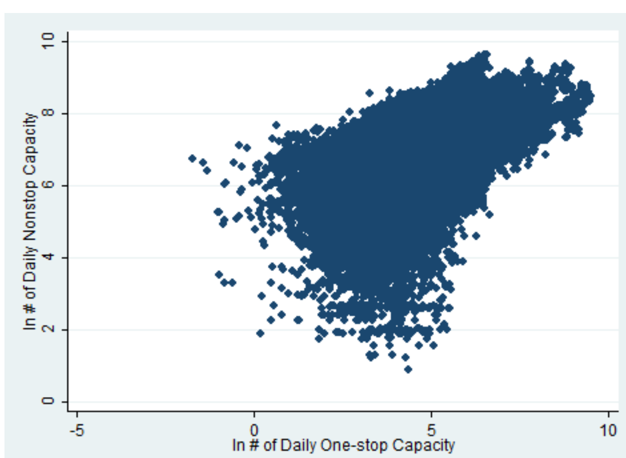


Figure 3 illustrates the relationship between nonstop and one-stop capacities. Only those observations where airlines have positive capacities in both nonstop and one-stop services are recorded in the figure. The figure has an interesting triangle shape: airlines build large capacities in both nonstop and one-stop services in large market like New York - Chicago. In some markets where it is costly to provide nonstop service like Seattle - Orlando, airlines schedule fewer nonstop flights but offer many one-stop seats. On the other hand, in the markets between two relatively close cities, many nonstop flights are scheduled but airlines don't provide much one-stop capacity. In relatively small markets, we do not frequently observe airlines providing both nonstop and one-stop services.

## 3.3 Descriptive Analysis

At the beginning of the sample period, there are 12 major airlines operating in the United States. Virgin America enters in 2008. Continental merged with Delta, AirTran merged with Southwest, Northwest merged with United Airline and US Airway merged with American Airlines during the sample period.[26] So in the second quarter of 2014, there are ten major airlines.[27]

Table 1 summarizes the number of nonstop segments, the number of city-pairs served with one-stop services, and the share of passengers carried and revenue collected from both nonstop and one-stop services for each airline. With connecting service, airlines can serve ten times more city-pairs than the number of nonstop services. Continental Airlines operates nonstop flights in only 97 segments in the second quarter of 2007 but it can provide one-stop service in over 2000 city-pairs. The network structure of Southwest is not designed for connecting service. Even though Southwest operates nonstop services in more city-pairs than any other airline, it operates one-stop services in fewer city-pairs.

Airlines usually carry more nonstop passengers compared to one-stop passengers. However, the revenue from one-stop service is a significant source of airline revenue. In the second quarter of 2014, 37.7 percent of the domestic revenue of Delta Air Lines comes from one-stop service. Even for Southwest, the well-known point-to-point service provider, provides one-stop service to 21.4 percent of its consumers and receives 26.3 percent revenue from one-stop service in the second quarter of 2014. On average, 26.4 percent of domestic

[26] Details of mergers and the construction of the dataset can be found in Appendix B.

[27] I drop small airlines such as Allegiant Air from the estimation and focus on the major airlines for the following three reasons: First, those small airlines concentrate their services in small markets and with negligible presence in the sampled dataset. Second, most of these small airlines employ point-to-point business model and usually carry negligible portion of connecting passengers. Third, elimination of these airlines can save plenty of the computational time which is proportional to the number of airlines in the dataset. However, the competition effects from these small airlines are included in the analysis.

TABLE 1: Summary Statistics: Nonstop Service versus One-stop Service

| | 2007Q1 | | | | | |
|---|---|---|---|---|---|---|
| | **Nonstop Service** | | | **One-stop Service** | | |
| Airline Code (Name) | # Segments | % of Pass | % of Rev | # City-pairs | % of Pass | % of Rev |
| WN (Southwest Airlines) | 364 | 85.9% | 81.0% | 1244 | 14.1% | 19.0% |
| DL (Delta Air Lines) | 316 | 64.1% | 64.8% | 3236 | 35.9% | 35.2% |
| US (US airway) | 273 | 65.7% | 62.0% | 2360 | 34.3% | 38.0% |
| AA (American Airlines) | 260 | 71.9% | 69.2% | 2414 | 28.1% | 30.8% |
| UA (United Airlines) | 166 | 70.7% | 67.9% | 2780 | 29.3% | 32.1% |
| NW (Northwest Airlines) | 155 | 71.2% | 70.4% | 2462 | 28.8% | 29.6% |
| CO (Continental Airlines) | 97 | 78.5% | 76.5% | 2397 | 21.5% | 23.5% |
| FL (AirTran Airways) | 95 | 75.6% | 73.3% | 531 | 24.4% | 26.7% |
| B6 (JetBlue Airways) | 67 | 91.3% | 90.0% | 433 | 8.7% | 10.0% |
| F9 (Frontier Airlines) | 46 | 77.2% | 71.4% | 575 | 22.8% | 28.6% |
| AS (Alaska Airlines) | 45 | 93.3% | 92.1% | 131 | 6.7% | 7.9% |
| NK (Spirit Airlines) | 22 | 100.0% | 100.0% | 13 | 0.0% | 0.0% |
| VX (Virgin America) | - | - | - | - | - | - |
| Total | 1906 | 75.8% | 72.1% | 18576 | 24.2% | 27.9% |

| | 2014Q2 | | | | | |
|---|---|---|---|---|---|---|
| | **Nonstop Service** | | | **One-stop Service** | | |
| Airline Code (Name) | # Segments | % of Pass | % of Rev | # City-pairs | % of Pass | % of Rev |
| WN (Southwest Airlines) | 529 | 78.6% | 73.7% | 2158 | 21.4% | 26.3% |
| DL (Delta Air Lines) | 417 | 63.7% | 62.3% | 3224 | 36.3% | 37.7% |
| US (US airway) | - | - | - | - | - | - |
| AA (American Airlines) | 442 | 63.6% | 61.5% | 3267 | 36.4% | 38.5% |
| UA (United Airlines) | 258 | 74.3% | 73.3% | 2979 | 25.7% | 26.7% |
| NW (Northwest Airlines) | - | - | - | - | - | - |
| CO (Continental Airlines) | - | - | - | - | - | - |
| FL (AirTran Airways) | - | - | - | - | - | - |
| B6 (JetBlue Airways) | 96 | 94.8% | 93.9% | 435 | 5.2% | 6.1% |
| F9 (Frontier Airlines) | 52 | 76.2% | 69.3% | 390 | 23.8% | 30.7% |
| AS (Alaska Airlines) | 70 | 93.7% | 92.4% | 239 | 6.3% | 7.6% |
| NK (Spirit Airlines) | 77 | 96.9% | 95.2% | 119 | 3.1% | 4.8% |
| VX (Virgin America) | 26 | 94.4% | 94.6% | 74 | 5.6% | 5.4% |
| Total | 1967 | 73.6% | 70.0% | 12885 | 26.4% | 30.0% |

Note: pass is abbreviation of passengers and rev is abbreviation of revenue.

passengers are one-stop passengers and the revenue from them consists of 30 percent of the airline revenue. It seems that average fare in one-stop service is higher than the average fare in nonstop service.[28] If the revenue and profit that airlines make from one-stop service are ignored, an important component of service and competition in this industry will be missing.[29].

# 4 Estimation and Identification

I first analyze the technological relationship between one-stop capacity and nonstop capacity, then specify and estimate the empirical models.

## 4.1 Technological Relationship between One-stop and Nonstop Capacities

I assume a symmetric Cobb-Douglas function for the relationship between one-stop capacity and nonstop capacity.

$$s_{nij}^{OS(k)} = H_{nij}^{(k)}\left(s_{nik}^{NS}, s_{nkj}^{NS}\right) = exp\left(h_{nijt}^{(k)}\right) \times \left(s_{nik}^{NS}\right)^{\alpha} \times \left(s_{nkj}^{NS}\right)^{\alpha},$$

where $h_{nijt}^{(k)}$ is an index which captures the heterogeneity in connecting possibilities across routes. I can further specify $h_{nijt}^{(k)} = h + \epsilon_{nijt}^{h(k)}$. In the estimation equation, where $\epsilon_{nijt}^{h(k)}$ is assumed to be i.i.d distributed, I obtain the following estimation equation:

$$\ln s_{nijt}^{OS(k)} = h + \alpha \times \left(\ln s_{nikt}^{NS} + \ln s_{nkjt}^{NS}\right) + \epsilon_{nijt}^{h(k)}.$$

Capacity change in nonstop service may change the capacity in one-stop with this nonstop service as a leg. The marginal effect of $s_{nikt}^{NS}$ on $s_{nijt}^{OS(k)}$ is equal to

$$\frac{\partial s_{nijt}^{OS(k)}}{\partial s_{nikt}^{NS}} = \alpha \frac{s_{nijt}^{OS}}{s_{nikt}^{NS}} = \alpha h_{nijt}^{(k)} \times \left(s_{nikt}^{NS}\right)^{\alpha-1} \times \left(s_{nkjt}^{NS}\right)^{\alpha}.$$

## 4.2 Empirical Specification

In this subsection, I discuss in detail the empirical specification of the network competition model.

[28] One-stop service usually has longer distance compared to nonstop service.

[29] Additional Summary Statistics can be found in Appendix E

#### 4.2.1 Fixed Cost

Airline $n$'s entry cost into segment $ij$: $FC_{nijt}$ depends upon many factors, such as the number of gates or time slots the airline has[30], the availability of a common gate within the airports, and even the vertical relationship between legacy carriers and regional carriers[31]. However, it is difficult to incorporate all information in the estimation process due to data limitations and computational issues. In this paper, I consider a simple specification of the airlines' fixed cost of operation in one segment, which includes both airline fixed effect and contractual relations between the airline and the airport. Moreover, I maintain the assumption that the fixed costs of the airlines in different segments are independent across segments.

I specify $FC_{nijt}$ as a function of market characteristics, the number of gates the airline[32] has in the two endpoints and a random term

$$FC_{nijt} = \underbrace{\eta_i^{FC}}_{Airline\ FE} + \underbrace{\eta_t^{FC}}_{Quarter\ FE} + \gamma^{FC} \underbrace{(GS_{nit} + GS_{njt})}_{Number\ of\ Gates\ at\ Two\ Endpoints} + \varepsilon_{nijt}^{FC}$$

where $\eta_i^{FC}$ represents airline fixed effect, $\eta_t^{FC}$ represents quarter fixed effect, $GS_{nit}$ and $GS_{njt}$ are the number of gates city $i$ and $j$ leased to airline $n$ in quarter $t$, respectively.

#### 4.2.2 Variable Cost of Building Capacity

In airline operation, variable cost comes from two different sources: first, there is a cost associated with building capacities ($VC_n^S$). The direct cost includes at least the cost of operating flights between the two cities. This depends on the aircrafts model, structure and availability of fleets, fuel price and market characteristics such as distance between two endpoints. Other costs include the cost of setting up counters and recruiting crews. Airline operations in the two endpoints may also affect the variable cost of building capacity due to economics of scale or scope. Second, there is another cost to serving passengers ($VC_n^Q$) which is proportional to the number of consumers. It includes the cost of selling tickets, boarding and serving passengers. To simplify the problem, usually one source of variable cost is considered. Most previous research[33] takes into account only the variable cost of serving passengers and assumes this variable cost is proportional to the number of passengers. However, in this paper, I am more interested in how airlines compete in their

[30] See Ciliberto and Williams (2010)

[31] See Forbes and Lederman (2009)

[32] Gate usage information is downloaded from a website that publishes all flight scheduling information.

[33] See Aguirregabiria and Ho (2012).

network structures and capacity allocations, so I focus on the variable cost associated with building capacity but assume the variable cost of serving passengers is negligible. Moreover, it is easier to estimate the model and conduct counterfactual analysis if one source of variable cost is considered. Variable cost of building capacity is assumed to additively separable across segments. And it is assumed that there is no additional cost of constructing one-stop capacity: two nonstop seats from two different flights with a desirable connecting time will automatically construct a one-stop seat.

I further assume variable cost is linear in capacity, i.e. $VC^S_{nijt} = AVC^S_{nijt} \times s_{nijt} = MC_{nijt} \times s_{nijt}$. Since variable cost is linear in capacity, average variable cost of building capacity ($AVC_{nijt}$) equals to marginal cost of building capacity ($MC_{nijt}$). The marginal cost $MC_{nijt}$ can be specified as follows

$$\ln MC_{nijt} = \underbrace{\eta^{MC}_{ni} + \eta^{MC}_{nj}}_{Airline-City\ FE} + \underbrace{\eta^{MC}_{t}}_{Quarter\ FE} + \underbrace{\gamma^{MC}_1 \ln Dist_{ij} + \gamma^{MC}_2 \left(\ln Dist_{ij}\right)^2}_{Flexible\ Function\ of\ Distance} + \varepsilon^{MC}_{nijt}$$

where $\eta^{MC}_{ni}$ and $\eta^{MC}_{nj}$ capture airline-city fixed effect, $\eta^{MC}_{t}$ captures time fixed effect and $\gamma^{MC}_1$ and $\gamma^{MC}_2$ capture the effect from distance.

#### 4.2.3 Equilibrium Prices and Quantities

In Appendix A, I have specified a demand system in the airline industry. However, in the current research, 'semi-reduced form' equilibrium equations are estimated instead of the structural demand and variable costs (for actual passengers). Specifically, I attribute equilibrium price and quantity to market characteristics and other factors such as capacities for all airlines. The estimation of fixed costs and the costs of building capacity requires calculating equilibrium prices and quantities for many different counterfactual values of capacity. Therefore, it is convenient to have a model where it is computationally simple to recalculate these equilibrium prices and quantities for different values of capacity.

This estimation approach comes with a price in terms of the type of counterfactual experiments that can be implemented. Since structural parameters in demand are not estimated, I cannot implement counterfactual experiments that change these parameters. In this paper, I am more interested in how airline entry or the change in capacities impacts the entire network structure but not the structure parameters such as price elasticity or the substitution ratio between nonstop and one-stop services. The parameters in the hedonic models of equilibrium prices and quantities are functions of demand and marginal cost parameters. These parameters are constant when I conduct counterfactual experiment. Hence, hedonic models of equilibrium prices and quantities can be used to conduct counterfactual experiment without solving for structural parameters in the demand system.

There are multiple benefits associated with using a hedonic model. The first benefit is a computational advantage and the simplicity of the hedonic model. Since I consider a multi-stage model, the characteristics of the product such as capacities may change. Though it is possible to estimate a demand system where capacities are endogenized, it is difficult to re-solve the demand systems or best responses for every counterfactual network structure. Hedonic models can generate simple explicit expression of revenue which can simplify the estimation and avoid the repeated solution of the Bertrand game or dynamic pricing competition for different network structures and capacity allocations.

Second, my approach is more robust[34] than other approaches that estimate structural models of demand. The specification of equilibrium prices and quantities are very flexible and I do not need the type of exclusion restrictions that are necessary to identify demand.

Third, it is also easier to give economic interpretation to the hedonic model. There are at least two effects from capacity increments. First, higher capacity usually comes with larger aircrafts or more frequent schedules, both of which are valued by the passengers. Thus, the quality of airline service may increase. Second, higher capacity means lower shadow cost of carrying passengers because the opportunity cost of ticket sell out is low. Fares charged by airlines may be lower as a result of capacity expansion. Both these effects will affect the equilibrium price and quantity. In general, if capacity increases, I expect the number of passengers will increase but the effect on price is ambiguous. On the other hand, if the capacity of the competitors increases, both the number of passengers and price should decrease. In the hedonic model, the effect of capacity expansion on price and quantity is easily separated.

Equilibrium price and quantity in both nonstop and one-stop services are specified as functions of market characteristics, the capacities of airline $n$ and the competitors in both nonstop and one-stop services. Fixed effects are also controlled.

[34]No assumptions on the conduct of the airlines have been made such as Bertrand competition or collusion.

I specify hedonic equation of quantity in nonstop service as

$$
\begin{aligned}
\ln Q_{nijt}^{NS} \quad = \quad & \beta^{NSQ} \ln \underbrace{s_{nijt}^{NS}}_{Nonstop\ Capacity} + \theta^{NSQ} \ln \underbrace{\left(\sum_{k \neq i, k \neq j} s_{nijt}^{OS(k)} + 1\right)}_{Onestop\ Capacity} \\
& + \delta_1^{NSQ} \ln \underbrace{\left(\sum_{n' \neq n} s_{n'ijt}^{NS} + 1\right)}_{Comp\ Nonstop\ Capacity} + \delta_2^{NSQ} \ln \underbrace{\left(\sum_{n' \neq n} \sum_{k \neq i, k \neq j} s_{n'ijt}^{OS(k)} + 1\right)}_{Comp\ Onestop\ Capacity} \\
& + \underbrace{\eta_n^{NSQ}}_{Airline\ FE} + \underbrace{\eta_{ij}^{NSQ}}_{Segment\ FE} + \underbrace{\eta_t^{NSQ}}_{Quarter\ FE} + e_{nijt}^{NSQ}.
\end{aligned} \tag{1}
$$

where $\beta^{NSQ}$ is the elasticity of the nonstop capacity, $\theta^{NSQ}$ captures the cannibalization effect from one-stop service of airline $n$, $\delta_1^{NSQ}$ and $\delta_2^{NSQ}$ represent strategic interactions from competitors' nonstop and one-stop capacities. The one-stop capacities from both airline $n$ and the competitors are equals to one-stop capacities in all possible one-stop routes with the other $C-2$ cities as connections. The details of the construction of one-stop capacity have been discussed in Appendix C. Airline fixed effect $\eta_n^{NSQ}$, segment fixed effect $\eta_{ij}^{NSQ}$ and time fixed effect $\eta_t^{NSQ}$ are also included in the specification.

For the specification of hedonic quantity equation in one-stop service, I define

$$
\begin{aligned}
\ln Q_{nijt}^{OS} \quad = \quad & \beta^{OSQ} \ln \underbrace{\sum_{k \neq i, k \neq j} s_{nijt}^{OS(k)}}_{Onestop\ Capacity} + \theta^{OSQ} \ln \underbrace{\left(s_{nijt}^{OS} + 1\right)}_{Nonstop\ Capacity} \\
& + \delta_1^{OSQ} \ln \underbrace{\left(\sum_{n' \neq n} s_{n'ijt}^{NS} + 1\right)}_{Comp\ Nonstop\ Capacity} + \delta_2^{OSQ} \ln \underbrace{\left(\sum_{n' \neq n} \sum_{k \neq i, k \neq j} s_{n'ijt}^{OS(k)} + 1\right)}_{Comp\ Onestop\ Capacity} \\
& \underbrace{+ \gamma_1^{OSQ} \ln Dist_{ij} + \gamma_2^{OSQ} \left(\ln Dist_{ij}\right)^2}_{Flexible\ Function\ of\ Dist} \\
& + \underbrace{\eta_n^{OSQ}}_{Airline\ FE} + \underbrace{\eta_i^{OSQ} + \eta_j^{OSQ}}_{City\ FE} + \underbrace{\eta_t^{OSQ}}_{Quarter\ FE} + e_{nijt}^{OSQ}.
\end{aligned} \tag{2}
$$

where $\beta^{OSQ}$ is the elasticity of the one-stop capacity, $\theta^{OSQ}$ captures the cannibalization effect from the nonstop service of airline $n$, $\delta_1^{OSQ}$ and $\delta_2^{OSQ}$ represent strategic interactions from competitors' nonstop and one-stop capacities. Airline fixed effect $\eta_n^{OSQ}$, city fixed effect $\eta_i^{OSQ}$,$\eta_j^{OSQ}$ and time fixed effect $\eta_t^{OSQ}$ are also included in the specification.

Hedonic equations of price in nonstop and one-stop services are similarly defined as their counterparts in equilibrium quantity equations.

For all hedonic models, I can further specify the elasticities as functions of different demographic variables or allow the cannibalization effect and strategic interactions to vary for different quantiles of the service:

$$
\begin{aligned}
\beta^x &= \beta_1^x + \beta_2^x \ln Pop_i + \beta_3^x \ln Pop_j + \beta_4^x \ln Dist_{ij} + \beta_5^x \left(\ln Dist_{ij}\right)^2 \\
\theta^x &= \theta_1^{x(1)} 1\left(1st\_qtl\right) + \theta_1^{x(2)} 1\left(2nd\_qtl\right) + \theta_1^{x(3)} 1\left(3rd\_qtl\right) + \theta_1^{x(4)} 1\left(4th\_qtl\right) \\
\delta_1^x &= \delta_1^{x(1)} 1\left(1st\_qtl\right) + \delta_1^{x(2)} 1\left(2nd\_qtl\right) + \delta_1^{x(3)} 1\left(3rd\_qtl\right) + \delta_1^{x(4)} 1\left(4th\_qtl\right) \\
\delta_2^x &= \delta_2^{x(1)} 1\left(1st\_qtl\right) + \delta_2^{x(2)} 1\left(2nd\_qtl\right) + \delta_2^{x(3)} 1\left(3rd\_qtl\right) + \delta_2^{x(4)} 1\left(4th\_qtl\right)
\end{aligned}
$$

where $x \in \{NSP, NSQ, OSP, OSQ\}$. $\ln Pop_i$ and $\ln Pop_j$ are the logarithm population in the two endpoints, $\ln Dist_{ij}$ represents the logarithm distance between the two endpoints and $1(.)$ is an index function which indicates whether the value belongs to the corresponding quartile or not.

## 4.3 Model Estimation and Identification

In this subsection, I discuss the identification assumptions and the empirical approaches of estimation. The three-stage model is estimated sequentially. I first estimate equilibrium prices and quantities. Then, I estimate the airlines' marginal cost of building capacity according to the marginal condition of optimality. Lastly, I infer fixed cost by exploiting the inequality restrictions implied by the airlines' revealed preference.

### 4.3.1 Estimation of Stage 3

Possible estimation issues may arise in the estimation of equilibrium prices and quantities. Airline services are endogenous: entry and capacity decisions may be correlated with demand shocks. In order to deal with the endogenous issues, I impose the following assumptions.

**Assumption 2** ***AR*** *$e^x_{nijt}$ follows an AR(1) process: $e^x_{nijt} = \rho^x e^x_{nijt-1} + u^x_{nijt}$, where $u^x_{nijt}$ is i.i.d distributed and $x \in \{NSP, NSQ, OSP, OSQ\}$*

**Assumption 3** ***TIME TO BUILD*** *At the beginning of period $t$, airlines form expectations on demand and costs in this period and then make their entry and capacity decisions in all city-pairs. These entry and capacity decisions are not effective until quarter $t+1$ because airlines need one quarter to set up their network and build capacity.*

According to **ASSUMPTION 2** ***AR*** and **ASSUMPTION 3** ***TIME TO BUILD*** , shocks $\{u^x_{nijt}\}$ are realized at the end of period $t$, where $x \in \{NSP, NSQ, OSP, OSQ\}$. Thus, capacity decisions ($\mathbf{s}_{nijt}$) in period $t$ is independent of$\{u^x_{nijt}\}$ because airlines need one period to set up their networks and build capacities.

I can then rearrange the hedonic pricing and quantity equations, subtract all variables by $\rho^x$ times their lagged values and estimate these new equations.

All four hedonic equations are estimated using both OLS and Cochrane–Orcutt estimation.

### 4.3.2 Estimation of Stage 2

Once equilibrium prices and quantities are estimated, I can calculate the marginal revenue associated with building additional capacity in any segment. Marginal revenue comes from different sources and the details have been discussed in Section 2.3.1.

Estimation of equilibrium prices and quantities shed light on the cost structure of building capacity. Once the marginal revenue associated with the additional capacity is known, the marginal cost of building capacity ($MC_{nijt}$) can be backed out according to marginal condition of optimality. The expected marginal revenue from additional capacity ($MR_{nijt}$) equals to the marginal cost of building additional capacity ($MC_{nijt}$):

$$MR_{nijt} = MC_{nijt}.$$

The estimation equation becomes

$$\ln MR_{nijt} = \underbrace{\eta^{MC}_{ni} + \eta^{MC}_{nj}}_{Airline-City\ FE} + \underbrace{\eta^{MC}_{t}}_{Quarter\ FE} + \underbrace{\gamma^{MC}_1 \ln Dist_{ij} + \gamma^{MC}_2 \left(\ln Dist_{ij}\right)^2}_{Flexible\ Function\ of\ Dist} + e^{MC}_{nijt}. \tag{3}$$

### 4.3.3 Estimation of Stage 1

Once the structure of equilibrium prices, quantities and marginal cost are estimated, I can infer the structure of the entry cost according to revealed preferences:

For those airlines that provide nonstop service in city-pair $ij$, the fixed cost is lower than the difference between observed revenue $R_{nt}\left(s^{NS}_{nijt}, s^{OS}_{nijt}, \mathbf{s}_{n(-ij)t}, \mathbf{s}_{-nt}\right)$ and counterfactual revenue if it exits from this segment $R_{nt}\left(0, s^{OS}_{nijt}, \mathbf{s}_{n(-ij)t} - s^{NS}_{nijt}, \mathbf{s}_{-nt}\right)$ minus the saving in variable cost of building capacities $MC_{nijt} \times s_{nijt}^{NS}$. Thus,

$$\begin{aligned}
FC_{nijt} &\leq \underbrace{R_{nt}\left(s_{nijt}^{NS}, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t}, \mathbf{s}_{-nt}\right)}_{Observed\ Revenue} - \underbrace{R_{nt}\left(0, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t} - s_{nijt}^{NS}, \mathbf{s}_{-nt}\right)}_{Counterfactual\ Revenue\ if\ Exit} - \underbrace{MC_{nijt} \times s_{nijt}^{NS}}_{Saving\ in\ MC} \\
&\equiv \Delta\overline{R_{nijt}^{*}}(1)
\end{aligned}$$

where $s_{nijt}^{NS}$ and $s_{nijt}^{OS}$ represent the airline $n$'s nonstop and one-stop capacities in city-pair $ij$, respectively. $\mathbf{s}_{n(-ij)t}$ represents the capacities of airline $n$ in all city-pairs except for city-pair $ij$, both nonstop and one-stop. $\mathbf{s}_{n(-ij)t} - s_{nijt}^{NS}$ represents the counterfactual capacities of airline $n$ in all city-pairs except for city-pair $ij$ if airline $n$ exits from segment $ij$. $\mathbf{s}_{-nt}$ represents the network structure of the other airlines in all city-pairs, both nonstop and one-stop. $FC_{nijt}$ represents airline $n$'s entry cost into city-pair $ij$ in period $t$.

For those airlines that don't provide nonstop service in city-pair $ij$, the fixed cost is higher than the difference between counterfactual revenue if it enters into this segment with optimal capacity $s_{nijt}^{NS*}$: $R_{nt}\left(s_{nijt}^{NS*}, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t} + s_{nijt}^{NS*}, \mathbf{s}_{-nt}\right)$ and the observed revenue $R_{nt}\left(0, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t}, \mathbf{s}_{-nt}\right)$ minus variable cost of building capacities $MC_{nijt} \times s_{nijt}^{*}$.

$$\begin{aligned}
FC_{nijt} &\geq \underbrace{\max_{s_{nijt}^{NS*}} R_{nt}\left(s_{nijt}^{NS*}, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t} + s_{nijt}^{NS*}, \mathbf{s}_{-nt}\right)}_{Counterfactual\ Revenue\ if\ Enter} - \underbrace{R_{nt}\left(0, s_{nijt}^{OS}, \mathbf{s}_{n(-ij)t}, \mathbf{s}_{-nt}\right)}_{Observed\ Revenue} - \underbrace{MC_{nijt} \times s_{nijt}^{*}}_{Cost\ in\ MC} \\
&\equiv \Delta\underline{R_{nijt}^{*}}(0)
\end{aligned}$$

where $s_{nijt}^{NS*}$ represents the optimal nonstop capacity level of firm $n$ in city-pair $ij$ if $n$ provides nonstop service in city-pair $ij$. To sum up, I have the following inequalities

$$\begin{aligned}
a_{nijt}\left(\Delta\overline{R_{nijt}^{*}}(a_{nijt}) - FC_{nijt}\right) &\geq 0 \\
(a_{nijt} - 1)\left(\Delta\underline{R_{nijt}^{*}}(a_{nijt}) - FC_{nijt}\right) &\geq 0.
\end{aligned}$$

Thus, the inequalities can be represented as

$$\begin{aligned}
a_{nijt}\left(\Delta\overline{R_{nijt}^{*}}(a_{nijt}) - \left(\eta_i^{FC} + \gamma^{FC}\left(GS_{nit} + GS_{njt}\right) + \varepsilon_{nijt}^{FC}\right)\right) &\geq 0 \\
(a_{nijt} - 1)\left(\Delta\underline{R_{nijt}^{*}}(a_{nijt}) - \left(\eta_i^{FC} + \gamma^{FC}\left(GS_{nit} + GS_{njt}\right) + \varepsilon_{nijt}^{FC}\right)\right) &\geq 0.
\end{aligned}$$

Then I can construct conditional moment inequalities

$$\begin{aligned} E\left[a_{nijt}\left(\Delta\overline{R^*_{nijt}}\left(a_{nijt}\right)-\left(\eta_i^{FC}+\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)+\varepsilon^{FC}_{nijt}\right)\right)|x\right] &\geq 0 \\ E\left[\left(a_{nijt}-1\right)\left(\Delta\underline{R^*_{nijt}}\left(a_{nijt}\right)-\left(\eta_i^{FC}+\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)+\varepsilon^{FC}_{nijt}\right)\right)|x\right] &\geq 0 \end{aligned}$$

where $x$ is a vector of market characteristics.

Usually, contracts between an airline and an airport on gate leasing arrangements are signed years before the airline's entry decision into a segment. These contracts are long term contracts with a duration of 5 to 10 years. Thus, ownership of gates can be treated exogenously when airlines make entry decisions into a segment.

However, there may be a selection issue on the error term $E\left[\varepsilon^{FC}_{nijt}\left(a_{nijt}\right)|x, a_{nijt}=1\right] \neq 0$. In order to obtain consistent estimates of the parameters, the following structure on the error term is imposed:

**Assumption 4** ***SM/FS*** *$\varepsilon^{FC}_{nijt}$ is symmetrically distributed with full support on* $\mathbf{R}$.

If the unconditional expectation of $\varepsilon^{FC}_{nijt}$ is finite[35], a bound $B$ can be imposed to replace $\varepsilon^{FC}_{nijt}$ in the inequalities.

$$\begin{aligned} E\left[a_{nijt}\left(\Delta\overline{R^*_{nijt}}\left(a_{nijt}\right)-\eta_i^{FC}-\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)+B\right)|x\right] &\geq 0 \\ E\left[\left(a_{nijt}-1\right)\left(\Delta\underline{R^*_{nijt}}\left(a_{nijt}\right)-\eta_i^{FC}-\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)+B\right)|x\right] &\geq 0. \end{aligned}$$

I follow Andrews and Shi (2013) and transform the conditional moment inequalities to their unconditional counterparts.

$$\begin{aligned} E\left\{z\left(x\right)\left[a_{nijt}\left(\Delta\overline{R^*_{nijt}}\left(a_{nijt}\right)-\eta_i^{FC}-\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)+B\right)\right]\right\} &\geq 0 \\ E\left\{z\left(x\right)\left[\left(a_{nijt}-1\right)\left(\Delta\underline{R^*_{nijt}}\left(a_{nijt}\right)-\eta_i^{FC}-\gamma^{FC}\left(GS_{nit}+GS_{njt}\right)\right)+B\right]\right\} &\geq 0. \end{aligned}$$

where $z\left(x\right)$ can be any nonnegative instruments based on the market characteristics. For the selection of instruments $z\left(x\right)$, all city-pairs are separated into 49 groups according to market size (the product of number of population between two endpoints) and distance. In each group, an instrument is constructed for each airline and each action. $z\left(x\right)$ includes all these dummies.

[35] This condition holds under very general distributions.

The criterion function follows Chernozhukov, Hong, and Tamer (2007) :

$$Q(\theta, B) = \min\left\{z(x)\left[a_{nijt}\left(\Delta\overline{R^*_{nijt}}(a_{nijt}) - \eta_i^{FC} - \gamma^{FC}(GS_{nit} + GS_{njt}) + B\right)\right], 0\right\}^2 + \min\left\{z(x)\left[(a_{nijt} - 1)\left(\Delta\underline{R^*_{nijt}}(a_{nijt}) - \eta_i^{FC} - \gamma^{FC}(GS_{nit} + GS_{njt}) + B\right)\right], 0\right\}^2. \quad (4)$$

# 5 Empirical Results

## 5.1 Technological Relationship between One-stop and Nonstop Capacities

Table 2 summarizes the technological relationship between one-stop capacity and nonstop capacity (Equation (4.1)).[36]

TABLE 2: Technological relationship between one-stop capacity and nonstop capacity

| ln(# of one-stop seats) | OLS Coef./SE. | OLS Coef./SE. | OLS Coef./SE. |
|---|---|---|---|
| ln(# of seats in first leg) | .403*** | .417*** | .463*** |
| + ln(# of seats in second leg) | (.003) | (.003) | (.002) |
| Airline FE | | X | X |
| City-pair FE | | | X |
| Constant | –3.218*** | –3.677*** | –4.087*** |
| | (.045) | (.047) | (.032) |
| Pseudo. $R^2$ | .541 | .644 | .849 |
| Obs | 3275396 | 3275396 | 3275396 |

As we have discussed, one-stop capacity is a complex function of nonstop capacity in its two legs, which depends on the capacities and schedules of each flights. With fixed effects, the technological relationship fits the data quite well with $R^2 = 0.849$. If the number of seats in the first leg or the second leg doubles, the one-stop capacity in this route will increase by 46.3 percent. If the number of seats in both legs doubles, the one-stop capacity in this route will increase by 92.6 percent, which is close to constant returns to scale.

[36] Standard errors are clustered over the airline-market.

## 5.2 Stage 1: Estimation of Equilibrium Price and Quantity

Hedonic models of equilibrium prices and quantities are estimated using data from the first quarter of 2007 to the second quarter of 2014. My main empirical results are reported in Table 3. Column (1) and (2) report estimates of equilibrium quantity and price in nonstop service, respectively. Column (3) and (4) report estimates of equilibrium quantity and price in one-stop service, respectively.[37] Estimation results of other specifications can be found in Appendex F.

TABLE 3: Empirical Result: Equilibrium Quantity and Price

| | (1) $Q^{NS}$ Coef./SE. | (2) $P^{NS}$ Coef./SE. | (3)$Q^{OS}$ Coef./SE. | (4)$P^{OS}$ Coef./SE. |
|---|---|---|---|---|
| Nonstop Capacity of $n$ | .760*** | .031*** | –.046*** | .023*** |
| | (.014) | (.003) | (.003) | (.001) |
| One-stop Capacity of $n$ | .016*** | .006*** | .232*** | –.010*** |
| | (.004) | (.001) | (.002) | (.001) |
| Nonstop Capacity of $-n$ | –.025*** | –.024*** | –.023*** | –.004*** |
| | (.004) | (.002) | (.001) | (.001) |
| One-stop Capacity of $-n$ | –.001 | –.004 | –.019*** | –.041*** |
| | (.011) | (.004) | (.003) | (.002) |
| Airline FE | X | X | X | X |
| Quarter FE | X | X | X | X |
| Market FE | X | X | | |
| City FE | | | X | X |
| Pseudo. $R^2$ | .386 | .589 | .424 | .186 |
| Obs | 51342 | 51342 | 430941 | 430941 |

Column (1) of Table 3 contains the estimates for equilibrium quantity in nonstop service. The elasticity of nonstop capacity on equilibrium quantity in nonstop service is 0.760. It means that if nonstop capacity in the segment increases by one percent, the passengers it carries from nonstop service will increase by 0.76 percent. It displays a decreasing returns to scale property. One surprising finding is that the cannibalization effect of one-stop capacity on nonstop quantity is positive. One percent increases in one-stop service will boost equilibrium quantity from nonstop service by 0.016 percent. There are two possible explanations for this positive cannibalization effect. The first is, a round-trip itinerary may contain an one-stop route and a nonstop route. Thus, there is complementarity between nonstop service and one-stop service. Second, with more (one-stop) service in an airport, airlines can benefit from consumer loyalty program and the revenue from nonstop service

[37] All standard errors are clustered at the route level.

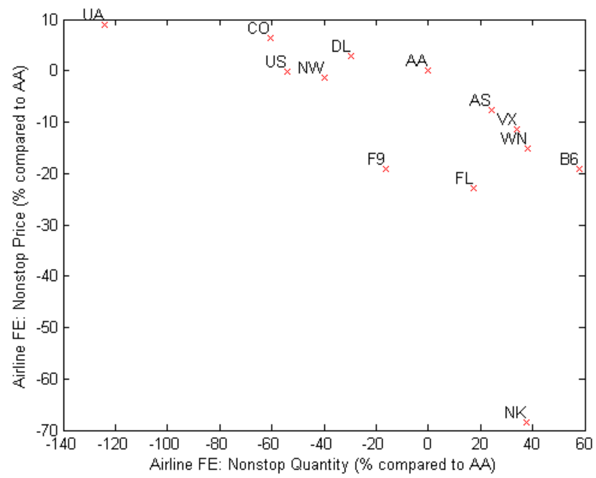
may be higher. For the competition effect from the competitors, I find that if competitors' nonstop capacities double, the equilibrium quantity of nonstop service will decrease by 2.6 percent. If one-stop capacities from the competitors increase, the equilibrium quantity of nonstop service will decrease but the effect is not significant.

I also find that the low cost carriers (LCCs) have stronger competition effect than the from legacy carriers. If the parameters are allowed to depend upon market characteristics, I find that distance has a positive impact on the elasticity of nonstop capacity but the effect decreases when distance gets larger. Markets with larger cities have larger elasticities, which is consistent with the intuition. If the cannibalization effect from one-stop service is allowed to vary for different quantiles of service, one-stop capacity can reduce equilibrium quantity in nonstop service when it is low. However, when one-stop capacity is high, it has a positive effect on equilibrium quantity in nonstop service. These findings are consistent with the explanations for the positive cannibalization effect from consumer loyalty and the complementarity between nonstop service and one-stop service. If the competitors schedule more nonstop capacity in the segment, the equilibrium quantity will be lower. However, the effect from one-stop capacity is different, with more one-stop capacity, airlines will suffer less from competition, and the effect may even be positive.

Column (2) of Table 3 contains the estimates for equilibrium price in nonstop service. If an airline allocates one percent more nonstop capacity in a segment, the price of nonstop service will increase by 0.031 percent. However, economic theory predicts that price should decrease if nonstop capacity increases. One explanation could be that the model treats all capacity as homogeneous but abstract from some heterogeneity in capacity by using differences in airplanes or times of departure. In reality, higher nonstop capacity in a city-pair usually comes with larger airplanes, better departure times or higher service frequencies, which all lead to higher prices. Change in one-stop capacity from the airline itself has negligible impact on equilibrium price. Once the competitors schedule more nonstop and one-stop capacity in the segment, nonstop fare charged by airline $n$ is expected to be lower.

The estimated airline dummies in nonstop service are summarized in Figure 4. American Airline (AA) is the benchmark with airline-fixed-effect in both quantity and price set to 0. The distances that other airlines are relative to the origin reflect their airline-fixed-effects in both quantity and price. There is a clear production frontier: given the value of nonstop capacity, legacy carriers such as American (AA), Delta (DL) and United (UA) charge higher fares but carry fewer passengers in their nonstop service. Low cost carriers such as Southwest (WN), JetBlue (B6) and Virgin American (VX) charge lower fare but carry more passengers compared to the legacy carriers. Frontier (F9) and AirTran (FL) fall behind the nonstop production frontier but they may carry more passengers in its connecting service.

Figure 4: Airline Dummies: Nonstop Service




Conditional on value of nonstop capacity, Spirit (NK) carries more nonstop passengers than American Airline (AA) but charges significantly lower nonstop fares.

The scatter plot provides evidence on whether the main source of heterogeneity across airlines is in demand (i.e., product quality) or in marginal costs. If the main source of airline heterogeneity is in demand (quality), then there should be a positive correlation between quantity and price airline-fixed-effects, i.e., an upward sloping scatter plot. Airlines with better product quality tend to have both larger quantities and prices. In contrast, if the main source of airline heterogeneity is in the marginal costs, then there should be a negative correlation between quantity and price airline-fixed-effects, i.e., an downward sloping scatter plot. Airlines with lower marginal costs tend to have larger quantities but lower prices. Since Figure 4 presents a downward sloping scatter plot, this is evidence that the main source of heterogeneity between airlines variable profits is in their marginal costs, and not so much in their product qualities. Southwest (WN) and JetBlue (B6) are among the most cost efficient airlines, and United (UA) and Continental (CO) are the less efficient in their domestic nonstop service.

Column (3) of Table 3 contains the parameter estimates for equilibrium quantity in one-stop service. If one-stop capacity increases by 1 percent, the equilibrium number of one-stop passengers will increase by 0.232 percent. It also displays decreasing returns to scale property. Nonstop capacity has a negative cannibalization effect on one-stop quantity. One percent increase in nonstop capacity will reduce equilibrium quantity from one-stop service by 0.046 percent. Thus, I may conclude that nonstop service has significant cannibalization effect on one-stop service but one-stop service has little impact on nonstop service. The competition effects from nonstop and one-stop capacity are negative.

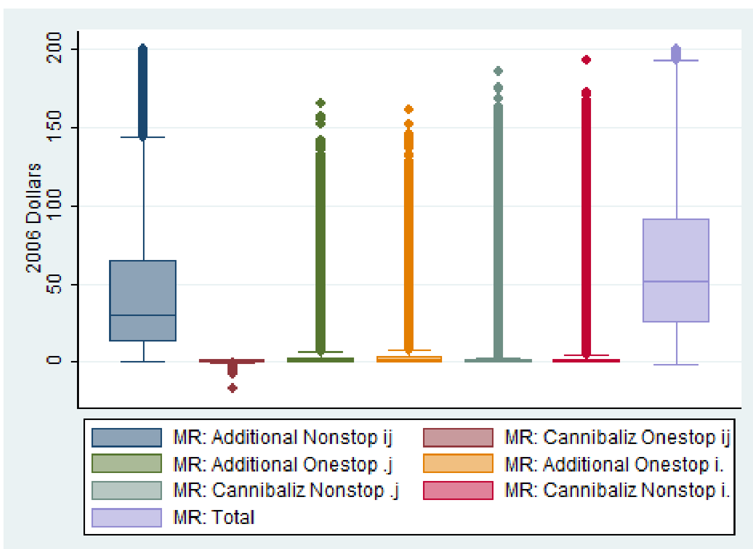
Column (4) of Table 3 contains the estimates for equilibrium price in one-stop service. If an airline builds more one-stop capacity in a city-pair, price in one-stop service decreases. This is consistent with the conjecture that price should decrease with higher capacity. However, nonstop capacity has positive cannibalization effect on one-stop price, which contradicts with the intuition. The argument that nonstop service and one-stop service are complement products may also be valid here. Increments in competitors' capacity in both nonstop and one-stop service will reduce price in the one-stop service.

From the estimation of equilibrium demand and quantity in one-stop service, we find that one-stop capacity

## 5.3 Stage 2: Estimation of Marginal Cost

The estimates in Table 3 are used to calculate marginal revenue associated with the additional nonstop capacity within each segment.

Figure 5: Decomposition of Marginal Revenue




The marginal revenue from adding an extra seat is decomposed and summarized in Figure 5. Out of all seven columns, the first column reports marginal revenue from increments in nonstop service. The second column reports the cannibalization effect from nonstop service on one-stop service. The third and forth column report the marginal revenue from increments in one-stop service. The following two columns report cannibalization effect from one-stop service on nonstop service and the last column reports the total marginal revenue which equals the marginal cost.

On average, if an airline schedules an extra seat, it can collect a marginal revenue of $44 from nonstop service and $9 from one-stop service. The average marginal cost of building capacity is equal to $64. I also compare the marginal cost derived from the model with the cost measure within the industry. One common cost measure within the industry is the cost per available seat-mile with a median of 11 cents per seat-mile. The median distance in the sample is 750 miles[38] which is equal to a cost of $82.5 per seat. The difference between these two numbers may come from the following two restrictions: first, all itineraries with more than one connection and international operations or code-sharing tickets are dropped from our analysis. Thus, the revenue in the analysis may be underestimated. Second, available seat-miles is a measure of the average cost but the outcome of the model is the marginal cost to the airline.

Even though revenue from one-stop service sustains over a quarter of the total revenue, marginal revenue from one-stop service is lower. The reason is that the elasticity of nonstop revenue from nonstop service is higher than the elasticity of one-stop revenue from one-stop service.

Figure 6: Estimation Result: Decomposition of Marginal Quantity

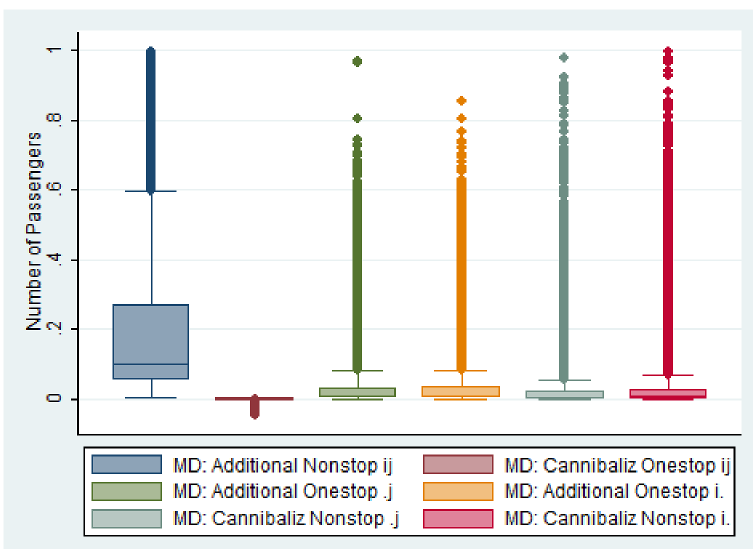



Figure 6 reports the number of extra passengers the airline can carry from an additional nonstop seat. All six columns correspond to the first six columns in Figure 5. With 1000 additional nonstop seats, it is expected that the airline can carry an average of 247 passengers in the nonstop service and 67 passengers in the one-stop service.

Figure 7 summarizes the relationship between marginal cost of building capacity and

[38] which is close to the distance from New York to Atlanta or from San Francisco to Seattle

Figure 7: Relationship between Marginal Cost and Distance

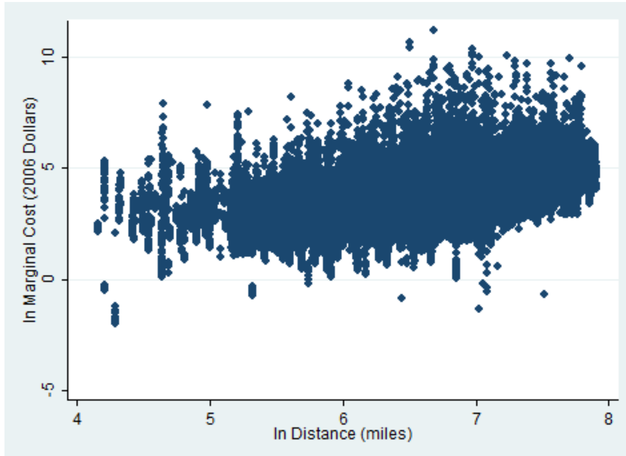



TABLE 4: Empirical Result: Marginal Cost

| | MC<br>Coef./SE. |
|---|---|
| ln Dist | –1.851*** |
| | (.336) |
| ln Dist Squared | .215*** |
| | (.026) |
| Airline-City FE | X |
| Quarter FE | X |
| Pseudo. $R^2$ | .698 |
| Obs | 56693 |

distance. It is clear that service with larger distance comes with higher marginal cost. Table 4 reports the estimation results of the cost structure. There is a U-shape relationship between distance and marginal cost. On average, if distance increases by 1 percent, the marginal cost increases by 0.82 percent.

Most previous literature in the airlines industry infers marginal cost of serving passengers from demand estimates. However, the cost of building capacity should be more important because airplanes are scheduled before selling tickets. In this paper, I estimate the marginal cost of building capacities, which are comparable with the cost measure in the airline industry. I also find that marginal cost can be underestimated by around a third if one-stop service is ignored.

## 5.4 Stage 3: Estimation of Entry Cost

Based on the estimation of equilibrium prices, quantities, marginal cost of building capacity and the observed network structure, the upper and lower bounds of the entry cost can be inferred according to revealed preference.

Table 5 reports the results of fixed cost estimation for the second quarter of 2014. Two different specifications are estimated. Column (1) reports estimates without incorporating gate information, i.e. average fixed cost across airlines. Column (2) reports airline-fixed-effects and the effect of number of gates on fixed cost of entry. Estimation is based on a total of 8212 observations. There are 1967 airline-segment pairs where airlines are active. Profit differences between the observed profit and the counterfactual profit if airlines exit from a segment create the upper bounds of the fixed cost. Similarly, there are 6245 airline-segment pairs where airlines are not active. Profit differences between the observed profit and the counterfactual profit if airlines enter into a segment with optimal capacity create the lower bounds on the fixed cost. Parameters are estimated by minimizing the criterion function in Equation (4).

There is significant heterogeneity in the entry cost across airlines. From column (1), all low cost carriers have high entry cost. Southwest has an average fixed cost of $ 0.397 million, which is higher than the legacy carriers. The average entry cost of Virgin America ($ 2.785 million) is five times higher than the average entry of American Airline ($ 0.497 million). This is consistent with the fact that though Virgin America is a successful low cost carrier, the number of segments it operates in (26 segments) is much less than American Airline (442 segments).[39]

Column (2) reports the airline-fixed-effects in fixed cost and the effect from number of gates each airline has after controlling for the total number of gates in the both endpoints. An interesting finding is that the airline-fixed-effects in fixed cost of the low cost carriers (such as Spirit, Virgin, Frontier and JetBlue) are now lower than the airline-fixed-effects of the legacy carriers. The number of gates an airline controls in both endpoints of a segment can explain the ranking difference between column (1) and column (2). On average, if the number of gates one airline controls in one city increases by one, the fixed cost of operation decreases by $ 0.11 million, which is a significant portion of the fixed cost. Legacy carriers control more gates compared to the low cost carriers, which reduces their fixed cost, facilitates their entry decisions and operations of the legacy carriers. I conclude that the gate ownership in airports is an important element of airline operation and competition.

[39]The estimates of fixed cost are close to those in Aguirregabiria and Ho (2012).

TABLE 5: Fixed Cost Estimation Result (using 2014Q2 data)

| Airline Code (Name) | Fixed Cost (Million $) (1) | (2) |
|---|---|---|
| WN (Southwest Airlines) | 0.397 | 2.325 |
| | [0.373,0.437] | [0.667,2.352] |
| DL (Delta Air Lines) | 0.411 | 2.227 |
| | [0.4,0.426] | [1.729,4.565] |
| AA (American Airlines) | 0.497 | 2.155 |
| | [0.474,0.53] | [0.754,2.327] |
| UA (United Airlines) | 0.314 | 5.515 |
| | [0.302,0.319] | [1.459,5.456] |
| B6 (JetBlue Airways) | 2.995 | 0.821 |
| | [2.86,3.101] | [0.23,1.474] |
| F9 (Frountier Airlines) | 2.37 | 1.245 |
| | [2.281,2.424] | [0.491,2.068] |
| AS (Alaska Airlines) | 1.175 | 0.853 |
| | [1.17,1.225] | [0.426,1.627] |
| NK (Spirit Airlines) | 3.561 | 4.29 |
| | [3.423,3.621] | [2.123,7.824] |
| VX (Virgin America) | 2.785 | 2.356 |
| | [2.64,2.823] | [-0.257,2.47] |
| Number of Gates one airline operates in the two endpoints | | -0.11 |
| | | [-0.119,-0.064] |
| Sum of Number of Gates in both endpoints | | 0.004 |
| | | [0.003,0.009] |
| Number of Obs. | 8212 | 8212 |

Note: 90% confidence intervals are reported in the parentheses.
Confidence intervals are constructed from 500 group samplings.

## 5.5 Goodness of Fit

In this subsection, we discuss the goodness of fit of the model. The goodness of fit of the pricing model and cost model are measured by their $R^2$, respectively. For the goodness of fit of the model in the entry stage, I report the comparison of model prediction and data in Table 6. The model predicts 96% of the airline-segment pairs when airlines stay out and 75% of the data when airlines entry. Overall, the model prediction matches with 95% of the observations.

TABLE 6: Goodness of Fit of the Entry Model

| | Model Prediction | | |
|---|---|---|---|
| | Stay Out | Entry | Total |
| Data: Stay Out | 30373 | 1143 | 31516 |
| Data: Entry | 534 | 1619 | 2153 |
| Data: Total | 30907 | 2762 | 33669 |

# 6 Policy Experiment

In the counterfactual study, I study how airline entry into a segment affects the entire network structure. The entry can be a result from fixed cost reduction in a major city. Specifically, given network structure in the second quarter of 2014, I study the impact on the network structures and capacity allocations of all major airlines if JetBlue is allowed to enter into Atlanta (ATL) - New York (NY) segment.

Since it is difficult to characterize the equilibrium of network competition, I evaluate the impact of airline entry on the entire network in three tiers sequentially. The algorithm has been discussed in detail in Section 2.6.2. Specifically, it is reasonable to assume that airlines will change their capacities in the Atlanta - New York segment first in response to the entry, then change capacities in the other segments connected to New York or Atlanta. Thereafter, airlines will change their capacities in the other part of the network. The three tiers of impacts are presented in Figure 8.

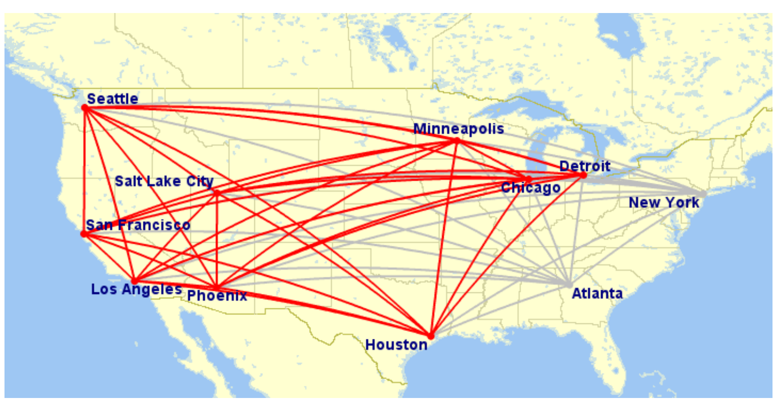
I start from the observed network in the second quarter of 2014 and separate all segments into three groups: the first group includes only the Atlanta - New York segment, the second group includes those segments connected to Atlanta or New York, and the third group includes those segments that are not connected to either Atlanta or New York. Since it is computationally infeasible to solve for an equilibrium of the network model, in this section, I propose two different approaches to approximate the effect of airline entry into one city-pair.

Figure 8: Three Tiers of Impacts

(a) First Tier Impact: Atlanta - New York


(b) Second Tier Impact: Atlanta or New York


(c) Third Tier Impact: Other segments



## 6.1 Effect of Airline Entry: A Series of Best Responses

In the first counterfactual, instead of computing for an equilibrium, I evaluate a series of best responses. I evaluate changes in all segments from the first group to the third group sequentially. For the segments within the same group, it is assumed that the segment connected to the city with more population will be evaluated first.[40] In each segment, it is assumed that airline with the larger capacity will change its capacity first followed by airline with smaller capacity. Best responses are evaluated segment by segment and airline by airline. The network structure will be updated every time an airline makes its best response. The sequence of best responses conveys useful information about how the network will move from the old equilibrium to a new (counterfactual) equilibrium. Once all three groups of segments are evaluated, I obtain the counterfactual network and I can compare the counterfactual network with the observed network.[41]

Table 7 to Table 9 summarize the changes in capacities, the equilibrium numbers of passengers and the revenues in both nonstop and one-stop services for JetBlue and Delta. I compare the operations of both JetBlue and Delta in the following four scenarios: (1) model prediction[42] (Data); (2) the counterfactuals with entry (CT1a: Entry); (3) the counterfactuals if airlines schedule flights without receiving revenues from one-stop service[43] (CT1b: No One-stop); and (4) the counterfactuals if the entry and capacity decisions are made by myopic local managers who do not respond to the network change in the other part of the network (CT1c: Local Manager).

Table 7 summarizes changes in the ATL - NY city-pair, Table 8 summarizes changes in all city-pairs connected to either ATL or NY, and Table 9 summarizes changes in all other city-pairs. Each table contains two panels with the upper panel for JetBlue and lower panel for Delta. In all six panels, the first row contains information from (1) model predictions and the second row reports (2) structure of the counterfactual network if entry happens. The third (fourth) rows in both panels of Table 8 and Table 9 report the number of city-pairs with capacity reductions (increments) if entry happens. The last two rows in all six panels report the counterfactuals with (3) no one-stop revenue and (4) myopic local managers.

In the data, JetBlue provides no nonstop service in the ATL - NY segment. If JetBlue is allowed to enter into this segment, it will schedule 1028 seats everyday in this segment, which are equivalent to ten daily flights. JetBlue can carry 414 nonstop passengers and

[40] New York - Los Angeles will be the first segment in the second group, followed by New York -Chicago.

[41] As a robustness check, I also randomize orders of the airline-segment pairs. Results are reported in Appendix G and close to the results in this subsection.

[42] Network structures and capacity allocations are the same in data and in model prediction, equilibrium quantity of passengers and revenues are model predictions

[43] See Berry (1990) and Ciliberto and Tamer (2009).

TABLE 7: Change in Capacity, Passenger, Revenue: ATL - NY city-pair

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 0 | 0 | 0 | 0 | 0 | 0 |
| | CT1a: Entry | 1028 | 414 | 62105 | 16 | 7 | 1505 |
| | CT1b: No One-stop | 811 | 345 | 51242 | 0 | 0 | 0 |
| | CT1c: Local Manager | 1028 | 414 | 62104 | 0 | 0 | 0 |
| Delta | Data | 6760 | 1254 | 235290 | 4175 | 47 | 11778 |
| | CT1a: Entry | 6094 | 1142 | 210786 | 4175 | 47 | 11700 |
| | CT1b: No One-stop | 3722 | 797 | 146742 | 0 | 0 | 0 |
| | CT1c: Local Manager | 6094 | 1142 | 210809 | 4175 | 47 | 11720 |

TABLE 8: Change in Capacity, Passenger, Revenue: city-pairs connected to ATL or NY

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 31210 | 21916 | 3658129 | 7540 | 144 | 38465 |
| | CT1a: Entry | 32999 | 22441 | 3735691 | 7948 | 304 | 73769 |
| | Capacity - | 0 | 1 | 1 | 2 | 23 | 21 |
| | Capacity + | 36 | 38 | 38 | 63 | 56 | 58 |
| | CT1b: No One-stop | 26643 | 20839 | 3476564 | 0 | 0 | 0 |
| | CT1c: Local Manager | 31210 | 21916 | 3657997 | 7829 | 279 | 68281 |
| Delta | Data | 173985 | 28035 | 5646528 | 28261 | 2705 | 721395 |
| | CT1a: Entry | 173968 | 28020 | 5641906 | 28099 | 2694 | 718432 |
| | Capacity - | 127 | 123 | 122 | 161 | 157 | 149 |
| | Capacity + | 15 | 19 | 20 | 6 | 10 | 18 |
| | CT1b: No One-stop | 57156 | 14774 | 2934201 | 0 | 0 | 0 |
| | CT1c: Local Manager | 173985 | 28036 | 5646626 | 28099 | 2695 | 718616 |

TABLE 9: Change in Capacity, Passenger, Revenue: Other city-pairs

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 30960 | 20987 | 3401031 | 16858 | 1579 | 375819 |
| | CT1a: Entry | 35177 | 23597 | 3822238 | 17136 | 1684 | 399035 |
| | Capacity - | 2 | 14 | 14 | 12 | 23 | 24 |
| | Capacity + | 21 | 54 | 54 | 612 | 633 | 632 |
| | CT1b: No One-stop | 28330 | 19872 | 3219462 | 0 | 0 | 0 |
| | CT1c: Local Manager | 30960 | 20987 | 3401031 | 16858 | 1579 | 375819 |
| Delta | Data | 125603 | 25326 | 5603649 | 65153 | 35204 | 8590109 |
| | CT1a: Entry | 125553 | 25319 | 5601907 | 65128 | 35202 | 8589863 |
| | Capacity - | 195 | 196 | 196 | 2867 | 2823 | 2823 |
| | Capacity + | 93 | 92 | 92 | 576 | 620 | 620 |
| | CT1b: No One-stop | 55671 | 15847 | 3467604 | 0 | 0 | 0 |
| | CT1c: Local Manager | 125603 | 25326 | 5603649 | 65153 | 35204 | 8590109 |

collect $62105 on a daily basis. It can now carry one-stop passengers from Atlanta to the other cities with a connection in New York. Moreover, JetBlue may also enter into other segments from Atlanta or New York. Without motivation to construct one-stop capacity, JetBlue will reduce its capacity in the segment between ATL - NY by 217 seats (21 percent of the capacity in the counterfactual).

Delta will reduce its capacity by 666 daily seats in this segment in response to the entry from JetBlue, which is about 65 percent the capacity expansion of JetBlue. In addition to the reduction of one-stop capacities, Delta is expected to carry fewer passengers and receive less revenue from nonstop service due to increment in competition effect. Atlanta is the largest hub for Delta. However, if Delta schedules its flights without considering one-stop service, its operation in the ATL - NY segment will reduce by 39 percent. It reflects the importance of one-stop service in the airline industry.

New York is the major hub for JetBlue. JetBlue can now carry passengers from Atlanta to many other cities with a connection in New York. JetBlue may also expand its nonstop capacity in the segments connected to New York to facilitate its one-stop service from Atlanta to other cities. Moreover, JetBlue has stronger incentive to enter into more segments. As a result, JetBlue will increase its capacity in most segments connected to New York. Nonstop capacity of JetBlue increases by 1789 seats daily and one-stop capacity increase by around 5.4 percent. On the other hand, Delta will reduce its capacity in most segments connected to both New York and Atlanta because it can carry less one-stop passengers through the ATL - NY segment. If there is no incentive to create one-stop service, JetBlue will schedule 19 percent less nonstop capacity. However, this number is 67 percent for Delta. It indicates that Delta relies more on connecting service.

Though entry happens in the ATL - NY segment, an interesting finding is that city-pairs that are not connected to either Atlanta or New York may also be affected. The entire network changes a lot due to the initial change. In general, both nonstop and one-stop capacity of JetBlue increases. Delta will schedule more nonstop flights but its one-stop capacity will decrease because the ATL - NY segment is very important within Delta's network structure.

Another interesting finding is that the 'third-tier' effects are heterogeneous across segments, with capacity increments in some city-pairs and capacity reductions in others. I observe increments in both nonstop and one-stop capacities in most segments. However, capacity may decrease in some segments due to increments in the cannibalization effect, strategic interactions or reductions in the incentives to build one-stop capacities. The heterogeneity across segments is summarized in the "capacity -" and "capacity +" rows.

For the ATL - NY segment, nonstop capacity in the counterfactual with myopic local managers (CT1c) is the same as the counterfactual with entry, because it is the first tier effect and the network structure remains the same in the other part of the network. However, in all other city-pairs, nonstop capacities in the counterfactual with local managers are the same as the data because the local managers will not take into account the network structure change in the other part of the network. The optimal capacities for the local managers are the same as the data. As a result, one-stop capacity between ATL and NY remains the same because one-stop capacity between ATL and NY is determined not by the flights between ATL and NY but by flights in the segments connected to both ATL and NY. However, one-stop capacity, number of passengers or revenue in the other part of the network may change due to the nonstop capacity change in ATL-NY segment.

## 6.2 Effect of Airline Entry: Equilibrium with Local Managers

For the second counterfactual, I order all segments the same way as in the first counterfactual and compute an equilibrium in each segment sequentially. To compute an equilibrium in each "local" city-pair, I assume that airlines can be ranked in order of profitability in spirit of Berry (1992). It is reasonable to assume that the "local" managers of the incumbents make entry decisions first followed by "local" managers of the potential entrants.[44] Local managers make entry decisions according to this order. In equilibrium, the profits of the

[44] I order incumbents by decreasing capacity and then potential entrants by decreasing potential profitability. I assume that the incumbents enter with the observed capacity level and potential entrants enter with the optimal counterfactual capacity level.

entered airlines are higher than the counterfactual profits if they exit from this segment while entry is unprofitable for the other airlines.

TABLE 10: Change in Capacity, Passenger, Revenue: ATL - NY city-pair

| | | **Nonstop Service** | | | **One-stop Service** | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 0 | 0 | 0 | 0 | 0 | 0 |
| | CT1a: Entry | 1028 | 413 | 61837 | 15 | 7 | 1484 |
| Delta | Data | 6760 | 1254 | 235290 | 4175 | 47 | 11778 |
| | CT1a: Entry | 6760 | 1235 | 228547 | 4175 | 46 | 11577 |

TABLE 11: Change in Capacity, Passenger, Revenue: city-pairs connected to ATL or NY

| | | **Nonstop Service** | | | **One-stop Service** | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 31210 | 21916 | 3658129 | 7540 | 144 | 38465 |
| | CT1a: Entry | 32388 | 22279 | 3708549 | 7890 | 291 | 70922 |
| | Capacity - | 0 | 16 | 16 | 0 | 11 | 11 |
| | Capacity + | 4 | 4 | 4 | 39 | 39 | 39 |
| Delta | Data | 173985 | 28035 | 5646528 | 28261 | 2705 | 721395 |
| | CT1a: Entry | 173985 | 28025 | 5643270 | 28261 | 2705 | 721164 |
| | Capacity - | 0 | 18 | 18 | 0 | 20 | 20 |
| | Capacity + | 0 | 0 | 0 | 0 | 0 | 0 |

Table 10 to Table 12 summarize the changes in capacities, the equilibrium numbers of passengers and the revenues in both nonstop and one-stop services for JetBlue and Delta. After JetBlue entry, the nonstop capacity of Delta will not change in the city-pair between ATL and NY because airlines are assumed to enter with fixed capacity levels. JetBlue will enter into 4 segments connected to the affected segment. As a third tier effect, JetBlue enters into 2 segments that are not connected to the affected segment. The entry decisions of Delta are not affected by JetBlue's entry[45]. The capacity increments of JetBlue are lower in the second counterfactual compared to the first one because airlines must enter with a given capacity in the second counterfactual.

[45]Delta usually moves before JetBlue and the increment in competition effect is not high enough.

TABLE 12: Change in Capacity, Passenger, Revenue: Other city-pairs

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 30960 | 20987 | 3401031 | 16858 | 1579 | 375819 |
| | CT1a: Entry | 31915 | 21365 | 3446968 | 16896 | 1604 | 381113 |
| | Capacity - | 0 | 6 | 6 | 0 | 5 | 5 |
| | Capacity + | 2 | 2 | 2 | 15 | 15 | 15 |
| Delta | Data | 125603 | 25326 | 5603649 | 65153 | 35204 | 8590109 |
| | CT1a: Entry | 125603 | 25326 | 5603634 | 65153 | 35203 | 8589968 |
| | Capacity - | 0 | 2 | 2 | 0 | 8 | 8 |
| | Capacity + | 0 | 0 | 0 | 0 | 0 | 0 |

# 7 Conclusion

In this paper, I have proposed and estimated one of the first models of airline network competition where airlines compete in three stages. The model endogenizes network structures, capacities, prices and quantities for every nonstop and one-stop route. I implement the marginal condition of optimality to estimate the cost of building capacities and infer fixed cost by exploiting the inequality restrictions implied by airlines' revealed preferences. The model is estimated without the computation of an equilibrium. Since it is computational infeasible to solve for an equilibrium, I have proposed and implemented a method to predict the effect of airline entry into one segment upon the entire network structure.

I use this model and methods to study the effect of the marginal cost, fixed cost, revenue and strategic interactions in both nonstop and one-stop services on network formation. I find that the synergies across city-pairs are crucial in airline entry decisions. One driving force why airlines strategically make segment entry and capacity building decisions is the incentive to construct connecting service. Without incorporating one-stop service in the analysis, marginal cost of building capacity may be underestimated by a third. For the counterfactual study, I find that JetBlue's entry into the segment between Atlanta and New York would have substantial competition effects on other city-pairs, even at segments that are not directly connected to Atlanta or New York.

As an extension, this framework can be applied to study other types of counterfactuals such as analyzing the effects from a merger, an airline's decision to close a hub, or the effect of a new airport on the airline networks.

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# A Demand Model

Below I propose a standard demand model of discrete choice. In any non-directional city-pair $ij$, let $MS_{ij}$ denote total number of potential travelers in the city-pair. Each traveler may demand one trip and choose from several differentiated products. An airline can provide at most two products in the city-pair: nonstop service and one-stop service.[46] Products are indexed as a combination of $n$ and $x$ where $x \in \{NS, OS\}$.[47]

The indirect utility of traveler $a$ from purchasing service $x$ from airline $n$ in city-pair $ij$ is $U^x_{anij} = b^x_{nij} - P^x_{nij} + v^x_{anij}$ where $P^x_{nij}$ is the price of the product, $b^x_{nij}$ is the average willingness to pay for the product and $v^x_{anij}$ is the consumer-specific component. The utility of the outside good (not traveling or another form of transportation) is normalized to zero ($U_{a0ij} = 0$). The average willingness to pay may depend on aircraft type, flight frequency, time scheduled during the day, flight frequency programs, airline presence in the origin-destination airports[48], the number of flight frequency or airline capacity in the two endpoints, etc. Consumer purchases one unit of the product with the highest utility. The aggregated demand equals to the sum of all individual demands. I can consider either a nested logit demand model or a BLP type of model.

Let $Q^{NS}_{nij}$ and $Q^{OS}_{nij}$ represent the number of passengers airline $n$ serves with nonstop and one-stop services in city-pair $ij$, respectively. Thus,

$$Q^{NS}_{nij} = MS_{ij} \times \int 1\left[U^{NS}_{anij} > U^{OS}_{anij}, U^{NS}_{anij} > U^{NS}_{a,-n,ij}, U^{NS}_{anij} > U^{OS}_{a,-n,ij}, U^{NS}_{anij} > U_{a0ij}\right] dv^{NS}_{anij}$$

and

$$Q^{OS}_{nij} = MS_{ij} \times \int 1\left[U^{OS}_{anij} > U^{NS}_{anij}, U^{OS}_{anij} > U^{NS}_{a,-n,ij}, U^{OS}_{anij} > U^{OS}_{a,-n,ij}, U^{OS}_{anij} > U_{a0ij}\right] dv^{OS}_{anij}.$$

The total variable cost of serving passengers will be a function of both capacity and the number of passengers served in the network, i.e. $VC^Q_n = VC^Q_n\left(\mathbf{s}_n, \mathbf{Q}^{NS}_n, \mathbf{Q}^{OS}_n\right)$, where $\mathbf{Q}^{NS}_n = \left\{Q^{NS}_{nij} : \forall i, \forall j\right\}$ and $\mathbf{Q}^{OS}_n = \left\{Q^{OS}_{nij} : \forall i, \forall j\right\}$. Similarly, if the variable cost of serving passengers is additive separable across markets, $VC^Q_n\left(\mathbf{s}_n, \mathbf{Q}^{NS}_n, \mathbf{Q}^{OS}_n\right) = \frac{1}{2}\sum_i \sum_{j \neq i} VC^Q_{nij}\left(\mathbf{s}_{nij}, Q^{NS}_{nij}, Q^{OS}_{nij}\right)$, where $VC^Q_{nij}\left(\mathbf{s}_{nij}, Q^{NS}_{nij}, Q^{OS}_{nij}\right)$ includes the variable cost of serving passengers in city-pair $ij$, both nonstop and one-stop. Variable cost of serving passengers depends on the number of passengers because it is costly to provide

[46] As an extension in the future, I can consider one-stop services at different connecting cities to be different.

[47] Since I consider a non-directional city-pair, I didn't distinguish the service from i to j and service from j to i. However, the model can be extended to distinguish these two different routes.

[48] See Berry (1992).

check-in, luggage, food and beverage service to the travelers. However, the variable cost of accommodating passengers is lower if larger capacity has been built because the planes are less crowded.[49]

# B Bankruptcies and Mergers

There are some bankruptcies and mergers in the airline industry during the sample period. I consider three major mergers. Delta announced a merger with Northwest Apr. 14th, 2008 and the transaction complete in Dec. 31st, 2009; United Airlines merged with Continental on May. 3rd, 2010 and the closing day is Oct. 1st, 2010; Southwest controlled AirTran's assets after AirTran's bankruptcy on Sep. 27th, 2010. The former parent company of American Airlines, AMR Corporation and US Airways Group completed the merger on December 9, 2013. The two merging airlines are treated as the same airline after the closing day but as different airlines before the closing day. So Northwest brand disappeared in 2010 Q1; Continental flights are considered as United Airlines flights after 2010 Q4; and very few AirTran tickets in 2008 Q2 are considered to be Southwest tickets and US Airway tickets and operations are considered to be parts of American Airlines service after 2014Q1. I believe that these assumptions are correct and all these modifications are necessary.

# C Algorithm of Measuring One-stop Capacity

The algorithm which measures one-stop capacity of airline $n$ within city-pair A and C with a connection at B performs as follows:

Step (1): For any flight, which can be matched with multiple other flights[50], I separate all seats on this flight into several mutually exclusive sets. Each set correspond to one matched flight. The number of seats in each set is proportional to the number of seats on the other matched flights.

Step (2): I keep all flights airline $n$ operates from A to B and from B to C in a given day.

Step (3): All flights are separated into two groups. I call all flights from A to B group AB and all flights from B to C group BC. Flights are sorted in each group according to their schedules from earliest to the latest.

[49] Ryan (2012) provides a similar model in the cement industry where cement firms first build their capacity then determine the quantity to produce. Costs of building (or adjusting) capacity and production are separately considered in his model.

[50] Two flights match if they belong to the same airline and the first flight is scheduled 45 minutes to 4 hours after the departure of the second flight at the same airport.

Step (4): Start with the flight with the earliest schedule. Suppose the flight is in group AB(BC), I match it with the first flight in group BC(AB).

Step (5): If the scheduled departure time of the flight in group BC(AB) is 45 minutes to 4 hours after the scheduled arrival of the flight from group AB(BC), I count the number of one-stop seats that can be created between the two flights, which equals to the minimum of number of the seats in the corresponding sets of the two flights. A one-stop seat will occupy one seat in the flight from group AB and one seat in the flight from group BC.

Step (6): If the number of seats in the two flights equals, I proceed to the next flight which hasn't been visited before and repeat step (5). If there are uncounted seats on either flight, I set the number of seats of the flight with more seats to the number of uncounted seats and the number of seats of the flight with fewer seats to zero. And then I match the flight with uncounted seats with the next flight available in the other group by repeating step (5).

Step (7): If no more one-stop capacity can be constructed, I proceed to the next flight available and repeat step (5) and (6).

Step (8): Once all flights have been visited, I repeat the algorithm for everyday in the quarter and sum up all counted seats. The total number will be the number of one-stop seats.

# D Additional Description of Nonstop and One-stop Services

Figure 9: Histogram of Nonstop Capacity

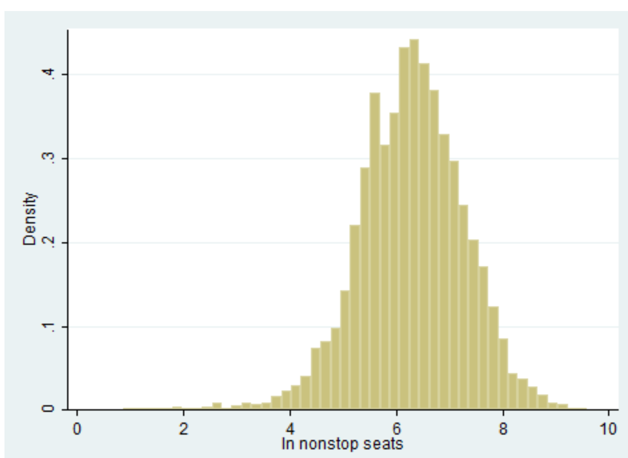
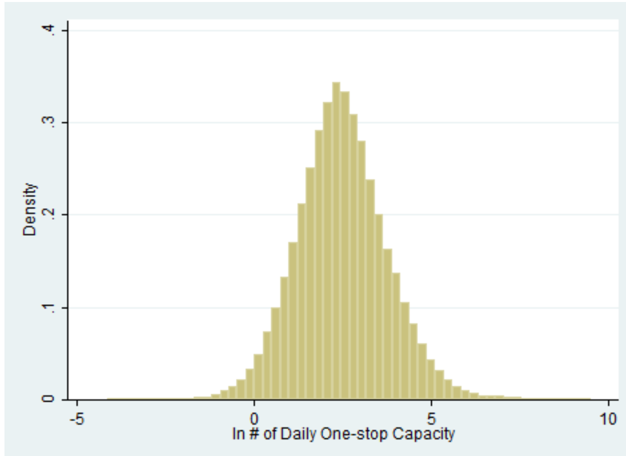



Figure 9 illustrates the distribution of the logarithm nonstop capacity.

Figure 10 represents the distribution of logarithm one-stop capacity.

Figure 10: Histogram of One-stop Capacity




# E Additional Summary Statistics

Table 13 summarizes the number of nonstop segment, number passengers, revenue and number of cities served for each airline. After several major mergers, the legacy carriers: American Airlines and Delta Air Lines serve almost all cities. United Airlines serves 74 cities and Southwest Airlines serves for 73 cities in 2014.

Comparing the two panels in Table 13, airlines receive more revenue in 2014. Possible explanation is that legacy carriers operate in more segments with larger capacities, and suffer from less competition due to airline mergers. Increments in service in hub cities due to merger also result in more flexible schedules which makes one-stop service more convenient.

Table 14 lists the top two hubs for all airlines and the hub concentration ratio using the top four hubs (airports) for each airline. Hub concentration ratio is defined as the share of all the nonstop routes of an airline that connect to the hub cities. This ratio is equal to one for a pure hub-and-spoke network, and it measures an airline's degree of 'hubbing' or concentration of its operation in a few airports. Most airlines in the dataset employ hub-and-spoke networks. For the legacy carriers, the top and second hubs usually connect to over 60 other cities and the hub concentration ratios are high. Frontier even employs nearly perfect hub-and-spoke network and all other cities it serves are connected to the hub city. Southwest has the lowest concentration ratio among all airlines. However, its top hub (Chicago) connects to 47 other cities, its second hub (Las Vegas) connects to 45 other cities in 2007, and its $CR4$ is closes to 40. It seems that Southwest use a multi-hub business model.

For the legacy carriers, the number of segments connected to the hub cities does not

TABLE 13: Summary Statistics: Airline

| | | | 2007Q1 | | | | |
|---|---|---|---|---|---|---|---|
| Airline Code (Name) | # of served Segments | % of served Segments | # of Pass (million) | % of Pass | Revenue (million) | % of Rev | # of served MSAs |
| WN (Southwest Airlines) | 364 | 19.1 | 20.2 | 21.4 | 2167.7 | 17.2 | 54 |
| DL (Delta Air Lines) | 316 | 16.6 | 12.1 | 12.8 | 1851.4 | 14.7 | 87 |
| US (US airway) | 273 | 14.3 | 11.7 | 12.4 | 1535.7 | 12.2 | 79 |
| AA (American Airlines) | 260 | 13.6 | 13.3 | 14.1 | 1975.9 | 15.7 | 80 |
| UA (United Airlines) | 166 | 8.7 | 10.2 | 10.7 | 1455.9 | 11.5 | 69 |
| NW (Northwest Airlines) | 155 | 8.1 | 6.9 | 7.3 | 1042.9 | 8.3 | 68 |
| CO (Continental Airlines) | 97 | 5.1 | 6.9 | 7.3 | 1048.4 | 8.3 | 51 |
| FL (AirTran Airways) | 95 | 5.0 | 4.1 | 4.4 | 398.4 | 3.2 | 38 |
| B6 (JetBlue Airways) | 67 | 3.5 | 4.3 | 4.5 | 531.3 | 4.2 | 37 |
| F9 (Frontier Airlines) | 46 | 2.4 | 1.9 | 2.0 | 214.8 | 1.7 | 45 |
| AS (Alaska Airlines) | 45 | 2.4 | 2.2 | 2.3 | 295.8 | 2.3 | 23 |
| NK (Spirit Airlines) | 22 | 1.2 | 0.8 | 0.8 | 91.4 | 0.7 | 13 |
| VX (Virgin America) | - | - | - | - | - | - | - |
| Total | 1906 | 100.0 | 94.7 | 100.0 | 12609.4 | 100.0 | 87 |
| | | | 2014Q2 | | | | |
| Airline Code (Name) | # of served Segments | % of served Segments | # of Pass (million) | % of Pass | Revenue (million) | % of Rev | # of served MSAs |
| WN (Southwest Airlines) | 529 | 26.9 | 29.4 | 28.6 | 4163.3 | 25.5 | 73 |
| DL (Delta Air Lines) | 417 | 21.2 | 21.1 | 20.6 | 3561.7 | 21.8 | 86 |
| US (US airway) | - | - | - | - | - | - | - |
| AA (American Airlines) | 442 | 22.5 | 26.1 | 25.4 | 4275 | 26.2 | 87 |
| UA (United Airlines) | 258 | 13.1 | 12.4 | 12.1 | 2341 | 14.4 | 74 |
| NW (Northwest Airlines) | - | - | - | - | - | - | - |
| CO (Continental Airlines) | - | - | - | - | - | - | - |
| FL (AirTran Airways) | - | - | - | - | - | - | - |
| B6 (JetBlue Airways) | 96 | 4.9 | 5.0 | 4.9 | 807.6 | 5 | 42 |
| F9 (Frontier Airlines) | 52 | 2.6 | 2.2 | 2.1 | 232.5 | 1.4 | 42 |
| AS (Alaska Airlines) | 70 | 3.6 | 2.8 | 2.7 | 421.7 | 2.6 | 36 |
| NK (Spirit Airlines) | 77 | 3.9 | 2.1 | 2.0 | 189.7 | 1.2 | 22 |
| VX (Virgin America) | 26 | 1.3 | 1.6 | 1.6 | 314.6 | 1.9 | 16 |
| Total | 1967 | 100.0 | 102.7 | 100.0 | 16307.2 | 100 | 87 |

Note: pass is abbreviation of passengers and rev is abbreviation of revenue.

TABLE 14: Summary Statistics: Hub

| Airline Code (Name) | Top Hub | # Seg | Second Hub | # Seg | CR1 | CR2 | CR3 | CR4 |
|---|---|---|---|---|---|---|---|---|
| | | | | 2007Q1 | | | | |
| WN (Southwest Airlines) | Chicago | 47 | Las Vegas | 45 | 12.9 | 25.0 | 35.4 | 44.8 |
| DL (Delta Air Lines) | Atlanta | 83 | Cincinnati | 73 | 26.3 | 49.1 | 63.6 | 77.5 |
| US (US airway) | Charlotte | 61 | Philadelphia | 54 | 22.3 | 41.8 | 57.9 | 70.0 |
| AA (American Airlines) | Dallas | 75 | Chicago | 71 | 28.8 | 55.8 | 68.8 | 81.5 |
| UA (United Airlines) | Chicago | 55 | Denver | 44 | 33.1 | 59.0 | 78.9 | 89.8 |
| NW (Northwest Airlines) | Detroit | 56 | Minneapolis | 55 | 36.1 | 71.0 | 91.0 | 96.8 |
| CO (Continental Airlines) | Houston | 46 | New York | 37 | 47.4 | 84.5 | 96.9 | 100.0 |
| FL (AirTran Airways) | Atlanta | 37 | Orlando | 18 | 38.9 | 56.8 | 67.4 | 74.7 |
| B6 (JetBlue Airways) | New York | 36 | Boston | 19 | 53.7 | 80.6 | 91.0 | 97.0 |
| F9 (Frontier Airlines) | Denver | 44 | San Francisco | 3 | 95.7 | 100.0 | 100.0 | 100.0 |
| AS (Alaska Airlines) | Seattle | 22 | Portland | 14 | 48.9 | 77.8 | 91.1 | 97.8 |
| NK (Spirit Airlines) | Detroit | 10 | Miami | 8 | 45.5 | 77.3 | 90.9 | 90.9 |
| VX (Virgin America) | - | - | - | - | - | - | - | - |
| | | | | 2014Q2 | | | | |
| Airline Code (Name) | Top Hub | # Seg | Second Hub | # Seg | CR1 | CR2 | CR3 | CR4 |
| WN (Southwest Airlines) | Chicago | 62 | Las Vegas | 51 | 11.7 | 21.2 | 30.2 | 39.1 |
| DL (Delta Air Lines) | Atlanta | 82 | Detroit | 69 | 19.7 | 36.0 | 51.3 | 65.5 |
| US (US airway) | - | - | - | - | - | - | - | - |
| AA (American Airlines) | Dallas | 72 | Charlotte | 69 | 16.3 | 31.7 | 45.5 | 58.6 |
| UA (United Airlines) | Chicago | 58 | Houston | 43 | 22.5 | 38.8 | 53.9 | 68.2 |
| NW (Northwest Airlines) | - | - | - | - | - | - | - | - |
| CO (Continental Airlines) | - | - | - | - | - | - | - | - |
| FL (AirTran Airways) | - | - | - | - | - | - | - | - |
| B6 (JetBlue Airways) | New York | 33 | Boston | 32 | 34.4 | 66.7 | 76.0 | 84.4 |
| F9 (Frontier Airlines) | Denver | 40 | Miami | 9 | 76.9 | 92.3 | 94.2 | 98.1 |
| AS (Alaska Airlines) | Seattle | 35 | Portland | 20 | 50.0 | 77.1 | 85.7 | 91.4 |
| NK (Spirit Airlines) | Dallas | 20 | Las Vegas | 16 | 26.0 | 45.5 | 59.7 | 72.7 |
| VX (Virgin America) | San Francisco | 14 | Los Angeles | 12 | 53.8 | 96.2 | 100.0 | 100.0 |

change much during the sample period. However, the hubs are expanding for some airlines. For instance, Alaska Airlines increases its nonstop routes from Seattle from 22 to 35. Southwest can carry passengers to 62 other cities in 2014 compared to 47 other cities in 2007 from Chicago. However, if I compare the two panels, there is a reduction in the hub concentration ratio from 2007 to 2014. This may come from the major mergers in the airline industry. Airlines operate in more segments but the number of segments connected to the hub city remains the same.

TABLE 15: Summary Statistics: City-pair service decomposition

| | **2007Q1 city-pairs with** | | | **2014Q2 city-pairs with** | | |
|---|---|---|---|---|---|---|
| Airline Code (Name) | Only Nonstop | Only One-stop | Both | Only Nonstop | Only One-stop | Both |
| WN (Southwest Airlines) | 39 | 919 | 325 | 45 | 1674 | 484 |
| DL (Delta Air Lines) | 60 | 2980 | 256 | 37 | 2873 | 380 |
| US (US airway) | 27 | 2114 | 246 | - | - | - |
| AA (American Airlines) | 56 | 2210 | 204 | 54 | 2879 | 388 |
| UA (United Airlines) | 27 | 2641 | 139 | 21 | 2742 | 237 |
| NW (Northwest Airlines) | 27 | 2334 | 128 | - | - | - |
| CO (Continental Airlines) | 21 | 2321 | 76 | - | - | - |
| FL (AirTran Airways) | 24 | 460 | 71 | - | - | - |
| B6 (JetBlue Airways) | 20 | 386 | 47 | 25 | 363 | 71 |
| F9 (Frontier Airlines) | 43 | 572 | 3 | 48 | 386 | 4 |
| AS (Alaska Airlines) | 11 | 97 | 34 | 22 | 191 | 48 |
| NK (Spirit Airlines) | 20 | 11 | 2 | 27 | 69 | 50 |
| VX (Virgin America) | - | - | - | 5 | 53 | 21 |
| Total | 375 | 17045 | 1531 | 284 | 11230 | 1683 |

Airlines may provide both nonstop and one-stop services in the same city-pair. Table 15 summarizes airline operations in both nonstop and one-stop services. Nonstop service and one-stop service are highly overlapped. In the first quarter of 2007, Southwest provides nonstop service in 364 city-pairs. Out of them, Southwest provides one-stop service in 325 city-pairs.

# F Detailed Estimation Results

Hedonic models of equilibrium prices and quantities are estimated using data from the first quarter of 2007 to the second quarter of 2014. My main empirical results are presented in Table 16 to 19. Table 16 and 17 report the estimates of the equilibrium quantity and price equations in nonstop service respectively. Table 18 and 19 report the estimates of the equilibrium quantity and price equations in one-stop service respectively. In all tables, column (1) and (2) contain the estimation results without fixed effects, column (3) and (4) contain the results with fixed effects and column (5) and (6) allow for flexible specification of the parameters. Column (1), (3) and (5) contain results from OLS estimation and column (2), (4) and (6) contain results from Cochrane-Orcutt estimation. All standard errors are clustered at route level.

Competition effects from legacy carriers are low and sometimes they are positive. There are at least two possible explanations for this. First, the conducts among airlines are not clear. Ciliberto and Williams (2014) has documented the potential collusion among airlines. There is a recent investigation on the major carriers such as Delta, American, United and Southwest, accusing them colluding on prices and limit capacity. Second, there may be some code-sharing factors that are not captured in the model. Passengers may travel from A to B with Delta and travel back with Continental. In this case, products from different airlines will be both substitutes and complements. The equilibrium equations summarize the total effect of the two.

# G Counterfactuals with Random Orders

I consider randomized orders of airline-segment pairs and the counterfactual results are reported in Table 20 to Table 22.

TABLE 16: Estimation Result: Nonstop Quantity

| | (1) OLS Coef./SE. | (2) C-O Coef./SE. | (3) OLS Coef./SE. | (4) C-O Coef./SE. | (5) OLS Coef./SE. | (6) C-O Coef./SE. |
|---|---|---|---|---|---|---|
| ln nonstop Capa | 1.069*** | .704*** | 1.300*** | .840*** | 1.158*** | .788*** |
| | (.021) | (.013) | (.042) | (.030) | (.027) | (.015) |
| ln nonstop Capa * ln dist | | | | | .430 | .815*** |
| | | | | | (.535) | (.273) |
| ln nonstop Capa * ln dist sq | | | | | –.048 | –.070*** |
| | | | | | (.040) | (.021) |
| ln nonstop Capa * ln pop city 1 | | | | | .075** | .019 |
| | | | | | (.029) | (.015) |
| ln nonstop Capa * ln pop city 2 | | | | | .079*** | .049*** |
| | | | | | (.025) | (.015) |
| ln onestop Capa | .085*** | .021*** | .026** | .019*** | | |
| | (.010) | (.004) | (.012) | (.006) | | |
| ln onestop Capa 1 | | | | | –.048 | –.032 |
| | | | | | (.034) | (.020) |
| ln onestop Capa 2 | | | | | –.040 | .004 |
| | | | | | (.026) | (.008) |
| ln onestop Capa 3 | | | | | –.030** | .011** |
| | | | | | (.015) | (.005) |
| ln onestop Capa 4 | | | | | .005 | .016*** |
| | | | | | (.010) | (.005) |
| Comp: ln nonstop Capa (Legacy) | | | –.048*** | –.034*** | | |
| | | | (.010) | (.006) | | |
| Comp: ln nonstop Capa (LCC) | | | –.134*** | –.112*** | | |
| | | | (.048) | (.031) | | |
| Comp: ln nonstop Capa 1 | | | | | –.036*** | –.022*** |
| | | | | | (.008) | (.004) |
| Comp: ln nonstop Capa 2 | | | | | –.078*** | –.026*** |
| | | | | | (.010) | (.005) |
| Comp: ln nonstop Capa 3 | | | | | –.102*** | –.028*** |
| | | | | | (.011) | (.006) |
| Comp: ln nonstop Capa 4 | | | | | –.113*** | –.030*** |
| | | | | | (.012) | (.006) |
| Comp: ln onestop Capa (Legacy) | | | –.034 | .013 | | |
| | | | (.025) | (.013) | | |
| Comp: ln onestop Capa (LCC) | | | –.012 | –.005 | | |
| | | | (.020) | (.007) | | |
| Comp: ln onestop Capa 1 | | | | | .065* | –.004 |
| | | | | | (.034) | (.013) |
| Comp: ln onestop Capa 2 | | | | | .049* | –.005 |
| | | | | | (.029) | (.012) |
| Comp: ln onestop Capa 3 | | | | | .018 | .001 |
| | | | | | (.026) | (.012) |
| Comp: ln onestop Capa 4 | | | | | .002 | .002 |
| | | | | | (.023) | (.012) |
| Airline FE | | | X | X | X | X |
| Quarter FE | | | X | X | X | X |
| Mkt FE | | | X | X | X | X |
| $\rho$ | .674*** | | .626*** | | .614*** | |
| | (.004) | | (.004) | | (.004) | |
| Pseudo. $R^2$ | .453 | .197 | .753 | .367 | .758 | .370 |
| Obs | 56697 | 51342 | 56697 | 51342 | 56697 | 51342 |

TABLE 17: Estimation Result: Nonstop Price

| | (1) OLS Coef./SE. | (2) C-O Coef./SE. | (3) OLS Coef./SE. | (4) C-O Coef./SE. | (5) OLS Coef./SE. | (6) C-O Coef./SE. |
|---|---|---|---|---|---|---|
| ln nonstop Capa | –.022*** | –.004 | .103*** | .086*** | .019*** | .024*** |
| | (.006) | (.003) | (.007) | (.006) | (.004) | (.004) |
| ln nonstop Capa * ln dist | | | | | .019 | –.012 |
| | | | | | (.176) | (.139) |
| ln nonstop Capa * ln dist sq | | | | | –.002 | .001 |
| | | | | | (.013) | (.010) |
| ln nonstop Capa * ln pop city 1 | | | | | .002 | .005* |
| | | | | | (.003) | (.003) |
| ln nonstop Capa * ln pop city 2 | | | | | .003 | .003 |
| | | | | | (.003) | (.003) |
| ln onestop Capa | .036*** | .005*** | .013*** | .009*** | | |
| | (.003) | (.002) | (.002) | (.001) | | |
| ln onestop Capa 1 | | | | | –.027*** | –.015** |
| | | | | | (.009) | (.006) |
| ln onestop Capa 2 | | | | | –.004 | –.002 |
| | | | | | (.005) | (.004) |
| ln onestop Capa 3 | | | | | –.003 | .000 |
| | | | | | (.002) | (.002) |
| ln onestop Capa 4 | | | | | .004*** | .005*** |
| | | | | | (.002) | (.001) |
| Comp: ln nonstop Capa (Legacy) | | | –.005*** | –.004*** | | |
| | | | (.002) | (.001) | | |
| Comp: ln nonstop Capa (LCC) | | | –.083*** | –.074*** | | |
| | | | (.009) | (.008) | | |
| Comp: ln nonstop Capa 1 | | | | | –.026*** | –.021*** |
| | | | | | (.002) | (.002) |
| Comp: ln nonstop Capa 2 | | | | | –.030*** | –.024*** |
| | | | | | (.002) | (.002) |
| Comp: ln nonstop Capa 3 | | | | | –.039*** | –.029*** |
| | | | | | (.002) | (.002) |
| Comp: ln nonstop Capa 4 | | | | | –.050*** | –.034*** |
| | | | | | (.002) | (.002) |
| Comp: ln onestop Capa (Legacy) | | | .003 | .006 | | |
| | | | (.005) | (.004) | | |
| Comp: ln onestop Capa (LCC) | | | –.007** | –.004* | | |
| | | | (.004) | (.002) | | |
| Comp: ln onestop Capa 1 | | | | | .002 | –.000 |
| | | | | | (.007) | (.005) |
| Comp: ln onestop Capa 2 | | | | | .004 | .000 |
| | | | | | (.005) | (.004) |
| Comp: ln onestop Capa 3 | | | | | –.001 | .001 |
| | | | | | (.005) | (.004) |
| Comp: ln onestop Capa 4 | | | | | –.006 | –.001 |
| | | | | | (.004) | (.003) |
| Airline FE | | | X | X | X | X |
| Quarter FE | | | X | X | X | X |
| Mkt FE | | | X | X | X | X |
| $\rho$ | .674*** | | .626*** | | .614*** | |
| | (.004) | | (.004) | | (.004) | |
| Pseudo. $R^2$ | .183 | .009 | .755 | .567 | .764 | .593 |
| Obs | 56697 | 51342 | 56697 | 51342 | 56697 | 51342 |

TABLE 18: Estimation Result: Onestop Quantity

| | (1) OLS<br>Coef./SE. | (2) C-O<br>Coef./SE. | (3) OLS<br>Coef./SE. | (4) C-O<br>Coef./SE. | (5) OLS<br>Coef./SE. | (6) C-O<br>Coef./SE. |
|---|---|---|---|---|---|---|
| ln onestop Capa | 1.054*** | .265*** | 1.080*** | .237*** | 1.062*** | .246*** |
| | (.008) | (.003) | (.009) | (.003) | (.008) | (.003) |
| ln onestop Capa * ln dist | | | | | 1.118*** | 1.178*** |
| | | | | | (.190) | (.114) |
| ln onestop Capa * ln dist sq | | | | | –.076*** | –.084*** |
| | | | | | (.014) | (.008) |
| ln onestop Capa * ln pop city 1 | | | | | –.036*** | –.002 |
| | | | | | (.006) | (.003) |
| ln onestop Capa * ln pop city 2 | | | | | –.012** | .006** |
| | | | | | (.006) | (.002) |
| ln nonstop Capa | –.200*** | –.009*** | –.148*** | –.035*** | | |
| | (.005) | (.003) | (.006) | (.003) | | |
| ln nonstop Capa 1 | | | | | –.089*** | –.031*** |
| | | | | | (.008) | (.003) |
| ln nonstop Capa 2 | | | | | –.163*** | –.042*** |
| | | | | | (.008) | (.004) |
| ln nonstop Capa 3 | | | | | –.210*** | –.052*** |
| | | | | | (.008) | (.004) |
| ln nonstop Capa 4 | | | | | –.266*** | –.060*** |
| | | | | | (.009) | (.004) |
| Comp: ln nonstop Capa (Legacy) | | | –.026*** | –.026*** | | |
| | | | (.004) | (.002) | | |
| Comp: ln nonstop Capa (LCC) | | | –.047*** | –.021*** | | |
| | | | (.004) | (.002) | | |
| Comp: ln nonstop Capa 1 | | | | | .059*** | .006** |
| | | | | | (.010) | (.003) |
| Comp: ln nonstop Capa 2 | | | | | .055*** | .003 |
| | | | | | (.009) | (.003) |
| Comp: ln nonstop Capa 3 | | | | | .053*** | –.001 |
| | | | | | (.009) | (.003) |
| Comp: ln nonstop Capa 4 | | | | | .087*** | –.001 |
| | | | | | (.009) | (.004) |
| Comp: ln onestop Capa (Legacy) | | | –.002 | –.018*** | | |
| | | | (.013) | (.003) | | |
| Comp: ln onestop Capa (LCC) | | | –.056*** | –.003 | | |
| | | | (.011) | (.003) | | |
| Comp: ln onestop Capa 1 | | | | | .016 | –.014*** |
| | | | | | (.015) | (.004) |
| Comp: ln onestop Capa 2 | | | | | .021 | –.014*** |
| | | | | | (.013) | (.003) |
| Comp: ln onestop Capa 3 | | | | | .007 | –.019*** |
| | | | | | (.013) | (.003) |
| Comp: ln onestop Capa 4 | | | | | –.022* | –.028*** |
| | | | | | (.013) | (.003) |
| ldist | 7.191*** | 4.033*** | 7.010*** | 7.598*** | 2.982*** | 4.077*** |
| | (.310) | (.297) | (.416) | (.389) | (.552) | (.404) |
| ldist2 | –.473*** | –.245*** | –.442*** | –.516*** | –.153*** | –.262*** |
| | (.023) | (.022) | (.031) | (.029) | (.041) | (.030) |
| Airline FE | | | X | X | X | X |
| City FE | | | X | X | X | X |
| Quarter FE | | | X | X | X | X |
| $\rho$ | .725*** | | .691*** | | .675*** | |
| | (.001) | | (.001) | | (.001) | |
| Pseudo. $R^2$ | .527 | .250 | .604 | .426 | .612 | .430 |
| Obs | 475391 | 430941 | 475391 | 430941 | 475391 | 430941 |

TABLE 19: Estimation Result: Onestop Price

| | (1) OLS<br>Coef./SE. | (2) C-O<br>Coef./SE. | (3) OLS<br>Coef./SE. | (4) C-O<br>Coef./SE. | (5) OLS<br>Coef./SE. | (6) C-O<br>Coef./SE. |
|---|---|---|---|---|---|---|
| ln onestop Capa | –.021*** | –.013*** | .003 | .005*** | –.023*** | –.011*** |
| | (.001) | (.001) | (.002) | (.001) | (.001) | (.001) |
| ln onestop Capa * ln dist | | | | | .088 | .034 |
| | | | | | (.055) | (.051) |
| ln onestop Capa * ln dist sq | | | | | –.006 | –.002 |
| | | | | | (.004) | (.004) |
| ln onestop Capa * ln pop city 1 | | | | | .002 | .001 |
| | | | | | (.001) | (.001) |
| ln onestop Capa * ln pop city 2 | | | | | .005*** | .004*** |
| | | | | | (.001) | (.001) |
| ln nonstop Capa | .030*** | .025*** | .032*** | .030*** | | |
| | (.001) | (.001) | (.001) | (.001) | | |
| ln nonstop Capa 1 | | | | | .030*** | .027*** |
| | | | | | (.001) | (.001) |
| ln nonstop Capa 2 | | | | | .033*** | .029*** |
| | | | | | (.001) | (.001) |
| ln nonstop Capa 3 | | | | | .034*** | .031*** |
| | | | | | (.001) | (.001) |
| ln nonstop Capa 4 | | | | | .039*** | .034*** |
| | | | | | (.002) | (.001) |
| Comp: ln nonstop Capa (Legacy) | | | .004*** | .004*** | | |
| | | | (.001) | (.001) | | |
| Comp: ln nonstop Capa (LCC) | | | –.008*** | –.008*** | | |
| | | | (.001) | (.001) | | |
| Comp: ln nonstop Capa 1 | | | | | –.012*** | –.009*** |
| | | | | | (.002) | (.001) |
| Comp: ln nonstop Capa 2 | | | | | –.015*** | –.011*** |
| | | | | | (.002) | (.001) |
| Comp: ln nonstop Capa 3 | | | | | –.017*** | –.013*** |
| | | | | | (.001) | (.001) |
| Comp: ln nonstop Capa 4 | | | | | –.016*** | –.012*** |
| | | | | | (.002) | (.001) |
| Comp: ln onestop Capa (Legacy) | | | –.033*** | –.019*** | | |
| | | | (.003) | (.002) | | |
| Comp: ln onestop Capa (LCC) | | | –.039*** | –.027*** | | |
| | | | (.003) | (.002) | | |
| Comp: ln onestop Capa 1 | | | | | –.046*** | –.033*** |
| | | | | | (.004) | (.003) |
| Comp: ln onestop Capa 2 | | | | | –.060*** | –.040*** |
| | | | | | (.003) | (.002) |
| Comp: ln onestop Capa 3 | | | | | –.064*** | –.042*** |
| | | | | | (.003) | (.002) |
| Comp: ln onestop Capa 4 | | | | | –.059*** | –.039*** |
| | | | | | (.003) | (.002) |
| ldist | –1.199*** | –1.273*** | –1.607*** | –1.810*** | –1.721*** | –1.836*** |
| | (.072) | (.073) | (.070) | (.070) | (.153) | (.145) |
| ldist2 | .099*** | .104*** | .130*** | .146*** | .136*** | .148*** |
| | (.005) | (.005) | (.005) | (.005) | (.011) | (.010) |
| Airline FE | | | X | X | X | X |
| City FE | | | X | X | X | X |
| Quarter FE | | | X | X | X | X |
| $\rho$ | .725*** | | .691*** | | .675*** | |
| | (.001) | | (.001) | | (.001) | |
| Pseudo. $R^2$ | .174 | .049 | .357 | .184 | .363 | .189 |
| Obs | 475391 | 430941 | 475391 | 430941 | 475391 | 430941 |

TABLE 20: Change in Capacity, Passenger, Revenue: ATL - NY city-pair

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 0 | 0 | 0 | 0 | 0 | 0 |
| | CT1a: Entry | 1028 | 414 | 62107 | 16 | 7 | 1498 |
| | CT1b: No One-stop | 811 | 345 | 51242 | 0 | 0 | 0 |
| | CT1c: Local Manager | 1028 | 411 | 61138 | 0 | 0 | 0 |
| Delta | Data | 6760 | 1254 | 235290 | 4175 | 47 | 11778 |
| | CT1a: Entry | 6099 | 1143 | 210954 | 4174 | 47 | 11709 |
| | CT1b: No One-stop | 3722 | 797 | 146742 | 0 | 0 | 0 |
| | CT1c: Local Manager | 6760 | 1215 | 221551 | 4175 | 46 | 11377 |

TABLE 21: Change in Capacity, Passenger, Revenue: city-pairs connected to ATL or NY

| | | Nonstop Service | | | One-stop Service | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 31210 | 21916 | 3658129 | 7540 | 144 | 38465 |
| | CT1a: Entry | 32342 | 22261 | 3710574 | 7902 | 292 | 71261 |
| | Capacity - | 0 | 1 | 1 | 3 | 22 | 22 |
| | Capacity + | 34 | 36 | 36 | 55 | 53 | 53 |
| | CT1b: No One-stop | 26643 | 20839 | 3476564 | 0 | 0 | 0 |
| | CT1c: Local Manager | 31210 | 21916 | 3657986 | 7829 | 279 | 68271 |
| Delta | Data | 173985 | 28035 | 5646528 | 28261 | 2705 | 721395 |
| | CT1a: Entry | 173657 | 27995 | 5638626 | 28092 | 2695 | 718546 |
| | Capacity - | 126 | 120 | 112 | 159 | 154 | 145 |
| | Capacity + | 16 | 22 | 30 | 8 | 13 | 22 |
| | CT1b: No One-stop | 57156 | 14774 | 2934201 | 0 | 0 | 0 |
| | CT1c: Local Manager | 173985 | 28035 | 5646436 | 28261 | 2705 | 721237 |

TABLE 22: Change in Capacity, Passenger, Revenue: Other city-pairs

| | | **Nonstop Service** | | | **One-stop Service** | | |
|---|---|---|---|---|---|---|---|
| Airline | | Capacity | Quantity | Revenue | Capacity | Quantity | Revenue |
| JetBlue | Data | 30960 | 20987 | 3401031 | 16858 | 1579 | 375819 |
| | CT1a: Entry | 33229 | 22681 | 3689130 | 17027 | 1626 | 386760 |
| | Capacity - | 3 | 17 | 16 | 33 | 39 | 31 |
| | Capacity + | 10 | 45 | 46 | 550 | 555 | 562 |
| | CT1b: No One-stop | 28330 | 19872 | 3219462 | 0 | 0 | 0 |
| | CT1c: Local Manager | 30960 | 20987 | 3401031 | 16858 | 1579 | 375819 |
| Delta | Data | 125603 | 25326 | 5603649 | 65153 | 35204 | 8590109 |
| | CT1a: Entry | 125474 | 25311 | 5601619 | 65018 | 35187 | 8587261 |
| | Capacity - | 178 | 178 | 178 | 2266 | 2246 | 2260 |
| | Capacity + | 110 | 110 | 110 | 1176 | 1196 | 1182 |
| | CT1b: No One-stop | 55671 | 15847 | 3467604 | 0 | 0 | 0 |
| | CT1c: Local Manager | 125603 | 25326 | 5603649 | 65153 | 35204 | 8590109 |