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

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Abstract

This paper proposes a structural model of oligopoly competition where the set of endogenous strategic decisions of an airline includes its network structure, flight frequency, and pricing for all nonstop and one-stop services. Furthermore, this paper proposes a simple methodology for both model estimation and counterfactual experiment evaluation that avoids the computation of a network equilibrium. Applying the estimated model to evaluate the consequences of a hypothetical merger between Alaska Airlines and Virgin America shows that the hypothetical post-merger airline would re-optimize its network structure, entering 32 markets and exiting 13 markets, with consumer surplus increasing in larger markets.

Key words: Airline industry, Entry models, Network competition, Moment inequalities, Counterfactual experiments

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1 Introduction

The U.S. airline industry helps drive nearly $1.5 trillion in U.S. economic activity (almost 10% of U.S. GDP) and is relevant to more than 11 million jobs. One of the most important strategic choices for an airline is deciding the markets in which to operate direct flights.[1] This entry decision determines the network structure of the airline, or specifically, the set of markets that the airline serves and whether these markets are served with direct flights or flights with connections. There are substantial interdependence and synergies between an airline's entry decisions into different markets. 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 could be lower if the airline already operates in other markets in addition to A or B. However, the most obvious interdependence between the entry decisions for different markets is that they determine the set of markets with connections (or stops) that the airline operates. For instance, suppose an airline operates direct flights between cities A and B, and is deciding whether to start operating flights either between cities B and C or between C and D. Supposing that the operating costs and demand of these new markets are similar, one would expect this airline to choose to operate between cities B and C rather than between C and D simply because the first choice would also attract new passengers travelling between A and C with a stop in city B.

This paper wants to answer two research questions related to airline networks: first, how do airlines' entry, exit and flight frequency decisions depend on the network structure, or specifically, the market structures in the other parts of the network. Second, if two airlines merge into a new airline, how does this post-merger airline optimize its network structure. The network of the post-merger airline is not a simple combination of the two pre-merger networks. There may be entries, exits or flight frequency re-allocations in many markets, even in markets where airlines are not active before.

Structural papers studying the airline industry, pioneered by Berry (1992), have answered important questions related to airline demand, cost structure, strategic interactions, and entry deterrence.[2] However, most models of entry in this literature have ignored or simplified the interconnectionness of markets and treated airline networks as exogenously given, often making the

[1] A market is a non-directional city pair in which airlines transport passengers from wither city to the other 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 (2017), Kundu (2014), Onishi and Omori (2014), Blevins (2015) and Gayle and Yimga (2015).

assumption that the airline entry, exit, and flight frequency decisions in one market is independent to its structure across markets. This would make sense if there were no synergies across markets, since airlines would make entry and flight frequency decisions based on local market characteristics without considering overall market network structure. However, network structure is the key feature of this industry. For example, suppose two airlines merge into a new airline. The optimal network of the post-merger airline would not merely be a combination of the two pre-merger networks but a much larger network with a potential re-allocation of flight frequencies across its network and/or entry into new markets. Without a model endogenizing the network structure of the airlines, it would not be possible to study can not answer the research questions of this paper.

To answer these questions, I develop a three-stage model of airline network competition, modelling airline competition as a static game of complete information in which network structure, flight frequency, and price for every nonstop and one-stop market are endogenized. In the first (entry) stage, airlines choose their network structure, i.e., the set of markets in which they operate nonstop flights, which determines the set of nonstop and one-stop products available to consumers. In the second (flight frequency) stage, airlines decide their flight frequency for every nonstop market, which determines the total number of nonstop and one-stop service offerings in all markets. In the third stage, airlines compete with respect to prices in every market given their network structure and flight frequencies. Consumers decide which airline service to purchase after observing the prices and quality of all products. Airlines earn variable profits from both nonstop and one-stop products.

It is computationally challenging to estimate a three-stage network competition model. The number of strategies or networks of an airline increases exponentially with the number of markets in the network and estimating the complete information game usually requires computing for an equilibrium of the model (Berry, 1992) or solving for the upper and lower bounds of choice probabilities (Ciliberto and Tamer, 2009).[3] For network competition games, computation of an equilibrium is infeasible even for a simple entry game with only a small number of players. While Jia (2008) makes use of the supermodularity of the game to compute Nash equilibria for network competition games with two players. Her method, nonetheless, doesn't apply to the US airline industry where there are more than two major players. Furthermore, estimation of incomplete information games usually requires estimating conditional choice probabilities, which is impossible with high-dimensional

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

strategy space. The existing literature proposes various assumptions to reduce the dimensionality of strategy space. For example, Aguirregabiria and Ho (2012) assume that every airline has a local manager in every market who decides whether the airline will enter or exit the local markets independently, which substantially reduces the dimensionality of the strategy space.

As an alternative, the current paper proposes and implements a simple methodology for model estimation and the evaluation of counterfactual experiments that does not require solving for a network equilibrium. First, I estimate the demand systems and back out the marginal costs of serving passengers. Both consumer utility and airline marginal cost of serving passengers depend on airline flight frequency. Next, I estimate the cost structure of airlines associated with network structure. Assuming that the network structures observed in the data are those of Nash equilibrium, I estimate airline' cost of scheduling flight frequencies using the flight frequency marginal condition of optimality. In other words, an airline that is active in a market will schedule flights in this market until the marginal variable profit (MVP) of an additional flight equals the marginal cost (MC) of scheduling this flight. Specifically, the MVP of an additional flight is the sum of the following four components: (a) a MVP from additional nonstop service, (b) a MVP from additional one-stop services, (c) a cannibalization effect from additional nonstop service and (d) a cannibalization effect from additional one-stop services. Finally, I estimate entry costs by exploiting the inequality restrictions implied by airline best response conditions in the entry game. If an airline operates direct service in a market, its entry cost is lower than its counterfactual variable profit if it exits this market. This generates an upper bound for entry cost. If an airline does not operate direct service in a market, its entry cost is higher than its counterfactual variable profit if it enters this market with optimal flight frequency. This generates a lower bound for entry cost. These two model restrictions minimize violations of entry cost estimates.

In a counterfactual experiment, I investigate the network structure after an exogenous hypothetical merger between Alaska Airline and Virgin America. Since it is computationally infeasible to obtain a Nash equilibrium of this simultaneous-move network competition game, I reconstruct this simultaneous game as a sequential-move game. I start by proposing a sequence by which all airline-market pairs move. Airlines first move in larger markets followed by smaller markets. Within each market, airlines move sequentially by profitability. In this way, I obtain the order by which all airline-market pairs move in this massive sequential move game. While it would be ideal to solve for the sub-game perfect Nash equilibrium using backward induction, it is impossible to compute airline profits at all branches of the game tree, so I use a forward-induction algorithm to search for an equilibrium. Starting with an empty network where no airlines are active in any market, I repetitive airline best response, airline-market pair by airline-market pair according to the sequence defined above. Specifically, starting with the most profitable airline in the largest market, I determine the optimal action of this airline in that specific market. I update the airline's network structure each time it enters, exits, or changes flight frequency in a market. Then, I proceed to the second most profitable airline in the largest market, evaluate the best response of this airline in the market and update its network structure, and so on. After visiting all airline-market pairs, I return to the first airline-market pair and re-evaluate the best responses of the entire airline-market sequence. If there is no incentive to deviate, this convergence of best responses in the network serves as an approximation of the subgame perfect Nash equilibrium of the sequential-move game.

The empirical finding shows that, on average, marginal variable cost and marginal variable profit from scheduling an additional flight is $7553. However, if endogenous network structures are ignored, these values would be underestimated by 13%. The counterfactual experiment shows that, if Alaska Airline and Virgin America merge in the first quarter of 2014, the new post-merger airline will enter 32 nonstop markets and exit 13 nonstop markets. Though overall consumer surplus increases post-merger, there is heterogeneity in consumer surplus change across markets in that consumer surplus will increase in larger markets but slightly decrease in smaller markets.

There are four main contributions in this paper. First, I construct and estimate an equilibrium model of network competition, endogenizing network structures, product quality (flight frequencies), price and number of consumers for every nonstop and one-stop market and estimating consumer demand together with endogenous product characteristics (flight frequencies) and endogenous network structures (entry decisions). Second, this paper implements a moment inequality method to obtain a consistent estimator of entry 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. I extend and implement a swapping method in the spirit of Pakes, Porter, Ho, and Ishii (2015) and Ellickson, Houghton, and Timmins (2013), and the bound estimator proposed in Aguirregabiria, Clark, and Wang (2016), and obtain consistent estimates of fixed cost under mild conditions. Third, I propose a novel algorithm to investigate the consequences of an exogenous merger between two airlines. This algorithm allows me to compare the change in network structures and consumer welfare pre-merger and post-merger. Fourth, I propose measures of flight frequency for both nonstop and one-stop services, which are measures of product quality and incorporated as important endogenous choices of the airlines.

This paper also makes important contributions to the research on network competition. First, this paper studies a new type of network synergy — economies of scope. Suppose an airline operates direct flights in market AB, its entry into market BC generates two new products to consumers: nonstop service in market BC and one-stop service in market AC with a stop at city B. In contrast, existing models on network competition focus on economies of scale: a firm has a lower cost if it operates many stores in this market. Second, this paper allows for rich heterogeneity in synergy between any two markets. In the airline industry, synergy between two markets is the profitability of the one-stop service through the two markets. This synergy depends on not only the number of direct flights in these two markets but also technology determinifng the feasibility and efficiency of the connecting service. I use two matrices to represent the network structures of an airline: one matrix for nonstop service and another matrix for one-stop service. As a comparison, other papers measure synergy by the distance between two stores (Jia, 2008), the number of airline routes connected to a city (Aguirregabiria and Ho, 2012), or the number of stores in a market (Ellickson, Houghton, and Timmins, 2013). Third, this paper explicitly models consumer utility and airline product quality decisions, both of which are abstracted in other models of network competition. Lastly, I propose an algorithm to compute a network equilibrium such that I can compare the airline networks pre-merger and post-merger.

This paper builds on and contributes to three streams of literature. In terms of research on the airline industry, previous studies have discussed the benefits of airline hubs, including cost efficiency (Berry, 1990, 1992; Brueckner and Spiller, 1994; Berry, Carnall, and Spiller, 2006; Ciliberto and Tamer, 2009), demand factors (Berry, 1990; Berry and Jia, 2010), and strategic entry deterrence (Hendricks, Piccione, and Tan, 1997, 1999; Aguirregabiria and Ho, 2012). Few structural models of entry in the airline industry study synergies between an airline entry decisions in different markets. Aguirregabiria and Ho (2012) is the first paper to empirically estimate a network competition game with exogenous network structure. Dou, Lazarev, and Kastl (2017) study the externalities of airline delays throughout airline networks. There are rich studies on the pricing strategies of the airlines. Williams (2008) estimates a dynamic equilibrium model where firms first invest in seating capacity and then play a capacity-constrained pricing game. Lazarev (2013) studies intertemporal price discrimination on monopoly routes in the airline industry and evaluate its welfare consequences. Williams (2017) separately studies both intertemporal price discrimination and dynamic adjustment to stochastic demand. Gedge, Roberts, and Sweeting (2017) propose a model of limited pricing to explain that incumbent prices are lower when Southwest becomes a potential entrant.

This paper also relates to research on the estimation of entry games with network competition. Most entry models ignore interconnections across markets with several exceptions: Seim (2006) studies spatial competition in the video rental industry. Her model 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. While her model allows for the economies of density, it ignores cannibalization effects and spatial competition between stores of different chains at different locations. Nishida (2014) extends Jia's model by allowing for multiple stores in the same location and incorporates spatial competition. Ellickson, Houghton, and Timmins (2013) and Aguirregabiria, Clark, and Wang (2016) estimate network economics in retail chains and the banking industry, respectively.

Lastly, this paper contributes to research on airline mergers. Richard (2003) finds that mergers are associated with increased flight frequencies and that the overall effect of mergers on welfare varies by markets. Peters (2006) uses merger simulations to predict post-merger prices for six major airline mergers from the 1980's, and compares these predictions with actual post-merger prices. Ciliberto, Murry, and Tamer (2016) and Li, Mazur, Park, Roberts, Sweeting, and Zhang (2018) study endogenous market entry with post-merger selection. Ciliberto, Cook, and Williams (2018) use measures of centrality from graph theory to study the effect of consolidation on airline network connectivity. There is also an extensive literature on mergers in other industries. For instance, Nevo (2000) studies how prices and consumer welfare change after a merger in the ready-to-eat cereal industry. Fan (2013) allows for changes in both prices and product characteristics after ownership consolidation. Most research on mergers study within market mergers but few papers study mergers between two networks. The closest research to this paper is Benkard, Bodoh-Creed, and Lazarev (2010), which estimates dynamic changes in the airline industry after mergers. Their merger analysis is based on simulation of policy functions (choice probabilities) and assume that firms' strategy functions do not change pre-merger and post-merger. Though my model is static, it is based on profit maximization behaviors of players and has a clear equilibrium concept.

The remainders of the paper are organized as follows. Section 2 a model of airline competition. Section 3 describes the data and construction of the working sample. Section 4 presents the assumptions and empirical strategy. Section 5 presents the empirical results. Section 6 discusses the counterfactual analysis. Section 7 summarizes and concludes.

2 Model

The model is a game of network competition, as in the models of competition between retail networks in Jia (2008), Ellickson, Houghton, and Timmins (2013), and Aguirregabiria, Clark, and Wang (2016).[4] However, the game of competition between airline networks has some important distinguishing features with respect to existing models of retail networks. Network synergies in retail industries are about economies of scale or density at the local market level: firms receive higher profit if they have more stores in a market. In contrast, network synergy in the airline industry is about economics of scope: if an airline operates two direct flights, it may operate an additional one-stop flight which introduces an important interconnection between airlines' entry and flight frequency decisions in different markets. While most existing literature treats airline network structures as exogenous, I construct a game of airline network competition that endogenizes the network structure of the airlines.

2.1 Notation and Timeline

The industry is configured by N airlines (indexed by n) and C cities. 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. In a world with C cities, there are $M = \frac{C\times(C-1)}{2}$ markets.[5] Markets are indexed by ij, with i and j representing the two endpoint cities. Airlines can provide both nonstop and one-stop services in this market.

Airline n can provide at most two different types of services (or two products) in a market ij. Service in market ij without a stop is referred to as nonstop service and service between i and j with a stop in a third city is referred to as one-stop service.[6] Airlines usually connect passengers in their hub cities. For instance, if a passenger travels from New York to San Francisco, she may take a connection in Chicago or Atlanta. To simplify the model, I do not distinguish amongst one-stop

[4] 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 (2016).

[5] I follow the approach of 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. This paper ignores competition between airports.

[6] My analysis is restricted to nonstop and one-stop services but ignore services with more than one-stop because services with two or more stops comprise of less than 3% of air travel. However, the model and estimation method can be extended to accommodate services with more than one-stop.

services with different connecting cities, but aggregate all possible one-stop services in market ij into one product and refer to it as one-stop service in market ij. The network structure of an airline consists of both nonstop and one-stop services in all markets. The product of an airline includes its nonstop and one-stop services in all markets.

In every market ij, airline n's cost structure includes its entry cost (FC_{nij}), variable cost of flight frequency (VC^{f}_{nij}), variable cost of serving nonstop passengers (VC^{NSQ}_{nij}), and variable cost of serving one-stop passengers (VC^{OSQ}_{nij}). Airlines compete in three stages: In the first stage, airlines simultaneously determine their network structures, or specifically, the set of markets in which to operate direct flights (entry decisions a_{nij}). In the second stage, airlines decide their flight frequencies for every market in which they are active (flight frequencies f^{NS}_{nij} and f^{OS}_{nij}). In the third stage, airlines compete in prices (p^{NS}_{nij} and p^{OS}_{nij}) in all markets given their network structures and flight frequency allocations, both of which are determined in the first two stages.

The model assumes that consumers choose products that maximize their utility given individual and product characteristics. Airlines are assumed to maximize their profits in a three-stage competition with simultaneous moves in each stage.

2.2 Three-stage Model of Airline Competition

This subsection discusses the details of the three-stage model of airline network competition.[7]

2.2.1 Firm Behavior: First Stage (Network Stage)

In the first stage, aka the entry or network stage, every airline simultaneously decides whether or not to operate direct (nonstop) flights in all M markets. This determines the network structures of the airlines.

Entry Decision

Let $a_{nij} = 1$ if airline n enters market ij, and $a_{nij} = 0$ otherwise. The entry decision of airline n is measured by a $C \times C$ symmetric matrix $\mathbf{A}_n$ where a_{nij} is the (i, j)-th element of $\mathbf{A}_n$. Airline n can provide one-stop service between city-pair ij with a connection in k if it operates direct flights in both market ik and market kj (i.e.: $a_{nik} = 1$ and $a_{nkj} = 1$).

[7] Alternatively, first stage and second stage may be aggregated into a single stage wherein airlines choose flight frequency, and zero flight frequency refers to staying out. However, the current three-stage model has several advantages. The first stage and second stages represent the extensive and intensive margins, respectively. Though I could describe these decisions in a single stage, it is convenient to describe the model and methods to separate the extensive and intensive margins in two stages.

Entry Cost

The total entry cost of airline n sums up the airline's fixed cost in all markets:

$$FC_n(\mathbf{A}_n) = \frac{1}{2} \sum_i \sum_{j \neq i} FC_{nij} \times \mathbf{1}\left[a_{nij} = 1\right], \tag{1}$$

where FC_{nij} denotes airline n's entry cost into market ij.

2.2.2 Firm Behavior: Second Stage (Flight Frequency Stage)

In the second stage, airlines determine their flight schedules, or specifically, the types of aircrafts and time of departure and arrival for their flights in all markets. This determines the set of nonstop and one-stop products of airlines as well as product quality.

Flight Frequencies

I distinguish between two products and two corresponding flight frequency variables. If airline n operates f_{nij}^{NS} direct flights in market ij, it provides a nonstop product to consumers with quality $b(f_{nij}^{NS})$. Alternatively, if airline n operates f_{nij}^{OS} one-stop flights in market ij, it provides a one-stop product to consumers with quality $b(f_{nij}^{OS})$. These flight frequencies measure heterogeneity in airline nonstop and one-stop services and are important determinants of product quality.

Airline n's nonstop flight frequency in market ij (f_{nij}^{NS}) is the number of direct flights it operates in market ij. I ignore heterogeneity in aircraft type and departure (arrival) time of flights. The concept of one-stop flight frequency is more subtle. Airline n's one-stop flight frequency in market ij with a stop at city k ($f_{nij}^{OS(k)}$) is the number of possible one-stop flights airline n provides between city i and city j with a connection in city k. One-stop flight frequency depends not only on the number of flights but also on their departure and arrival schedules such that connections are feasible. I assume airlines can connect one-stop passengers only in hub cities.[8] The set of hubs of airline n is denoted by $\mathbf{H}_n$. Thus, airline n's one-stop flight frequency in market ij sums up its one-stop flight frequencies in all markets with a connection at all hub cities,

$$f_{nij}^{OS} = \sum_{k \in \mathbf{H}_n} f_{nij}^{OS(k)}. \tag{2}$$

The details of measuring one-stop flight frequencies and selecting hub cities are described in Section

[8]More than 90% of the connections occur in hub cities.

3.4.

Nonstop and one-stop flight frequencies of airline n are measured by two $C \times C$ symmetric matrices $\mathbf{F}_n^{NS}$ and $\mathbf{F}_n^{OS}$ where their (i,j)-th elements are f_{nij}^{NS} and f_{nij}^{OS}, respectively. Let $\mathbf{F}_n = \left\{\mathbf{F}_n^{NS}, \mathbf{F}_n^{OS}\right\}$ denote airline n's flight frequencies in the network, let $\mathbf{F}_{-n} = \{\mathbf{F}_{n'}, n' \neq n\}$ denote the flight frequencies of other airlines in the entire network, and let $\mathbf{f}_{-nij} = \left\{\mathbf{f}_{-nij}^{NS}, \mathbf{f}_{-nij}^{OS}\right\}$ denote flight frequencies of other airlines in market ij.

Technological Relationship between Nonstop/One-stop Flight Frequencies

As discussed in the previous subsection, airline n's one-stop flight frequency between i and j with a connection in k ($f_{nij}^{OS(k)}$) depends on the flight schedules of its two legs: f_{nik}^{NS} and f_{nkj}^{NS}. For the sake of simplicity, I assume $f_{nij}^{OS(k)}$ is a symmetric function of f_{nik}^{NS} and f_{nkj}^{NS}:

$$f_{nij}^{OS(k)} = \Lambda_{nij}^{(k)}\left(f_{nik}^{NS}, f_{nkj}^{NS}\right), \tag{3}$$

where $f_{nij}^{OS(k)}$ is non-decreasing in both f_{nik}^{NS} and f_{nkj}^{NS}. This function is specific for each airline-market-connection city because airlines may have different schedules or connection technologies in different markets or in different connection cities.[9]

Function $\Lambda_n(.)$ summarizes the technological relationship between airline n's nonstop and one-stop flight frequencies in the network:

$$\mathbf{F}_n^{OS} = \Lambda_n(\mathbf{F}_n^{NS}). \tag{4}$$

Variable Cost of Flight Frequency

For airline n in market ij, variable cost of scheduling flight frequency is the cost of operating flights between city i and j. This variable cost depends on the number of daily flights in this market, the type of aircraft, availability of fleets, fuel price, cost of recruiting a crew, other market characteristics such as distance between two endpoints, as well as airline operations at the two endpoints due to economies of scale or scope. I assume there is no additional cost associated with one-stop flight frequencies. Once direct flights are scheduled, one-stop flight frequencies are determined. Airline

[9] $\Lambda_{nij}^{(k)}(.,.)$ is a symmetric function because nonstop flight frequency in one leg should impact the flight frequencies of one-stop service the same as the nonstop flight frequency in the other leg. For instance, there is no reason to assume that the number of flights in market AB impacts the one-stop flight frequency from A to C with a connection at B differently than the number of flights in market BC.

n's total variable cost of flight frequency, summed up across all markets is:

$$VC_n^f(\mathbf{A}_n, \mathbf{F}_n^{NS}) = \frac{1}{2}\sum_i \sum_{j \neq i} VC_{nij}^f(F_{nij}^{NS}) \times \mathbf{1}[a_{nij} = 1]. \tag{5}$$

2.2.3 Firm Behavior: Third Stage (Price Competition Stage)

Airlines also incur a variable cost for serving passengers. This variable cost of serving passengers includes the cost of selling tickets, boarding, and accommodating passengers. Airline n's variable cost of serving nonstop (one-stop) passengers in market ij is denoted by $VC_{nij}^{NSQ}(q_{nij}^{NS})$ ($VC_{nij}^{OSQ}(q_{nij}^{OS})$), where q_{nij}^{NS} (q_{nij}^{OS}) denotes number of nonstop (one-stop) consumers traveling with airline n's in market ij.

In the third stage, the price competition stage, airlines compete in prices at every market and receive variable profits from both nonstop and one-stop services, given flight frequencies determined in the first two stages and the cost of serving passengers.[10]

2.2.4 Consumer Behavior

A typical consumer observes the price and quality of all products and chooses one product that maximizes his/her utility. The demand model follows the classic discrete-choice literature.[11] Let MS_{ij} denote the total number of potential travelers in market ij. Each traveler has a unit demand (one trip or no trip) and chooses from several differentiated products.[12] For notational simplicity, index g represents the following three-tuple market and product characteristics: (1) airline n; (2) market ij; and (3) nonstop product indicator variable x.

Consumers' average willingness to pay for an airline's nonstop (one-stop) service depends on its nonstop (one-stop) flight frequency in the market. Consumers value higher flight frequencies because they provide more flexible departure times and more connecting possibilities if it is an one-stop service. Given that the quality or average willingness to pay for product g is $b_g(f_g)$ and price of product g is p_g, the indirect utility of traveler ι purchasing product g is $U(f_g, p_g, v_{\iota g}) = b_g(f_g) - p_g + v_{\iota g}$, where $v_{\iota g}$ is the consumer-product specific component. Let $\mathbf{v}_\iota$ denote a vector that contains all product-specific random tastes of individual ι. The utility of the outside good (not traveling or taking an alternative form of transportation) is normalized to zero ($U_{\iota 0} = 0$).

[10] I assume in each market, airlines charge a uniform price for its nonstop service and another uniform price for its one-stop service, which is a common assumption in the literature.

[11] The growing literature is pioneered by Berry (1994) and Berry, Levinsohn, and Pakes (1995).

[12] Since a market is a non-directional city-pair, I do not distinguish between service from i to j and service from j to i. However, the model can be extended to directional markets.

A consumer demands one unit of the product that gives him/her the greatest utility, including the outside alternative. I integrate individual demands over the consumer-idiosyncratic variable $v_{\iota g}$ to obtain aggregate demand:

$$q_g(f_g, p_g, \mathbf{f}_{-g}, \mathbf{p}_{-g}) = MS_{ij} \times \int \mathbf{1}\left[U(f_g, p_g, v_{\iota g}) \geq U(f_{g'}, p_{g'}, v_{\iota g'}), \forall g' \neq g\right] d\mathbf{v}_{\iota}, \tag{6}$$

where $\mathbf{f}_{-g}$ and $\mathbf{p}_{-g}$ are vectors of product characteristics and prices of competing products, respectively.

2.2.5 Firm Profit

The variable profit an airline receives from product g is π_g:

$$\pi_g(f_g, p_g, \mathbf{f}_{-g}, \mathbf{p}_{-g}) \;\; = \;\; p_g \times q_g(f_g, p_g, \mathbf{f}_{-g}, \mathbf{p}_{-g}) - VC_g^Q(q_g(f_g, p_g, \mathbf{f}_{-g}, \mathbf{p}_{-g})). \tag{7}$$

Airline n's variable profit in market ij sums up variable profit from both nonstop and one-stop products in this market. I specify variable profit of airline n in market ij as a function of market conditions:

$$\pi_{nij}(f_{nij}^{NS}, f_{nij}^{OS}, p_{nij}^{NS}, p_{nij}^{OS}, \mathbf{f}_{-nij}^{NS}, \mathbf{f}_{-nij}^{OS}, \mathbf{p}_{-nij}^{NS}, \mathbf{p}_{-nij}^{OS}) \;\; = \;\; \sum_{g \in \mathbf{G}_{nij}} \pi_g(f_g, p_g, \mathbf{f}_{-g}, \mathbf{p}_{-g}), \tag{8}$$

where $\mathbf{G}_{nij}$ is the set of products of airline n in market ij, which includes nonstop and one-stop products of airline n in market ij.

Airline n's total variable profit (π_n) sums up variable profit in all markets

$$\pi_n \;\; = \;\; \frac{1}{2} \sum_i \sum_{j \neq i} \pi_{nij}. \tag{9}$$

Finally, airline n's overall profit in the network can be specified as

$$\Pi_n \;\; = \;\; \pi_n - VC_n^f - FC_n. \tag{10}$$

2.3 Best Responses and Equilibrium

An equilibrium of this three-stage complete information game is a Nash equilibrium with the following sequential structure.

(i) In the first (entry or network) stage, given an equilibrium selection in the flight frequency stage $(\mathbf{F}_n^{NS*}, \mathbf{F}_{-n}^{NS*})$ and in the pricing stage $(\mathbf{P}_n^{NS*}, \mathbf{P}_n^{OS*}, \mathbf{P}_{-n}^{NS*}, \mathbf{P}_{-n}^{OS*})$, airlines' entry decisions can be described as an N-tuple $\{\mathbf{A}_n^* : \forall n\}$ such that for every airline n, the following best response condition is satisfied:

$$\mathbf{A}_n^* = \underset{\mathbf{A}_n}{argmax} \quad \Pi_n(\mathbf{A}_n) \tag{11}$$

(ii) In the second (flight frequency) stage, conditional on entry decisions $(\mathbf{A}_n^*)$, given an equilibrium selection in the pricing stage $(\mathbf{P}_n^{NS*}, \mathbf{P}_n^{OS*}, \mathbf{P}_{-n}^{NS*}, \mathbf{P}_{-n}^{OS*})$, and given the technological relationship between nonstop and one-stop flight frequency $\Lambda_n(.)$, airlines' flight frequency decisions can be described as an N-tuple $\{\mathbf{F}_n^{NS*} : \forall n\}$ such that for every airline n, the following best response function is satisfied:

$$\begin{gathered}\mathbf{F}_n^{NS*} = \underset{\mathbf{F}_n^{NS}}{argmax} \quad \pi_n(\mathbf{F}_n^{NS}, \mathbf{F}_n^{OS}, \mathbf{F}_{-n}^{NS*}, \mathbf{F}_{-n}^{OS*}) \\ \text{subject to: } \mathbf{F}_n^{OS} = \Lambda_n(\mathbf{F}_n^{NS}) \quad \forall n.\end{gathered} \tag{12}$$

The profit maximization problem in this stage is subject to the technological relationship between nonstop and one-stop service $\Lambda_n(.)$.

(iii) In the third (pricing) stage, airlines compete in prices in each local market. In each market ij, given airlines' flight frequencies in this market $(\mathbf{f}_{nij}^{NS*}, \mathbf{f}_{nij}^{OS*}, \mathbf{f}_{-nij}^{NS*}, \mathbf{f}_{-nij}^{OS*})$, the following pricing best response function of airline n is satisfied:

$$(p_{nij}^{NS*}, p_{nij}^{OS*}) = \underset{(p_{nij}^{NS}, p_{nij}^{OS})}{argmax} \quad \pi_{nij}(p_{nij}^{NS}, p_{nij}^{OS}, \mathbf{p}_{-nij}^{NS*}, \mathbf{p}_{-nij}^{OS*}). \tag{13}$$

2.4 Properties of the Model

2.4.1 Marginal Variable Profit of Flights

This airline network competition model has some distinguishing properties. Below I discuss how airline n's variable profit changes with respect to increasing its nonstop flight frequency in a market. When all markets are isolated, a change in airline flight frequency will affect variable profit only in this local market. However, when markets are interconnected, a change in airline flight frequency will affect variable profit in not only this market but also other markets connected to this market. Specifically, this airline may make use of this direct flight to construct more one-stop flights and serve more one-stop passengers, which, in turn, may also have a cannibalization effect on existing nonstop service.

To evaluate the impact of a change in direct flights, I impose a simplifying assumption on flight frequency:[13]

Assumption 1. ***CO*** *Flight frequency, either nonstop or one-stop, is a continuous variable. The variable profit and variable cost functions are continuously differentiable with respect to this variable. Nonstop flight frequency is measured by the aggregate number of flights over a quarter, regardless of flight time or aircraft type.*

Flight frequency is continuous in the sense that an airline can always change its flight frequency by scheduling or eliminating flights. The current model assumes homogeneous flights. In future, this model may be extended to accommodate flight schedules and choice of aircraft type.

Taking the derivative of equation (9) with respect to airline n's nonstop flight frequency in market ij (i.e. f^{NS}_{nij}), the following expression shows how variable profit of airline n changes with f^{NS}_{nij}:

$$\frac{\partial \pi_n}{\partial f^{NS}_{nij}} = \frac{\partial \pi^{NS}_{nij}}{\partial f^{NS}_{nij}} + \frac{\partial \pi^{OS}_{nij}}{\partial f^{NS}_{nij}} + \sum_{i' \neq i} \frac{\partial \pi^{OS}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{OS}_{nij'}}{\partial f^{NS}_{nij}} + \sum_{i' \neq i} \frac{\partial \pi^{NS}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{NS}_{nij'}}{\partial f^{NS}_{nij}}, \tag{14}$$

where

$\frac{\partial \pi^{NS}_{nij}}{\partial f^{NS}_{nij}}$ is the marginal variable profit from additional nonstop flight frequency in market ij;

$\frac{\partial \pi^{OS}_{nij}}{\partial f^{NS}_{nij}}$ is the cannibalization effect from additional nonstop flight frequency on existing one-stop service in market ij;

$\sum_{i' \neq i} \frac{\partial \pi^{OS}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{OS}_{nij'}}{\partial f^{NS}_{nij}} = \sum_{i' \neq i} \frac{\partial \pi^{OS}_{ni'j}}{\partial f^{OS}_{ni'j}} \frac{\partial \Lambda^{(i)}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{OS}_{nij'}}{\partial f^{OS}_{nij'}} \frac{\partial \Lambda^{(j)}_{nij'}}{\partial f^{NS}_{nij}}$ are the marginal variable profits from additional one-stop flight frequencies;

$\sum_{i' \neq i} \frac{\partial \pi^{NS}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{NS}_{nij'}}{\partial f^{NS}_{nij}} = \sum_{i' \neq i} \frac{\partial \pi^{NS}_{ni'j}}{\partial f^{OS}_{ni'j}} \frac{\partial \Lambda^{(i)}_{ni'j}}{\partial f^{NS}_{nij}} + \sum_{j' \neq j} \frac{\partial \pi^{NS}_{nij'}}{\partial f^{OS}_{nij'}} \frac{\partial \Lambda^{(j)}_{nij'}}{\partial f^{NS}_{nij}}$ are the cannibalization effect from additional one-stop flight frequencies on existing nonstop services from city i or j to other cities.

[13] In the online appendix, I present a histogram of scheduled daily flight frequencies of the airlines. It shows that flight frequency can be treated as a continuous choice. Airlines sometimes schedule flights on a daily basis and sometimes choose a flight only in some selected days. For instance, AA1184 which served Albuquerque to Dallas and had 7 flights per week in early 2014, suspended its Tuesday and Saturday services in November and resumed its Saturday services in December. I could not find other AA flights in this market which matched the missing Tuesday or Saturday flights. In the flight frequency stage, it is easier to estimate a model with choices that is continuous rather than discrete. I use marginal conditions of optimality to compute the marginal costs of flight frequencies and do not need to use moment inequality in this stage.

Again, in these expressions, $\Lambda_{nij}^{(k)} = \Lambda_{nij}^{(k)}(f_{nik}^{NS}, f_{nkj}^{NS})$ denotes the one-stop flight frequency from city i to city j with a connection at city k, where f_{nik}^{NS} and f_{nkj}^{NS} represent flight frequency in market ik and market kj, respectively.

The six sub-figures in Figure 1 correspond to the four different channels. This is a unique property of network models.

2.4.2 Computation of Counterfactual Network Structure

To estimate entry costs and the variable cost for additional flight frequency, as well as to conduct a counterfactual experiment, I need to know how an airline's network structure will change when it enters/exits a market or changes its flight frequency in a market, i.e., the counterfactual network structure. Let $\{\mathbf{F}_n^{NS}, \mathbf{F}_n^{OS}\}$ denote airline n's network structure and $\mathbf{F}_{-n}$ denote competitors' network structures. Suppose airline n changes its nonstop flight frequency from $\mathbf{F}_n^{NS}$ to $\mathbf{F}_n^{NS'}$, according to the technological relationship between nonstop service and one-stop service, its one-stop flight frequency changes according to the following technological function $\mathbf{F}_n^{OS'} = \Lambda_n(\mathbf{F}_n^{NS'})$.

Let $\mathbf{F}_n^{NS} \pm f_{nij}^{NS}$ ($\mathbf{F}_n^{OS} \pm f_{nij}^{NS}$) denote the counterfactual nonstop (one-stop) flight frequency structure of airline n if its nonstop flight frequency in market ij increases/decreases by f_{nijt}^{NS}. Specifically, let $\mathbf{F}_n^{NS} \pm 1_{nij}^{NS}$ ($\mathbf{F}_n^{OS} \pm 1_{nij}^{NS}$) denote the counterfactual nonstop (one-stop) flight frequency structure of airline n if its nonstop flight frequency in market ij increases or decreases by one.

3 Data

My sample includes the 100 busiest airports in the continental U.S., aggregated into 87 Metropolitan Statistic Areas (or cities).[14] In each quarter, every airline makes $M = \frac{C \times (C-1)}{2} = 3741$ entry decisions.

The working dataset consolidates three databases: Data Bank 1B (DB1B), OAG databases and Airport Gate database. DB1B is part of TranStats, the Bureau of Transportation Statistics' (BTS) online collection of databases, which contains a 10% sample of all US domestic ticket information. The Official Airline Guide (OAG) database contains all domestic flight schedules in the United States. I use all flight scheduling and flight frequency information to construct measures of one-stop flight frequencies. I also construct an Airport Gate database which contains all airport gate usage information. This information is collected from a flight statistics website that reports daily

[14] Some cities have more than one airport.

domestic flight departure and arrival gate information.[15] Since this dataset identifies which airlines are using which gate, it can be used to determine whether a gate belongs solely to one airline or is a common use gate.[16] The unit of observation in my working dataset is year-quarter-market-airline-product.

The working dataset ranges from the first quarter of 2007 to the fourth quarter of 2014 for a total of 32 quarters and 341110 observations.[17]

3.1 Descriptive Analysis

At the beginning of the sample period, 12 major airlines operate in the United States. Virgin America enters in 2008.[18] After several major mergers, there are nine major airlines at the end of this sample period.[19]

Table 1 reports the number of nonstop (one-stop) markets in which the airline operates, the share of nonstop (one-stop) passengers, and the percentage of revenue from nonstop (one-stop) service. Legacy carriers usually operate direct flights in 200-300 markets. Given these direct flight offerings, they can provide one-stop services in thousands of markets.

Revenues from one-stop service tend to comprise a substantial portion of airline profit. In the first quarter of 2014, Delta Air Lines brought in 23.7 percent of its domestic revenue from one-stop service. Even Southwest, well-known for employing a point-to-point business model, provides one-stop service to 15.3 percent of its consumers and brings in 12.1 percent of its revenue from one-stop service.[20] On average, airlines provide one-stop service to 25.1 percent of their domestic passengers and bring in 17 percent of their revenue from one-stop service. One-stop service is therefore an important portion of airline operation and competition that should not be ignored.

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[15] Domestic flight departure and arrival gate information are collected from http://www.flightstats.com/. I use a Python to collect the departure and arrival gates of all flights in the United States in 2014.

[16] A gate is considered to belong to one airline if 80% of the flights departing from this gate are provided by that particular airline. Otherwise, it is considered a common gate.

[17] Standard sample selection thresholds apply. All code-sharing tickets are dropped.

[18] Virgin America begins its commercial service in late 2007 but enters my dataset in 2008.

[19] Merger and dataset construction details can be found in Appendix A. I drop small airlines such as Allegiant Air from the estimation and focus on the major airlines for three reasons: First, small airlines tend to concentrate their services in small markets and have negligible presence in the sample dataset. Second, most of these small airlines employ a point-to-point business model and usually carry a negligible proportion of connecting passengers. Third, eliminating these airlines can save substantial computational time which is proportional to the number of airlines in the dataset. During the sample periodm, Continental merged with United Airlines, AirTran merged with Southwest, Northwest merged with Delta Air Lines, and US Airways merged with American Airlines.

[20] A point-to-point business model is often employed by low-cost-carriers, who do not have major hubs. Airlines using point-to point business models tend to provide direct service to passengers.

3.2 Measure of Nonstop Flight Frequency

Nonstop flight frequency measures the number of daily direct flights offered by an airline between two cities in a quarter. On average, an airline schedules 7.4 daily direct flights in a market with a median of 5.5. Southwest operates in the busiest nonstop market, connecting Southern California and the Bay area, with over 108 daily flights.

3.3 Hub cities

Airlines can connect one-stop passengers only at airline hubs. A list of airline hubs is given in the Appendix. In the dataset, over 90% of the one-stop passengers travel with a stop at hub cities.[21]

Table 2 lists the top two hubs and the operation concentration ratio at the top four airports for each airline. I define the hub index of airline n at city i (H_{ni}) as the number of nonstop markets connected to city i. The operation concentration ratio of an airline at a city is defined as its hub index at this city divided by the number of direct markets of this airline. This ratio measures degree of 'hubbing' or concentration of an airline's operations in a given city and equals one for pure hub-and-spoke networks. The top two hubs of legacy carriers usually connect with over 60 other cities and have high hub concentration ratios. Frontier Airlines employs a nearly perfect hub-and-spoke network.[22] Southwest Airlines has the lowest operation concentration ratio. In 2007, its top hub (Chicago) connected with 47 other cities, its second hub (Las Vegas) connected with 45 other cities, and its $CR4$ was less than 40, which is consistent with the fact that the airline employs a point-to-point business model.

Some airlines expand their hubs during the sample period. For instance, Alaska Airlines increased its nonstop service in Seattle from 22 to 35. Southwest increased its nonstop markets in Chicago from 47 (2007) to 62 (2014). There has been a reduction in hub concentration ratios from 2007 to 2014 due to several major mergers, since the merged airlines have a greater number of hubs.

[21] I allow airlines to connect one-stop passengers only at hub cities so as to not over-estimate one-stop flight frequencies. To see these, suppose an airline has two hubs: A and B, both of which connect to spoke city C. I may conclude that there are many one-stop flights between A and B with a stop at C, though in fact no passengers connect at spoke city C.

[22] In a perfect hub-and-spoke network, there is a sole hub city and there are direct flights from other cities to the hub city.

3.4 Measure of One-stop Flight Frequency

One-stop service introduces important interconnections between airline operation decisions across markets.[23] In this paper, I propose a new measure of one-stop flight frequency based on airline schedules, flight frequencies and the technology of connecting service.

I measure one-stop flight frequency from city A to city C with a connection at city B as follows. Suppose an airline schedules a first flight from city A to city B, and a second flight from city B to city C. These two direct flights are considered to create a one-stop flight if the scheduled departure time of second flight is anywhere from 45 minutes to 4 hours after the scheduled arrival time of the first flight.[24] When there are multiple flights in market AB connecting with multiple flights in market BC, the one-stop flight frequency is the total number of connecting possibilities available to one-stop passengers. The detailed algorithm is described in detail in Appendix.

To the best of my knowledge, no measures of one-stop flight frequency have been proposed in the literature. This measure introduces a clear definition of airline entry with one-stop service (two flights with a layover of 45 minutes to 4 hours) as well as heterogeneity or quality in one-stop service (measured by one-stop flight frequencies). This measure is important for understanding competition and profitability in this industry. Airlines can receive more revenue from one-stop service if they construct their networks strategically and increase one-stop flight frequency. They also face more intensive competition if their competitors have more one-stop flight frequencies.

There are 273814 airline-market-quarter observations with positive flight frequency for one-stop service. On average, an airline carries 6.8 one-stop passengers between two cities on a daily basis with a median of 2.5.

4 Empirical Implementation

This section discusses the empirical specification of the network competition model. I first specify the entry cost of the airlines, followed by the variable costs, which include the variable cost of scheduling flights and serving passengers. Finally, I discuss the demand model and technological relationship between nonstop and one-stop flight frequencies.

[23] Previous literature measures one-stop service in a relatively simple way and assumes an airline provides one-stop service in a market if the number of one-stop passengers exceeds a threshold. However, this measure is an equilibrium result from a 10 percent sample and ignores heterogeneity in one-stop service.

[24] I use the same threshold (45 minutes to 4 hours) as in Molnar (2013). The minimum time for domestic connection is usually 45 to 75 minutes. The maximum time for domestic connection is usually 4 hours.

4.1 Entry cost

Airline n's entry cost into market ij in quarter t (FC_{nijt}) depends upon many factors, such as the number of gates or time slots of the airline at the two endpoint cities, etc.[25]

I specify FC_{nijt} as follows

$$FC_{nijt} = \gamma_G^{FC} \underbrace{(G_{nit} + G_{njt})}_{\text{Gate Share at the Airport}} + \underbrace{\eta_n^{FC}}_{\text{Airline FE}} + \underbrace{\eta_t^{FC}}_{\text{Quarter FE}} + \underbrace{\eta_i^{FC} + \eta_j^{FC}}_{\text{City FE}} + \varepsilon_{nijt}^{FC}, \tag{15}$$

where η_n^{FC} represents airline fixed-effect, η_t^{FC} represents quarter fixed-effect, η_i^{FC} and η_j^{FC} represent city fixed-effects at the two endpoints of the market, G_{nit} and G_{njt} are the share of gates leased to airline n at city i and j in quarter t, respectively. So $\eta_t^{FC}/100$ measures how fixed cost changes if the gate share of the airline at an airport increases by 1%.

4.2 Variable Costs

This paper distinguishes two different types of variable costs of the airlines: variable cost of scheduling flights and variable cost of serving passengers.

Variable Cost of Scheduling Flights

I assume variable cost of scheduling flights is proportional to flight frequency, i.e. $VC_{nijt}^f(f_{nijt}^{NS}) = c_{nijt}^f \times f_{nijt}^{NS}$. Marginal cost of flight frequency (c_{nijt}^f) is given by

$$\ln c_{nijt}^f = \gamma_H^f \underbrace{(H_{nit} + H_{njt})}_{\text{Hub Indexes}} + \underbrace{\gamma_1^f d_{ij} + \gamma_2^f d_{ij}^2}_{\text{Distance}} + \underbrace{\eta_{ni}^f + \eta_{nj}^f}_{\text{Airline-City FE}} + \underbrace{\eta_t^f}_{\text{Quarter FE}} + \varepsilon_{nijt}^f, \tag{16}$$

where γ_H^f measures changes in variable cost of flight frequency if hub index increases by one. H_{nit} and H_{njt} are the hub indexes of the airline at the two endpoints. η_{ni}^f and η_{nj}^f are airline-city fixed effect, η_t^f is time fixed-effects and γ_1^f and γ_2^f capture the effect from distance.

Variable Cost of Serving Passengers

In the empirical specification, a product g represents the following four-tuple of market and product characteristics: (1) airline n, (2) market ij, (3) quarter t and (4) nonstop product indicator variable

[25] Ciliberto and Williams (2010) find that cost of entry decrease with the number of gates an airline operates in an airport.

x.

Marginal cost of serving passengers who travel with product g (c_g) is given by

$$\begin{aligned} c_g &= \underbrace{\delta_1 \mathbf{1}[x = NS]}_{\text{Nonstop Dummy}} + \underbrace{\delta_2 l\left(f_g^{NS}\right) \times \mathbf{1}[x = NS] + \delta_3 l\left(f_g^{OS}\right) \times \mathbf{1}[x = OS]}_{\text{Flight Frequency}} \\ &\quad + \underbrace{\delta_3 H_{nit} + \delta_4 H_{njt}}_{\text{Hub Indexes}} + \underbrace{\delta_5 d_{ij} + \delta_6 d_{ij}^2}_{\text{Distance}} + \underbrace{\omega_{ni}^{(1)} + \omega_{nj}^{(2)}}_{\text{Airline-City FE}} + \underbrace{\omega_t^{(3)}}_{\text{Quarter FE}} + \omega_g^{(4)}, \end{aligned} \tag{17}$$

where δ_1 measures the cost difference between nonstop and one-stop services, $l\left(f_g\right)$ is a non-decreasing function of f_g, H_{nit} and H_{njt} are airline hub indexes at each respective endpoint, $\omega_{ni}^{(1)}$ and $\omega_{nj}^{(2)}$ are airline-city fixed-effects, $\omega_t^{(3)}$ represents quarter fixed-effects, and $\omega_g^{(4)}$ is product-specific cost shock.[26]

4.3 Demand Model

Product quality, b_g, is given by:

$$\begin{aligned} b_g = & \underbrace{\alpha_1 \mathbf{1}[x = NS]}_{\text{Nonstop Dummy}} + \underbrace{\alpha_2 l(f_g^{NS}) \times \mathbf{1}[x = NS] + \alpha_3 l(f_g^{OS}) \times \mathbf{1}[x = OS]}_{\text{Flight Frequencies}} \\ & + \underbrace{\alpha_4 H_{nit} + \alpha_5 H_{njt}}_{\text{Hub Indexes}} + \underbrace{\alpha_6 d_{ij} + \alpha_7 d_{ij}^2}_{\text{Distance}} + \underbrace{\xi_n^{(1)}}_{\text{Airline FE}} + \underbrace{\xi_i^{(2)} + \xi_j^{(3)}}_{\text{City FE}} + \underbrace{\xi_t^{(4)}}_{\text{Quarter FE}} + \xi_g^{(5)}, \end{aligned} \tag{18}$$

where α_1 measures average passenger utility from nonstop service over the utility of one-stop service; H_{nit} and H_{njt} are hub indexes at the two endpoint cities; $\xi_n^{(1)}$ is an airline fixed-effects which captures between-airlines differences in quality that are constant over time and across markets; $\xi_i^{(2)}$ and $\xi_j^{(3)}$ are city fixed-effects; $\xi_t^{(4)}$ is quarter fixed-effects; $\xi_g^{(5)}$ is product-specific demand shock for product g.[27]

I consider a nested logit demand model with two nests.[28] The first nest represents the consumer decision of which airline to travel with, while the second nest is the choice between nonstop and one-stop flights. Suppose $v_{\iota g} = \sigma_1 v_{\iota nijt}^{(1)} + \sigma_2 v_g^{(2)}$, where $v_{\iota nijt}^{(1)}$ and $v_g^{(2)}$ are independently Type 1 extreme value distributed, and σ_1 and σ_2 are parameters which measure within/between group

[26] Empirically, I define $l(f_g) = \ln(14 \times f_g - 13)$ to ensure variable profit is a concave function with respect to flight frequency. Since the minimum daily flight frequency in this paper is one, $l(1) = 0$. Suppose I choose $l(f_g) = ln(f_g)$ or $l(f_g) = f_g$, variable profit is a convex function of f_g and airlines should schedule an infinite number of flights in this market.

[27] These hub indexes are measured by the number of nonstop markets an airline serves to other destinations.

[28] The model can be extended into a random coefficient model.

substitutions.

Let s_g denote the market share of product g in market ij, i.e., $s_g = q_g/MS_{ij}$. Let s^*_g be the within group market share of product g, i.e., $s^*_g = s_g/\sum_{g' \in \mathbf{G}_g} s_{g'}$, where $\mathbf{G}_g$ is the set of products airline n offers in the same market as product g.

The demand system can be represented using the following closed-form demand equations. For each g

$$ln(s_g) - ln(s_0) = \frac{b_g - p_g}{\sigma_1} + (1 - \frac{\sigma_2}{\sigma_1})ln(s^*_g). \tag{19}$$

4.4 Technological Relationship between One-stop and Nonstop Flight Frequencies

I assume airline n's one-stop flight frequency between city i and j with a stop at city k in quarter t ($f^{OS(k)}_{nijt}$) is a symmetric Cobb-Douglas function with respect to its nonstop flight frequencies in market ik (f^{NS}_{nikt}) and market kj (f^{NS}_{nkjt}).

$$f^{OS(k)}_{nijt} = \Lambda^{(k)}_{nijt}\left(f^{NS}_{nikt}, f^{NS}_{nkjt}\right) = exp\left(h^{(k)}_{nijt}\right) \times \left(f^{NS}_{nikt}\right)^{\lambda} \times \left(f^{NS}_{nkjt}\right)^{\lambda}, \tag{20}$$

where $h^{(k)}_{nijt}$ measures the heterogeneity in connection technologies across the one-stop markets. Furthermore, I specify $h^{(k)}_{nijt} = h + \epsilon^{h(k)}_{nijt}$, where $\epsilon^{h(k)}_{nijt}$ is assumed to be i.i.d distributed with mean zero and thus obtain the following regression equation:

$$\ln f^{OS(k)}_{nijt} = h + \lambda \times \left(\ln f^{NS}_{nikt} + \ln f^{NS}_{nkjt}\right) + \epsilon^{h(k)}_{nijt}. \tag{21}$$

This technological model predicts counterfactual network structure given nonstop flight frequency changes. Specifically, when nonstop flight frequency in market ik changes, one-stop flight frequency in market ij with a stop at city k changes according to the following equation:

$$\frac{\partial f^{OS(k)}_{nijt}}{\partial f^{NS}_{nikt}} = \lambda \times \frac{f^{OS(k)}_{nijt}}{f^{NS}_{nikt}}. \tag{22}$$

5 Identification and Estimation

This section discusses the empirical strategy and identification assumptions. The three-stage model is estimated sequentially. I first estimate consumers' utility functions and back out airlines' marginal cost of serving consumers according to Bertrand Nash conditions. Then, I estimate airlines' marginal cost of flight frequencies according to marginal conditions of optimality for flight frequency choice. The estimation of airline entry cost suffers from high dimensionality in strategy space and it is impossible to compute a Nash equilibrium. My empirical strategy is based on partial identification: I treat the observed network structure as a Nash equilibrium outcome. Airlines' revealed preference in entry decisions generates a set of inequality restrictions on entry cost. I infer entry cost exploiting these inequality restrictions.

5.1 Estimation of Demand and Variable Cost of Passengers

According to the quality specification in Equation (18) and demand system in Equation (19), the demand model can be expressed as a linear-in-parameters system of equations represented by:

$$ln(s_g) - ln(s_0) = \mathbf{W}_g\alpha - \frac{p_g}{\sigma_1} + (1 - \frac{\sigma_2}{\sigma_1})ln(s_g^*) + \xi_g^{(4)}, \tag{23}$$

where $\mathbf{W}_g$ is a vector of regressors that includes a nonstop product dummy, functions with respect to flight frequencies in both nonstop and one-stop services, hub indexes at the two endpoint cities, distance between two endpoint cities, airline dummies, city dummies and quarter dummies. In this regression equation, price p_g and conditional market share $ln(s_g^*)$ are endogenous. Products with larger demand shocks ($\xi_g^{(4)}$) are more likely to have higher prices as well as higher conditional market shares. Moreover, airline flight frequency may be an endogenous regressor in the current demand system because airlines may schedule more flights in markets with higher demand.

I impose two assumptions to construct valid instrumental variables to identify demand.

Assumption 2. ***INDEPENDENT*** ξ *Product-specific demand shocks* $\{\xi_g^{(4)}\}$ *are independently distributed over time.*

Assumption 3. ***TIME-TO-BUILD*** *At the beginning of quarter* t*, airlines form expectations about demand and costs before making their entry and flight frequency decisions in all markets. These entry and flight frequency decisions are not effective until quarter* $t+1$ *because airlines require one quarter to set up their networks and schedule their flights.*

Assumption **INDEPENDENT** ξ establishes that, after controlling for airline fixed-effects, time fixed-effects and market fixed-effects, the unobserved component of product demand does not exhibit time dependence. Assumption **TIME-TO-BUILD** assumes that airline network structure at quarter t is pre-determined in quarter $t-1$, before demand shocks at quarter t are realized.[29] These two assumptions imply that demand shock $\xi_g^{(4)}$ is independent of airline market entry and flight frequency decisions.[30]

I use GMM to estimate the differentiated products demand systems. Characteristics of other products in the same market are used as instruments.[31] In the current model, instrument variables include average flight frequencies in both nonstop and one-stop services, hub indexes at both origin and destination cities and nonstop product dummies of competing products. These two assumptions establish that product characteristics of competitors in quarter t are independent of demand shock $\xi_g^{(4)}$ because they are pre-determined in quarter $t-1$. Moreover, competitor product characteristics are correlated with product price through price competition, but are not correlated with product-specific demand shocks. Thus, they can be valid instruments for both prices p_g and within nested market share $ln(s_g^*)$.

Given estimates of demand parameters and under Nash-Bertrand competition assumptions, I back-out marginal cost of serving passengers from $\hat{c}_g = p_g - \hat{\sigma}_1(1-\bar{s}_g)^{-1}$.[32] I further decompose variable cost of serving passengers to factors listed in Equation (17). Assuming no further issues of endogeneity, I use OLS to estimate marginal cost of serving passengers.

5.2 Estimation of Marginal Cost of Flight Frequencies

I infer cost of flight frequency from demand estimation. After obtaining estimates of consumer utility and airline marginal cost of serving passengers, I back out marginal cost of flight frequency (c^f_{nijt}) according to marginal conditions of optimality for flight frequency choice. Setting the expected marginal variable profit from additional flight frequency ($\frac{\partial \pi_{nt}}{\partial f^{NS}_{nijt}}$) equal to the marginal cost of scheduling additional flight frequency (c^f_{nijt}) gives:

$$\frac{\partial \pi_{nt}(\mathbf{F}^{NS}_{nt}, \mathbf{F}^{OS}_{nt})}{\partial f^{NS}_{nijt}} = c^f_{nijt}. \tag{24}$$

[29] These two identification assumptions are in the same spirit as those in the estimation of demand in Aguirregabiria and Ho (2012) and Sweeting (2013).

[30] Assumption **INDEPENDENT** ξ is testable. I test this assumption with estimated residuals $\hat{\xi}_g^{(4)}$ from a GMM estimation of the demand system.

[31] This is in the spirit of Berry (1992) and Berry, Levinsohn, and Pakes (1995).

[32] $\bar{s}_g = (\sum_{g' \in \mathbf{G}_{nijt}} e_{g'})^{\frac{\sigma_2}{\sigma_1}}[1 + \sum_{n'=1}^{N}(\sum_{g' \in G_{n'ijt}} e_{g'})^{\frac{\sigma_2}{\sigma_1}}]^{-1}$ where $e_g = I_g exp\{(b_g - p_g)/\sigma_1\}$ and I_g is the indicator of the event "product g is available or not".

Thus, the regression equation becomes

$$\ln \frac{\partial \pi_{nt}}{\partial f^{NS}_{nijt}} = \gamma^f_H \underbrace{(H_{nit} + H_{njt})}_{\text{Hub Indexes}} + \underbrace{\gamma^f_1 d_{ij} + \gamma^f_2 d^2_{ij}}_{\text{Distance}} + \underbrace{\eta^f_{ni} + \eta^f_{nj}}_{\text{Air-City FE}} + \underbrace{\eta^f_t}_{\text{Qtr FE}} + \varepsilon^f_{nijt}. \tag{25}$$

The value of $\frac{\partial \pi_{nt}}{\partial f^{NS}_{nijt}}$ is numerically computed from

$$\frac{\partial \pi_{nt}}{\partial f^{NS}_{nijt}} = \frac{\pi_{nt}(\mathbf{F}^{NS}_{nt} + 1^{NS}_{nijt}, \mathbf{F}^{OS}_{nt} + 1^{NS}_{nijt}) - \pi_{nt}(\mathbf{F}^{NS}_{nt} - 1^{NS}_{nijt}, \mathbf{F}^{OS}_{nt} - 1^{NS}_{nijt})}{2}, \tag{26}$$

where, as described in Section 2.4.2, $\pi_{nt}(\mathbf{F}^{NS}_{nt}+1^{NS}_{nijt}, \mathbf{F}^{OS}_{nt}+1^{NS}_{nijt})$ is the variable profit of airline n if it increases its nonstop flight frequency in market ij in quarter t by 1 while $\pi_{nt}(\mathbf{F}^{NS}_{nt}-1^{NS}_{nijt}, \mathbf{F}^{OS}_{nt}-1^{NS}_{nijt})$ is the variable profit of airline n if it reduces its nonstop flight frequency in market ij in quarter t by 1.

5.3 Estimation of Entry Cost

Having obtained estimates for demand and marginal costs, I now turn my attention to the parameters governing fixed cost. These parameters show the heterogeneity in entry cost for airlines with different numbers of gates at airports and heterogeneity across airlines, quarters, and cities. Traditional estimation methods for entry models are unfeasible in my case: the total number of cities and airlines implies too large a state space to be solved numerically. To circumvent this curse of dimensionality, I approach the problem using a partial identification approach.

5.3.1 Two Sets of Inequality

I use two sets of moment inequality to construct bounds on the fixed cost. If airline n operates direct flight in a market ij, its entry cost into this market is lower than the difference between variable profit in the observed network $\pi_{nt}\left(\mathbf{F}^{NS}_{nt}, \mathbf{F}^{OS}_{nt}\right)$ and the counterfactual variable profit if it does not operate direct flight in this market $\pi_{nt}\left(\mathbf{F}^{NS}_{nt} - f^{NS}_{nijt}, \mathbf{F}^{OS}_{nt} - f^{NS}_{nijt}\right)$ minus savings in variable cost of flight frequency $c^f_{nijt} \times f^{NS}_{nijt}$.[33] Thus,

$$FC_{nijt} \leq \underbrace{\pi_{nt}\left(\mathbf{F}^{NS}_{nt}, \mathbf{F}^{OS}_{nt}\right)}_{\text{Observed Var Profit}} - \underbrace{\pi_{nt}\left(\mathbf{F}^{NS}_{nt} - f^{NS}_{nijt}, \mathbf{F}^{OS}_{nt} - f^{NS}_{nijt}\right)}_{\text{Counterfactual Var Profit if Exit}} - \underbrace{c^f_{nijt} \times f^{NS}_{nijt}}_{\text{Cost (Frequency)}} \equiv \overline{FC_{nijt}}, \tag{27}$$

where $\mathbf{F}^{NS}_{nt} - f^{NS}_{nijt}$ ($\mathbf{F}^{OS}_{nt} - f^{NS}_{nijt}$) denotes the counterfactual nonstop (one-stop) flight frequencies network structure if airline n exits market ij. This is an upperbound for fixed cost.

If airline n does not operate direct flights in market ij, its entry cost into market ij is higher than the difference between counterfactual variable profit $\pi_{nt}\left(\mathbf{F}^{NS}_{nt} + f^{NS*}_{nijt}, \mathbf{F}^{OS}_{nt} + f^{NS*}_{nijt}\right)$ if it enters with optimal flight frequency f^{NS*}_{nijt} and the variable profit in the observed network $\pi_{nt}\left(\mathbf{F}^{NS}_{nt}, \mathbf{F}^{OS}_{nt}\right)$ minus variable cost of building flight frequencies $c^f_{nijt} \times f^{NS*}_{nijt}$.

$$FC_{nijt} \geq \max_{f^{NS}_{nijt}} \underbrace{\pi_{nt}\left(\mathbf{F}^{NS}_{nt} + f^{NS}_{nijt}, \mathbf{F}^{OS}_{nt} + f^{NS}_{nijt}\right)}_{\text{Var Profit if Optimal Frequency Entry}} - \underbrace{\pi_{nt}\left(\mathbf{F}^{NS}_{nt}, \mathbf{F}^{OS}_{nt}\right)}_{\text{Observed Var Profit}} - \underbrace{c^f_{nijt} \times f^{NS}_{nijt}}_{\text{Cost (Frequency)}} \equiv \underline{FC_{nijt}}, \tag{28}$$

where $\mathbf{F}^{NS}_{nt} + f^{NS}_{nijt}$ ($\mathbf{F}^{OS}_{nt} + f^{NS}_{nijt}$) denotes the counterfactual nonstop (one-stop) flight frequencies in all markets if airline n exits market ij. When airline n determines its flight frequency in market ij, it will take into account its entire network structure and maximize its total variable profit in the network. This generates a lowerbound for fixed cost.

5.3.2 Identification Issues and Assumptions

There are two identification issues in the estimation of entry cost. First, given that an airline is active in a market, it may own, lease or operate more gates at the two endpoints of the market. As a result, the share of gates an airline leasing at an airport may be endogenous. The following identification assumption is imposed to ensure the consistency of the fixed cost estimates.

Assumption 4. ***GATE*** *The number of gates an airline has at an airport is exogenous. Airlines determine their gate allocations before they determine their network structures.*

Assumption **GATE** is reasonable because gate leasing arrangements between airlines and airports are usually signed several years before the airline's operation decisions. Thus, the entry

[33] $\mathbf{F}^{NS}_{nt} - f^{NS}_{nijt}$ is the counterfactual nonstop flight frequency if airline n exits market ij and $\mathbf{F}^{OS}_{nt} - f^{NS}_{nijt}$ is the counterfactual one-stop flight frequency if airline n exits market ij.

decision of an airline into a market will not affect the percentage of gates an airline leases at the airport.

The second issue is selection associated with random disturbance. The random disturbance associated with the observed choice comes from the possible values that make the observed choice the optimal choice. As a result, even though a priori mean of the random disturbance for any fixed choice is zero, the mean of the random disturbance may be nonzero. In other words, airlines that are active in a market may have received a good draw, i.e. $E\left[\varepsilon_{nijt}^{FC}|X_{nijt}, a_{nijt}=1\right] \geq 0$. In contrast, airlines that are inactive in a market may have receive a bad draw, i.e. $E\left[\varepsilon_{nijt}^{FC}|X_{nijt}, a_{nijt}=0\right] \leq 0$. In order to deal with this selection issue and obtain consistent estimates of parameters in the entry cost function, I impose the following identification assumption.

Assumption 5. ***BOUND*** *The conditional expectation of* ε_{nijt}^{FC} *is finite*

Under Assumption **BOUND**, there is a finite bound B such that $|E[\varepsilon_{nijt}^{FC}|a_{nijt}=1]| \leq B$ and $|E[\varepsilon_{nijt}^{FC}|a_{nijt}=0]| \leq B$.[34]

When the distribution of the error term is not specified, the true value of B is unknown and selection of B becomes an empirical question. I evaluate the fit of the model at different values of B and select a $B=B^*$ such that the model estimates optimize the overall fit of the model. Details on how I select B are in Section 5.3.5.

5.3.3 Estimation Procedure

I restrict my analysis to 2014 data for which detailed gate operation information are available. If I observe an airline is active in a market, I have an upperbound for fixed cost. Conversely, if I observe an airline is not active in a market, I have a lowerbound for fixed cost. There are 6934 upperbounds and 14626 lowerbounds for entry cost.[35] There are one hundred parameters (or fixed-effects) in the entry cost function. I estimate all parameters simultaneously using Inequalities (27) and (28). However, estimation of one hundred parameters with thousands of inequality may result in imprecise and uninformative estimates. Moreover, there may be numerical errors when I estimate a model with one hundred parameters as the optimizing algorithm may stop at a local

[34] Pakes, Porter, Ho, and Ishii (2015) and Ellickson, Houghton, and Timmins (2013) assume that after controlling for firm fixed-effects and market fixed-effect, conditional expectation of the error terms have mean zero. This is a special case when $B=0$.

[35] This paper focuses on observations where an airline is active in a market or active in both endpoints of the market. For an entry cost, I can either observe an upperbound or a lowerbound, because the airline can either be active or inactive.

minimum rather than global minimum.[36] Therefore I propose a sequential estimation procedure and obtain estimates of different sets of fixed cost parameters sequentially.

An overview of this estimation procedure is as follows: I first estimate the effects from gate ownership on fixed cost (γ_G^{FC}). When an airline is active in market ij but inactive in market $i'j'$ and another airline is inactive in market ij but active in market $i'j'$ in the same quarter, the difference in their entry decisions comes from the difference in their gate allocations at different markets. I make use of Inequality (27) and (28), construct swapping pairs, eliminate airline fixed-effects, quarter fixed-effects, and city fixed-effect, and focus on a set of new inequality with only parameter γ_G^{FC} involved. After obtaining estimate $\hat{\gamma}_G^{FC}$, I replace the true γ_G^{FC} with $\hat{\gamma}_G^{FC}$ in both sets of inequality and proceed to estimate quarter fixed-effects. If an airline is active in a market in a quarter but inactive in the same market in another quarter, I can obtain upper and lower bounds for quarter fixed-effects differences. I construct swapping pairs, eliminate airline fixed-effects and city fixed-effects and obtain inequality with only quarter fixed-effect γ_t^{FC}, where I estimate and obtain $\hat{\gamma}_t^{FC}$. Then I replace the true γ_t^{FC} with estimates $\hat{\gamma}_t^{FC}$ in the two sets of inequality and estimate airline fixed-effects. If I observe an airline is active in a market and another airline is inactive in the same market, I obtain bounds for the difference between the airlines' fixed-effects in fixed cost. I obtain inequality with only γ_n^{FC} and obtain its estimate $\hat{\gamma}_n^{FC}$. Finally, I estimate city fixed-effects. I replace the γ_G^{FC}, γ_n^{FC}, and γ_t^{FC} with their estimates in Inequality (27) and (28). The estimates of city fixed-effects minimize these two sets of inequality.

The main advantage of this sequential estimation procedure is that I eliminate some fixed-effects and focus on the estimation of a set of key parameters. There will be less estimation error associated with these key parameters. However, a drawback of this estimation procedure is that estimation error in earlier steps may propagate to later steps.

Estimation of γ_G^{FC}

When estimating γ_G^{FC}, I construct incumbent and potential entrant pairs at two markets to eliminate time fixed-effects, airline fixed-effects and market fixed-effects. This swapping is in the spirit of Ellickson, Houghton, and Timmins (2013) and Pakes, Porter, Ho, and Ishii (2015). Specifically, suppose airline n operates direct flights in market ij but not in market $i'j'$ and airline n' operates direct flights in market $i'j'$ but not in market ij.

[36] The criterion function is continuous but not differentiable. To search for a global minimum I may have to start at trillions of initial values. For instance, for 100 parameters with ten values each, I would need to evaluate 10^{100} different initial values.

Airline n receives positive profit in market ij

$$\overline{FC_{nijt}} - \gamma_G^{FC}\left(G_{nit} + G_{njt}\right) - \left(\eta_n^{FC} + \eta_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{nijt}^{FC}\right) \quad \geq \quad 0. \tag{29}$$

Airline n receives negative profit if it enters $i'j'$

$$\gamma_G^{FC}\left(G_{ni't} + G_{nj't}\right) + \left(\eta_n^{FC} + \eta_t^{FC} + \eta_{i'}^{FC} + \eta_{j'}^{FC} + \varepsilon_{ni'j't}^{FC}\right) - \underline{FC_{ni'j't}} \quad \geq \quad 0. \tag{30}$$

Airline n' receives negative profit if it enters ij

$$\gamma_G^{FC}\left(G_{n'it} + G_{n'jt}\right) + \left(\eta_{n'}^{FC} + \eta_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{n'ijt}^{FC}\right) - \underline{FC_{n'ijt}} \quad \geq \quad 0. \tag{31}$$

Airline n' receive positive profit when it operates in $i'j'$

$$\overline{FC_{n'i'j't}} - \gamma_G^{FC}\left(G_{n'i't} + G_{n'j't}\right) - \left(\eta_{n'}^{FC} + \eta_t^{FC} + \eta_{i'}^{FC} + \eta_{j'}^{FC} + \varepsilon_{n'i'j't}^{FC}\right) \quad \geq \quad 0. \tag{32}$$

Summing up (29) to (32) gives

$$\Delta FC_{nijt}^{n'i'j't} - \gamma_G^{FC}\Delta G_{nijt}^{n'i'j't} - \varepsilon_{nijt}^{FC} + \varepsilon_{ni'j't}^{FC} + \varepsilon_{n'ijt}^{FC} - \varepsilon_{n'i'j't}^{FC} \geq 0, \tag{33}$$

where $\Delta FC_{nijt}^{n'i'j't} \equiv \overline{FC_{nijt}} - \underline{FC_{ni'j't}} - \underline{FC_{n'ijt}} + \overline{FC_{n'i'j't}}$ and $\Delta G_{nijt}^{n'i'j't} \equiv G_{nit} + G_{njt} - G_{ni't} - G_{nj't} + G_{n'it} + G_{n'jt} - G_{n'i't} - G_{n'j't}$. All airline fixed-effects η_n^{FC}, time fixed-effects η_t^{FC} and city fixed-effects η_i and η_j are canceled out in Inequality (33).

I transform these inequality to conditional moment inequality

$$E[\Delta FC_{nijt}^{n'i'j't} - \gamma_G^{FC}\Delta G_{nijt}^{n'i'j't} - \varepsilon_{nijt}^{FC} + \varepsilon_{ni'j't}^{FC} + \varepsilon_{n'ijt}^{FC} - \varepsilon_{n'i'j't}^{FC}|X_t, A_t] \geq 0, \tag{34}$$

where X_t is a vector of market and airline characteristics, which include market size, distance between endpoints and other explanatory variables for entry cost and A_t is a vector of airline's entry and exit decisions in quarter t.

Under Assumption **Bound**, I obtain the following inequality

$$E[\Delta FC_{nijt}^{n'i'j't} - \gamma_G^{FC}\Delta G_{nijt}^{n'i'j't} + 4B|X_t] \geq 0 \tag{35}$$

where $\Delta FC_{nijt}^{n'i'j't}$ and $\Delta G_{nijt}^{n'i'j't}$ are obtained in the data.[37] When $\Delta G_{nijt}^{n'i'j't}$ is positive, I have an upperbound for γ_G^{FC}. Otherwise, I have a lowerbound for γ_G^{FC}.

Andrews and Shi (2013) show that by properly choosing instruments, conditional moment inequalities are transformed into their unconditional counterparts without losing identification power. So the conditional inequality can be rewritten as the following unconditional inequality

$$E\{z_G[\Delta FC_{nijt}^{n'i'j't} - \gamma_G^{FC}\Delta G_{nijt}^{n'i'j't} + 4B]\} \geq 0, \tag{36}$$

where $\{z_G\}$ are non-negative instruments based on market characteristics.

Specifically, I separate all inequality into different groups and the instruments are dummy variables indicating whether an inequality belongs to a group or not. All inequality representing the upperbound of γ_G^{FC} (those inequality with $\Delta G_{nijt}^{n'i'j't} > 0$) are aggregated to 4, 6, 8, 10, 12 and 14 groups. Again, all inequality representing the upperbound of γ_G^{FC} (those inequality with $\Delta G_{nijt}^{n'i'j't} < 0$) are aggregated to 4, 6, 8, 10, 12 and 14 groups. The selection of groups are based on the quantiles of $\Delta G_{nijt}^{n'i'j't}$. For instance, when I separate all inequality into four groups (four different quantiles), the first group includes all inequality whose $\Delta G_{nijt}^{n'i'j't}$ falls in its first quantile and the last group includes those inequality whose $\Delta G_{nijt}^{n'i'j't}$ falls in its fourth quantile.

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

$$Q_\gamma \;=\; \sum_{z_G} \min\{\sum_t \sum_n \sum_{n'\neq n} \sum_{ij} \sum_{i'j'\neq ij} z_G[\Delta FC_{nijt}^{n'i'j't} - \gamma_G^{FC}\Delta G_{nijt}^{n'i'j't} + 4B], 0\}^2. \tag{37}$$

I estimate γ_G^{FC} to minimize the criterion function Q_γ.

Estimation of Time Fixed-effects (η_t^{FC})

I estimate time fixed-effects by exploiting cross quarter entry decisions. In a given market, if an airline n is active in this market in quarter t but not active in quarter t', I construct inequality, eliminate other fixed-effects and focus on the estimation of time fixed-effects η_t^{FC}.

Airline n receives positive profit when it operates in ij in t

$$\overline{FC_{nijt}} - \gamma_G^{FC}\left(G_{nit} + G_{njt}\right) - (\eta_n^{FC} + \eta_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{nijt}^{FC}) \;\;\geq\;\; 0. \tag{38}$$

[37] The absolute value of all conditional expectation of error terms $|E[\varepsilon_{nijt}^{FC}|X_t, A_t]| \leq B$.

Airline n receives negative profit if it enters ij in t'

$$\gamma_G^{FC}\left(G_{nit'}+G_{njt'}\right)+(\eta_n^{FC}+\eta_{t'}^{FC}+\eta_i^{FC}+\eta_j^{FC}+\varepsilon_{nijt'}^{FC})-\underline{FC_{nijt'}} \quad \geq \quad 0. \tag{39}$$

Summing up these two inequality and replacing γ_G^{FC} with estimates $\hat{\gamma}_G^{FC}$, I have

$$\Delta FC_{nijt}^{nijt'}-\hat{\gamma}_G^{FC}\Delta G_{nijt}^{nijt'}-\eta_t^{FC}+\eta_{t'}^{FC}-\varepsilon_{nijt}^{FC}+\varepsilon_{nijt'}^{FC} \quad \geq \quad 0, \tag{40}$$

where $\Delta FC_{nijt}^{nijt'}\equiv\overline{FC_{nijt}}-\underline{FC_{nijt'}}$ and $\Delta G_{nijt}^{nijt'}\equiv G_{nit}+G_{njt}-G_{nit'}-G_{njt'}$.

Following the same steps as before, I have the following criterion function.

$$Q_T \quad = \quad \sum_{z_T}\min\{\sum_{nij}\sum_{t}\sum_{t'\neq t}z_T[\Delta FC_{nijt}^{nijt'}-\hat{\gamma}_G^{FC}\Delta G_{nijt}^{nijt'}-\eta_t^{FC}+\eta_{t'}^{FC}+2B],0\}^2. \tag{41}$$

The $\hat{\eta}_t^{FC}$ minimizes this criterion function. I normalize the first quarter fixed effect to 0. $\{z_T\}$ are dummy variables that select different combination of quarters. Since there are four quarters in the working database, there are $C_2^4=12$ different combinations.

Estimation of Airline Fixed-effects (η_n^{FC})

After obtaining estimates of quarter fixed-effects, I estimate airline fixed-effects by exploiting variation in airlines' entry decisions in the same market. For any two airlines n and n' in market ij, if n is active in the market but n' is not active in the same market, I construct inequalities and eliminate market fixed-effects and time fixed-effects. Summing up (29) and (31) and replacing γ_G^{FC} with its estimates, I obtain

$$\Delta FC_{nijt}^{n'ijt}-\hat{\gamma}_G^{FC}\Delta G_{nijt}^{n'ijt}-\eta_n^{FC}+\eta_{n'}^{FC}-\varepsilon_{nijt}^{FC}+\varepsilon_{n'ijt}^{FC} \quad \geq \quad 0, \tag{42}$$

where $\Delta FC_{nijt}^{n'ijt}\equiv\overline{FC_{nijt}}-\underline{FC_{n'ijt}}$ and $G_{nijt}^{n'ijt}\equiv G_{nit}+G_{njt}-G_{n'it}-G_{n'jt}$. Again, I have the following criterion function

$$Q_N \quad = \quad \sum_{z_N}\min\{\sum_{ijt}\sum_{n}\sum_{n'\neq n}z_N[\Delta FC_{nijt}^{n'ijt}-\hat{\gamma}_G^{FC}\Delta G_{nijt}^{n'ijt}-\eta_n^{FC}+\eta_{n'}^{FC}+2B],0\}^2, \tag{43}$$

where $\{z_N\}$ are indicator variables for all possible airline-pairs. I normalize the airline fixed-effect of American Airline to 0 and estimate η_n^{FC} to minimize this criterion function.

Estimation of City Fixed-effects

To estimate city fixed-effects, I replace gate fixed-effects of gate (γ_G^{FC}), time fixed-effects (η_t^{FC}) and airline fixed-effects (η_n^{FC}) with their estimates and estimate city fixed-effects utilizing airline market entry decisions. For any market ij, if airline n is active in quarter t, I obtain an upper bound for the city fixed-effect:

$$a_{nijt}(\overline{FC_{nijt}} - \hat{\gamma}_G^{FC}(G_{nit} + G_{njt}) - (\hat{\eta}_n^{FC} + \hat{\eta}_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{nijt}^{FC})) \geq 0, \tag{44}$$

whereas if airline n is not active in the same quarter, I obtain a lower bound for the city fixed-effects.

$$(a_{nijt} - 1)(\underline{FC_{nijt}} - \hat{\gamma}_G^{FC}(G_{nit} + G_{njt}) - (\hat{\eta}_n^{FC} + \hat{\eta}_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{nijt}^{FC})) \geq 0. \tag{45}$$

Summing up these two inequality,

$$\begin{aligned} a_{nijt}\overline{FC_{nijt}} + (a_{nijt} - 1)\underline{FC_{nijt}} - (2a_{nijt} - 1)\hat{\gamma}_G^{FC}(G_{nit} + G_{njt}) \\ -(2a_{nijt} - 1)(\hat{\eta}_n^{FC} + \hat{\eta}_t^{FC} + \eta_i^{FC} + \eta_j^{FC} + \varepsilon_{nijt}^{FC}) \geq 0. \end{aligned} \tag{46}$$

Again, estimates $\hat{\eta}_i^{FC}$ minimize the following criterion function

$$\begin{aligned} Q_C = \sum_{a_{nijt}=\{0,1\}} \sum_{z_C} \min\{\sum_{nijt} z_C[a_{nijt}\overline{FC_{nijt}} + (a_{nijt} - 1)\underline{FC_{nijt}} \\ -(2a_{nijt} - 1)(\hat{\gamma}_G^{FC} + (G_{nit} + G_{njt})\,\hat{\eta}_n^{FC} + \hat{\eta}_t^{FC} + \eta_i^{FC} + \eta_j^{FC}) + B], 0\}^2 \end{aligned} \tag{47}$$

where $\{z_C\}$ are indicator variables for different quantiles of market size.

The true γ values should satisfy all the inequality if the model is correctly specified. If multiple (sets of) estimates satisfy all inequality (when $\gamma = \hat{\gamma}$, the value of criterion function $= 0$), then a set estimate is obtained. If there is no estimate that satisfies all inequality (i.e. there is no $\gamma = \hat{\gamma}$ such that the value of criterion function $= 0$), I select a $\hat{\gamma}$ that minimizes the criterion function as a point estimate. Thus, though a set identification approach is being employed, it may still result in a point estimate.[38]

[38] It is very difficult to describe a set estimate when there are 100 parameters.

5.3.4 Computation of Goodness of Fit and the Selection of B^*

To estimate the entry cost, I first determine the value of B. Since the true value of B is unknown, I numerically search for the optimal B^* in the empirical analysis. I try different values of B ranging from 0 to 1000 in steps of five. For any trial of B, I estimate fixed cost according to the procedures described in Section 5.3.3. Then, I predict airline entry decisions in all markets. According to Inequality (27), the model predicts that an airline will enter the market if its expected variable profit is higher than its estimated entry cost. On the other hand, according to Inequality (28), the model predicts that the airline will not enter the market if its expected variable profit is lower than its estimated entry cost. By comparing the predicted and observed entry decisions, I compute overall model fit for the fixed cost estimates as the fraction of model predictions that are consistent with airline entry/exit decisions in the data. Finally, I select B^* to maximize the overall fit of the model.

5.3.5 Estimation of SD of Individual Shock ε_{nijt}^{FC}

In the counterfactual experiment, I simulate errors from the estimated distribution of individual shocks. This subsection estimates the distribution of error terms in the fixed cost. If airline n is active in ij, Inequality (29) imposes an upper bound for ε_{nijt}^{FC}. If airline n is active in ij in quarter t, I replace parameters with their estimates and obtain

$$\varepsilon_{nijt}^{FC} \leq \overline{FC_{nijt}} - \hat{\gamma}_G^{FC}\left(G_{nit} + G_{njt}\right) - \hat{\eta}_n^{FC} - \hat{\eta}_t^{FC} - \hat{\eta}_i^{FC} - \hat{\eta}_j^{FC} \equiv \bar{\varepsilon}_{nijt}^{FC}. \tag{48}$$

Otherwise, Inequality (30) imposes a lower bound for ε_{nijt}^{FC}. If airline n is inactive in ij in quarter t,

$$\varepsilon_{nijt}^{FC} \geq \underline{FC_{nijt}} - \hat{\gamma}_G^{FC}\left(G_{nit} + G_{njt}\right) - \hat{\eta}_n^{FC} - \hat{\eta}_t^{FC} - \hat{\eta}_i^{FC} - \hat{\eta}_j^{FC} \equiv \underline{\varepsilon}_{nijt}^{FC}. \tag{49}$$

To identify the distribution of individual shocks from these two sets of inequality, I impose the following assumption on the distribution of ε.

Assumption 6. ε ***Distribution*** *Suppose ε_{nijt}^{FC} is i.i.d normally distributed with mean zero and variance σ_ε^{FC}.*

I estimate σ_ε^{FC} according to maximum likelihood estimation. The estimates $\hat{\sigma}_\varepsilon^{FC}$ maximize the following log-likelihood function:

$$Q_\sigma(\sigma_\varepsilon^{FC}) = \sum_{nijt} \mathbf{1}[a_{nijt}=1] \ln \Phi(\frac{\overline{\varepsilon}_{nijt}^{FC}}{\sigma_\varepsilon^{FC}}) + \sum_{nijt} \mathbf{1}[a_{nijt}=0] \ln(1-\Phi(\frac{\underline{\varepsilon}_{nijt}^{FC}}{\sigma_\varepsilon^{FC}})) \tag{50}$$

6 Empirical Results

6.1 Technological Relationship between One-stop and Nonstop Flight Frequencies

Table 3 summarizes the estimates of the technological relationship between one-stop flight frequency and nonstop flight frequency (Equation (21)).[39]

As I have discussed, airline n's one-stop flight frequency in market ij with connection city k ($f_{nij}^{OS(k)}$) is a complex function of nonstop flight frequencies for market ik and market kj. Even without any fixed-effects, the technological relationship fits the data quite well with R^2 close to 0.8. If the number of nonstop flights in market ik or kj doubles, the one-stop flight frequency in market ij with a stop at k will increase by 74.6 percent. If the number of flights in both market ik and kj double, the one-stop flight frequency in this market will increase by 149.2 percent, which is increasing returns to scale. These results are quite robust when airline-fixed-effects and market-fixed-effects are included in the estimation. Not all nonstop flights can be used to create one-stop flights. On average only $exp\,(-2.949) = 5.2\%$ of the nonstop flights can be used to create one-stop flights in a market. However, scheduling an additional flight in a market may induce the airline to also schedule new one-stop flight frequencies in many other markets.

6.2 Stage 1 (a): Demand Estimation

Table 4 reports estimates of demand systems. Columns (1) and (2) display estimates with both flight frequency and hub indexes as explanatory variables. Columns (3) and (4) display estimates with only hub indexes as explanatory variables. Columns (5) and (6) display estimates are estimates with only flight frequencies as explanatory variables. Columns (1), (3), and (5) report OLS estimates and Columns (2), (4), and (6) report IV estimates. Since the coefficient of the price variable measures indirect utility from one hundred dollars, I obtain dollar denominated estimates of consumer willingness to pay towards different product characteristics.

I find that, on average, consumers are willing to pay \$150 more for nonstop service than one-stop

[39] Standard errors are clustered at the airline-market level.

service.[40] Consumers are willing to pay for greater flight frequencies in both nonstop and one-stop services. Given that the average nonstop flight frequency is 7.7 daily flights, if airline n increases one daily direct flight in a market, consumer willingness-to-pay for airline n's nonstop service in this market increases by $11.20. On the other hand, given average one-stop flight frequency is 10.5 daily flights, if airline n increases its one-stop flight frequency by one daily flight, consumers' willingness-to-pay for airline n's one-stop service in this market increases by $4.80. One percent increase in hub-size implies an increase in consumer willingness-to-pay by 0.37 percent to 0.44 percent.[41] When travel distance is greater, consumers are more willing to travel by air. These demand estimates are consistent with estimates in the literature.

Airlines generally provide more frequent flights in markets connected to hub cities so hub indexes and airline flight frequencies are correlated. While both affect consumer willingness-to-pay, they are different, as discussed above. Comparing estimates in columns (2) and (4), consumer willingness-to-pay for airline hubs are over-estimated if flight frequency variables in demand estimation are not included in the regression.

6.3 Stage 1 (b): Variable Cost of Serving Passengers

Given estimates of demand parameters and using Nash-Bertrand equilibrium prices, I estimate the marginal cost of serving passengers as $\hat{c}_g = p_g - \hat{\sigma}_1(1 - \bar{s}_g)^{-1}$.[42] I further decompose this marginal cost of serving passengers into different factors. I assume that shocks to the cost of serving passengers are not correlated with airline hub indexes or flight frequencies because these are pre-determined in the price competition stage. Thus, I use OLS to estimate the variable cost of serving passengers.

Table 5 reports the estimated marginal cost of serving consumers. Column (1) reports estimates, accounting for both hub indexes and flight frequencies. Column (2) and (3) report estimates, accounting for only hub indexes and flight frequencies, respectively. Though consumers value nonstop service more than one-stop service, the marginal cost of serving a nonstop passenger is $37.40 lower than the marginal cost of serving an one-stop passenger, since one-stop passengers occupy seats on two different flights. If an airline increases its nonstop flight frequency by one, its marginal cost of serving nonstop passengers decreases by $0.80. On the other hand, increasing

[40] 150=1.472/0.981*100

[41] 0.37 = 0.36/0.981 and 0.44= 0.433/0.981

[42] $\bar{s}_g = (\sum_{g' \in \mathbf{G}_{nijt}} e_{g'})^{\frac{\sigma_2}{\sigma_1}} [1 + \sum_{n'=1}^{N} (\sum_{g' \in G_{n'ijt}} e_{g'})^{\frac{\sigma_2}{\sigma_1}}]^{-1}$.

flight frequency by one reduces marginal cost of serving one-stop passengers by \$0.60. Cost of serving passengers is also lower if any endpoint is a hub airport.

6.4 Stage 2: Estimation of Marginal Cost of Building Frequencies

I use estimates in Table 4 and Table 5 to calculate the marginal variable profit associated with an additional nonstop flight frequency in all markets.

Figure 2 decomposes and summarizes the marginal variable profit from an extra flight. The first row reports marginal variable profit from additional nonstop service. The second row reports its cannibalization effect on existing one-stop services. The third row reports marginal variable profit from additional one-stop service. The forth row reports its cannibalization effect on existing nonstop service. The last row reports the total marginal variable profit associated with an additional flight, which sums up the first four rows. According to marginal cost optimality for flight frequency, this total marginal variable profit should equal the marginal cost of scheduling an additional flight.

On average, if an airline schedules an extra flight, it can bring in marginal variable profit of \$6747 from nonstop service and \$1130 from one-stop service. The average marginal cost of scheduling flight frequency is equal to \$7554. This value is consistent with the industry measure of flight operation cost. So if ignoring airline network structure would underestimate the costs and benefits of an additional flight frequency by 11%.

Table 7 reports the estimates of the marginal cost of flight frequency. The relationship between distance and marginal cost resembles an inverted U-shape. The marginal cost of flight frequency in a market is higher when an endpoint of this market has a higher hub index. According to the estimates of demand and the marginal cost of serving passengers, higher hub indexes in a market result in higher demand and lower cost of serving passengers. Airlines that schedule more flights in their hub city suffer from higher cost of scheduling an additional flight due to congestion or capacity constraints.[43]

6.5 Stage 3: Estimation of Entry Cost

Empirically, I find that $B^* = 170$ optimizes model fit in fixed cost estimation. Table 8 reports entry cost estimates for the year 2014 when $B = B^* = 170$. Section 6.6 further discusses model goodness of fit.

[43] In this paper, I assume that the marginal cost of scheduling flight frequency is not a function of flight frequency. This assumption may be relaxed later.

When gate share at the two endpoints increases by 1 percent, entry cost decreases by \$0.22 million a quarter. So an airline that dominates an airport faces lower entry cost into markets connected to this airport. Legacy carriers control a greater proportion of gates compared to low cost carriers, which reduces their entry cost and facilitates their entry decisions and operations. I conclude that gate ownership at airports is an important element of airline operations and competition. There is heterogeneity in entry cost across airlines. The difference in entry cost among the legacy carriers: Delta Air Lines, American Airlines and United Airlines are not significant. On the other hand, Southwest Airline's entry cost is \$3.67 million higher than that of American Airlines, conditional on airport gate allocation. This is consistent with the fact that although Southwest is more profitable than legacy carriers, the number of markets it operates in (364 markets) is not significantly more than the other legacy carriers such as Delta Air Lines (322 markets). Variance estimates of error term in the fixed cost is $\hat{\sigma}_{\varepsilon}^{FC} = 2986$.

6.6 Goodness of Fit

In this subsection, I discuss the goodness of fit of the model in the entry stage. I compare model predictions with data in Table 9. Out of the 13850 stay-out predictions, 11292 of them (78%) are consistent with data. Out of 7609 entry predictions, 4376 of them (63%) are consistent with data . Overall, the model prediction is consistent with 73% of the observations.

7 Merger Simulation

In 2016, the U.S. Department of Justice approved a merger deal between Alaska Air Group (AS) and Virgin America (VX).[44] The post-merger airline network structure is not merely a combination of the two pre-merged airlines and there has been considerable discussion over how the merged airline will behave. For instance, which new markets will the new post-merger airline enter? How will this post-merger airline re-allocate its flights? How will other airlines respond? How will prices and consumer surplus change in the markets previously served by Alaska or Virgin American or even markets that were not served by the two airlines pre-merger? These interesting questions cannot be answered with existing models which treat network structures as exogenously given. In this counterfactual study, I investigate the consequences of an exogenous merger between the two airlines. This paper focuses on examining the extent to which the merger affects the network

[44] Alaska Airlines won a bidding war to acquire Virgin American in April 2016.

structures of all airlines; airline merger incentives are not explored.

7.1 Merger Simulation Set-up

Pre-Merger Network Set-up

To simulate a pre-merger network structure, I assume the values of primitives of the model are the same as their estimates.[45] Airlines will maintain their gate allocations at each airport. Specifically, I draw fixed cost from a normal distribution, using the fitted fixed cost estimate and its standard error as the mean and standard deviation, respectively, i.e., $FC^{simu}_{nijt} \sim N(\hat{\gamma}^{FC}_G(G_{nit}+G_{njt})+\hat{\eta}^{FC}_n+\hat{\eta}^{FC}_t+\hat{\eta}^{FC}_i+\hat{\eta}^{FC}_j, \hat{\sigma}^{FC}_{\varepsilon})$.

Post-Merger Network Set-up

To simulate the post-merger network structure, I assume that non-merging airlines maintain their gate allocations and unobserved product quality in consumer demand, marginal cost, and flight frequency. Merging airlines are eliminated post-merger and replaced with a new airline. The post-merger airline owns all gates from the merging airlines.[46] Post-merger unobserved product quality in demand and cost are calculated as the weighted average of the merging airlines. For markets in which both Alaska Airlines and Virgin America were active pre-merger, I determine these weights based on the merging companies' relative flight frequencies. For markets in which neither Alaska Airlines nor Virgin America were active pre-merger, I calculate weights based on their gates shares at the two endpoints.

7.2 Algorithm to Simulate An Equilibrium

Sequence of Moves

Since it is computationally infeasible to obtain a Nash equilibrium of this simultaneous-move network competition game, I reconstruct this simultaneous game as a sequential-move game. I propose a sequence by which all airline-market pairs move. Airlines first move in larger markets, then move in smaller markets. Within each market, airlines move sequentially by profitability.[47] For instance,

[45] The primitives of the model include consumer utility functions, variable costs of serving passengers and of increasing flight frequency, and fixed cost.

[46] In reality, there may be some gate or slot reallocation post-merger; for simplicity, I assume there is no change in gate allocations.

[47] Berry (1992) estimates a model of sequential market entry of the airlines. He orders airlines according to profitability and incumbency status of the airlines.

New York - Los Angeles is the largest market, in which JetBlue is the most profitable airline and American Airline is the second most profitable airline. My proposed sequence would therefore assign JetBlue and American Airline as the first and second movers, respectively, in the NY-LA market, followed by other airlines in descending market profitability order. After these airlines in the largest market have moved, the sequence moves on to airlines in the second largest market New York - Chicago. Again, airlines with higher profitability move first, followed by airlines with lower profitability. In this way, I obtain a sequence of all airline-market pairs.

For this massive sequential move game, I should ideally solve for the sub-game perfect Nash equilibrium using backward induction. However, since it is impossible to compute the profit of the airlines at all branches of the game tree, I use a forward induction algorithm to search for an equilibrium.

Starting with an empty network where no airlines are active in any market, I evaluate airline best response, airline-market pair by airline-market pair according to the sequence defined above. Specifically, starting with the first airline-market pair in the sequence, I evaluate the best response of this airline in that specific market.[48] I update airline network structures each time an airline enters, exits, or changes flight frequency in a market. Then, I proceed to the second airline-market pair in the sequence, evaluate the best response of this airline in the market and update its network structure. After all airline-market pairs are visited, I go back to the first airline-market pair and re-evaluate the best responses of the entire airline-market sequence. If there is no incentive to deviate, this convergence of best responses in the network serves as an approximation of the subgame perfect Nash equilibrium of the sequential-move game.[49]

Airline Best Response

This subsection describes how I derive the best responses of the airlines. When airline n determines its optimal entry decision and flight frequency for a given market, it treats as given not only its own entry and flight frequency decisions in other markets but also other airlines' entry and flight frequency decisions in all markets. Since there is no explicit solution for the optimal entry decision and flight frequency, I numerically calculate the profit of each airline associated with all possible flight frequencies in this market. For any possible flight frequency of an airline in a market, I first simulate the counterfactual network structure of this airline to determine the Bertrand Nash

[48] I will discuss how to compute the best response of the airline in the next subsection.

[49] In the robustness check, I consider other sequences of airline-market where the order of all airline-market pairs is randomized.

equilibrium in prices for all markets, which I use to calculate the overall profit of the airline associated with the given flight frequency. The airline will schedule its flights to maximize its overall profit. To reduce computation burden, I also restrict the choice set of the airlines. In any market, an airline has 6 possible options: it can out of the market, or it can enter this market and offer (2,4,6,8,10) daily flights.

7.3 Counterfactual Results

For this policy experiment, I draw 10 different sets of fixed costs, simulate both benchmark network structure and counterfactual network structures, and report the average of the 10 simulations.[50]

Table 10 and Table 11 compare the market structures of benchmark networks versus counterfactual networks. In both tables, the first three rows summarize airlines' nonstop networks (number of nonstop markets, number of nonstop flight frequencies, and revenue from nonstop services), the fourth to the sixth rows summarize airlines' one-stop networks (number of one-stop markets, number of one-stop flight frequencies, and revenue from one-stop services) and the last row summarizes the variable profit of the airlines.

In Table 10, the first two columns report the simulated benchmark networks of Alaska Airline and Virgin America, respectively. Averaged across all simulations, Alaska Airline operates nonstop service in 258 markets, which are six times the nonstop markets of Virgin America pre-merger. Virgin America does not operate one-stop service while Alaska operates one-stop flights in 52 markets. The third column reports the counterfactual network of the new post-merger airline. The post-merger airline will operate nonstop service in 291 markets and offer increased flight frequency (2302 daily flights) greater than the pre-merger offerings (1722+188=1910 daily flights). The post-merger airline will operate in more one-stop markets because it now has a larger network, which can facilitate its one-stop operations. In terms of revenue, the post-merger airline will bring in more variable profit compared to the two pre-merger airlines. On average, the post-merger airline will enter 32 nonstop markets and 1 one-stop markets but exit 13 nonstop markets.

Table 11 summarizes the network structures of all the other airlines before and after the AS-VX merger.[51] The first column reports the simulated benchmark network. Other airlines operate nonstop service in 8953 markets with 78064 daily flights and earn $253 billion dollars in a quarter.

[50] It takes approximately one day for one iteration to converge using an Intel i7 8-core, 16G RAM computer. The network converges in 3-6 iterations. The detailed network structure of each set of fixed costs can be found in the online appendix.

[51] Other airlines refer to all airlines except Alaska and Virgin America.

They also operate one-stop service in 6012 markets. Revenues from nonstop service are about three times that of one-stop service. The second column summarizes counterfactual networks of the other airlines and the third and fourth columns report entries and exits of the other airlines, respectively. Following the AS-VX merger, the other airlines are projected to slightly expand their operations, entering into 3 nonstop markets and exiting from 1 nonstop market.

Table 12 reports change in consumer surplus and number of entries and exits by market size. The first two columns report entries and exits of the airlines and the last three columns report change in welfare. The first four rows report different quantiles of markets and the last row reports the sum. In larger markets, there are more entries than exits, resulting in net entries.[52] In contrast, there are no entries in smaller markets and consumer welfare may slightly reduce in these markets. Overall, consumer surplus increases by 1.28% with consumer surplus in larger markets increasing more compared to the consumer surplus in smaller markets.

8 Conclusion

This paper proposes and estimates one of the first models of airline network competition to endogenize network structure, flight frequencies, prices and quantities for every nonstop and one-stop market. Since solving for an equilibrium is computationally infeasible, I estimate cost of increasing flight frequencies by making use of the marginal condition of optimality and infer entry cost by exploiting inequality restrictions implied by airlines' revealed preferences.

I use this model to study the effect of marginal costs, entry costs, variable profits and strategic interactions in both nonstop and one-stop services in airline network competition. I find that synergies across markets are crucial to determining airline entry decisions. Airlines construct their network structures and schedule their flights strategically to provide one-stop service to consumers. Ignoring one-stop products could therefore result in underestimating the marginal cost of flight frequency by up to 11%. The paper further applies the proposed methodology to predict the consequences of a hypothetical merger between Alaska Airlines and Virgin America in the first quarter of 2014. This counterfactual simulation predicts that the new post-merger airline would re-optimize its network structure, enter 32 nonstop markets, and exit 13 nonstop markets. The merger is expected to improve consumer welfare overall through increased airline entry, with welfare increasing in larger markets and decreasing in smaller markets.

[52] The identity of the airlines that operate in these markets may be different.

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Figure 1: Four Channels of Variable Profit Change

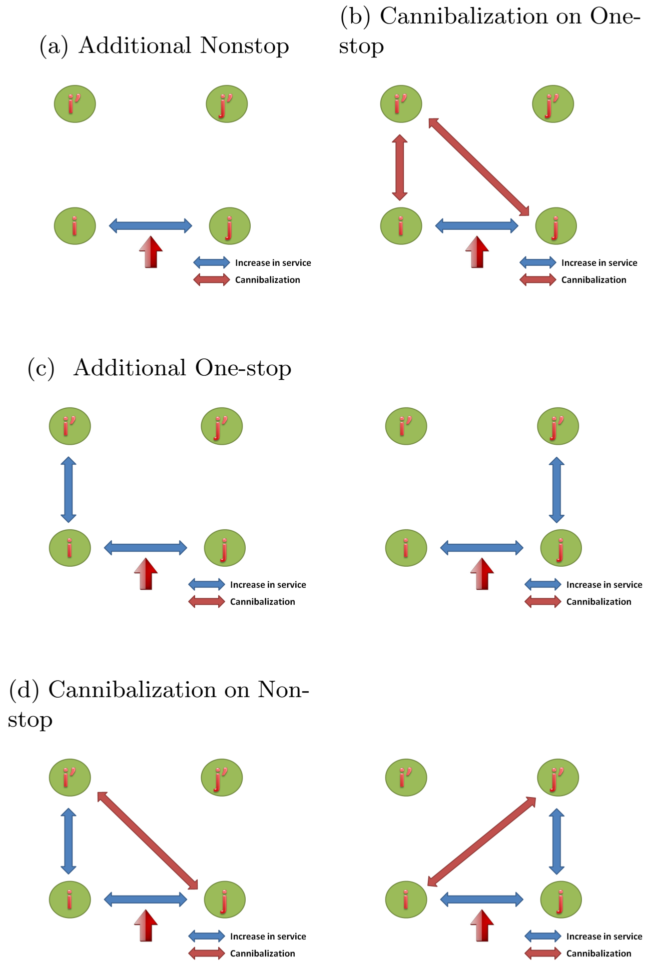

Table 12: Counterfactual Results: Welfare Analysis

Market Size	Market Entries and Exits		Change in Welfare (Million $)		
Quartile	Entry	Exit	Benchmark	CT	Change(%)
1	29	12	542857	555450	2.320
2	4	2	284280	285338	0.372
3	2	0	165476	165824	0.210
4	0	0	99883	99882	-0.001
Total	35	14	1092495	1106494	1.281

Note: Consumer surplus is measured by million dollars in a quarter.

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

	2007Q1					
	Nonstop Service			**One-stop Service**		
Airline Code (Name)	# Markets	% of Pass	% of Rev	# Markets	% of Pass	% of Rev
WN (Southwest Airlines)	364	84.7%	87.9%	1215	15.3%	12.1%
DL (Delta Air Lines)	322	60.5%	76.3%	3529	39.5%	23.7%
US (US Airway)	287	73.2%	82.3%	2318	26.8%	17.7%
AA (American Airlines)	265	67.8%	78.3%	3009	32.2%	21.7%
NW (Northwest Airlines)	207	65.9%	79.9%	3038	34.1%	20.1%
UA (United Airlines)	202	73.1%	82.2%	2615	26.9%	17.8%
CO (Continental Airlines)	186	78.5%	86.8%	2471	21.5%	13.2%
FL (AirTran Airways)	95	67.7%	78.9%	681	32.3%	21.1%
B6 (JetBlue Airways)	67	87.0%	92.1%	614	13.0%	7.9%
F9 (Frontier Airlines)	46	69.7%	77.6%	900	30.3%	22.4%
AS (Alaska Airlines)	45	96.4%	97.6%	209	3.6%	2.4%
NK (Spirit Airlines)	22	100.0%	100.0%	53	0.0%	0.0%
VX (Virgin America)	-	-	-	-	-	-
Total	2108	74.9%	83.0%	20652	25.1%	17.0%
	2014Q1					
	Nonstop Service			**One-stop Service**		
Airline Code (Name)	# Markets	% of Pass	% of Rev	# Markets	% of Pass	% of Rev
WN (Southwest Airlines)	521	78.6%	84.6%	2274	21.4%	15.4%
DL (Delta Air Lines)	421	58.6%	74.3%	3473	41.4%	25.7%
US (US Airway)	-	-	-	-	-	-
AA (American Airlines)	431	62.5%	75.8%	3347	37.5%	24.2%
UA (United Airlines)	347	80.8%	89.7%	2675	19.2%	10.3%
NW (Northwest Airlines)	-	-	-	-	-	-
CO (Continental Airlines)	-	-	-	-	-	-
FL (AirTran Airways)	-	-	-	-	-	-
B6 (JetBlue Airways)	91	95.4%	97.3%	662	4.6%	2.7%
F9 (Frontier Airlines)	43	58.4%	70.5%	567	41.6%	29.5%
AS (Alaska Airlines)	62	98.4%	98.8%	370	1.6%	1.2%
NK (Spirit Airlines)	65	97.2%	97.8%	136	2.8%	2.2%
VX (Virgin America)	26	95.7%	97.1%	101	4.3%	2.9%
Total	2007	71.9%	81.3%	13605	28.1%	18.7%

Note: Pass is abbreviation of passengers and Rev is abbreviation of revenue.

Table 2: Summary Statistics: Hub City

	2007Q1							
Airline Code (Name)	Top Hub	#Mkts	Second Hub	#Mkts	CR1	CR2	CR3	CR4
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	-	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)	-	-	-	-	45.5	77.3	90.9	90.9
VX (Virgin America)	-	-	-	-	-	-	-	-
	2014Q2							
Airline Code (Name)	Top Hub	#Mkts	Second Hub	#Mkts	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	-	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)	-	-	-	-	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

Table 3: Estimation of Tech Relationship between One-stop and Nonstop Flight Frequencies

ln(# of one-stop flights)	(1) OLS	(2) OLS	(3) OLS
ln(# of flights in first leg)	.746***	.729***	.746***
+ ln(# of flights in second leg)	(.002)	(.002)	(.002)
Airline FE		Yes	Yes
City-pair FE			Yes
Constant	–2.949***	–2.827***	–2.813***
	(.021)	(.030)	(.027)
Pseudo. R^2	.764	.774	.796
Obs	2,487,262	2,487,262	2,487,262

Notes: Standard errors are clustered at the airline-market level and displayed in parentheses. An observation is an origin-connectcity-destination in a quarter for an airline.
***1% significance level.
**5% significance level.
*10% significance level.

A Bankruptcies and Mergers

Some airline bankruptcies and mergers take place during the sample period. I consider four major mergers: Delta announced a merger with Northwest on Apr. 14th, 2008, completing the transaction on Dec. 31st, 2009; United Airlines merged with Continental on May. 3rd, 2010, with a closing day of Oct. 1st, 2010; Southwest controlled AirTran's assets after AirTran's bankruptcy on Sep. 27th, 2010. AMR Corporation, the former parent company of American Airlines, completed the merger with US Airways Group on December 9, 2013. For the analysis, two merging airlines are treated as the same airline after closing day but as different airlines before closing day. Given this, Northwest disappears in 2010 Q1; Continental flights are considered United Airlines flights after 2010 Q4; very few AirTran tickets in 2008 Q2 are considered to be Southwest tickets and US Airway tickets and operations are considered to be a part of American Airlines after 2014Q1.

B Computation of Consumer Welfare

Consumer welfare is computed according to the following formula

$$W = \sigma_1 ln[\sum_G (\sum_g exp(V_{g,G}))^{\frac{\sigma_2}{\sigma_1}}], \tag{51}$$

where V_i is the deterministic component of the indirect utility function.

Table 4: Demand Estimation

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Nonstop-Dummy	1.718***	1.472***	2.132***	1.813***	2.191***	2.164***
	(.028)	(.042)	(.010)	(.049)	(.029)	(.029)
ln-Nonstop-Flight-Frequency	.752***	.744***			.877***	.871***
	(.006)	(.010)			(.006)	(.007)
ln-Onestop-Flight-Frequency	.475***	.452***			.568***	.585***
	(.004)	(.005)			(.004)	(.005)
ln-Hub-Index-Origin	.278***	.360***	.444***	.585***		
	(.004)	(.019)	(.004)	(.019)		
ln-Hub-Index-Dest	.354***	.433***	.530***	.661***		
	(.004)	(.018)	(.005)	(.018)		
Distance	2.448***	2.642***	1.825***	2.139***	2.563***	2.667***
	(.022)	(.028)	(.022)	(.031)	(.022)	(.028)
Distance-squared	−.564***	−.543***	−.486***	−.462***	−.571***	−.563***
	(.008)	(.008)	(.008)	(.009)	(.008)	(.008)
Fare	−.394***	−.981***	−.405***	−1.282***	−.352***	−.699***
	(.005)	(.064)	(.005)	(.067)	(.005)	(.061)
Nest	.422***	.443***	.480***	.548***	.316***	.425***
	(.002)	(.019)	(.002)	(.020)	(.002)	(.022)
Pseudo. R^2	.631	.605	.594	.534	.619	.604
Obs	329448	329448	329448	329448	329448	329448

Notes: All specifications include airline fixed-effects, market fixed-effects and quarter fixed-effects. Standard errors are clustered at the airline-market-quarter level and displayed in parentheses.
***1% significance level.
**5% significance level.
*10% significance level.

Table 5: Marginal Cost Estimation

	(1) OLS	(2) OLS	(3) OLS
Nonstop-Dummy	–.374***	–.313***	–.375***
	(.032)	(.009)	(.032)
ln-Nonstop-Flight-Frequency	–.058***		–.058***
	(.007)		(.007)
ln-Onestop-Flight-Frequency	–.055***		–.055***
	(.005)		(.005)
ln-Hub-Index-Origin	.012	.007	
	(.022)	(.022)	
ln-Hub-Index-Dest	–.031*	–.031*	
	(.018)	(.018)	
Distance	.164***	.212***	.164***
	(.024)	(.024)	(.024)
Distance-squared	.104***	.101***	.104***
	(.009)	(.009)	(.009)
Pseudo. R^2	.428	.426	.428
Obs	37,777	37,777	37,777

Notes: All specifications include airline fixed-effects, market fixed-effects and quarter fixed-effects. Standard errors are clustered at the airline-market-quarter level and displayed in parentheses.
***1% significance level.
**5% significance level.
*10% significance level.

Table 6: Decomposition of Marginal Variable Profits for an Additional Flight (in $100's)

Variable	**Mean**	**Std. Dev.**
$\Delta\pi$ from Additional Nonstop Service	67.476	99.737
Cannibalization from One-stop Services	-2.562	10.472
$\Delta\pi$ from Additional One-stop	11.304	22.346
Cannibalization from Nonstop Services	-0.682	2.067
Total $\Delta\pi$	75.536	105.099
Obs.	6934	

Figure 2: Decomposition of Marginal Variable Profit

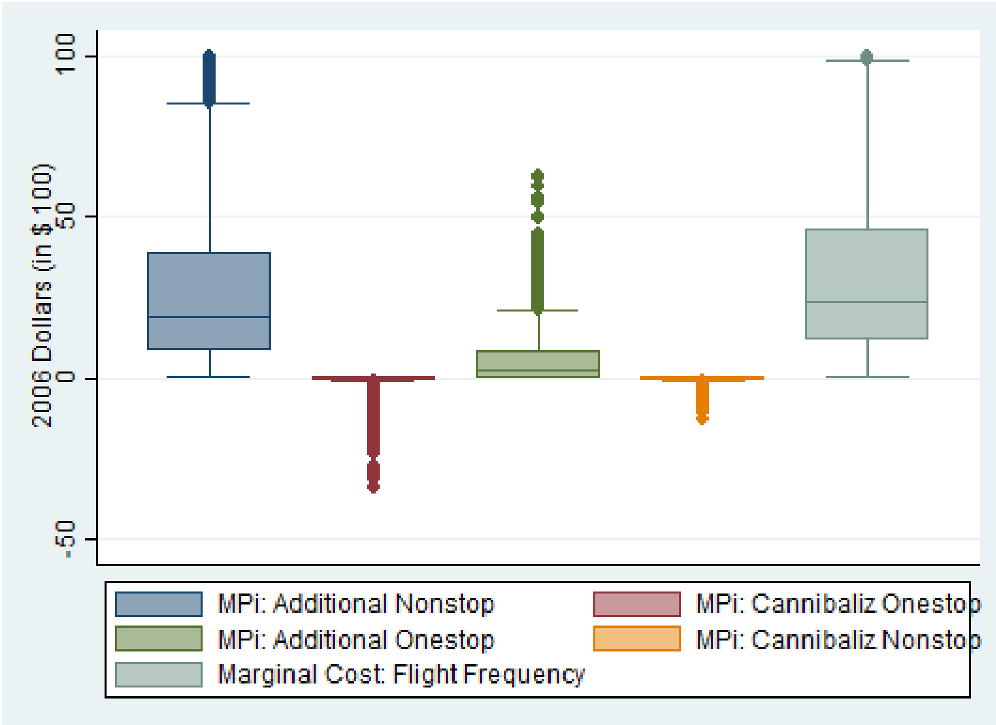

Table 7: Estimation Result: Marginal Cost of Building Flight Frequency

	(1) MCFF
ln-Hub-Index-Origin	.248***
	(.020)
ln-Hub-Index-Dest	.169***
	(.015)
Distance	2.335***
	(.017)
Distance-squared	−.514***
	(.007)
Pseudo. R^2	.984
Obs	6934

Notes: All specifications include airline-city fixed-effects and quarter fixed-effects. Standard errors are clustered at the airline-market-quarter level and displayed in parentheses.
***1% significance level.
**5% significance level.
*10% significance level.

Table 8: Entry Cost (in Millions $ a Quarter)

Characteristics	Estimates
Gate	-22.83 [-23.28,-22.32]
Quarter	**Estimates**
Q1	(Omitted) -
Q2	1.84 [0.66,2.49]
Q3	-0.75 [-1.62,-0.36]
Q4	-1.06 [-1.33,0.23]
Airline	**Estimates**
WN (Southwest Airlines)	3.67 [2.16,5.06]
DL (Delta Air Lines)	-0.05 [-0.85,5.62]
AA (American Airlines)	(Omitted) -
UA (United Airlines)	0.90 [-2.07,1.38]
B6 (JetBlue Airways)	0.20 [-5.17,3.16]
F9 (Frontier Airlines)	-1.13 [-6.07,-0.32]
AS (Alaska Airlines)	-1.26 [-2.99,0.18]
NK (Spirit Airlines)	-0.68 [-2.82,5.38]
VX (Virgin America)	-1.64 [-3.49,-0.23]
Obs	21459

Notes: 95% confidence intervals are displayed in parentheses. Confidence intervals are constructed from 500 group samplings.

Table 9: Goodness of Fit of the Entry Model

	Model Prediction		
	Stay Out	Entry	Total
Data: Stay Out	11292	3233	14525
Data: Entry	2558	4376	6934
Data: Total	13850	7609	21459

Table 10: Counterfactual Results: Network Structures of AS and VX

	Benchmark		CT	Change	
	AS	VX	AS + VX	Entry	Exit
Nonstop					
a^{NS}	258	42	291	32	13
f^{NS}	1722	188	2302	294	50
Rev^{NS}	9999	2680	19325	7497	10
One-stop					
a^{OS}	52	0	53	1	0
f^{OS}	105	0	132	0	0
Rev^{OS}	2080	0	1248	0	0
Variable Profit					
π	11371	2066	18580		

Note: revenue and profit are measured by million dollars in a quarter.

Table 11: Counterfactual Results: Network Structures of other airlines

	Benchmark	CT	Change	
	Other Air	Other Air	Entry	Exit
Nonstop				
a^{NS}	8953	8955	3	1
f^{NS}	78064	78064	110	20
Rev^{NS}	253098	281878	131	28
One-stop				
a^{OS}	6012	6012	0	0
f^{OS}	26980	26963	0	0
Rev^{OS}	109596	132410	0	0
Variable Profit				
π	346273	397955		

Note: Revenue and profit are measured by million dollars in a quarter.