ABSTRACT

Title of dissertation: ESSAYS ON INDUSTRIAL ORGANIZATION

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This dissertation covers two topics within the context of the U.S. airline mergers. In Chapter 1, I develop a structural model to evaluate the effectiveness of alternative slot divestiture schemes in the US airline industry, focusing on the divestiture of slots at Ronald Reagan Washington National Airport (DCA), which the government required as a condition of the American/US Airways merger. Departing from the existing literature, my model accounts for how the number of slots allocated to a route segment affects carrier costs, how passengers going to many different destinations may use the same segments, and how carriers choose to allocate slots to segments. In Chapter 2, I use counterfactuals to show that slot divestitures can result in the re-allocation of surplus between consumers; to estimate the proportion of slots that the merged American would have needed to divest to maximize total welfare; and, to evaluate the effects of allocating divested slots to different types of carriers. I find that the proposed divestiture raised consumer surplus significantly ($112M per year) compared to approving the merger without divestiture, but that it re-allocated surplus between consumers in different markets. I also find that the

policy of only allowing the slots to be divested to low-cost carriers raised consumer surplus relative to the policy of only allowing the slots to be divested to legacy carriers.

In Chapter 3, my coauthors and I develop an airline route competition entry model in which carriers first choose whether to offer nonstop or connecting service and then choose prices. In this setting carriers' quality and cost unobservables are known to every player throughout the game, so that carriers can self-select into choosing nonstop service. Accounting for selection when performing counterfactuals affects predictions about post-merger repositioning by rivals, likely price increases and the effectiveness of remedies, and allows the model to match observed changes after completed mergers.

ESSAYS ON INDUSTRIAL ORGANIZATION

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

To my dad and Eunjin in heaven.

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Chapter 1: An Assessment of Slot Divestitures in the American Airlines/US Airways Merger: Model and Estimation

1.1 Introduction

When large horizontal mergers are proposed, a number of standard approaches such as merger simulations and upward pricing pressure can be used to predict whether or not the merger may reduce competition. In cases when the merger may make select markets less competitive, antitrust authorities negotiate a set of remedies with the merging parties, rather than blocking the merger outright.[1] The preferred form of merger remedy is a structural remedy (asset divestiture), designed to redistribute assets to market rivals or new entrants in a way that they can restore competition that could be lost through the merger—see United States (2019).[2] These assets may include production capacity, distribution centers, wireless spectra,

[1]Merger remedies have become a dominant method for resolving merger-related competition concerns. For example, of the merger cases challenged by U.S. antitrust authorities between 2008 and 2016, eight times more cases were resolved with settlement/remedies than with court proceedings—see Hatzitaskos et al. (2019).

[2]Behavioral remedies (i.e. conditions imposed to mitigate or prohibit specified anticompetitive conduct) represent an alternative merger remedy. Examples of behavioral remedies include non-discrimination provisions, anti-retaliation provisions, and prohibitions on certain contracting practices. However, as behavioral remedies are often imposed against the merged firm's profit-maximizing incentives, these remedies are often less preferred than structural remedies. Additionally, most jurisdictions, including those in the U.S., have stated a preference for using asset divestitures over behavioral remedies in merger cases that present anti-competitive concerns —see Kwoka (2017).

airport slots or intellectual property. However, it is hard to apply the standard approaches to evaluate merger remedies because the link between these types of assets and their costs or the set of assets offered to consumers is not specified.

In this chapter, I develop a model of the domestic airline industry that can be used to evaluate alternative take-off/landing slot divestitures that may be proposed for airline mergers. I use the model to examine the slot divestitures imposed on the merger between American Airlines and US Airways (AA/US) at Ronald Reagan Washington National Airport (DCA); however – as I emphasize in the conclusion – this model could also be leveraged to evaluate a number of other slot-related policies.[3] As is the case at New York airports, carriers at DCA are required to hold a landing slot for each scheduled departure or arrival, with a cap on the number of slots each hour in order to mitigate congestion. AA/US transported a combined 60% of DCA passengers and a 56% share of the departures and arrivals pre-merger. Given the dominant position of both firms and the slot constraints at DCA, the U.S. Department of Justice (DOJ) argued that the slot constraints would prevent rivals from expanding or initiating their service if the merged American (NewAA) raised prices—see United States (2013). To gain approval for the merger, AA/US agreed to divest 104 slots (approximately 15% of its holdings) to low-cost carriers (LCCs), as well as forfeit their rights and interests at any associated gates or other ground facilities at the airport. Then, in Chapter 2, I use my model to quantify how divestitures may affect the welfare of passengers in different markets (defined

[3]Examples are the competition effects of exchanges or sales of landing slots within an airport (Reitzes et al. (2014)), slot swaps, or alternative mechanisms for controlling congestion (Ball et al. (2007)).

as origin-destination pairs) and predict how passenger welfare may be affected by different divestiture decisions—for instance, more or less slots, or divestitures where slots are allocated to legacy carriers instead of LCCs (a policy that legacy rivals, such as Delta, support).

The model that I develop extends both the existing frameworks for merger simulation and the existing models of airline markets in several important ways. A key contribution is that I model the connection between divested assets (landing slots) and both carrier costs and how the allocation of assets to products affects pricing and costs. This type of connection has been missing in the existing merger simulation models. In the context of airline merger cases, divested assets are landing slots that a carrier may choose to use on a wide range of possible route segments. Because many passengers make connections, a single slot may be used to serve passengers in many different origin-destination markets.[4] My model takes into account this industry feature and enables cross-market interactions. This model feature is an extension to the existing entry models in airline markets (Berry (1992), Ciliberto and Tamer (2009), Ciliberto et al. (2018)) where individual markets are typically assumed to be independent and there are no interactions across markets. Last, the existing airline entry models ignored the differences between flight segments (non-stop origin-destination pairs where carriers allocate capacity) and passenger markets, and they abstracted away from carriers' capacity choices. My model, on the other

[4] Slot or gate divestitures have been the remedy that policy makers have imposed in several completed mergers (e.g. IAG/Aer Lingus in 2015, American/US Airways in 2013, United/Continental in 2011, Ryanair/Aer Lingus in 2006, and Air France/KLM in 2004). In Chapter 3, we use a more standard merger simulation approach to consider the effect of a remedy proposed in the failed 2001 merger between United and US Airways in which American offered to guarantee that it would serve specific routes.

hand, allows carriers to endogenously choose their capacity, by distinguishing flight segments and markets.

I model a two-stage game. In the first stage, carriers choose which flight segments to serve, while in the second stage, carriers choose how many slots to allocate to each segment and set product prices in each market where their chosen selection of segments allows them to serve. I allow for increases in marginal costs associated with a carrier's load factor (passenger to seat ratio) on a particular segment. This implies that the allocation of capacity to a segment affects costs in a large number of passenger markets (for example, when American allocates more capacity to Raleigh-DCA, this will affect its costs of serving passengers traveling from Raleigh to DCA, from Raleigh to Hartford via DCA, Raleigh to Boston via DCA, etc). Key parameters of the model are estimated by using quarterly data taken from the publicly-available T-100 and DB1B databases from 2012-2013.

Before discussing the related literature, I highlight some of the simplifications I make to maintain tractability or to make use of publicly-available data. First, DCA slots are tied to specific hours of the day, and there are some differences across slots depending on whether the slots can only be used for small planes and whether they can be used on routes outside the usual 1,250 mile range allowed from DCA (perimeter rule). Slots in my model, however, are assumed to be not time specific, single type, and used only for routes within the perimeter rule. One airport slot in the model is interpreted as the average number of operations per day on a particular directional segment. Second, the divestitures involve gates and other ground facilities, as well as slots. My analysis treats slots as the only relevant asset. Third, while I consider discrete choices to serve particular routes, I treat slot allocation as a continuous choice. Fourth, while I consider a relatively rich set of connecting products, I perform some aggregations so that the number of prices that I have to solve for is not too large and overly burdensome. Fifth, I also ignore the important heterogeneity in the willingness of different types of customers (e.g. leisure, business and government passengers) to substitute across products in response to changes in the availability of connections or prices.

1.1.1 Related Literature

This thesis contributes to the literature on merger and merger remedies, as well as the empirical literature on market entry and airline competition. In the literature, there are a large number of merger retrospective studies but those mainly focus on general individual merger effects rather than merger remedies. Despite the recent growing interests in tightening merger policy, attempts to systematically analyze merger remedies *ex ante* are rare in the literature.

The U.S. airline industry has experienced a large number of mergers since deregulation in 1978. Ashenfelter et al. (2014) summarizes studies on the impact of airline mergers on price. Most studies find price increases after mergers, but the magnitudes of those effects depend on the sample selection and empirical strategies employed—see Borenstein (1990); Kim and Singal (1993); Kwoka and Shumilkina (2010). The studies of recent airline mergers provide mixed results. While Hüschelrath and Müller (2015) suggests that the merger between Delta Airlines and

Northwest Airlines increased short-run prices by 10%, Israel et al. (2013) claims that due to the network expansion of a merged firm, post-merger price increases may come from increases in a consumer's willingness to pay. However, the existing literature has not focused specifically on changes in market competition at slot-controlled airports even though it is at these airports where the Department of Justice has implemented remedies.

Studies that evaluate merger remedies are rare in the literature, and those that exist are skewed to *ex post* analysis. The Federal Trade Commission (FTC) conducted two studies, one in 1999 and another in 2017, that examine the efficacy of the merger remedies that the authority had ordered over the past two decades by closely analyzing the survival of divested assets—FTC (1999) and FTC (2017). They find that 70% of such divested assets remained in relevant markets and restored market competition; however, there has been criticism that the U.S. antitrust authorities are far too willing to accept remedies and fail to restore competition—Kwoka (2014). Similar analyses have been conducted in the context of other jurisdictions, including the EU, the UK, and Canada—see Duso et al. (2007); Wang and Rudanko (2012). While most merger remedy studies in this literature focus on descriptive analysis of what happen after remedies were imposed, my thesis provides an *ex ante* assessment to measure the effectiveness of a merger remedy with respect to market competition and passenger welfare.

Empirical entry models in the literature can be largely categorized into two groups. Without modeling equilibrium price competition, most of the early literature (Bresnahan and Reiss (1990), Seim (2006) and, applied to airlines, Berry

(1992), and Ciliberto and Tamer (2009)) allowed firms to make discrete entry decisions in independent markets. In contrast, Reiss and Spiller (1989), Eizenberg (2014), Fan and Yang (2018), Wollmann (2018), and Ciliberto et al. (2018) use two-stage models in which firms enter and then make explicit price choices. My model extends this second school of thought, allowing marginal costs to vary with load factors, interactions between multiple product markets, and choices of capacity, as well as price choices. I follow Eizenberg (2014), Fan and Yang (2018) and Wollmann (2018) in assuming that firms only learn product-specific demand and marginal cost unobservables after they have chosen which routes to serve. This choice allows me to estimate the fixed costs associated with serving a market separately from the demand and marginal cost functions. In contrast, Ciliberto et al. (2018) and the Chapter 3 of this dissertation allow for demand and marginal cost shocks to be known when entry choices are made, which increases the computational burden. Extending the model to allow for selection that arises under complete information is one obvious direction for future research.

There is a structural model based paper that does allow for elements of network competition—see Aguirregabiria and Ho (2012). Since the paper assumes that each carrier has a local manager on each route who maximizes his or her local profit, the computational burden associated with network choices is reduced. In contrast to the study, I allow carriers to optimize entry, capacity and price choices over all of the segments and routes that they might serve, while focusing on a single airport of particular interest to reduce the computational burden.

Section 1.2 provides institutional background on Ronald Reagan Washington

National Airport (DCA), a slot-controlled airport, as well as on slot divestitures. In Section 1.3, I develop a structural entry model. Section 1.4 describes the data used in this study. Section 1.5 discusses the estimation of the parameters. Section 1.6 reports the estimation results and model fit. Finally, Section 1.7 concludes the chapter.

1.2 Institutional Background

This section discusses the concept of airport landing slots, slot-controlled airports, and slot divestitures in the context of the AA/US merger.

1.2.1 Slot-Controlled Airports

In aviation, an airport landing slot refers to operational authorization to either take off or land at a particular airport on a particular day during a specific time period. For example, if an airline carrier holds a Monday 7:00-7:59AM landing slot at an airport, the carrier has the right to take off or land during the time slot at that airport. While runway access at most U.S. airports is on a first-come-first-served basis and those airports do not use any slot controlling system, a few so-called *slot-controlled airports* in the U.S. regulate the maximum number of flights per hour to mitigate heavy congestion and delays, implying that slots at those airports are scarce and are valuable assets to carriers.

In the context of U.S. aviation, the first slot control system, the High Density Rule (HDR), was instituted by the Federal Aviation Administration (FAA) in

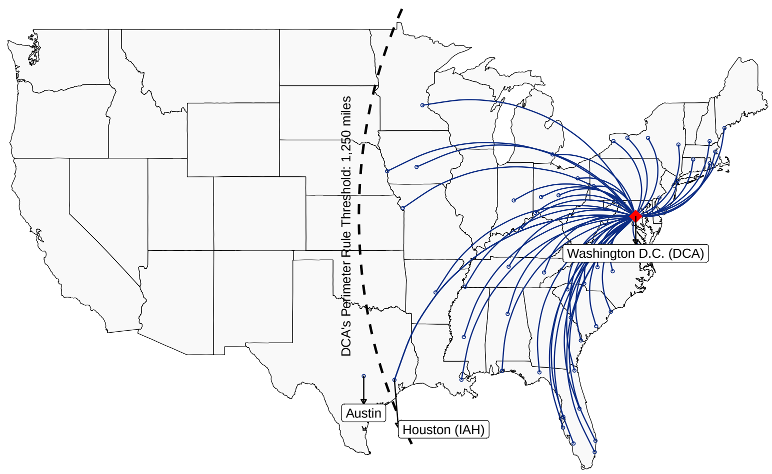
1968, and the cap on the number of hourly arrivals and departures was applied to five "high-density traffic airports"—John F. Kennedy (JFK), LaGuardia (LGA), and Newark (EWR) serving New York City; Ronald Reagan Washington National Airport (DCA) in Washington D.C.; and O'Hare (ORD) in Chicago. The FAA initially assigned slots to the carriers that already had them under scheduling committee agreements used prior to the HDR (i.e., "grandfather rights"). As slots are expected to be actively used, there is a "use-or-lose" provision that states that any slot not utilized 80 percent of the time over a period shall be recalled by the FAA. Generally, as long as airlines comply with the rules, they may continue to keep those slots.

While carriers can lease or trade their slots under FAA approval, secondary market slot sales are rare and prohibited at some airports. Trading slots is fairly common to facilitate airline schedules, and leasing slots is an attractive option for slot holders since they can control slots. However, the leasing of slots tends to be based on short-term agreements with early termination clauses, and leasing to new entrants is rare, as the entrants are considered direct competitors. A secondary market to buy/sell slots was created under the HDR in late 1980, but slot transactions were infrequent and airports other than DCA have not been authorized to buy or sell slots since early 2000, as the HDR was phased out and new slot control system was introduced at those airports.[5]

There are other airport-specific slot restrictions. First, a subset of airport

[5] More detailed information is available at the Federal Aviation Administration (FAA) website: `https://www.faa.gov/about/office_org/headquarters_offices/ato/service_units/systemops/slot_administration/`

Figure 1.1: DCA Nonstop Flights and the Perimeter Rule



Note: The 1,250 nautical mile perimeter from DCA is shown as a curved dotted line. As an illustration of the perimeter rule, the distance between DCA to Houston airport is within the boundary, while the distance between DCA to Austin airport is not.

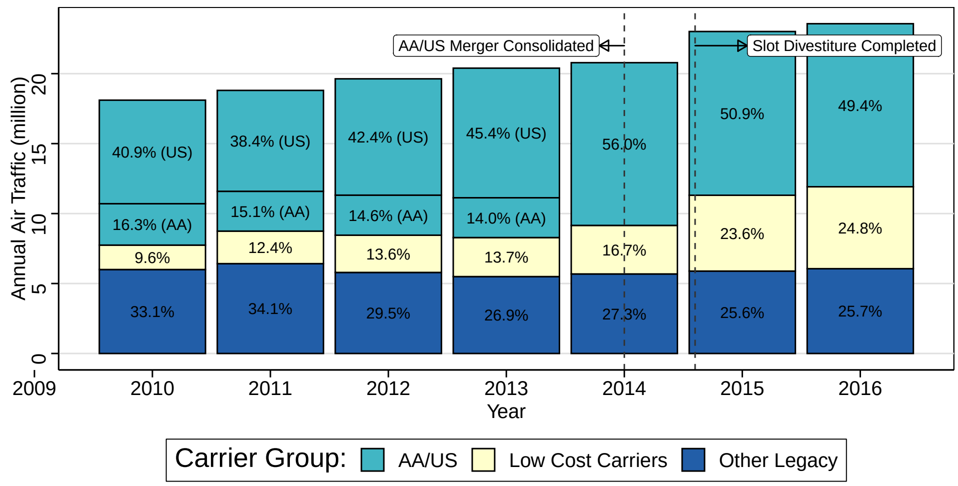
slots at slot-controlled airports is designated only for small airplanes. At DCA, for example, the maximum number of flights per hour is 48, and 11 of them are designated only for commuter aircraft—aircraft that may be used only for operations with turboprop and reciprocating engine aircraft with no more than 76 seats or turbojet aircraft with fewer than 56 seats. This restriction was introduced to balance maximizing the economic use of runway resources and preserving services to smaller communities. Second, nonstop flights from/to DCA (LGA) are not allowed to exceed 1,250 (1,500) nautical miles, which we call the "perimeter rule." For the purpose of reducing airport congestion and inducing passengers to use alternative airports, the FAA has imposed perimeter restrictions on DCA and LGA. Figure 1.1 visualizes the set of nonstop flights to/from DCA within the perimeter rule. There are a few slots at the airport specifically designated for routes beyond the perimeter rule, such as DCA to Los Angeles (operated by American) and DCA to Denver (operated by United). Those designated slots are exempted from the airport's slot regulation, and carriers are required to obtain special authorization to operate services on those routes.

1.2.2 Slot Divestitures of the AA/US Merger at Reagan National Airport

Slot-controlled airports are often of particular anticompetitive concern in airline mergers. In the most recent major airline merger case in the U.S., the proposed merger between American Airlines and US Airways in 2013, the U.S. Department of Justice expressed significant concern over airline markets associated with DCA. According to its complaint on the AA/US merger case (United States (2013)), the DOJ contends that "passengers to and from the Washington, D.C. area are likely to be particularly hurt. ... Competition at DCA cannot flourish where one airline increasingly controls an essential ingredient to competition. Without slots, other airlines cannot enter or expand the number of flights that they offer on other routes. As a result, D.C. area passengers would likely see higher prices and fewer choices if the merger were approved."

Slot divestitures were thus motivated by the desire to alleviate the anticompetitive concern regarding increased market power at this slot-controlled airport. The DOJ and the merging party reached a settlement that required the divestiture of slots and gates to LCCs at seven strategic airports. In this merger divestitures

Figure 1.2: Passenger Trends at Reagan National Airport (DCA)



Note: The merger between American and US Airways was completed in December 2013 (marked as a dotted vertical line in the figure). Annual air traffic is the sum of enplaned and deplaned passengers at DCA. The information on annual air traffic is from the Metropolitan Washington Airports Authority (MWAA) website.

process, only LCCs were approved by the government to purchase the divested assets, based on the government's view that LCCs are more suitable and effective competitors than legacy carriers.[6] The merging firms divested 104 landing slots at DCA, representing, on average, 6 slots per hour and roughly 15% of combined pre-merger slot holdings of merging firms. Figure A.1 in the Appendix shows that the divested slots at DCA were roughly evenly distributed across time and the gap of the slot holdings between NewAA and other carriers became much closer after the divestitures. As a result, the landscape of the passenger traffic changed sharply post-merger. As shown in Figure 1.2, US Airways and American Airlines together held a 59.4% passenger share at DCA in 2013 before the merger. After the merger and slot divestitures, the merging firms' passenger share noticeably decreased, while the passenger share held by LCCs increased post-merger.

[6]Delta was one of those expressing concern about the agreement, commenting, "by prescribing a remedy that forecloses network carriers from competing ... the government will distort the market and deny the traveling public the competitive benefits that only network carriers can deliver."

1.3 Model

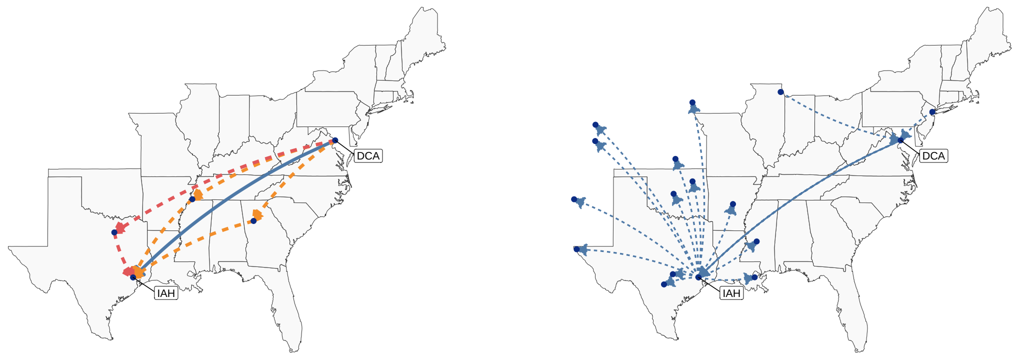
In this section, I develop a two-stage model that captures entry, capacity choice, and price competition at a slot-controlled airport. In the first stage of the model, airline carriers determine a set of flight segments to serve. Then, in the second stage, the carriers allocate their scarce airport slots across those segments and choose product prices. Similar to previous capacity-constrained models (e.g. Besanko and Doraszelski (2004) and Snider (2009)), I allow slot allocation and product pricing to affect marginal cost through a segment's load factor, which enables cross-market interactions in the model.

1.3.1 Environment

I define an airline market based on potential *directional* trips between two endpoints (e.g, airports or cities) regardless of the number of connections made *en route*, where markets are indexed by $m \in \mathcal{M}$. I also define a flight segment of carrier f, indexed by $s \in \mathcal{S}_f$, as a *directional* nonstop trip of carrier f between two endpoints. While a market is a place where passenger demand takes place, a flight segment for a carrier is an operational unit where the carrier allocates its capacity. I denote $A \Rightarrow B$ as the market of endpoint A to endpoint B, and let $(A \rightarrow B)_f$ be the flight segment from A to B operated by carrier f. Note that the baseline endpoints in this dissertation are airports unless otherwise stated.

A single market can be associated with multiple flight segments, and vice versa. The map in the left panel of Figure 1.3 shows multiple products and segments in the

Figure 1.3: Illustration of Markets and Flight Segments



(a) One Market with Multiple Segments (b) One Segment with Multiple Markets

Note: A solid line represents a nonstop product that requires one flight segment, while a dotted line represents a connecting product that requires more than one segments (two segments in this example). An arrow in each line shows a (flight) direction. Different line colors indicate different carriers. While the left panel describes that multiple segments are associated with a single market (DCA⇒IAH), the right panel shows that multiple markets are associated with a single flight segment $(\text{DCA}\rightarrow\text{IAH})_{UA}$.

DCA to Houston market, DCA⇒IAH. In this example, there are four products—one nonstop and three connecting products operated by three different carriers—and seven different flight segments associated with the DCA⇒IAH market. The map in the right panel of the figure, on the other hand, shows a subset of the flight products operated by United Airlines (UA) that share the flight segment $(\text{DCA}\rightarrow\text{IAH})_{UA}$. In that single segment (United's nonstop flight from DCA to IAH), there are different types of passengers in different markets: 1) those who simply took the flight, 2) those who took prior flights, and 3) those who are traveling on to other destinations. The feature that passengers from different markets can share the same flight segment will be the key to capturing interactions among markets, and I explain how my model incorporates this feature in the subsequent subsection.

1.3.2 Demand

A nested logit model is used to describe market demand. In market m, a consumer can choose the option of all possible flight products in the market or the option not to fly (outside option). The indirect utility of customer i purchasing flight product j in market m at time t is given by:

$$u_{ijmt} = \underbrace{x_{jmt}\beta - \alpha p_{jmt} + \xi_{jmt}}_{\text{product quality } (\delta_{jmt})} + \zeta_{ijmt}(\sigma) + (1-\sigma)\epsilon_{ijmt}, \tag{1.1}$$

where x_{jmt} is a vector of observable product characteristics, p_{jmt} is the airfare of product j, and ξ_{jmt} is a product-specific unobservable characteristic. I express $x_{jmt}\beta - \alpha p_{jmt} + \xi_{jmt}$ as a product quality δ_{jmt}. To control for variations in the consumers' tastes across carriers, time and markets, I include carrier, time and *non-directional* market fixed effects (ρ_j, τ_t, and ψ_m, respectively)[7] such that:

$$\Delta\xi_{jmt} = \xi_{jmt} - \rho_j - \tau_t - \psi_m. \tag{1.2}$$

Controlling for the fixed effects, I assume that $\Delta\xi_{jmt}$ has an i.i.d. distribution. ϵ_{ijmt} denotes consumer i's idiosyncratic preferences for product j, and it follows a type-1 extreme value distribution. Air travel products are nested in one group, and the no-flying option is nested in the other group. The parameter σ governs the degree of substitution between the two groups. As σ goes to one, air travel products

[7] For non-directional market fixed effects, I group products in both the A⇒B market and B⇒A market in the same category.

become closer substitutes; as σ goes to zero, there are no distinguishable substitution patterns among air travel options, and the nested logit model becomes similar to a simple multinomial logit model. I estimate the vector of demand parameters $\boldsymbol{\theta}^{\mathbf{D}} = (\beta', \alpha, \sigma)$.

Let s_{jmt} be the choice probability of product j among alternative products in market m at time t. Then, the probability can be expressed as the following formula under the nested logit model:

$$s_{jmt} = \frac{e^{\frac{\delta_{jmt}}{1-\sigma}}}{D_{mt}} \frac{D_{mt}^{1-\sigma}}{1 + D_{mt}^{1-\sigma}}, \tag{1.3}$$

where $D_{mt} = \sum_{k \in \mathcal{J}_{mt}} e^{\frac{\delta_{kmt}}{1-\sigma}}$ and $\mathcal{J}_{mt}$ is the set of all products in market m at time t. Finally, denote q_{jmt} as the model-predicted number of passengers who use product j in market m at time t. This equals the product's choice probability multiplied by market size, $M_{mt}s_{jmt}$. Market size is defined as the geometric mean populations (metropolitan statistical areas) of the two endpoints of the market.

1.3.3 Supply

To describe the optimal behavior of carriers at a slot-controlled airport, I consider markets that are restricted to those originating, ending, or connecting at a slot-controlled airport (DCA in this study). Denote $\mathcal{S}_f$ as the set of flight segments provided by carrier $f \in \mathcal{F}$ to/from the slot-controlled airport. Denote $\mathcal{J}_f(\mathcal{S}_f)$ as carrier f's products that use any segment in $\mathcal{S}_f$. In the model, I assume that product $j \in \mathcal{J}_f(\mathcal{S}_f)$ consists of up to two flight segments—while nonstop flight products require one segment, connecting flights require two.

$$|\mathcal{S}_{fj}| \leq 2, \qquad \forall j \in \mathcal{J}_f(\mathcal{S}_f), \forall f \in \mathcal{F}, \tag{1.4}$$

where $\mathcal{S}_{fj}$ is the set of flight segments that product j uses.

Capacity Choice Variable: Airport Slot

In this model, the capacity (or the number of available seats) that carrier f provides on a flight segment s at time t is defined as $z_{fst}K_{fst}$—the segment-specific average airplane size z_{fst} multiplied by the average number of daily slots assigned to flight segment s, K_{fst}. As one slot is equivalent to one flight, K_{fst} can be also interpreted as the average number of daily flights on s. I assume that the airplane size z_{fst} is exogenously given from the data, which will be discussed below in detail. On the other hand, carriers are able to allocate K_{fst} endogenously across flight segments in this model. I make several assumptions on K_{fst}, mainly due to model tractability and data limitation.

I assume that K_{fst} is continuous. Allowing K_{fst} to be continuous helps us to quickly solve the optimal solution via first order conditions, while reasonably approximating the carriers' actual slot allocations.[8] In addition, since K_{fst} is interpreted as the average number of daily flights on s, the number needs not be an integer. For example, if a carrier allocates its landing slots on s three times per day on week-

[8]There might be a potential concern on corner solutions for those segments with infrequent daily flights. In the data, however, Figure A.2 in the Appendix shows that flight segments that have on average less than 0.5 daily flights (one flight every other day) are very rare (1.2%).

days and two times per day on weekends, then K_{fst} will be $3 \times \frac{5}{7} + 2 \times \frac{2}{7} = 2.714$. Different airline schedules on weekdays and weekends are a very common practice in the airline industry.

Additionally, I make other assumptions on K_{fst}. First, K_{fst} is not time specific. In practice, airport landing slots are time specific (e.g. 7AM and 7PM slots are different). While one might argue that slots at certain hours would be more valuable than other hours, the model does not differentiate slots by time because time specific product prices and capacities are not available in the data. When it comes to DCA, however, slot holdings and flight operations are uniformly distributed across different hours, except late nights and weekend mornings in Figure A.3, and daily departure options of a product tend to be spread out across time of day. Second, I assume that an airport slot is a single type, and the model does not differentiate commuter slots from general slots. Instead, the size restriction on commuter slots will be mostly governed by the segment-specific airplane size z_{fst} from the data. Last, flight segments beyond the perimeter rule that require specially exempted slots are not considered in this analysis.

Second Stage: Slot Allocation and Product Price Choices

In the second stage, carrier f, which enters a set of flight segments $\mathcal{S}_f$, allocates its endowed slots $\overline{K_f}$ to the segments $s \in \mathcal{S}_f$ and sets product prices to maximize the carrier's aggregate variable profit, which is given by:

$$VP_f(\mathcal{S}_f, \mathcal{S}_{-f}) = \sum_{\{j,s|j\in\mathcal{J}_f(\mathcal{S}_f), s\in\mathcal{S}_{fj}\}} (p_{jm} - c_{jm})q_{jm}, \tag{1.5}$$

$$\sum_{s\in\mathcal{S}_f} K_{fs} \leq \overline{K_f}, \qquad \forall f \in \mathcal{F}, \tag{1.6}$$

where the time subscript t is suppressed for simplicity. $\mathcal{S}_{-f}$ is a set of flight segments offered by carriers other than f, and c_{jm} is the marginal cost of product j in market m. K_{fs} is defined as the average number of slots per day assigned to flight segment s by carrier f. The inequality condition (1.6) is a slot constraint that carrier f faces—the sum of slots to be allocated should not exceed the endowed slots of carrier f.

The marginal cost is flight segment specific. For example, a connecting flight consisting of two flight segments incurs costs from both segments. The marginal cost of a product is specified as:

$$c_{jm} = \underbrace{\sum_{s\in\mathcal{S}_{fj}} \Big(x_{fs}\gamma_1 + \gamma_2\big(\frac{Q_{fs}}{z_{fs}K_{fs}}\big)^{\nu}\Big)}_{\text{flight segment specific}} + \omega_{jm}, \tag{1.7}$$

where $\mathcal{S}_{fj}$ is the set of flight segments that product j uses, and x_{fs} is a vector of observable characteristics of flight segment s offered by f such as segment distance, hub dummy, or a slot constraint airport dummy. In this specification, assigning a slot on a segment affects the marginal cost via a load factor, $\frac{Q_{fs}}{z_{fs}K_{fs}}$, the ratio of passengers to total available seats on s. While the denominator, $z_{fs}K_{fs}$, is the total number of available seats on s operated by f, the numerator, Q_{fs}, is the total number of passengers flying on segment s offered by f, and is computed as the sum of all passengers that use the products offered by f and that share the segment s:

$$Q_{fs} = \sum_{j \in \mathcal{J}_f(\{s\})} q_{jm}. \tag{1.8}$$

Then, $\frac{Q_{fs}}{z_{fs}K_{fs}}$ captures the extent to which an average flight on s is full. Due to the nonlinear term ν, the marginal cost in this model increases exponentially in the load factor on s. This is associated with overbooking or hassle fees as an airplane becomes more full. Finally, a product-specific unobservable cost shock is denoted ω_{jm}, which captures product-level characteristics that are not observable to econometricians. For this model section, I assume that all the products in $\mathcal{J}_f(\{s\})$ for each segment s in $\mathcal{S}_f$ are available in the data. In practice, however, there may be some products in $\mathcal{J}_f(\{s\})$ that are not available in the data. In Appendix A.2.2, I explain how the model should be modified when some products are not available in the data.

Second Stage Optimality Conditions and Cross-Market Interaction

Conditional on the flight segment entry decision in the first stage and under the assumption that the slot constraint (1.6) holds with equality, the necessary equilibrium conditions in the second stage are characterized as the following system of equations:

$$\frac{dVP_f}{dK_{fs}} = \frac{dVP_f}{dK_{fs'}}, \qquad \forall s, s' \in \mathcal{S}_f, \qquad \forall f \in \mathcal{F}, \tag{1.9}$$

$$\frac{dVP_f}{dp_{jm}} = 0, \qquad \forall j \in \mathcal{J}_f(\mathcal{S}_f), \tag{1.10}$$

$$\sum_{s \in \mathcal{S}_f} K_{fs} = \overline{K_f}, \qquad \forall f \in \mathcal{F}. \tag{1.11}$$

The conditions above are derived from the Lagrangian method applied to the optimization problem in (1.5) focusing on interior solutions. The optimality condition for slot (1.9) implies that, conditional on prices, a carrier is able to obtain higher profits by transferring landing slots from abundantly allocated segments to relatively lower allocated segments using up all of the firm's endowed slots. Also, note that while there is no guarantee that a solution is unique, multiple solutions have not been found when starting with different sets of initial conditions.

The optimality condition for price (1.10) can be written as:

$$\frac{dVP_f}{dp_{jm}} = \underbrace{q_{jm} + \sum_{k \in \mathcal{J}_{mf}} (p_{km} - c_{km}) \frac{\partial q_{km}}{\partial p_{jm}}}_{\Delta VP\text{, direct impact of market competition}} - \underbrace{\sum_{l \in \mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'}}_{\Delta VP\text{, indirect impact}} = 0, \tag{1.12}$$

where $\mathcal{J}_{mf}$ is the set of products offered by f in market m and the carrier can offer more than one product in the market (e.g. a nonstop and a connecting flight). The first order condition (1.12) indicates that a product price change affects the variable profit of the carrier through two channels. First, when the price of product j in market m, p_{jm}, decreases, the variable profit of f changes through within-market competition and its sign will depend on the magnitude of the price elasticities of demand. This channel is widely seen in the literature in the context of differentiated product markets—see Nevo (2001); Villas-Boas (2007); Berry and Jia (2010). If there were no indirect impact term in (1.12), the equation would be the same as a classical mark-up equation.

In the second channel, changes in load factors affect the variable profit. Specifically, if a decrease in p_{jm} increases the number of passengers, q_{jm}, then the load factors of the flight segments that product j uses increase, and therefore the marginal costs associated with these segments also increase. As there are multiple products in different markets that share the flight segments, all the products in the network that use the same flight segment become relatively more expensive, and the carrier's variable profit thereby futher decreases.[9] This spillover appears in the slot allocation as well in (1.9). When carrier f transfers some slots from one segment to another, the load factors of those segments will be altered; hence, the marginal costs of all the products associated with those segments and the variable profit of the carrier will also be altered. Note that a change in price (or slot) simultaneously alters both the first order conditions for price and slots, as the optimality conditions (1.9) to (1.10) are interconnected. In equilibrium, we find the optimal slot allocation and product prices that satisfy those optimality conditions.

One remark is that the model can be potentially extended in such way that product demand is affected by slot allocation. In the current model setup, allocating slots on a segment only affects the supply side via a load factor. As suggested by

[9] In the data, 5.8 products share the same flight segment at DCA, on average.

Berry and Jia (2010), however, consumers may prefer a product with more daily departure options. Since one additional slot on a flight segment proportionally increases the number of daily departures of multiple products, it is natural to extend the model for the demand side. For this, I explore the demand specification when daily departure options are added to the baseline case. In addition, I describe the extension of the model and the challenges that it creates in Appendix A.4.2.

Under the marginal cost functional form (1.7), equation (1.12) can be written as a simple matrix notation for market m:

$$\mathbf{\Omega_m^{-1} q_m} + \mathbf{p_m} = \mathbf{c_m} + \frac{\mathbf{dc_m}}{\mathbf{dQ}}, \qquad \forall m \in \mathcal{M}. \tag{1.13}$$

where the bold face font in the equation indicates that variables are vector or matrix. $\mathbf{\Omega_m}$ is the element-wise multiplication of the response matrix containing the derivatives of market shares with respect to price, and the matrix indicating whether products i and j are owned by the same carrier. The (i, j) element of Ω_{ijm} is given by:

$$\Omega_{ijm} = \begin{cases} \frac{\partial q_{im}}{\partial p_{jm}} & \text{if } i, j \in \mathcal{J}_{mf} \\ 0 & \text{otherwise,} \end{cases} \tag{1.14}$$

and $\frac{\mathbf{dc_m}}{\mathbf{dQ}}$ is a vector with jth element

$$[\frac{\mathbf{dc_m}}{\mathbf{dQ}}]_j = \sum_{s \in \mathcal{S}_{fj}} \gamma_2 \nu (\frac{Q_{fs}}{z_{fs} K_{fs}})^{\nu}. \tag{1.15}$$

Equation (1.13), an extended version of the widely used standard pricing equation in a differentiated product market context, is used to estimate the vector of marginal cost parameters $\boldsymbol{\theta}^{\mathbf{C}} = (\gamma_1', \gamma_2, \nu)$. In Appendix A.2.1, I provide more detailed technical information on how to derive (1.13) from (1.12).

First Stage: Flight Segment Choices

In the first stage, carriers choose the set of flight segments that yield the highest expected profits among the alternatives. Following Eizenberg (2014) and Wollmann (2018), I assume that carriers only know the distributions of demand and marginal cost shocks (ξ and ω, respectively), while they know the realized unobservable shocks for fixed costs in this stage. This implies that carriers know their variable profit at a slot-controlled airport in expectation, while they exactly know the incurred fixed costs. Given others' segment offerings $\mathcal{S}_{-f}$, the expected profit of carrier f that offers flight segments $\mathcal{S}_f$ can be expressed as:

$$\Pi_f(\mathcal{S}_f, \mathcal{S}_{-f}) = \mathbb{E}_{\xi,\omega}\left[VP_f(\mathcal{S}_f, \mathcal{S}_{-f})\right] - \sum_{s \in \mathcal{S}_f} F_{fs}, \tag{1.16}$$

where F_{fs} is the fixed cost that carrier f pays every quarter to operate a nonzero frequency of flight services on segment s. In airline industry, if there were no fixed costs when carriers add a new segment, they would link any two airports with nonstop and make their network excessively dense. However, we do not see such pattern in the data, suggesting the existence of a barrier for carriers to provide nonstop services. I assume that the fixed cost has the following form:

$$F_{fs} = X_{fs}\eta + \phi_{fs}, \tag{1.17}$$

where X_{fs} is a vector of carrier-segment specific characteristics that affects fixed costs and ϕ_{fs} is a fixed cost error term that is unconditionally mean zero. In particular, X_{fs} includes a constant, LCC dummy (LCC_f), the ratio of f's total endowed slots to the total endowed slots by any carrier at DCA ($SlotRatio_f$), and the airport presence of carrier f on the non-DCA endpoint of segment s ($Presence_{fs}$). I include $SlotRatio_f$, as carriers with a large number of available slots at the slot-controlled airport may have a cost advantage of initiating a new service by more flexibly adjusting flight schedules.

The fixed cost parameter vector, $\boldsymbol{\theta}^{\mathbf{F}} = \eta'$, is estimated via a partial identification approach. To estimate the parameters, I use the revealed preference to form moment inequality conditions by adding or removing a flight segment to/from a carrier's network. The literature recognizes that the information assumption imposed in this model generates a selection problem (Holmes (2011); Eizenberg (2014); Wollmann (2018)). In brief, carriers may self-select into flight segments that have relatively cheaper fixed costs that are unobservable to econometricians. In Section 1.5.3, I will discuss how I address the selection issue when estimating the fixed cost parameters.

1.4 Data

This section discusses the data used in this study and the sample selection procedure. I combined the two publicly available datasets from the Department of Transportation – 1) the Airline Origin and Destination Survey (DB1B), and 2) the Air Carrier Statistics (T-100). While I use the entire sample for demand and marginal cost parameter estimations, a subset of the products associated with DCA is used for the fixed cost estimation and counterfactual analysis.

1.4.1 Airline Origin and Destination Survey (DB1B)

DB1B contains a 10% sample of all air travel passenger itineraries in the U.S. domestic airline industry. It includes the following information: the origin, destination, and connecting (if any) airports; the number of passengers; ticket prices; and the ticketing and operating carriers on each itinerary. To capture the products and markets before the AA/US merger was consummated in December 2013, I use a dataset spanning from the first quarter of 2012 to the last quarter of 2013. The dataset comprises 7,073 markets (across time) taken from the set of routes connecting the largest 100 U.S. domestic airports based on the number of passenger boardings in 2012.

I drop the itineraries that have more than one connection, as less than 1% of passengers use itineraries with more than one stops in the data. I also drop itineraries for which the ticket prices are outside the range of $12.50 to $1,250, as these are likely coding errors. I aggregate the tickets with the same itineraries and take the passenger-weighted average prices as a representative price for a product. Similar to Ciliberto and Williams (2014), I further drop products with fewer than 200 passengers in a market, as those are not likely to be effective competing services in the market. Note that I treat products that have the same origin and destination but different connections operated by the same carrier as distinct products. For example, the connecting products (DCA$\rightarrow$Atlanta (ATL)$\rightarrow$IAH)$_f$ and (DCA$\rightarrow$Dallas (DFW)$\rightarrow$IAH)$_f$ are distinct, while they are in the same market, DCA$\Rightarrow$IAH.

Panel A of Table 1.1 reports the descriptive statistics of the product characteristics from DB1B. In column "All Products," where I use the entire sample, we see that the average ticket price is $246 and that on average 1,749 passengers fly with the same product. While 11.5% of products are nonstop, nonstop passengers consist of more than 75% of the total passengers. "Daily Departures" is defined based on the average number of daily flights of a product, and I construct the variable following the procedure suggested by Berry and Jia (2010).[10] An average product has 3.38 daily flights. Presence at an origin airport, "Presence (Origin)," is defined by the ratio of the number of routes that a carrier serves nonstop to the total number of routes that any carrier serves nonstop at the origin airport. Of the products considered, 14.3% depart from, arrive at, or transfer at a slot-controlled airport. I restrict the data to those products associated with DCA, and the summary statistics of the subsample are reported in the column "DCA Products." While it seems that there is no distinguishable difference in prices, the number of passengers, and the

[10] Due to the lack of data, the Daily Departure values for 15.2% of connecting products are not extracted by using the method suggested by Berry and Jia (2010). They are imputed as the geometric mean of the daily departures of the two segments of a connecting product.

Table 1.1: Descriptive Statistics

	All Products		DCA Products	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Ticket Price ($100)	2.463	0.643	2.475	0.684
Passengers (1,000)	1.749	5.818	1.791	6.096
Nonstop (Dummy)	0.115	0.319	0.108	0.310
Daily Departures	3.388	2.532	4.055	2.702
Distance (1,000 miles)	1.322	0.651	1.173	0.674
Presence (Origin)	0.298	0.269	0.242	0.247
Slot Controlled (Dummy)	0.143	0.350	1.000	0.000
Market Size (Million)	3.005	2.262	3.443	2.171

(a) Panel A. Product Level (DB1B)

	All Segments		DCA Segments	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Quarterly Departures	279.230	250.751	309.461	277.525
Available Seats (1,000)	31.956	34.934	29.956	36.014
Passengers (1,000)	25.824	28.867	22.224	27.395
Airplane Size	114.641	42.322	96.512	41.771
Load Factor	0.803	0.108	0.741	0.124
Segment Distance	0.915	0.593	0.772	0.578

(b) Panel B. Flight Segment Level (T-100)

The descriptive statistics in Panel A for all products and DCA products are based on 358,880 and 14,819 observations, respectively. Similarly, the numbers of unique observations of Panel B for all products and DCA products are 42,958 and 1,650 respectively. The markets are based on airport pairs.

fraction of nonstop products between "All Products" and "DCA Products", "DCA Products" tend to have more daily departure options and less total miles flown than the average product in the industry.

1.4.2 Air Carrier Statistics (T-100)

The T-100 dataset provides monthly flight-level information, including the number of passengers, available seats, types of aircraft, and flight frequency on a segment. To match the units of T-100 and DB1B, different aircraft types of the same carrier within a segment are aggregated at the quarterly level. Regional affiliates shown in T-100 are converted to their affiliated ticketing carriers by matching the operating carriers shown in DB1B.

Panel B of Table 1.1 summarizes the flight segment characteristics. An average flight segment has 31,956 seats, approximately 80% of which are filled with passengers, and the average airplane size is 114.64 (seats). In terms of the DCA segment, the average airplane size, load factor, and segment distance are smaller than the industry average. This is partially due to the fact that approximately 20% of slots at the airport are designated as commuter slots, and partially due to the perimeter rule, which restricts flight operations to within 1,250 miles. Small-sized aircraft are more appropriate for short-haul routes where flights tend to be less full.

1.4.3 DCA Products

While I use the sample "All Products" to estimate the demand and marginal cost parameters, I further refine the "DCA Products" shown in Table 1.1 to conduct the counterfactual analysis in Chapter 2 as well as to estimate the fixed cost parameters. I start with the set of all products that include any DCA segments within 1,250 miles in the second quarter of 2013, and I denote $\mathcal{M}$ as the set of markets to which those products belong. In this way, those long haul DCA segments beyond the perimeter rule using the specially exempted slots are excluded.

Some markets in $\mathcal{M}$ may not be to/from DCA, and some products of those markets may not be in the "DCA Products." For example, suppose there are two products in ATL⇒Boston (BOS) market—1) a connecting product $(\text{ATL}\to\text{DCA}\to\text{BOS})_f$ by carrier f, and 2) a nonstop product $(\text{ATL}\to\text{BOS})_{f'}$ by carrier f'. Because the first connecting product uses DCA segments, the ATL⇒BOS market should be included in $\mathcal{M}$. However, the nonstop product is not included in the "DCA Products," as it does not contain DCA flight segments. While adding more products to the sample may allow a more realistic counterfactual analysis, doing so would also increase the computational burden of finding the optimal slot allocation and product prices. For a viable counterfactual exercise, I reduce the number of products by taking the simplifications described below.

First, any product of markets in $\mathcal{M}$ that does not contain any DCA segment is not included in "DCA Products" (e.g. the nonstop flight in ATL⇒BOS in the example above). Instead, its product quality (δ), defined in (1.1), is calculated from a demand estimation, and is used to adjust the consumer choice probability of "DCA Products" in (1.3). In the earlier example of the ATL⇒BOS market, the choice probability of the connecting product $(\text{ATL}\to\text{DCA}\to\text{BOS})_f$ in (1.3) is calculated as if there is the nonstop product by taking into account the quality of the nonstop product. In this way, market competition can be reasonably described, while we remove a subset of products from the sample.

Second, I create composite products for connecting services of a carrier that share the same DCA segment. There are a number of connecting flights for which one end is DCA and the other end is located in the Midwest or West, connecting at large hub airports (e.g. the itinerary DCA→Detroit (DTW)→Los Angeles (LAX) offered by American Airlines). While those connecting products have a negligible presence

Table 1.3: Statistics of Refined DCA Products in 2013Q2

	Products		Passengers		Segments/Slots	
Carrier	N.	Nonstop (%)	Pass. N. (mil.)	Nonstop (%)	Seg. N.	Endowed Slot
US Airways	315	31.11	1.38	82.48	98	369.59
American	84	16.67	0.48	76.95	14	91.55
Delta	195	7.18	0.49	65.40	14	88.56
United	105	11.43	0.33	78.41	12	62.89
JetBlue	23	34.78	0.25	94.04	8	32.87
Southwest	71	14.08	0.20	67.69	10	27.08
Total	793		3.12		156	672.54

Note: In the sample, there are 28 composite products in four composite markets, accounting for 7% of DCA passenger traffic.

in their corresponding markets, the sum of those passengers has non-negligible effects on the load factors on its DCA segment (7% of the total passengers using any DCA segments fall into this group). Therefore, instead of eliminating those products from the sample, I combine them into a single composite product. To be specific, I combine those connecting products that share the same flight segment ending at DCA and have a market (nonstop) distance beyond the perimeter rule threshold. Figure A.4 illustrates two examples of composite products—one is DL's composite product connecting at Atlanta, and the other is AA's composite product connecting at Dallas.[11] I assume that those composite products are in one of two composite markets depending on the location of connecting airports (south or north), which creates a moderate market competition.

Table 1.3 reports the number of products, passengers, and segments of those in the "DCA Products" category by carrier in the second quarter of 2013. The subsample contains 793 products, which represent 3.12 million passengers, and 79% of those passengers use nonstop products. On average 5.8 products share the same

[11] Note that a connecting flight in the DCA to Miami (MIA) market is not aggregated, as the market distance is less than 1,250 miles.

flight segment. I calculate a carrier-level slot endowment at DCA by counting the total number of quarterly departures to/from DCA segments shown in T-100 for each carrier, excluding the flight segments beyond the perimeter rule threshold. Then, I divide this number by 91 days so that its unit becomes the average number of slot holdings per day. The result is shown in the last column. There are 156 carrier-specific flight segments in this sample, and US Airways and American held 54.9% and 13.6% of the slots pre-merger, respectively. The calculated slot holdings are consistent with the DOJ's complaint claiming that "US Airways holds 55% of slots at DCA pre-merger, and the proportion would increase to 69% when AA/US merge."[12]

1.5 Estimation

This section discusses the estimation of the model parameters. While the demand and marginal cost parameters are point estimated, the bounds on the fixed cost parameters are estimated by using moment inequalities.

1.5.1 Demand

As proposed by Berry (1994), the estimation of the demand parameters $\boldsymbol{\theta}^{\mathbf{D}} = (\beta', \alpha, \sigma)$ is based on the regression equation (1.18) inverted out from observed mar-

[12]The validity of the slot holdings measure that I construct can be checked using an alternative source. Since June 2017, the FAA has uploaded information on slot holdings at slot-controlled airports (Figure A.3 is based on this information). By considering the actual slot divestitures, I backed out the number of slots that each carrier would have held before the merger. While the backed-out number is slightly greater than what I construct, as it includes slots that are exempted from the perimeter rule, I find that the two measures are consistent.

ket shares in (1.3):

$$\log(s_{jmt}) - \log(s_{0mt}) = x_{jmt}\beta - \alpha p_{jmt} + \sigma \log(s_{Gjmt}) + \xi_{jmt}, \qquad (1.18)$$

where s_{0mt} is the market share of the not flying option, and s_{Gjmt} is the within-group market share of product j. Given the model's information assumption that unobserved demand and cost shocks are not realized when carriers make flight segment entry decisions, selection is not present unless carriers regret their entry decision and reverse their entry choice.

There are two parameters for which the estimates are subject to endogeneity bias in the equation above—the price coefficient (α) and the nesting parameter (σ). Since carriers may account for unobservable product characteristics (ξ_{jmt}) when they make price decisions, prices are likely endogenous, and s_{Gjmt} is mechanically correlated with ξ_{jmt}. I address the endogeneity concerns with rich fixed effects specifications and instrumental variables (IV).

First, I include carrier, quarter, and *non-directional* market fixed effects to control for unobservables that are constant along those dimensions. Second, I use instrumental variables that are correlated with prices but uncorrelated with the unobservable product characteristics (ξ_{jmt}) in (1.18). I exploit market structure changes as a shock to shift markups, such as the number of within market nonstop carriers and whether any LCC exists within market. The validity of these instruments is based on the timing assumption of the model. Since a flight segment entry decision occurs before unobservable demand shocks are realized, market structure changes via entry/exit are not correlated with those unobservables. Additionally, I use LCC dummy variables interacted with slot-controlled airport dummies as a cost shifter IV, since LCCs at slot-controlled airports are faced with a tight capacity constraint leading to an increase in operational cost. These demand estimates allow me to obtain demand residuals $\hat{\xi}_{jmt}$, and the distribution of the residuals will be used to calculate the expected variable profit for the fixed cost estimation and counterfactual analysis.

1.5.2 Marginal Cost

The estimation of the marginal cost parameters $\boldsymbol{\theta}^{\mathbf{C}} = (\gamma_1', \gamma_2, \nu)$ is based on the pricing equation (1.13). The j'th element of the equation can be written as:[13]

$$
\begin{aligned}
\left[\mathbf{\Omega_m^{-1} q_m + p_m}\right]_j &= \left[\mathbf{c_m} + \frac{\mathbf{dc_m}}{\mathbf{dQ}}\right]_j \\
&= \sum_{s \in \mathcal{S}_{fj}} \Big(x_{fs}\gamma_1 + \gamma_2(1+\nu)\big(\frac{Q_{fs}}{z_{fs}K_{fs}}\big)^{\nu} \Big) + \omega_{jm}. \qquad (1.19)
\end{aligned}
$$

I adapt a nonlinear IV-GMM method to estimate both the linear and nonlinear parameters in (1.19). Similar to the BLP demand estimation proposed by Berry et al. (1995), the nonlinear IV-GMM has inner and outer loops. In the outer loop, I search over the nonlinear parameter ν that minimizes the objective function of the

[13] The equation will be slightly different if missing products exist. In Appendix A.2.2, I explain this in detail.

generalized method of moments (GMM):

$$\hat{\nu} = \arg\min_{\nu} (Z'\omega) W^{-1} (Z'\omega)', \tag{1.20}$$

where Z and ω are the stacked versions of the set of instrumental variables and the marginal cost error term, respectively, and W^{-1} is the inverse of the weighting matrix. As *non-directional* market, carrier and time fixed effects are included as well as load factor, what is left in ω will be more fundamental unobservables that are uncorrelated to instruments Z. Conditional on ν, in the inner loop, γ_1 and γ_2 are recovered by an IV regression. Then, the marginal cost residuals $\widehat{\omega}$ are fed into the moment condition (1.20) until we find the $\widehat{\nu}$ that minimizes the GMM objective function.

The load factor term is endogenous in (1.19). Specifically, a lower unobservable marginal cost tends to cause a lower price and a higher load factor holding slot allocation fixed. To address the endogeneity problem, in the spirit of Fan (2013), I introduce an IV that measures the market competitiveness of the "neighboring markets"—the market of the products that share the same flight segment. To illustrate this, consider two products in the right panel of Figure 1.3 that share the flight segment $(\text{DCA}\rightarrow\text{IAH})_f$—one is a nonstop flight in the DCA⇒IAH market, and the other is a connecting flight in the DCA⇒Denver (DEN) market connecting at IAH. When the competition in the DCA⇒DEN market changes, the number of passengers using the connecting flight changes and, hence, the load factor of $(\text{DCA}\rightarrow\text{IAH})_f$ affects both products. The change in load factor for the nonstop product in (DCA→IAH)$_f$ is not caused by marginal cost unobservables of the product but by the market structure changes in DCA⇒DEN market that the connecting flight belongs to. Given the information assumption that the flight segment entry decision of carriers is chosen prior to the realization of marginal product shocks, ω, the exclusion restriction holds for the introduced instrumental variable.

The variables related to market competitiveness in the "neighboring market" are constructed in the following way. When product j is a nonstop product, I list the set of products other than j that share the flight segment that j uses. Then, I find the market of the product that brings the highest number of passengers to the flight segment other than j, which I call a "neighboring market". Similar to the instrumental variables in the demand estimation, I use the number of nonstop carriers and any LCC dummy in the "neighboring market" as IVs for the endogenous load factor variable of j. In terms of a connecting product, analogously, I separately calculate the IVs of the two flight segments that the product has.

1.5.3 Fixed Cost

Given the demand and marginal cost point estimates $\hat{\boldsymbol{\theta}}^{\mathbf{D}}$ and $\hat{\boldsymbol{\theta}}^{\mathbf{C}}$, the estimation of the fixed cost parameters $\boldsymbol{\theta}^{\mathbf{F}} = \eta'$ relies on a partial identification strategy. Due to the discrete nature of an entry decision, there is no guarantee of a unique equilibrium for choosing the set of flight segments—see Eizenberg (2014). Therefore, it is challenging to obtain the point estimates of the fixed cost parameters without an additional assumption (e.g. the sequential order of carriers for entry decisions).

Instead, following a growing literature on fixed cost estimations (Eizenberg (2014); Ho and Rosen (2015); Wollmann (2018)), I adopt a partial identification approach, and use the "DCA Products" sample discussed in Section 1.4.3.

I assume that the observed set of flight segments constitutes a pure strategy Nash equilibrium and that any unilateral deviation from the set of flight segments will not increase the expected profits of a carrier. To illustrate this, suppose that $\mathcal{S}^*_f$ and $\mathcal{S}^*_{-f}$ are the observed sets of flight segments offered by f and carriers other than f, respectively, at a slot-controlled airport. Removing a flight segment s from the existing airline network does not increase f's expected profit, and this condition forms an upper bound on the fixed cost F_{fs}, $\overline{F}_{fs}$:

$$F_{fs} \leq \mathbb{E}_{\xi,\omega}\left[VP_f(\mathcal{S}^*_f, \mathcal{S}^*_{-f}) - VP_f(\mathcal{S}^*_f \backslash \{s\}, \mathcal{S}^*_{-f})\right] \equiv \overline{F}_{fs}, \qquad \forall s \in \mathcal{S}^*_f, \forall f \in F, \tag{1.21}$$

where $\mathcal{S}^*_f \backslash \{s\}$ is the set of flight segments offered by f excluding the segment s. Analogously, a lower bound, $\underline{F}_{fs}$, on the fixed cost can be formed by using the condition that adding a new flight segment s to the existing network cannot make f better off:

$$F_{fs} \geq \mathbb{E}_{\xi,\omega}\left[VP_f(\mathcal{S}^*_f \cup \{s\}, \mathcal{S}^*_{-f}) - VP_f(\mathcal{S}^*_f, \mathcal{S}^*_{-f})\right] \equiv \underline{F}_{fs}, \qquad \forall s \in \mathcal{S}_f \text{ and } s \notin \mathcal{S}^*_f, \forall f \in F, \tag{1.22}$$

where $\mathcal{S}^*_f \cup \{s\}$ is the set of flight segments of f that adds a new segment s to $\mathcal{S}^*_f$. Although a wide range of moment conditions are possibly formed by removing/adding multiple flight segments, I use only one segment deviation to ease the computational burden.

When a carrier adds a new flight segment to its airline network, the carrier pays a fixed cost and commits to providing nonstop service on the segment. There may be a set of potential connecting service offerings when the new flight segment is added, and those service offerings will depend on the characteristics of the origin/destination airports (e.g. hubs), the carrier's network type (e.g. hub-to-spoke or point-to-point system) and the structures of the markets for which the new connecting services are possible.

In this study, however, when carriers add a new segment to their existing network, I assume that they offer only a nonstop product and no connecting products for two reasons. First, since US Airways is the only carrier that considered DCA as a hub pre-merger, those itineraries connecting at DCA are mostly from that carrier—94% of one-stop passengers connecting at DCA were flown by the US Airways. When examining the data, the carrier connected most of its flight segments at DCA, leaving only a few small communities with a small-sized demand as segments to be added. This implies that the connecting passenger flows from those new flight segments based on the small community would be very small. Second, in terms of carriers other than US Airways that do not consider DCA as a hub, it is not likely that they offer products connecting at DCA for transferring passengers on the new segments. The only remaining scenario in which these other carriers could generate connecting passengers is when the non-DCA endpoint of the new segments is their hub airport. However, the data indicate that those carriers already linked their hubs to DCA, and that there are no new segments considered as their hubs.

Airplane Size for a New Segment

While the available seats for an existing segment can be directly obtained from the data (T-100), the airplane size multiplier of a new segment s, z_{fs} in (1.7) needs to be predicted. For this prediction, I use the sample of those flight segments which daily flight is at least one from 2012Q1 to 2013Q4. Airline carriers allocate their airplanes on a segment based on a number of factors, including aircraft fleet portfolio, flight length, and contracts with regional operators. Typically, a smaller airplane is used for a short-haul distance route. To predict the airplane size, I regress the segment-level average airplane size on distance, and distance squared. In addition, I include fixed effects of both origin-carrier pairs and destination-carrier pairs in the regression to control carrier-airport specific unobservable characteristics that affect fleet choices.

I report the regression result in Table A.1 in the Appendix. Airplane size tends to increase as the segment distance increases but in a diminishing way. Airplane size is likely to be smaller at slot-controlled airports, partly because operations at those airports are affected by perimeter rules. Furthermore, airplanes at high-tourism airports (airports in Fort Lauderdale, Orlando, or Las Vegas) or international hubs tend to be large. The preferred specification used to predict airplane size is column (3) where origin-carrier and destination-carrier specific fixed effects denote the specification with the highest predicted power. Last, when the model relaxes the assumption that all products are available in the data, the load factor on s originating from unavailable products also needs to be predicted in order to describe available seats and load factors realistically. In Appendix A.2.2, I explain the prediction procedure for doing so.

Selection Issue

The information structure of this model setup entails a selection problem. Recall that the fixed cost parameter has a mean-zero error term ϕ_{fs} in (1.17) that affects the entry decision of flight segment s by carrier f. Since the error term is observed by carrier f but not by econometricians, the carrier may selectively enter those flight segments with lower fixed costs. In other words, ϕ_{fs} is not mean zero conditional on those segments that the carrier decides to enter, while its unconditional mean is zero. This leads to a biased fixed cost parameter estimation.

There are several methods introduced in the literature to address the selection problem. Ciliberto and Tamer (2009) assumes the parametric distribution of fixed cost error terms and obtains a bound on fixed costs by computing the probability of observing equilibrium offerings. However, this method is computationally very expensive in my model setting because it needs to analyze every possible combination of flight segments. Next, Eizenberg (2014) assumes that conservatively wide bound exists for any fixed cost, and he uses the wide bound for counterfactual inequality conditions to obtain unbiased parameter bounds. Following Eizenberg (2014), I address the selection issue by assuming that the support of a fixed cost is the minimum and maximum of the support of the expected change in variable profit coming from a single flight segment change:

Assumption 1 *$|F_{fs}| < \infty$ and $[\min(F_{fs}), \max(F_{fs})] \subset [\min(\Delta VP_f), \max(\Delta VP_f)]$, $\forall f \in F$ where ΔVP_f is an expected change in variable profit due to the elimination or addition of a single flight segment by carrier f.*

Under the Assumption 1, I use $\min(\Delta VP_f)$ and $\max(\Delta VP_f)$ for the lower bound of (1.21) and the upper bound of (1.22), respectively. Then, I combine (1.21) and (1.22) and take the unconditional expectation for F_{fs}:

$$\mathbb{E}[LB_{fs}] \leq \mathbb{E}[F_{fs}] \leq \mathbb{E}[UB_{fs}] \tag{1.23}$$

$$\mathbb{E}[LB_{fs}] \leq X_{fs}\eta \leq \mathbb{E}[UB_{fs}] \qquad (\because \mathbb{E}[\phi_{fs}] = 0)$$

where

$$LB_{fs} = \begin{cases} \underline{F}_{fs} & \text{if } s \in \mathcal{S}_f \text{ but } s \notin \mathcal{S}_f^* \\ \min(\Delta VP_f) & \text{otherwise,} \end{cases} \qquad UB_{fs} = \begin{cases} \overline{F}_{fs} & \text{if } s \in \mathcal{S}_f^* \\ \max(\Delta VP_f) & \text{otherwise.} \end{cases}$$

Moments and Inferences

Similar to Pakes et al. (2015) and Wollmann (2018), I form the following moment inequality conditions from (1.23):

$$\frac{1}{N} \sum_{s \in \mathcal{S}_f} [X_{fs}\eta - LB_{fs}] \geq 0, \qquad \forall f \in \mathcal{F} \tag{1.24}$$

and

$$\frac{1}{N}\sum_{s\in\mathcal{S}_f}[UB_{fs} - X_{fs}\eta] \geq 0, \qquad \forall f \in \mathcal{F} \tag{1.25}$$

where N is the number of new and existing flight segments of f. Following the procedure suggested by Andrews and Soares (2010), the confidence sets of fixed cost parameters are estimated. The procedure is as follows: 1) for a given set of η, compute the objective function $Q_n(\eta) = \sum_i \left(\left[\frac{\bar{m}_i(\eta)}{\hat{\sigma}_i(\eta)}\right]_-\right)^2$, where $\bar{m}_i(\eta)$ and $\hat{\sigma}_i(\eta)$ are the ith moment's sample mean and standard error, and $[x]_-$ operator is defined as x if $x < 0$, and equals 0 otherwise. 2) Draw a large number of bootstrap samples R and compute the objective function for sample at η. 3) Compute a critical value ($c_{1-\alpha}$) at the ($1 - \alpha\%$) quantile of the distribution of the objective based on the bootstrapped samples. 4) Include η in the bound if $Q_n(\eta) < c_{1-\alpha}$. 5) Repeat steps 1-4 for all possible parameter vectors.

1.6 Estimation Results and Model Fit

1.6.1 Demand

Table 1.4 reports the estimation results of the demand system. The first three columns show the baseline demand estimates under different market definitions (airport-airport pair in (1) and (2), and city-city pair in (3)), and the demand parameter estimates are sensible. All other things being equal, air travel passengers strongly prefer nonstop to connecting flights, and carriers with higher airport presence are preferred. As the non-directional market fixed effects are included in the regression, factors constant at the market level such as market distance are not identified in the demand specification. Instead, I add to the regression "Extra-miles," measured by the total distance flown divided by the nonstop market distance.[14] The estimates suggest that connecting flights with longer detours (more extra-miles) are less preferred to consumers, but this effect diminishes as the ratio increases. As expected, airfares negatively affect consumer demand, and nesting parameters are moderately estimated in a way that product substitutions within a nest are more likely than those across nests.

Labeled "Frequency in Demand," the last two columns report the estimation result when daily departure-related variables are added to the baseline specification. Passengers prefer a flight that has more daily departure options, and this preference is much stronger for a nonstop flight than for a connecting flight. For 15.2% of the connecting products in the sample, there is no information on daily departures, and for each of those connecting products, I impute this value as the geometric mean of the daily flight frequency of the two segments. I separately estimate the impact on preference by adding its interaction term. While the estimated interaction coefficient is negative, it varies with how the functional form of the imputation is defined. The willingness to pay of a passenger for an additional daily departure of a nonstop (connecting) product is calculated as \$39.0 (\$8.17), in dollar terms. When all flights additionally increase one daily departure, the aggregate demand would

[14] For example, the total distance flown for a connecting flight from ATL to ORD connecting at DCA, is 1,159 miles—the sum of the two flight segments distances (547 miles for ATL→DCA and 612 miles for DCA→ORD). As the nonstop flight distance between ATL→ORD is 606 miles, the value of Extra-miles for this product is 1.893.

Table 1.4: Demand Parameter Estimation Results

	(1) Baseline	(2) Baseline	(3) Baseline	(4) Frequency in Demand	(5) Frequency in Demand
Nonstop	0.128***	0.502***	0.367***	0.157***	0.496***
	(0.005)	(0.051)	(0.073)	(0.006)	(0.035)
Presence (Origin)	0.026***	0.159***	0.148***	0.013***	0.105***
	(0.001)	(0.011)	(0.013)	(0.002)	(0.010)
Extra-miles	−0.031***	−0.520***	−0.630***	−0.106***	−0.570***
	(0.011)	(0.093)	(0.162)	(0.012)	(0.077)
Extra-miles squared	0.008**	0.132***	0.160***	0.028***	0.152***
	(0.004)	(0.023)	(0.040)	(0.004)	(0.020)
Fare (α)	−0.058***	−0.339***	−0.352***	−0.071***	−0.384***
	(0.002)	(0.026)	(0.031)	(0.003)	(0.025)
Nesting (σ)	0.955***	0.794***	0.814***	0.932***	0.765***
	(0.001)	(0.021)	(0.033)	(0.002)	(0.018)
Daily Departure (DDep)				0.013***	0.047***
				(0.0005)	(0.003)
DDep X Nonstop				0.016***	0.051***
				(0.001)	(0.006)
DDep X Connecting (Imputed)				−0.006***	−0.026***
				(0.0004)	(0.002)
OLS or IV?	OLS	IV	IV	OLS	IV
O-D Pair (Airport or City)	Airport	Airport	City	Airport	Airport
Median Elasticity	-2.699	-3.535	-4.101	-2.180	-3.514
Diversion Ratio					
(Nonstop $\rightarrow$ Nonstop)	0.722	0.555	0.560	0.696	0.529
(Nonstop $\rightarrow$ Connecting)	0.201	0.148	0.191	0.192	0.140
Observations	358,880	358,880	291,930	358,880	358,880

Note: $*** < 0.01$, $** < 0.05$, $* < 0.10$. All the specifications include time, carrier, and route fixed effects.

increase by 8.8%. This result is relatively smaller than the previous finding in Berry and Jia (2010) that claims that adding one daily departure to all flights increases the aggregate demand by 16% in 2006.

Sensible elasticities and a diversion ratio are calculated under the demand system. The median own-price elasticities range from -4.10 to -3.51 conditional on columns with IVs. For example, the median and mean elasticities in Ciliberto and Williams (2014) range from -3 and -4. Compared to an airport-airport pair, demand tends to be more elastic under the city-city pair market definition, as there are a wide range of products that passengers can choose in the city-pair market. For those markets where there are at least two nonstop carriers and one connecting carrier, I report the diversion ratio to explore substitution patterns when a nonstop product price increases.[15] The mean diversion ratio of nonstop to nonstop is three to four times greater than that of nonstop to connecting; this indicates a strong preference for nonstop service. The distribution of the demand residual for the baseline (2) is reported in Figure A.5a.

1.6.2 Marginal Cost

Table 1.5 reports flight segment-level marginal cost estimates. All the results in the table are based on the airport-pair market definition, and the results based on the city-pair market definition are not included, as it is less straightforward to allocate slots to city-based segments at a slot-controlled airport. While load factors are overestimated when the mark-up values are calculated based on the OLS demand results (in column (1) and (3) in Table 1.5), the load factors under the IV-based demand estimates are estimated in a way that it moderately affects the marginal cost. For example, the combination of ν and γ_2 in column (2) indicates that a load factor of 0.8 for a flight (sample average) increases the marginal cost by \$15.8, while

[15] I use the following formula (classified in Conlon and Mortimer (2018)) to calculate the diversion ratio of product j to product k in the nested logit setting: $\frac{\partial s_k}{\partial p_j}/|\frac{\partial s_j}{\partial p_j}| = \frac{\sigma s_{k|g} - (1-\sigma)s_k}{1-\sigma s_{j|g} - (1-\sigma)s_j}$, where s_j and $s_{j|g}$ are the market share and the within group market share of product j, respectively, and σ is a nesting parameter.

Table 1.5: Marginal Cost Estimation Results

	(1) Baseline	(2) Baseline	(3) Frequency in Demand	(4) Frequency in Demand
Load Factor (ν)	0.229***	1.979***	0.289***	2.240***
	(0.001)	(0.006)	(0.001)	(0.0006)
Load Factor (γ_2)	0.975***	0.229***	0.970***	0.204***
	(0.042)	(0.009)	(0.038)	(0.009)
Distance	0.457***	0.246***	0.471***	0.238***
	(0.046)	(0.020)	(0.043)	(0.019)
Distance sq.	0.005	0.022***	0.002	0.022***
	(0.012)	(0.006)	(0.012)	(0.006)
Slot Constraint	−0.085***	−0.039***	−0.090***	−0.036***
	(0.015)	(0.006)	(0.014)	(0.006)
Slot Constraint X LCC	0.282***	0.048**	0.311***	0.035*
	(0.055)	(0.019)	(0.055)	(0.019)
Hub	−0.012	0.015***	−0.014	0.017***
	(0.014)	(0.004)	(0.013)	(0.004)
Base Demand Spec in Table 1.4?	(1)	(2)	(4)	(5)
O-D Pair (Airport or City)	Airport	Airport	Airport	Airport
Cost Impact of Load Factor (LF)				
LF = 0.6	\$ 39.0	\$ 6.2	\$ 38.5	\$ 5.0
(Sample Average) LF = 0.8	\$ 43.4	\$ 15.8	\$ 44.1	\$ 14.4
LF = 1.0	\$ 45.7	\$ 24.6	\$ 47.1	\$ 23.8
First stage F-Stat (Load Factor)	232883.7	4885.5	151080.9	3884.3
Observations	358,880	358,880	358,880	358,880

Note: $*** < 0.01$, $** < 0.05$, $* < 0.10$. Time, carrier, and non-directional market fixed effects are included in all regressions. The coefficients are reported in units of \$100.

a load factor of 1.0 increases it by \$24.6. The estimation suggests that the marginal cost increases exponentially as flights become more full. In terms of other variables, marginal cost increases in distance with a small but an increasing rate. A distance of 1,000 miles of a flight is associated with a marginal cost increase of \$26.8. The role of slot constraints and hub airports on marginal cost seems small. Lastly, the regression result suggests that low cost carriers have a higher marginal cost at slot constraint airports, reflecting that their operation scale is relatively low at those airports.

Table 1.6: Fixed Cost Parameter Estimation Results

x_{fs}	(1)		(2)	
Constant	[0.837,	2.918]	[1.759,	3.729]
Low Cost Carrier			[−1.976,	1.191]
Slot Ratio at DCA			[−5.370,	1.909]
Presence at Non-DCA			[−8.837,	2.201]

Note: Unit is a million dollar.

Instrumental variable techniques are used to deal with the endogeneity of the load factor variable γ_2, and its first stage estimates are reported Table A.3 in the Appendix. The market competitiveness of neighboring markets has a positive impact on the load factor. To be specific, the load factor of a segment that a product uses increases when a high level of competition exists in its neighboring market (e.g. higher number of nonstop carriers or existence of low cost carrier). This suggests that higher competition in the neighboring market induces more passengers from the market to take the segment's seats, leading to an increase in the load factor of the segment.

1.6.3 Fixed Cost

Table 1.6 reports the estimation result for the fixed cost parameters. In the fixed cost specification where only a constant variable is used in column (1), the mean fixed cost ranges from \$0.83(M) to \$2.91(M). When I add more observable variables to the fixed cost in column (2), the bounds of the parameters are wider, partially because of the Assumption 1 that confidence sets bound of counterfactual segments are wide enough for the purpose of dealing with the selection bias. The constant parameter is positive ranging from \$1.76(M) to \$3.23(M), but the sets of the rest parameters include zero. Fairly recently, a new working paper that simplifies the confidence set construction for linear conditional moment inequalities (Andrews et al. (2019)) was released. As their approach is similar to my setting, I plan to utilize their approach to compute the bounds of fixed cost parameters which may allow me to estimate more narrow and precise confidence sets.

For the counterfactual analysis in Chapter 2, I use $\tilde{\eta}' = (3, -0.7, -1.2, -3)$ in column (2) for three reasons: 1) These values are within the range in column (2); 2) none of the moment conditions are violated at the values; and, 3) the values allow the model to fit well with data in terms of entry/exit decisions made by Southwest, JetBlue, and the merging firms.

1.6.4 Model Fit

In this section, I discuss the second stage model fit (i.e. the pre-merger model fit conditional on flight segment decisions), while the model fit regarding the post-divestitures flight segment entry and exit decisions will be discussed in Chapter 2. For this, I simulate 50 sets of all of the demand and cost variables for "DCA Products" from the estimated distributions. Table 1.7 shows the model performance, conditional on entry (i.e., second-stage only). The model seems to reasonably predict slot allocation, (weighted) average price, and the number of passengers. However, the model slightly overestimates (underestimates) slots on segments with a lower (higher) slot frequency, and the average price seems to be underestimated for the high-price product group.

To further understand the second stage model fit, I examine the model prediction at an individual flight-segment level. Figure A.6 highlights the fact that while the average number of daily slots for a large fraction of flight segments is reasonably well predicted, there is a set of flight segments for which daily slot prediction is not so accurate. Those flight segments with poor predictions, measured by the absolute gap of daily slots between the data and the model being greater than 2 in the figure, mostly contain composite products that are associated with hub airports at which passengers transfer to go to other destinations beyond the perimeter rule. Since the demand qualities of composite products and the sizes of the markets that they belong to are manually chosen to roughly capture the number of connecting passengers, the daily slot gap between data and model predictions for those segments is large. By appropriately assigning demand qualities of the composite products and market sizes of their markets, the second stage model prediction can be further improved.

1.7 Conclusion

I have developed an endogenous entry model that features the carriers' flight segment entry decisions, product price choices and slot allocation choices at a slot-controlled airport. In this model framework, the marginal costs increase as a carrier's load factor on a flight segment increases, enabling a change in capacity of a segment to affect product costs in a large number of markets.

The model I developed can potentially be extended not only to non-merger

Table 1.7: Model Fit (Pre-merger): Slot Allocation, Average Prices and Passengers

	Group	Data	Model Prediction
Slot Allocation			
Daily Departure Frequency Group	1st Tercile	1.53	1.92 (0.11)
	2nd Tercile	3.56	3.53 (0.17)
	3rd Tercile	7.85	7.48 (0.29)
	All	4.31	4.31 (0.19)
Average Price (Weighted by Passengers)			
Data Price Dist. Group	1st Tercile	$156.1	$158.5 (5.5)
	2nd Tercile	$205.4	$196.2 (5.4)
	3rd Tercile	$283.6	$240.7 (5.6)
	All	$196.2	$187.7 (5.5)
Average Passengers			
Data Price Dist. Group.	1st Tercile	5,598.3	5,225.0 (422.7)
	2nd Tercile	3,131.7	3,192.4 (292.8)
	3rd Tercile	2,517.5	2,645.8 (254.1)
	All	3,796.7	3,727.9 (325.8)

I simulate 50 sets of all of the demand and cost variables for "DCA Products" from the estimated distributions. Bootstrapped standard errors are in parenthesis (n = 40). For the average prices and passengers, I exclude those composite products.

issues in the airline industry, but also to merger remedies in other industries. One example is slot swap—exchanges in which airlines that are dominant at slot-controlled airports trade slots with one another in an attempt to increase their competitive advantage (e.g. DL/US in 2011). Antitrust authorities often find these transactions to be anticompetitive, as slot swapping may further enable the carriers involved to raise prices at their dominant airports. Simply by extending the scope of the airline network from one slot-controlled airport to two, my model can be applied to analyze this policy. In terms of the merger remedy analysis in other industries, retail mergers are an example where divestitures of stores or distribution centers are commonly used. As those assets affect product costs in multiple local markets via transportation costs or inventory controls, my model can be naturally extended to those merger remedies.

Some limitations of my model provide an agenda for future research. While I believe the key features in my model—capacity choice via airport slots and cross-market interactions—extend the existing frameworks for merger simulation and airline models, the model faces a few limitations. First, due to model tractability, this model does not capture that consumers may prefer a product with more frequent departure options in which slots allocated to a segment (hence a product) can direct affect consumer demand. However, if the model can account for the relationship between divested assets and market demand (e.g. daily departure options in airline mergers or shopping distance to stores/branches in retail or banking mergers), the analysis will be richer. Second, my model does not incorporate the carrier's fleet assignment decision. While this model assumes that a segment-specific airplane size is exogenously given, carriers may change their post-merger fleet portfolio in the long run. Last, I examined only a subset of products and markets in the U.S. airline industry that is associated with the slot divestiture in the AA/US merger. Although the model feature in which markets are interconnected with each other is a clear extension of the existing literature, the scope of airline networks in this study is limited to a slot-controlled airport.

Chapter 2: An Assessment of Slot Divestitures in the American Airlines/US Airways Merger: Counterfactual Analysis

2.1 Introduction

In this chapter, I perform a set of counterfactual exercises to aid antitrust authorities in measuring the effect of alternative slot divestitures schemes on passenger welfare and market competition *ex ante*. — 1) comparing the merger outcomes of the realized divestitures scenario with those in the case when the merger occurred without slot divestitures; 2) comparing the merger outcomes when slots were granted to different types of carriers (e.g. legacy vs. low cost carriers); and 3) comparing the merger outcomes by varying the number of carriers who received the slots.

The counterfactual analysis shows that requiring American Airlines and US Airways to divest slots raised aggregate consumer surplus, but harmed a subset of DCA passengers. Compared to the case where the merger was allowed with no divestitures, the divestiture of 15% of American's slots is estimated to have raised total consumer surplus by \$28M per quarter (roughly, \$112M per year). I estimate that slot divestitures would have raised consumer surplus, although total surplus increased little. However, these divestitures caused American to eliminate service on some marginally profitable routes, and the model predicts that the carriers that are allocated the slots would be unlikely to serve either these eliminated routes or the routes where American and US Airways were both active before the merger (overlapped routes) and for which competitive concerns are likely to be the greatest (e.g. DCA-Raleigh and DCA-Nashville markets). I therefore consider alternative divestiture policies through which the recipients of the divested slots are either required to use them to serve particular routes or the slots are granted to different carriers whose incentives to serve different types of routes might differ from the LCCs that were actually granted the slots. I find that requiring the slot recipients to serve the overlapped routes can create a net surplus gain. Additionally, I find that legacy carriers are likely to serve routes based in large cities (e.g. Miami, Boston) and are less likely to serve those routes based in small communities to which they expressed their intention to expand services.

2.2 Counterfactual Description

The merger simulations in this section are based on the demand and marginal cost estimates of "Baseline" specifications in column (2) of Tables 1.4 and 1.5 respectively, and on the fixed cost parameters $\tilde{\eta}'$ described in 1.6.3.

2.2.1 Counterfactual Scenarios

In the context of the AA/US merger case, 104 landing slots that the merging firms had at DCA prior to the merger were divested; these divested slots represented approximately 15% of the average daily flights of the merging firms at the airport.[1] Southwest, JetBlue, and Virgin America ended up purchasing 56, 40, and 8 of the DCA landing slots, respectively, from the merged carrier through a slot auction.[2] The most natural way to measure the effectiveness of the slot divestitures is to compare the simulated merger outcomes in the case in which slot purchasers and the number of divested slots are the same to what actually happened with those in the case in which the merger occurred without slot divestitures. I call this scenario *Baseline*. In this scenario, I also examine to what extent consumer surplus and producer surplus change as the fraction of divested slots increases.

Next, I explore the likely competition effects if slots were granted to different types of carriers (i.e. legacy carriers vs. LCCs). As product demand and the cost structure are heterogeneous across segments and markets, carriers may have different segment entry decisions when additional slots are given to them. This implies distinct welfare effects depending on who receives the divested slots. A particularly interesting case is the AA/US merger, where based on the view that LCCs are more suitable and effective competitors than are legacy carriers, the government approved only LCCs as purchasers of the divested assets. A legacy rival (i.e., Delta) claimed that legacy carriers would bring more services to small and medium-sized communities through its expansive domestic and international network, while the LCCs' business would mainly focus on carrying leisure-based passengers be-

[1] In this merger deal, the merged carrier was also required to divest 34 landing slots at LaGuardia (LGA) and some airport gate access at Reagan National (DCA), LaGuardia (LGA), Boston Logan (BOS), Chicago O'Hare (ORD), Dallas Love Field (DAL), and Los Angeles (LAX).

[2] Of the 40 acquired landing slots, JetBlue won 24 via the auction, and the remaining 16 were obtained by permanently controlling the slots that had been leased to JetBlue before the merger by American Airlines.

tween large domestic destinations—see Gravath, Swaine & Moore LLP (2014). In this counterfactual, I examine merger outcomes when slots are divested to different types of carriers. Additionally, I check if Delta would be likely to enter those flight segments in small communities as it claimed under a scenario in which additional slots are given to Delta. I call this scenario *Purchaser Type*.

Last, I explore the likely competition effect of slot divestitures when the number of slot purchasers varies. Conditional on a fixed number of divested slots, the fraction of slots that each purchaser obtains would be smaller as the number of slot purchasers increases. The likely market structure when the divested slots are evenly split among a few carriers will differ from when they are split among many. However, its prediction is not clear because the flight segment entry decisions differ by carriers. In this exercise, I compare merger outcomes by gradually increasing the number of purchasers from one to four. I call this scenario *Number of Purchasers*.

2.2.2 Marginally Profitable Flight Segments

While the model allows carriers to endogenously choose flight segments, it is computationally infeasible to compute the expected profits for all possible combinations of flight segments. For example, if there are 60 different flight segments from DCA, 2^{60} sets of endogenous routes are possibly chosen by each carrier, and it is computationally very expensive to compute equilibrium slot allocations and prices for all of the combinations. To overcome this, I assume that carriers can endogenously choose only a subset of flight segments that are marginally profitable.

Table 2.1: List of Marginally Profitable Flight Segments from DCA

	Entry				Exit
Rank	Southwest	JetBlue	Delta	United	NewAA
1	FLL	PBI	MIA	PNS	CAK
2	TPA	SRQ	BOS	FLL	AGS
3	BNA	BDL	FLL	TYS	MYR
4	MSY	JAX	MCO	PVD	TLH
5	MCI	RSW	JAX	SAV	JAN
6	PVD	CHS	IND	MIA	PNS
7	CMH	MSY	BDL	DSM	GSP
8	BHM	PWM	PVD	TPA	BNA
9	JAX	CLT	OMA	DAY	ROC
10	IND	MSP	MSY	JAX	TYS

A simple logit model of the actual entry decision made by Southwest and JetBlue after the AA/US merger is used to predict the likelihood of entry/exit. The logit estimate can be found in Appendix A.3.1. Additionally, the three-letter airport codes used in this table are defined by the International Air Transport Association (IATA). Table A.4 shows the full airport names of those codes.

The merged carrier that has a reduced number of landing slots following the slot divestitures has an incentive to remove from its airline network the existing flight segments that make a relatively small contribution to the carrier's profit. Analogously, carriers that purchase additional landing slots from the divestitures could add new flight segments to their networks that were previously considered not as profitable because those segments already exist in their networks.

To obtain marginally profitable flight segments, based on a simple logit model, I predict the likelihood of new entry by using the information of the post-merger entry decisions made by the actual slot purchasers in the AA/US merger—Southwest and JetBlue.[3] The expected variable profit change when a carrier adds a counterfactual segment is included as a main explanatory variable in the model. Additionally, a carrier's airport presence at a counterfactual segment's endpoints is included as

[3]While I use the *ex post* information in this *ex ante* analysis, we can build a similar logit model by leveraging the information of the previous events such as historical mergers with slot divestitures or slot swap events.

the variable plays an important role in entry decisions—see Goolsbee and Syverson (2008). While the detailed prediction procedure is available in Appendix A.3.1, Table 2.1 lists by carrier the top ten flight segments that are most likely to be added/removed from DCA. The three-letter airport codes defined by the International Air Transport Association (IATA) are used in the Table, and their full names can be found in Table A.4 in the Appendix.

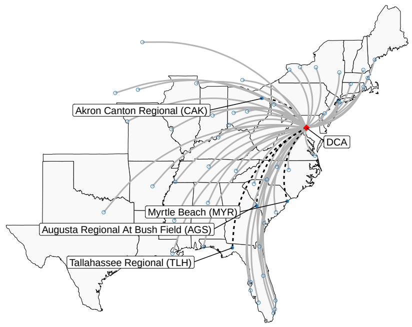
I make several post-merger assumptions. First, I compute the counterfactual outcomes based on the assumption that NewAA takes the average observed characteristics of the two merging firms pre-merger. As Ciliberto et al. (2018) point out, I recognize that merger simulation outcomes may change substantially, depending on our assumptions about the characteristics of the merging firms post-merger. In this counterfactual exercise, however, as we are more interested in the relative differences between various divestiture schemes than in the absolute surplus measures for each scenario, I make a single assumption about the quality of NewAA. Second, the entry game in this counterfactual analysis assumes that the order of moves is an equilibrium selection mechanism. In the endogenous entry game setting, there are concerns over multiple equilibria when carriers simultaneously make entry decisions. Following Wollmann (2018) and Lee and Pakes (2009), to alleviate this concern, I sort the carriers based on their airport passenger shares at DCA and assume that the carrier with the highest passenger share moves first in the sequential game, followed by the second highest one and so forth. Last, I assume that the segment-specific airplane size post-merger is the same as the one pre-merger. There might be a concern that NewAA could change its fleet allocation after the merger, which could systematically alter the segment-specific airplane size. However, a regression exercise in Appendix A.3.2 suggests that this did not occur.

2.2.3 Equilibrium: Brute Force Search vs. Heuristic Search

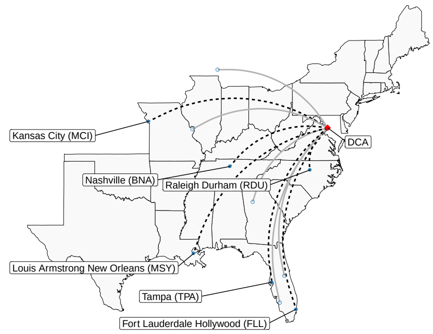
I take two approaches to find the set of flight segments that carriers choose at the equilibrium. One approach, which I call a "Brute Force Search," is to compute the expected profit for every possible combination of endogenous flight segments. While the "Brute Force Search" guarantees the accuracy of the model solution within the choice of the set of endogenous flight segments, it becomes computationally intensive as the number of endogenous segments increases. For example, if carriers were allowed to select all the segments in the list of Table 2.1, there would be 2^{50} combinations to analyze (each carrier has 2^{10} combinations), which is an examination that is computationally infeasible. For this search, therefore, I further refine a set of marginally profitable routes from the list in Table 2.1. I describe the refinement in the following sections.

The other approach, a "Heuristic Search," allows the equilibrium to be found quickly with a relatively large number of endogenous segments. Similar to the approach Fan and Yang (2018) take in their counterfactual analysis, this approach is based on the iterated best response in which each carrier takes a turn and grows/shrinks a set of endogenous segments until they reach to the point where there is no profitable deviation for all carriers. In contrast to the "Brute Force Search," carriers are allowed to grow/shrink the set of segments by up to one flight

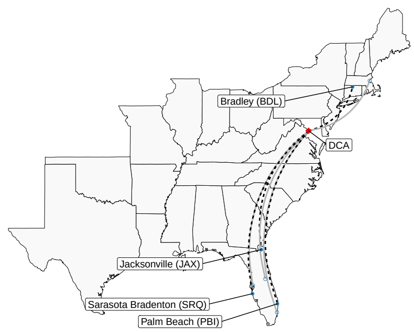
Figure 2.1: Marginally Profitable Routes by Carrier (*Baseline*)



(a) NewAA



(b) Southwest



(c) JetBlue

Note: Gray solid lines indicate the flight segments treated as exogenous, and black dotted lines indicate those segments that carriers endogenously choose. Those endogenous segments are labeled on the maps.

segment for each turn in this search. This potentially implies that flight segment composition can vary if carriers are allowed to add/remove more than one flight segments. In Appendix A.3.3, I describe how the "Heuristic Search" works in detail.

2.3 Counterfactual Results

2.3.1 Baseline

In this scenario, I compare the simulated merger outcomes in the case in which slot purchasers and the number of divested slots are the same as in the case in which the merger occurred without slot divestitures. I assume that Southwest and JetBlue take 60% and 40% of divested slots, respectively, based on the ratio of slots that they actually obtained through the divestiture process. I exclude Virgin America in this analysis as it did not operate any nonstop flights within the perimeter rule at DCA pre-merger. For the "Brute Force Search," I choose the first four, five, and four endogenous segments to/from DCA for NewAA, Southwest, and JetBlue, respectively, in Table 2.1. There were two overlapping markets from/to DCA where the merging firms were duopolists—Nashville (DCA⇒BNA) and Raleigh (DCA⇒RDU). In these routes, NewAA has an efficiency gain by getting rid of redundant fixed cost payment, but it may exercise its market power as it becomes a nonstop monopolist. To assess whether slot purchasers had an incentive to constrain the market power of the merged firm in those overlapping markets, I allow Southwest to endogenously choose the two flight segments.[4] Figure 2.1 visualizes the list of endogenous segments marked as a dotted black line, while the existing exogenous segments are marked as a solid gray line.

Table 2.2 shows the result of the simulated merger outcomes of *Baseline* case under the "Brute Force Search" approach. The simulation results show that the average price would increase and that the number of passengers would decrease when there were no slot divestitures. As the number of divested slots increase, DCA markets become more competitive and consumers would be better off. The effect of slot divestitures on the surplus is substantial. For example, the consumer

[4] As Southwest obtained more than 60% of the divested slots when excluding those slots leased to JetBlue, the carrier had greater flexibility to enter new routes than other LCCs.

Table 2.2: Post-merger Outcomes (*Baseline*) Using Brute Force Search

	Pre-merger	Post-merger (Slot Divestitures Ratio)			
		0%	10%	15%	20%
All DCA Markets					
Price	\$180.26	+5.25%	-0.37%	-1.66%	-2.78%
Passengers	2,856(k)	-2.91%	+0.42%	+0.91%	+1.45%
Consumer Surplus		-25.51(M\$)	+0.07(M\$)	+2.60(M\$)	+5.35(M\$)
All DCA Markets Consumer Surplus Decomposition (M\$)					
No Change		-28.76	-18.11	-17.80	-13.74
Segments Added		+4.03	+22.09	+25.12	+24.32
Segments Removed		-0.77	-1.32	-2.13	-2.66
Overlapped Markets					
Price	\$249.89	+37.47%	+20.34%	+19.28%	-9.76%
Passengers	62(k)	-36.63%	-25.77%	-25.45%	+2.56%
Consumer Surplus		-6.71(M\$)	-4.72(M\$)	-4.66(M\$)	+0.47(M\$)

Note that units in Post-merger columns are all relative to Pre-merger values. Overlapped markets to/from DCA include DCA⇒BNA, BNA⇒DCA, DCA⇒RDU, and RDU⇒DCA markets. I use 40 draws to obtain the expected profit for each combination of flight segments.

surplus gap between the 15% slot divestitures case and no divestiture is computed as \$28.1(M) per quarter or roughly \$112.4(M) per year.

The merger simulation suggests that the merger remedy will have distributional effects across markets. To understand this, I decompose the consumer surplus into three categories in the second panel of the table—1) “No Change” refers to the markets where there are no product entries or exits after the merger; 2) “Segments Added” is a group of markets in which new products are introduced due to new segment entries; and 3) “Segment Removed” is a group of markets in which the existing products are removed as carriers exit the corresponding flight segments. As the ratio of divested slots increases, slot purchasers initiate new nonstop services in new markets and passengers in those markets are better off due to intense market competition. This is explained by the fact that the consumer surplus change in “Segments Added” is greater than the one in “No Change.”

Table 2.3: Surplus Changes When a Purchaser is Forced to Enter Overlapped Markets

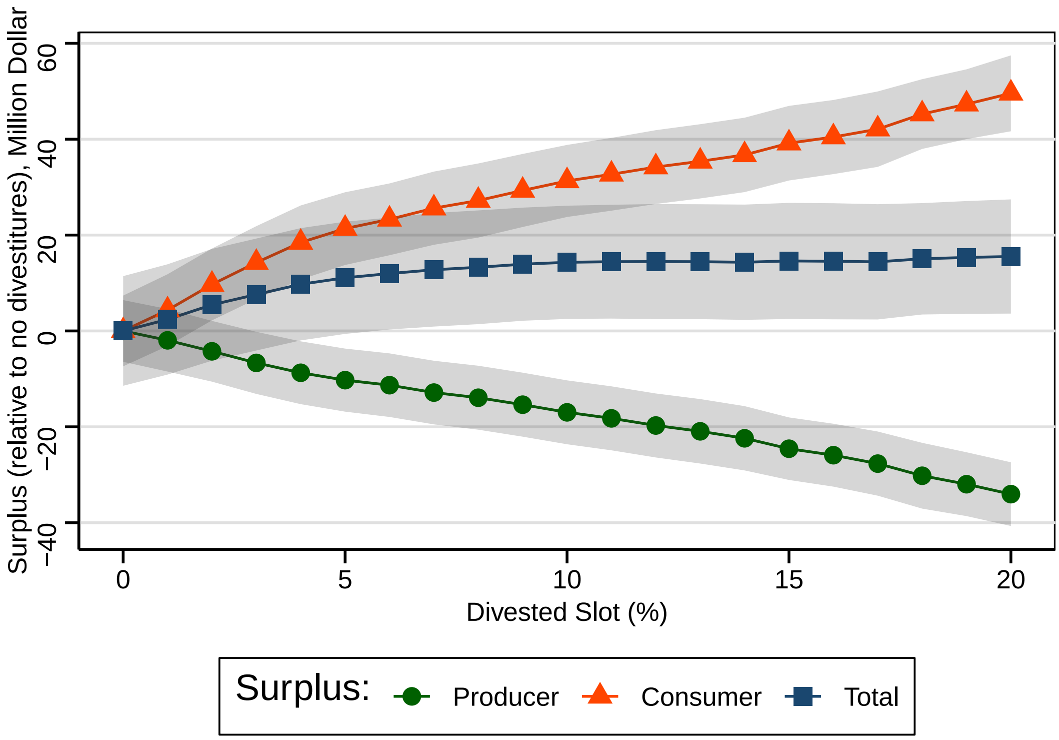
	Consumer Surplus (M$)			Producer Surplus (M$)		
divest	Baseline (B)	Forced (F)	(F)-(B)	Baseline (B)	Forced (F)	(F)-(B)
All DCA Markets						
10%	0.07	3.78	3.71	33.19	31.09	-2.10
15%	2.60	6.68	4.08	30.89	28.87	-2.02
20%	5.35	5.35	0.00	27.86	27.86	0.00
Overlapped Markets						
10%	-4.72	0.10	4.82			
15%	-4.66	0.32	4.99			
20%	0.47	0.47	0.00			

Note: 'Baseline (B)' shows merger outcomes without government intervention (*Baseline*), while 'Forced (F)' shows merger outcomes when Southwest is forced to enter the overlapped markets (DCA⇔RDU and DCA⇔BNA). The values in those columns indicate the post-merger surplus relative to the pre-merger one. I use 40 draws to obtain the expected profit for each combination of flight segments.

However, slot divestitures are not necessarily good for everyone. For example, consumers in the "Segment Removed" markets will be negatively affected by the divestitures. The products of NewAA in those markets are no longer available as the firm exits the markets and redistributes its relatively scarcer slots to other more profitable segments. This leads to a consumer surplus loss in those markets. Additionally, there is no guarantee that slot purchasers will enter segments to serve the overlapping markets(i.e., the markets in which the merging firms were duopolists pre-merger). In the last panel of the Table 2.2, the consumer surplus in the overlapped markets tends to stay negative. This is because Southwest would prioritize entering more profitable segments over entering the segments related to the overlapped markets. The model predicts that the carrier would enter all the overlapped markets when it has abundant slots (20% slot divestiture case).

The potential concern that slot purchasers may not serve overlapped markets motivates an alternative merger policy. What if, as a condition for buying slots,

Figure 2.2: Post-merger Outcomes (*Baseline*) Using Heuristic Search



I use 20 draws for each set to compute the expected variable profits and to find the equilibrium. Then, I use 25 sets to calculate the 95% confidence interval of surpluses.

the antitrust authorities require a slot purchaser to serve a set of flight segments? Table 2.3 shows the comparison of consumer/producer surplus in the case in which Southwest is required to enter those overlapped markets vs. the case in which it is not required to enter the markets. Compared to the Baseline (B) where there is no government intervention (same numbers in the *Baseline* case), when Southwest is forced to enter the Nashville and Durham segments, there are consumer surplus gains and producer surplus losses. Consumers in the overlapped markets will be better off in this intervention. In terms of producer surpluses, as the slot purchaser would have been more profitable if it were freely choosing segments, its profit under the intervention would be lower than in the baseline case.

Next, I examine the extent to which surpluses change as the amount of divested slots increases in Figure 2.2 using the heuristic approach. For this figure, ten endogenous flight segments for NewAA, Southwest and JetBlue shown in Table 2.1 are used. For each set of 20 draws of demand and marginal cost unobservables, I calculate the expected profit, and 25 sets are used to obtain the confidence intervals of surpluses, as each set may have a different equilibrium flight segment choice.

As the slot divestiture ratio increases, consumer and produce surpluses tend to go in the opposite directions. On the one hand, consumer surplus tend to increase in slot divestiture as in Figure 2.2 because of those new flight segments initiated by slot purchasers and of the existing products getting cheaper from a relaxed capacity constraint. The increase in market competition allows consumers to be better off. On the other hand, the model predicts that the NewAA would have less seats and its capacity constraint is likely to be binding, as there are more slots to be divested. This leads to a profit loss of the NewAA, and this loss outweighs the profit gains by slot purchasers. Last, the total surplus, i.e., the sum of the consumer and producer surpluses, is provided in this analysis which helps understand the merger effect as a social planner's point of view. The total surplus in Figure 2.2, marked as the blue square, increase but is saturated for the higher ratio of slot divestitures.

My model fits the data well in terms of the post-divestiture flight segment entry decisions. In Table A.5, I list the actual new flight segments offered by Southwest and JetBlue post-divestitures (in regular font face) and the model predicted new segments (in bold font face) when using the heuristic search under the 15% slot divestitures scenario (the realized divestiture scenario). The table shows that, first, the list of new segments in the data highly overlaps with the list of marginally profitable flight segments in Table 2.1 (e.g. the matching rate is 80% for Southwest and 100% for JetBlue, respectively). Second, while there are more new segments in the data than what the model predicts, the proportion of correctly matching the new entry segments is high. For example, the proportion of the number of the model-predicted segments to the number of actual segments for Southwest and JetBlue is 70% and 60%, respectively. In terms of the flight segment exit decisions, we see clearly in the data that NewAA eliminated a set of small community-based flight segments post-divestiture (e.g. AGS, LIT, MYR, OMA, and TLH). However, the LIT and OMA segments are not considered endogenous segments in Table 2.1, and MYR is the only segment that the model correctly predicted. Potentially, the existence of commuter slots and how NewAA allocates those slots to small community-based segments can be attributed to this discrepancy between the model and data, given that the actually divested slots are regular not commuter slots.

2.3.2 Purchaser Type

While slots were solely granted to LCCs in *Baseline*, I explore the case where legacy carriers were considered as slot purchasers as a comparison. To do so, I assume that Delta and United take 60% and 40% of the divested slots and allow them to endogenously choose up to the first six and four flight segments in Table 2.1, respectively. Under the "Brute Force Search," Table 2.4 compares the merger simulation outcomes by slot purchaser types. When additional slots were granted to

Table 2.4: Post-merger Outcomes (*Purchaser Type*) Using Brute Force Search

Purchaser Type?	LCCs		Legacy Carriers	
Slot Divestitures Ratio?	10%	15%	10%	15%
All DCA Markets				
Price	-0.37%	-1.66%	0.66%	-0.04%
Passengers	0.42%	0.91%	-0.57%	-0.50%
Consumer Surplus	0.07(M$)	2.60(M$)	-6.97(M$)	-7.89(M$)
List of Flight Segments Added(+)/Removed(-)				
Merging Firm (-)	CAK MYR	CAK MYR TLH	CAK MYR	CAK MYR TLH
Southwest (+)	FLL TPA BNA MSY	FLL TPA BNA MSY MCI		
JetBlue (+)	PBI BDL JAX	PBI BDL JAX		
Delta (+)			MIA BOS FLL	MIA BOS FLL
United (+)				

Note that units in Post-merger columns are all relative to Pre-merger values. Overlapped markets to/from DCA include DCA⇒BNA, BNA⇒DCA, DCA⇒RDU, and RDU⇒DCA markets. The full airport names of those three-letter airport codes used in this table can be found in Table A.4.

them, carriers have heterogeneous preference on adding new flight segments, depending on their segment level demand and cost characteristics.

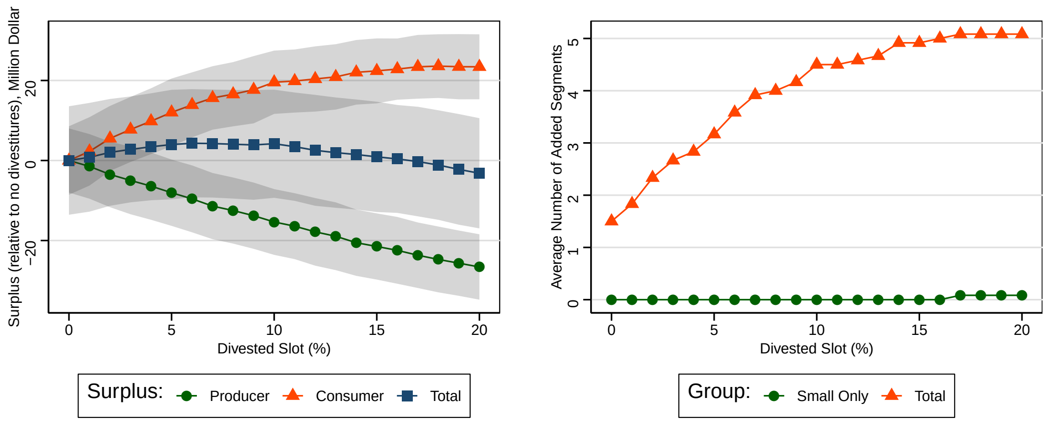
The model result does not suggest that the legacy carriers would serve small- or medium-sized communities from/to DCA, in contrast to Delta's claim. This is largely because the model predicts that the carrier would earn more profit by serving popular destinations such as Boston and Miami rather than small-sized communities. Interestingly, United would increase the frequency of the existing segments rather than open new segments, as its fixed cost to open a new segment is high. In addition, the results of the table suggest that for slot divestitures of both 10% and 15%, the overall consumer surplus under LCC purchasers are calculated to be larger than that under legacy purchasers.

The tendency of a legacy carrier to choose those segments related to big cities or leisure-based destinations over those segments related to small- medium-sized communities can be seen more clearly when using the heuristic approach as in Figure 2.3. For this figure, I assume that the NewAA's divested slots (15%) go to Delta, allowing the carrier to endogenously choose five big community-based segments from DCA (MCO, ORD, BOS, MIA, and FLL) and five small/medium community-based segments (IND, CMH, MKE, JAX, and BDL) that the carrier said it would be willing to enter if it were a slot purchaser in its complaint Gravath, Swaine & Moore LLP (2014). The left panel of the figure shows the surplus change as the amount of divested slots increases. The total surplus relative to the no divestitures case increases first but eventually decreases and goes below zero when the ratio of divested slots is high. In the right panel, the average number of newly added segments by Delta is reported. While the number of new segments increases in the ratio of slot divestitures, those new segments are mostly big community-based segments and the line "Small Only"—the average number of newly added small/medium community-based segments — is near zero for each divestiture considered.

2.3.3 Number of Purchasers

In this alternative divestiture scheme, I vary the number of slot purchasers, keeping the divested slots at 15% of the merging firms' total endowed slots, and assume that carriers as slot purchasers have the following orders of modifying their flight segment portfolio—Southwest, JetBlue, Delta, and United. While the number of endogenous flight segments of NewAA is kept as four (e.g. CAK, MYR, AGS,

Figure 2.3: Expected Post-merger Outcomes (*Purchaser Type*) Using Heuristic Search



(a) Surplus Changes

(b) Average Number of Added Segments

Note: I use 20 draws for each set to compute the expected variable profits and to find the equilibrium. The 95% confidence interval of surpluses in (a) is based on 25 sets of draws.

and TLH), the sets of endogenous segments of carriers other than NewAA vary in the number of slot purchasers—1) in the one-slot purchaser scenario, Southwest can choose ten segments in Table 2.1; 2) in the two-slot purchaser scenario, Southwest can choose five segments, and JetBlue can choose five segments; 3) in the three-slot purchaser scenario, Southwest can choose four, JetBlue three, and Delta three; and, 4) in the four-slot purchaser scenario, Southwest can choose three, JetBlue two, Delta two, and United two. Additionally, I assume that divested slots are evenly split among purchasers. For example, if there are three slot purchasers (Southwest, JetBlue, and Delta), each carrier takes a third of the divested slots.

Table 2.5 shows the simulated merger outcomes by varying the number of purchasers. In this result, the likely consumer surpluses (relative to pre-merger) in the four cases differ with a range of \$2.6(M) to \$7.4(M). More importantly, varying the number of slot purchasers leads to a distributional welfare effect on passengers, as

Table 2.5: Post-merger Outcomes (*Number of Purchasers*) Using Brute Force Search

Number of Purchasers?	One	Two	Three	Four
All DCA Markets				
Price	-2.21%	-1.66%	-2.31%	-2.20%
Passengers	1.19%	0.91%	1.34%	1.07%
Consumer Surplus	6.20(M$)	2.60(M$)	7.40(M$)	5.02(M$)
List of Flight Segments Added(+)/Removed(-)				
Merging Firm (-)	CAK MYR TLH	CAK MYR TLH	CAK MYR TLH	CAK AGS TLH
Southwest (+)	FLL TPA BNA MSY RDU PVD CMH JAX	FLL TPA BNA MSY MCI	FLL TPA MSY	FLL TPA
JetBlue (+)		PBI BDL JAX	PBI BDL	PBI BDL
Delta (+)			MIA BOS	MIA BOS
United (+)				

Note that the units in Post-merger columns are all relative to the Pre-merger values. The number of endogenous segments for each column is the following. i) 'One': Southwest 10 segments; ii) "Two": Southwest 5, and JetBlue 5; iii) "Three": Southwest 4, JetBlue 3, and Delta 3; and iv) "Four": Southwest 3, JetBlue 3, Delta 2, and United 2.

slot purchasers choose different sets of endogenous flight segments. If a few carriers buy the divested slots, there will be a reduction in fixed cost due to an increase in their endowed slot ratio at DCA, facilitating their entry into new flight segments. On the other hand, when more carriers become slot purchasers, carriers will focus on fewer segments where carriers find it the most profitable.

2.4 Conclusion

In this chapter, I perform a set of counterfactual exercises in which we analyze alternative slot divestitures scenarios by varying 1) the ratio of divested slots; 2) types of carriers who receive the slots; and 3) number of carriers granted the slots. The analysis suggests that while reasonable amount of divested slots can potentially recover overall consumer welfare post-merger, the divestitures may redistribute the consumer welfare across markets largely due to new entries and exits. Also, this redistribution may vary depending on the ratio of divested slots and which carriers receive slots.

Entry selection is not considered in these counterfactuals. Demand and marginal costs unobservables are assumed to be unknown to carriers in the first stage and the unobservables become known once carriers choose which flight segments to enter. While the assumption is taken from the literature (Eizenberg (2014), Fan and Yang (2018), Wollmann (2018)) to reduce the computational burden, it does not capture that carriers can self-select into entering a market and carriers may regret entering it. In the next chapter, however, my coauthors and I relax the assumption in a way that carriers know unobservables throughout the game and we explore the role of unobservables on entry selection and its implications on merger analysis.

Chapter 3: Repositioning and Market Power After Airline Mergers

3.1 Introduction

Market power created by a horizontal merger may be limited if it induces either new entry or existing rivals to reposition to compete more directly with the merging firms. Several court decisions at the end of the 1980s, including *Waste Management*, *Baker Hughes* and *Syufy*[1], indicated that ease-of-entry arguments could "trump" (Baker (1996)) anti-competitive concerns unless an agency opposing the merger could show that potential entrants would face higher entry barriers than the merging parties had overcome when they entered.

From an economic perspective, the entry barrier test was flawed because it did not examine whether entry or repositioning would be profitable, and therefore likely to happen, and whether, if either happened, prices would be prevented from rising. In response, since 1992, the *Horizontal Merger Guidelines* have laid out that the parties need to show that entry or repositioning will be "timely, likely and sufficient" to prevent prices from rising (Shapiro (2010), p. 65). While economists accept these criteria, they are rarely evaluated in a rigorous and quantitative way

[1] *United States v. Waste Management, Inc.*, 743 F.2d 976, 978, 983-84 (2d Cir. 1984), *United States v. Baker Hughes Inc.*, 908 F.2d 981, 988-89 (D.C. Cir. 1990) and *United States v. Syufy Enterprises*, 903 F.2d 659, 661 (9th Cir. 1990).

similar to how merger simulations are used to quantify likely price changes with a fixed set of products. Instead, as in the 1980s, court decisions and agency analysis continue to focus on barriers to entry or repositioning without clear connections to profitability or price effects.[2] In the spirit of the *Guidelines*, we present a framework for assessing the likelihood and the sufficiency of repositioning in the context of mergers in differentiated product markets.

Our empirical analysis examines service choices and competition in airline route markets, using a two-stage model where carriers first choose their service types (nonstop or connecting) and then choose prices. To understand the issues involved, consider a route where US Airways and American provide nonstop service, have large market shares and propose to merge, while Delta and Southwest provide lower quality connecting service. In the absence of synergies, the merger is likely to raise prices unless it creates a profitable opportunity for another carrier to launch nonstop service. We want to predict the probability that Delta or Southwest will launch nonstop service and how this would affect prices. Both calculations require making assumptions about the demand and marginal costs of products, such as nonstop service on Delta, that are not observed in the data. More specifically, even with an estimated model that relates demand and marginal costs to observables, we have to take a stand about the value of the demand and marginal cost residuals ("shocks") for these products that will affect prices, market shares and profits.

[2] For example, Coate (2008) describes the FTC's conclusions about the likelihood of entry in internal memoranda as lacking a "solid foundation" in the evidence, while Kirkwood and Zerbe (2009) classify only one of 35 post-1992 court opinions as reviewing the criteria in the *Guidelines* systematically. Some decisions, such as *Oracle* (331 F.Supp. 2d 1098 (N.D. Cal. 2004)) discuss new entry but are primarily decided on prior questions of market definition.

One approach to modeling positioning choices in the literature (for example, Draganska et al. (2009), Eizenberg (2014), Wollmann (2018) and Fan and Yang (2018)) is to assume that firms do not know these residuals when they make entry/positioning choices, either in the data or in counterfactuals. This assumption is computationally convenient, because it implies that carriers cannot select a service choice based on these residuals (i.e., a carrier cannot choose nonstop service because it would have particularly high (low) nonstop demand (marginal cost) residuals). On the other hand, it will often be implausible that firms do not have better information than researchers about the value of demand and marginal cost unobservables, and the assumption implies that firms may regret their predicted choices ex-post. This is an undesirable property when trying to predict whether repositioning could sustainably replace lost competition after a merger. More importantly, the assumption, while convenient, can really matter for what the researcher will predict will happen after the merger, a point which we illustrate using a computational example in Appendix A.[3]

We make the opposite assumption that carriers know the value of all of the demand and marginal cost unobservables when they make service choices, an assumption that we will label "full information".[4] The demand and marginal cost

[3]The Appendix example also illustrates the extent of regret when we assume that carriers make service choices without knowing their demand and marginal cost unobservables: for instance, for one particular market size, 48% of carriers that choose nonstop service would have realized higher profits if they had chosen connecting service. This happens even though the example assumes complete information (i.e., all carriers have the same information about expected payoffs) and sequential service choices so that, in equilibrium, each carrier knows which service choice other carriers will make.

[4]One could argue that a better specification would allow for firms to have better, but still imperfect, information than the researcher. Roberts and Sweeting (2013) and Bhattacharya et al. (2014) consider this type of specification for values in models of entry into auction, but it is difficult to adapt this type of approach to a setting where there is demand, marginal cost and fixed cost

equations and the service choice game are estimated simultaneously to account for how residuals may affect service choices. Our first contribution comes from showing how estimation can be done with a moderate computational burden. We use a simulated method of moments estimator where the moments of the model are approximated using importance sampling, following Ackerberg (2009). While Ackerberg's Example 2 explains how the method could be applied to this type of game, and the method has been used by Laffont et al. (1995), Roberts and Sweeting (2013) and Wang (2015), amongst others, we believe that we are the first to apply the method in the context of a discrete choice-and-price competition game with up to nine players and several player-specific unobservables.

Our second, and more novel, contribution comes from performing a set of merger simulations that allow for repositioning where we show how to account for the selection on unobservables implied by pre-merger service choices. Merger simulations with fixed products assume that products will have the same demand and marginal cost unobservables in the post-merger environment that they have in the pre-merger data. We extend this logic by assuming that the same applies to unobservables for product-types that firms chose not to offer in the data. We form distributions of unobservables that are consistent with ("conditioned on") pre-merger service choices, as well as pre-merger prices and market shares, and we illustrate how this type of conditioning affects our predictions of likelihood and sufficiency.

Our counterfactuals consider three mergers that were completed after the period of data that we use to estimate the model (Q2 2006) and one merger, between

heterogeneity.

United and US Airways, that was proposed but blocked in 2001. In each case, we focus on markets where the merging parties were nonstop duopolists. We find that when we condition on pre-merger service choices, our predictions match what actually happened after completed mergers: specifically, with conditioning, we predict that rivals should launch nonstop service on 18% of routes, whereas they are observed to do so on 25% of routes within two years of the merger. In contrast, if we do not condition on pre-merger service choices, we would predict three times as many nonstop launches, even though our estimates imply that observable variables explain much of the heterogeneity in prices and market shares. The intuition behind our results is straightforward: when firms know demand and marginal costs in different types of service they will tend to select into the service type where they will be most competitive. When we condition on these choices, we will tend to become more pessimistic about how competitive they will be if they offered other types of product, decreasing the likelihood that repositioning will be profitable and that the merged firm's prices will be constrained. This is consistent with a common antitrust agency argument that courts should be skeptical that rivals will reposition after a merger when they have chosen not to do so previously (Baker (1996), p. 364). Conditioning also tends to make mergers themselves appear to be significantly more profitable.

Before briefly discussing related literature, we briefly note several features of our model. First, our model is static rather than dynamic. This is consistent with the two or three year focus of typical merger analyses (Carlton (2004)) and the types of analyses that are presented in actual cases, but it means that we cannot speak directly to the "timely" criterion in the *Guidelines*. Aguirregabiria and Ho (2012) and Benkard et al. (2018) provide dynamic models of changes in airline networks without accounting for selection. Second, in common with almost all airline papers, we will take the underlying structure of each airline's network (e.g., where it has its major domestic and international hubs) as given, even though mergers can result in hubs, such as Continental's hub in Cleveland, being eliminated.[5]

Third, we focus on the possibility that connecting rivals will launch nonstop service after mergers rather than modeling new entry. An earlier working paper, Li et al. (2015), estimated a model with both service choice and entry margins. Performing counterfactuals with both margins was computationally burdensome, partly because, as we note below, observed variables have limited ability to explain which connecting carriers have enough passengers to meet standard thresholds for counting as an entrant. The reader should recognize, however, that our approach to estimation and counterfactuals can be applied to binary enter/do not enter decisions in any market with a well-defined set of potential entrants (illustrated by Monte Carlos in Li et al. (2018)), as well as repositioning choices. Fourth, we do not model choices of route-level capacity or schedules, or how carriers manage revenues by choosing multiple prices for passengers on the same route. Including these choices would be an interesting extension. Finally, our baseline assumption will be that service choices are made sequentially, which guarantees a unique equilibrium.

[5] There are likely to be substantial sunk costs involved in creating hubs, which mean that it is difficult to analyze de-hubbing decisions using a static model. For example, United is locked into paying over $1.1 million/month in rent for Concourse D at Cleveland until 2027 (`https://www.cleveland.com/cityhall/2014/02/what_will_become_of_concourse.html`). Our static approach assumes that adding incremental airport-to-airport nonstop routes out of airports where they already operate may involve non-trivial fixed costs, but not large sunk costs, which is broadly consistent with carriers only offering nonstop flights seasonally on some routes, although this is not true for the relatively large routes in our sample.

This is a convenient but potentially controversial assumption given that much of the literature has assumed simultaneous moves and designed econometric methods for estimating games where there may be multiple equilibrium outcomes. We will discuss this assumption and explain why it does not affect our results, given our focus on service choices, in Section 3.5.

Section 3.2 details our model. Section 3.3 describes the data used in estimation and observed changes after mergers. Section 3.4 outlines the estimation procedure, with complete details in the online Appendices. Section 3.5 presents the parameter estimates, model fit and what the estimates imply for selection. Section 3.6 presents the method and the results of the counterfactuals. Section 3.7 concludes.

Related Literature

The Civil Aeronautics Board and the Department of Transportation approved many airline mergers in the 1980s, explicitly using arguments that entry or repositioning would prevent incumbents from behaving anticompetitively (Keyes (1987)). Fisher (1987) and Schmalensee (1987) used airlines as examples when discussing how entry and repositioning should be considered in merger analysis. A reduced-form literature has estimated how mergers affected prices after these mergers (summarized in Ashenfelter et al. (2014)) and more recent ones (Hüschelrath and Müller (2014), Hüschelrath and Müller (2015), Israel et al. (2013) and Carlton et al. (2017)). These retrospectives typically find that prices increased, but the results are sensitive to the chosen control group and time-window.[6] Surprisingly, these analyses have not quantified post-merger entry or repositioning by rival carriers and how repositioning relates to price changes[7], and there are also no retrospective studies analyzing whether post-merger repositioning has constrained prices in other industries. We will present some results on what happens after recent mergers in Section 3.3, but our primary contribution comes from providing a model that can rationalize the observed changes allowing for alternative assumptions that can be made about what a merger actually does (for example, whether the merged firm will receive the best demand and marginal cost draws of the merging parties). Our ability to match post-merger repositioning and prices changes contrasts with Peters (2006) who found that merger simulations with fixed products could not explain what happened after mergers in the 1980s.

The early literature on models of entry and product positioning (for example, Berry (1992), Ciliberto and Tamer (2009) and Seim (2006)) used reduced-form payoff specifications without modeling price competition explicitly. Subsequent papers that have modeled competition (for example, Draganska et al. (2009), Eizenberg (2014), Wollmann (2018) and Fan and Yang (2018)), often motivated by merger counterfactuals, have assumed that firms do not know the value of unobservables, but only their distributions, when making entry or positioning choices. This allows the demand and marginal cost equations to be estimated separately from the service choice game, because the expected value of the unobservables should not depend on

[6] For example, Borenstein (1990), Werden et al. (1991), Morrison (1996) and Peters (2006) find different signs for price effects after the 1986 TWA/Ozark and Northwest/Republic mergers.

[7] Hüschelrath and Müller (2015) provides an analysis of entry in airline routes but without tying entry to pre-merger market structures.

the observed choice. Counterfactuals are performed by taking draws of demand and cost residuals for new types of product from their estimated distributions. We are not aware of previous work considering how counterfactual predictions depend on whether shocks are known, which is why we provide a comparison using a detailed example in Appendix A.

Two papers have estimated models using a full information assumption and both papers also have airline applications. Reiss and Spiller (1989) estimated a model of service choice and price competition among carriers, recognizing "that entry introduces a selection bias in equations explaining fares or quantities" (p. S201). They simplified their analysis by imposing symmetry and allowing for at most one nonstop carrier, restrictions we relax.

Ciliberto et al. (2018) (CMT), developed contemporaneously with our paper, estimate a model of route-level competition where carriers decide whether to *enter*, with no distinction between service types, and then compete on prices. There are, however, important differences between the papers. CMT's focus is on identification and estimation. They propose a nested fixed point estimator which allows for multiple equilibria in a simultaneous move entry game. The resulting discontinuous objective function based on moment inequalities has to be minimized on a supercomputer. They perform counterfactuals without conditioning on the entry choices observed in the data. In contrast, our focus is on the effects of accounting for selection in counterfactuals that try to evaluate mergers based on the criteria laid out in the *Guidelines* and on explaining what is observed after actual mergers. We emphasize the design and results of our counterfactuals, rather than estimation, partly because the parameters used in merger analyses will often come from documents or testimony. We also focus on service choices because the evidence suggests that it is nonstop carriers that are typically able to exert market power.

3.2 Model

We model carrier choices at the route-market level, with a market, m, connecting two airports A and B. Carriers $i = 1, ..., I_m$ play a two-stage game, first choosing to provide nonstop or connecting service (a binary and mutually exclusive choice) and then simultaneously choosing prices.

3.2.1 Second Stage: Post-Entry Price Competition

Given service choices, carriers play static, simultaneous Bertrand Nash pricing games for passengers originating at each endpoint. We model directional demand and pricing on each route, as a carrier's presence at the origin clearly affects a carrier's market share.[8]

Demand is determined by a nested logit model, with all carriers in a single nest. For consumer k originating at endpoint A of route m, the indirect utility for

[8]Presence is defined by the number of nonstop routes that a carrier serves from an airport, divided by the number of nonstop routes served by any carrier. Reduced-form analysis indicates that presence has large effects on demand. For example, in a route fixed effects regression, a one standard deviation increase in the difference in a carrier's presence across the endpoints increases the difference in the carrier's directional market shares by 20% of the average directional share, which may reflect frequent-flyers preferring to travel on one carrier. Differences in origin presence also have significant, although smaller, effects on directional differences in average fares (Luttmann (2019)).

a return-trip on carrier i is

$$u_{kim}^{A\to B} = \beta_{im}^{A\to B} - \alpha_m p_{im}^{A\to B} + \nu_m + \tau_m \zeta_{km}^{A\to B} + (1-\tau_m)\varepsilon_{kim}^{A\to B} \tag{3.1}$$

where $p_{im}^{A\to B}$ is the price charged by carrier i for a return trip from A to B. The first term represents carrier quality associated with i's service type (CON for connecting and NS for nonstop), $\beta_{im}^{A\to B} = \beta_{im}^{CON,A\to B} + \beta_{im}^{NS}$ x $\mathcal{I}(i \text{ is nonstop})$ with $\beta_{im}^{CON,A\to B} \sim N(X_{im}^{CON}\beta_{CON}, \sigma_{CON}^2)$ and $\beta_{im}^{NS} \sim TRN(X_{im}^{NS}\beta_{NS}, \sigma_{NS}^2, 0, \infty)$, so that quality can depend on observed carrier-origin and route characteristics, and on a random component (the demand shock in the language of the introduction) that is unobserved to the researcher. TRN denotes a truncated normal distribution and the lower truncation of β_{im}^{NS} at zero implies that the nonstop service is always preferred to connecting service on the same carrier. The use of importance sampling to estimate the model will require some additional support restrictions that will be described in Section 3.4. The price coefficient and nesting parameters are heterogeneous across markets, with $\alpha_m \sim N(X^\alpha\beta_\alpha, \sigma_\alpha^2)$, where X^α will include the business index for the route, and $\tau_m \sim N(\beta_\tau, \sigma_\tau^2)$, although we will assume that α_m and τ_m are the same across directions in the same market. ν_m, distributed $N(0, \sigma_{RE}^2)$, is a route-specific random effect in demand. This is designed to capture the fact that on some routes more travelers are observed in both directions on several carriers than a model with independent quality shocks can rationalize given our market size definition, which is described in Section 3.3. $\varepsilon_{kim}^{A\to B}$ is a standard logit error for consumer k and carrier i.

Each carrier has a marginal cost draw for each type of service, $c_{im} \sim N(X_{im}^{MC}\beta_{MC}, \sigma_{MC}^2)$, where $X_{im}^{MC}\beta_{MC}$ allows costs to depend on the type of carrier, the type of service and the distance traveled. For nonstop service we measure distance as the nonstop distance, and for connecting service we use the distance via the connecting carrier's closest domestic hub.[9] The marginal cost is non-directional as the representative traveler is assumed to make a round-trip.

Our assumptions of nested logit demand, linear marginal costs and single product firms imply that there will be unique equilibrium prices and directional variable profits, $\pi_{im}^{A\to B}(s)$, given service choices, cost and quality draws (Mizuno (2003)). i's market-level variable profits are $\pi_{im}(s) = \pi_{im}^{A\to B}(s) + \pi_{im}^{B\to A}(s)$, as service choices are assumed to be the same in both directions.

3.2.2 First Stage: Service Type Choices

In the first stage carriers choose whether to commit to a fixed cost required for nonstop service, or to provide connecting service. For our baseline estimation, we model carriers as making their service choices *sequentially* in order of their average presence (see footnote 8 for the definition) at the endpoints. Their realized profits in the full game are therefore $\pi_{im}(s) - F_{im}$ x $\mathcal{I}(i \text{ is nonstop in } m)$ where F_{im} is a fixed cost draw associated with providing nonstop service. We assume that $F_{im} \sim TRN(X_{im}^F\beta_F, \sigma_F^2, 0, \infty)$. The exact values of all market-level and carrier-level demand, marginal cost and fixed cost draws are known to all carriers when

[9] For the composite Other Legacy and Other Low Cost carriers it is not straightforward to assign connecting routes. Therefore we use the nonstop distance for these carriers, but include additional dummies in the connecting marginal cost specification to provide more flexibility.

service choices are made.

F should be interpreted as a net effective fixed cost. Providing nonstop service involves committing gates and planes to a route, and these costs are fixed costs. However, a carrier generates additional profits, in the form of connecting passengers going to or from other destinations when it provides nonstop service, and we want F to reflect these additional benefits, which is why we include our connecting traffic and network variables in X_{im}^F.[10]

Sequential choice ensures the existence of a unique subgame perfect Nash equilibrium, and, coupled with the assumed order, it guarantees a unique predicted outcome for the whole game. The known sequential order is a strong assumption, but we will show that our results are robust to alternative assumptions, including the possibility that choices are simultaneous or are made sequentially but in an unknown order.

3.2.3 Solving the Model

Conditional on service choices, we solve for Nash equilibrium prices, shares and profits by solving the system of pricing first-order conditions in the usual way. One can solve for the outcome of the sequential service choice game by solving for profits given all possible combinations of service choices and then using backwards induction. However, as we describe in Appendix B.2.1, we solve for the equilibrium outcome more efficiently by *selectively growing the game tree forward*, ignoring

[10] Our specification does require that the net fixed cost is positive as this reduces the range of the importance draws that we need to take. We show that this does not prevent us from accurately matching service choices at major hubs.

branches involving dominated choices.

3.2.4 Selection and Correlation in the Unobservables

Our baseline assumption is that the various demand, marginal cost and fixed cost shocks are independent, although our market random demand effect can create cross-carrier correlations in demand. Selection arises from the fact that, under our information assumptions, carriers choosing connecting service will tend to have worse (lower quality/higher cost) nonstop unobservables and may also tend to face nonstop rivals with better nonstop unobservables. We show how accounting for this type of selection affects our counterfactuals, and we allow for it by estimating the demand, pricing and service choice models simultaneously. Richer correlations between service choices, demand and marginal cost unobservables could arise if the unobservables were themselves correlated. We allow for some restricted covariances in our robustness checks, and find that the estimated covariances are small and statistically insignificant. In contrast, as we note below (see footnote 23), observed variables generate quite strong correlations between a carrier's demand when it provides nonstop service and its costs from doing so.[11]

[11]CMT do allow for a more flexible covariance structure although with no cross-carrier correlations, and they estimate that some of the covarinaces are large. This may reflect the fact that their model does not allow for any differences between nonstop and connecting service which we explicitly model as having different demand and costs.

3.3 Data and Empirical Setting

We estimate our model using a cross-section of publicly-available DB1 (a 10% sample of domestic itineraries) and T100 (records of flights between airports) data for the second quarter of 2006. We use 2006 data so we can make predictions about subsequent mergers and avoid later years when carriers have been alleged to price cooperatively (Ciliberto and Williams (2014)). Appendix B.1 provides additional detail and analysis.

Market Selection and Carriers. We use data for 2,028 airport-pair markets linking the 79 busiest US airports in the lower 48 states. Excluded routes include short routes and routes where nonstop service is limited by regulation. We model seven named carriers, American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, Southwest Airlines (a low-cost carrier, LCC), United Airlines and US Airways, aggregating other ticketing carriers into composite "Other Legacy" (e.g., Alaska Airlines)[12] and "Other LCC" (e.g., JetBlue and Frontier) carriers. We attribute tickets and flights to mainline ticketing carriers when they are operated by regional affiliates.

Service Types, Market Shares and Prices. We define the competitors on a route as carriers ticketing at least 20 DB1 passengers and with at least a 1% share of traffic (a one-way passenger counts as half a return passenger). We define a carrier as

[12]Legacy carriers are carriers founded prior to deregulation in 1978, and they typically operate through hub-and-spoke networks. Our classification of carriers as LCCs follows Berry and Jia (2010).

nonstop if it has at least 64 T100 nonstop flights (5 flights per week) in each direction and at least 50% of its DB1 passengers do not make connections. The remaining competitors are classified as connecting. The exact level of these thresholds has little effect on our classification. We model carriers as providing either connecting or nonstop service, not both. While it is, of course, possible to travel between main pairs of airports either nonstop or making a connection on a single carrier, the assumption is consistent with the fact that when a carrier offers nonstop service it is usual for the vast majority of its passengers to use the nonstop service.[13]

A carrier's market share is calculated as the total number of passengers that it carries, regardless of service type, divided by a measure of market size. We define market size using an estimated gravity model (see Appendix B.1.1 and Sweeting et al. (ming)), accounting for total enplanements and route distance. This measure is a better predictor of service choices, and it reduces unexplained heterogeneity in market shares across routes and directions, compared with more common measures based on average MSA populations. We measure a carrier's price as the average round-trip price in DB1. A measure of the proportion of business travelers on a route is constructed based on data provided by Severin Borenstein (Borenstein (2010)).

Network Variables. We model route-level competition but recognize that network considerations affect service choices. For instance, a carrier may find it profitable to serve a segment nonstop because this generates traffic to other destinations. We

[13]For instance, less than 10% of passengers make connections for 80% of our nonstop carriers.

Table 3.1: Summary Statistics for the Estimation Sample

	Numb. of Obs.	Mean	Std. Dev.	10^{th} pctile	90^{th} pctile
Market Variables					
Market Size (directional)	4,056	24,327	34,827	2,794	62,454
Num. of Carriers	2,028	3.98	1.74	2	6
Num. of Nonstop	2,028	0.67	0.83	0	2
Total Passengers (directional)	4,056	6971	10830	625	17,545
Nonstop Distance (miles, round-trip)	2,028	2,444	1,234	986	4,384
Business Index	2,028	0.41	0.09	0.30	0.52
Market-Carrier Variables					
Nonstop Indicator	8,065	0.17	0.37	0	1
Price (directional, round-trip \$s)	16,130	436	111	304	581
Share (directional)	16,130	0.071	0.085	0.007	0.208
Airport Presence (endpoint-specific)	16,130	0.208	0.240	0.038	0.529
Indicator for Low Cost Carrier	8,065	0.22	0.41	0	1
≥ 1 Endpoint is a Domestic Hub	8,065	0.13	0.33	0	1
≥ 1 Endpoint is an International Hub	8,065	0.10	0.30	0	1
Connecting Distance (miles, round-trip)	7,270	3,161	1,370	1,486	4,996
Predicted Connecting Traffic (at domestic hubs)	1,036	8,664	7,940	2,347	52,726

capture these incentives by allowing the effective fixed cost of nonstop service to vary with whether the endpoints include one of the carrier's domestic or international hubs, and, for domestic hub routes, with a continuous estimate of the quantity of connecting traffic that will be generated by nonstop service. The construction of this variable is detailed in Appendix B.1.2, and while its calculation is not completely consistent with the strategic structure of our model, it helps to explain service choices and it may approximate the type of measure that carriers use internally to predict connecting passenger flows on new routes.

Table 3.2: Distribution of Market Structures in the Estimation Sample

Number of Nonstop Competitors	Number of Sample Markets	Percentage of Sample Passengers	Average Number of Connecting Carriers
0	1,075	15.0%	3.98
1	614	33.6%	2.91
2	277	35.5%	2.07
3	60	15.2%	1.25
4	2	0.10%	0

3.3.1 Patterns in the Data

Market Structure and Service Types. Table 3.1 shows that markets have an average of four carriers, with as many as nine on long routes, such as Orlando-Seattle, with many plausible connecting airports. Most markets have no nonstop carriers but most passengers travel in markets with at least two nonstop competitors (Table 3.2). These markets will be the focus in our counterfactuals. Most of these routes connect large cities or hub airports, but non-hub pairs such as Boston-Raleigh and Columbus-Tampa are also duopolies.[14]

The data clearly suggests that nonstop service has higher quality and that service choices affect competition. Nonstop fares are $43 higher than connecting fares and, based on our market definition, the average market share of a nonstop carrier is 18% compared to 4.9% for a connecting carrier (small connecting carriers are already excluded). Controlling for route characteristics, one nonstop carrier lowers connecting fares by $10, and a second nonstop carrier lowers nonstop fares by $40 and connecting fares by an additional $30.[15] LCC fares are, on average,

[14]If we had defined markets using city-pairs, rather than airport-pairs, there would still be 192 duopolies (out of 1,533 city-pair markets), with 90 city-pair markets having three or more nonstop carriers.

[15]These estimates are from regressions of a carrier's weighted (across directions) average fare on

$70 lower than legacy fares, consistent with lower costs and/or quality. We also find that our observed market and market-carrier variables are able to accurately predict service choices for the majority of carriers in the data (see Section 3.4 and Appendix B.3 for more details and discussion).

Full Information. We assume that carriers know their demand and costs when making service choices. There is some evidence in favor of this assumption in the data. If, instead, carriers could only learn demand and costs by offering a particular type of service, then, absent large sunk costs of providing nonstop service on incremental routes, we might expect to commonly observe carriers offering nonstop service for a few quarters before giving up once they realize it is unprofitable. To test this, we have identified all cases where the named carriers added nonstop service, other than through mergers, after Q1 2001 but before 2006, and then followed their service choices over subsequent years. On average, these carriers maintained nonstop service for 27 consecutive quarters, which seems too long to be consistent with experimentation given that the industry received several negative and large demand shocks during these years.

What Happened To Service and Prices After Legacy Mergers? We use our model to predict price and service changes after the Delta/Northwest (closed October 2008), United/ Continental (October 2010) and American/US Airways (December 2013) mergers completed after our data. Appendix B.1.3 uses panel data to estimate what

a route on nonstop distance, carrier dummies, a dummy for whether the carrier provides nonstop service and interactions between whether a carrier provides nonstop service and the number of nonstop carriers on a route.

actually happened after these mergers.

On routes where the merging carriers were nonstop duopolists, the merging parties always maintained nonstop service. Within two years of the merger closing (the Department of Transportation explicitly used two years when considering repositioning (Keyes (1987)), a rival launched nonstop service on no routes, out of five, for Delta/Northwest, one route, out of five, for United/Continental and three routes, out of six, for American/US Airways.[16] There were two additional nonstop launches in the third years following these mergers. The Appendix also presents analyses of changes in the prices and market shares of the merging firms on routes where the merging firms were nonstop duopolists for three years before the merger, using a comparison set of routes where one of the parties was nonstop and the other was either absent or a connecting carrier with a small share.[17] On routes where no rivals initiated nonstop service, we find that the merged carrier increased its prices by an average of 10%, with its number of local passengers (i.e., those only flying the route itself) falling by almost 30%. On routes where rival nonstop service was launched, prices did not rise, although the merged firm did lose market share, presumably reflecting the new competition. These patterns suggest that rivals tend not to launch nonstop service because they are poorly matched to providing nonstop service in these markets, rather than because the merged carrier enjoys large synergies. Our baseline counterfactual assumptions will assume that synergies are not realized, but we will show that an alternative assumption has only small effects

[16]There is no overlap in the routes across these mergers.

[17]We recognize that results for price changes may be affected by using different control groups, as suggested by the contrasting results in Hüschelrath and Müller (2015) and Carlton et al. (2017) for recent mergers.

on our predictions.

3.4 Estimation

This section describes the method for estimating the model parameters $\Gamma = (\beta, \sigma)$. Some additional details, including a discussion of the performance of algorithm and tests of whether the assumptions required for importance sampling to consistently estimate the moments of the model, are provided in Appendix B.2.

We minimize a simulated method of moments objective function

$$h(\Gamma)' W h(\Gamma)$$

where W is a weighting matrix, and $h(\Gamma)$ is a vector of moments where each element has the form $\frac{1}{2{,}028} \sum_{m=1}^{m=2{,}028} \left(y_m^{data} - E_m\widehat{(y|\Gamma, X_m)} \right) Z_m$, where the subscript m represents a market. y_m^{data} are observed outcomes and Z_m are a set of observed exogenous variables that serve as instruments. $E_m\widehat{(y|\Gamma, X_m)}$ are the predicted outcomes of the model for market m given the parameters Γ. We describe the moments (outcomes and instruments) that we use before describing how we compute $E_m\widehat{(y|\Gamma, X_m)}$.

Table 3.3 details how we form moments using prices, market shares and service choices defined at the market or market-carrier level. For example, market outcomes include weighted average connecting and nonstop prices in each direction, and the sum of squared market shares and the squared number of nonstop carriers. Market-carrier outcomes include a specific carrier's price and market share in each direction and an indicator for whether it provides nonstop service. The Z variables can

Table 3.3: Number of Moments Used in Estimation

Exogenous Variables (Z)	Market Level (y_M) Endogenous Outcomes 7 outcomes	Market-Carrier Level (y_C) Endogenous Outcomes 5 per carrier	Row Total
Market-Level Variables (Z_M) (7 per market)	49	315	364
Carrier-Specific Variables (Z_C) (up to 5 per carrier)	280	200	480
"Other Carrier"-Specific Variables (Z_{-C}) (5 per "other carrier")	315	225	540
Column Total	644	740	1,384

Notes: Z_M = {constant, market size, market (nonstop) distance, business index, number of low-cost carriers, tourist dummy, slot constrained dummy}
Z_C = {presence at each endpoint airport, our measure of the carrier's connecting traffic if the route is served nonstop, connecting distance, international hub dummy} for named legacy carriers and for Southwest (except the international hub dummy). For the Other Legacy and Other LCC Carrier we use {presence at each endpoint airport, connecting distance} as we do not model their connecting traffic. Carrier-specific variables are interacted with all market-level outcomes and carrier-specific outcomes for the same carrier.
Z_{-C} = {the average presence of other carriers at each endpoint airport, connecting passengers, connecting distance, and international hub dummy} for each other carrier (zero if that carrier is not present at all in the market).
y_M = {market level nonstop price (both directions), connecting price (both directions), sum of squared market shares (both directions), and the square of number of nonstop carriers}.
y_C = {nonstop dummy, price (both directions), and market shares (both directions)} for each carrier.

be divided into three groups: market-level variables (such as population, nonstop distance and the business index), the exogenous characteristics of individual carriers (such as their presence at each endpoint airport, and the distance of the connecting service), and variables that measure the exogenous characteristics of other carriers that are in the market (e.g., Delta's presence at the endpoint airports when we are looking at an outcome for a carrier other than Delta). We will describe how our results are robust to varying the set of moments used in estimation in Section 3.5.2.

Identification. We are not specifying moment conditions based on the orthogonality of structural residuals, such as an unobserved demand characteristic, precisely because the selection implied by our model means that standard conditions may not hold. Instead, we aim to match outcomes that are predicted when our entire model is solved and simulated to the observed outcomes in the data, minimizing correlations between our prediction errors and variables that are treated as exogenous and are allowed to affect demand, marginal costs or fixed costs. However, intuitive correlations will still identify the value of particular parameters. For example, suppose that fares tend to be higher and nonstop carriers have higher market shares in markets with a higher value of the business index. This is consistent with the business index reducing the absolute value of the price coefficient in the demand equation, while increasing the value of customers' preferences for nonstop service. Similarly, passenger preferences for carrier presence will be identified by differences in market shares, and potentially prices, across originating airports with different levels of presence (see footnote 8). The σ parameters that measure variances in cross-market and cross-carrier unobserved heterogeneity will be identified not only by unexplained variation in market shares and prices across carriers, but also by the included second moments such as the sum of squared market shares for all carriers and the square of number of nonstop carriers.

Our specifications also make exclusion restrictions that will provide identification. In particular, they provide an intuitive explanation for how the selection problem is overcome. Specifically, the network variables (for example, the hub dummies and the measure of generated connecting traffic) are only allowed to enter the fixed cost equation, and they provide variation in the identity and number of nonstop carriers that facilitates identification of the demand and marginal cost parameters through the effect of nonstop service on market shares and prices. As we show in Appendix B.3 and discuss in Section 3.5.2, these fixed cost shifters and market characteristics, such as market size, can almost entirely determine service choices for a large proportion of carriers and markets in the data (in the sense that predicted probabilities of nonstop service are very close to zero or very close to one). When these carriers make their predicted choices, there should be almost no selection on unobserved demand and cost shocks, implying that conventional identification arguments for the identification of demand and marginal cost parameters should apply. This feature of the data helps to explain why our estimates of several model features, such as own-price demand elasticities, are consistent with earlier work that has ignored the selection problem. However, as we shall illustrate, this does not mean that one can ignore the selection problem when performing counterfactuals which are focused on the subset of carriers that are on the margin of finding nonstop service profitable.

Computation of the Moments Using Importance Sampling. Computing $E_m(y|\Gamma, X_m)$ by resolving many games each time a parameter is changed, as a nested fixed point algorithm would do, is computationally very expensive and would lead to a discontinuous objective function because of the discrete nature of service choices. We instead approximate $E_m(y|\Gamma, X_m)$ using importance sampling following Ackerberg (2009). The idea is straightforward. Denoting a particular realization of all of the draws as θ_m,

$$E_m(y|\Gamma, X_m) = \int y(\theta_m, X_m) f(\theta_m|X_m, \Gamma) d\theta_m$$

where $y(\theta_m, X_m)$ is the unique equilibrium outcome given our baseline assumptions. This integral cannot be calculated analytically, but we can exploit the fact that

$$\int y(\theta_m, X_m) f(\theta_m|X_m, \Gamma) d\theta_m = \int y(\theta_m, X_m) \frac{f(\theta_m|X_m, \Gamma)}{g(\theta_m|X_m)} g(\theta_m|X_m) d\theta_m$$

where $g(\theta_m|X_m)$ is an "importance density" chosen by the researcher.[18]

This leads to a two-step estimation procedure. In the first step we take many draws, indexed by s, from $g(\theta_m|X_m)$ and solve for the equilibrium outcome, $y(\theta_{ms}, X_m)$, for each of these draws. In the second step we estimate the parameters, approximating $E_m(y)$ using

$$E_m\widehat{(y|\Gamma, X_m)} = \frac{1}{S} \sum_{s=1}^{S} y(\theta_{ms}, X_m) \frac{f(\theta_{ms}|X_m, \Gamma)}{g(\theta_{ms}|X_m)}$$

where we only need to recalculate $f(\theta_{ms}|X_m, \Gamma)$ when the parameters change. The objective function is smooth because the $f(\theta_{ms}|X_m, \Gamma)$ densities are smooth in the parameters.

[18] Ackerberg describes his approach as requiring a "change of variables". The change is implicit in the way we have written down our model. For example, in a traditional entry model a firm's fixed cost might be written as $F_{i,m} = X_{i,m}\beta_F + u^F_{i,m}$, and a NFXP estimation routine would integrate over the distribution of the us. An importance sampling approach requires a change of variables by taking draws of $F_{i,m}$ rather than draws of $u^F_{i,m}$. This is consistent with how we wrote down the model in terms of random draws of costs (e.g., $F_{im} \sim TRN(X^F_{im}\beta_F, \sigma^2_F, 0, \infty)$) and qualities in the previous section.

Table 3.4: Description of g For the Final Round of Estimation

Market Draw	Symbol	Support	g
Market Random Effect	υ_m	[-2,2]	$N(0, 0.411^2)$
Market Nesting Parameter	τ_m	[0.5,0.9]	$N(0.634, 0.028^2)$
Market Demand Slope (price in \$00s)	α_m	[-0.75,-0.15]	$N(X_m^{\alpha}\beta_{\alpha}, 0.022^2)$
Carrier Draw			
Carrier Connecting Quality	$\beta_{im}^{CON,A\to B}$	[-2,10]	$N(X_{im}^{CON}\beta_{CON}, 0.219^2)$
Carrier Incremental Nonstop Quality	β_{im}^{NS}	[0,5]	$N(X_{im}^{NS}\beta_{NS}, 0.257^2)$
Carrier Marginal Cost (\$00s)	c_{im}	[0,6]	$N(X_{im}^{MC}\beta_{MC}, 0.173^2)$
Carrier Fixed Cost (\$m)	F_{im}	[0,5]	$N(X_{im}^{F}\beta_{F}, 0.234^2)$

Notes: where the covariates in the Xs are the same as those in the estimated model, and the values of the βs for the final (initial) round of draws are as follows: β_{α}.constant= -0.668 (-0.700), β_{α}.bizindex=0.493 (0.600), β_{α}.tourist= 0.097 (0.2), β_{CON}.legacy= 0.432 (0.400), β_{CON}.LCC= 0.296 (0.300), β_{CON}.presence= 0.570 (0.560), β_{NS}.constant= 0.374 (0.500), β_{MC}.legacy= 1.802 (1.600), β_{MC}.LCC= 1.408 (1.400), β_{MC}.nonstop_distance= 0.533 (0.600), β_{MC}.nonstop_distance^2 = -0.005 (-0.01), β_{MC}.conn_distance= 0.597 (0.700), β_{MC}.conn_distance^2 = -0.007 (-0.020), the remaining marginal cost interactions are set equal to zero, β_F.constant= 0.902 (0.750), β_F.dom_hub= 0.169 (-0.25), β_F.conn_traffic= -0.764 (-0.01), β_F.intl_hub= -0.297 (-0.55), β_F.slot_constr= 0.556 (0.700). In the initial round the standard deviations of the draws were as follows: random effect 0.5, nesting parameter 0.1, slope parameter 0.1, connecting quality 0.2, nonstop quality premium 0.5, marginal cost 0.15, fixed cost 0.25.

Choice of g and W. The use of importance sampling implicitly assumes that the importance densities $g(\theta_m|X_m)$ and the distributions assumed by the model $f(\theta_m|X_m,\Gamma)$ have the same supports which do not depend on Γ. As discussed by Geweke (1989), consistency of the importance sampling estimator also requires that g is sufficiently similar to f that the variance of $y(\theta_{ms}, X_m)\frac{f(\theta_{ms}|X_m,\Gamma)}{g(\theta_{ms}|X_m)}$ is finite. These considerations lead to a multi-round estimation approach, as recommended by Ackerberg (2009), where we specify wide supports for the demand and cost draws, including all values that we believe may be relevant.[19] In the first round we matched a subset of the price, share and service choice moments through straightforward

[19] The one exception to the rule of using wide supports is that we restrict the nesting parameter to lie between 0.5 and 0.9. This range covers most estimates from the existing literature (for example, Berry and Jia (2010) and Ciliberto and Williams (2014)). We experimented using the full range of [0,1], but found that the objective function often had local minima where the estimated nesting parameter was very close to 0 or very close to 1, but the fit of the moments was poor.

experimentation to provide us with the initial parameterization reported in the notes to Table 3.4, and we then ran two further rounds of estimation of the whole model, with the resulting estimates providing the $g(\theta_m|X_m)$ densities (reported in the table) that we use in the final round of estimation that produces the estimates reported in Section 3.5. The final round uses 2,000 importance draws for each market, with $S = 1,000$ used in estimation and samples from the full pool of 2,000 used when estimating standard errors using a bootstrap where markets are resampled. The computational burden is reasonable for academic research: solving 2,000 games for 2,028 markets takes less than two days on a medium-sized cluster, and the parameters are estimated in one day on a laptop without any parallelization.[20]

We form the weighting matrix by using the results from the penultimate round of estimation (where we use an identity weighting matrix). As the number of moments (1,384) is large relative to the number of observations (16,130 carrier-market-directions) estimates of the covariances of the moments are likely to be inaccurate, so our final round uses a diagonal weighting matrix, with equal total weight on the groups of moments associated with price, share and service choice outcomes and, within each group, the weight on each moment is proportional to the reciprocal of the variance of that moment from the penultimate round.

Table 3.5: Parameter Estimates: Demand

				(1) Independent Unobservables	(2) Correlation Specific. 1	(3) Correlation Specific. 2
Market-Level Parameters						
Random Effect	Std. Dev.	σ_{RE}	Constant	0.311	0.538	0.469
				(0.138)	(0.151)	(0.122)
Nesting Parameter	Mean	β_τ	Constant	0.645	0.634	0.640
				(0.012)	(0.013)	(0.015)
	Std. Dev.	σ_τ	Constant	0.042	0.005	0.050
				(0.010)	(0.010)	(0.008)
Demand Slope	Mean	β_α	Constant	-0.567	-0.542	-0.612
(price in $100 units)				(0.040)	(0.045)	(0.031)
			Business Index	0.349	0.189	0.435
				(0.110)	(0.118)	(0.088)
	Std. Dev.	σ_α	Constant	0.015	0.043	0.013
				(0.010)	(0.011)	(0.013)
Carrier-Level Parameters						
Carrier Quality for Connecting Service	Mean	β_{CON}	Legacy Constant	0.376	0.322	0.465
				(0.054)	(0.064)	(0.047)
			LCC Constant	0.237	0.336	0.150
				(0.094)	(0.086)	(0.094)
			Presence at Origin	0.845	0.674	0.524
				(0.130)	(0.125)	(0.127)
	Std. Dev.	σ_{CON}	Constant	0.195	0.208	0.201
				(0.025)	(0.027)	(0.028)
Incremental Quality of Nonstop Service	Mean	β_{NS}	Constant	0.258	0.192	0.560
				(0.235)	(0.214)	(0.221)
			Distance	-0.025	-0.057	-0.009
				(0.034)	(0.037)	(0.036)
			Business Index	0.247	0.841	-0.396
				(0.494)	(0.455)	(0.479)
	Std. Dev.	σ_{NS}	Constant	0.278	0.241	0.213
				(0.038)	(0.042)	(0.034)

Notes: standard errors, in parentheses, are based on 100 bootstrap replications where 2,028 markets are sampled with replacement, and we draw a new set of 1,000 simulation draws (taken from a pool of 2,000 draws) for each selected market. Distance is measured in thousands of miles. See Table 3.6 for estimates of the cost and covariance parameters.

Table 3.6: Parameter Estimates: Marginal Costs, Fixed Costs and Covariances

				(1) Independent Unobservables	(2) Correlation Specific. 1	(3) Correlation Specific. 2
Carrier Marginal Costs	Mean	β_{MC}	Legacy	1.802	1.350	1.847
($100 units)			Constant	(0.168)	(0.146)	(0.190)
			LCC	1.383	0.961	1.344
			Constant	(0.194)	(0.169)	(0.207)
			Conn. X	0.100	0.443	0.040
			Legacy	(0.229)	(0.211)	(0.251)
			Conn. X	-0.165	0.288	0.140
				(0.291)	(0.255)	(0.273)
			Conn. X	-0.270	-0.213	-0.228
			Other Leg.	(0.680)	(0.166)	(0.160)
			Conn. X	0.124	0.046	-0.173
			Other LCC	(0.156)	(0.152)	(0.167)
			Nonstop	0.579	0.823	0.510
			Distance	(0.117)	(0.101)	(0.128)
			Nonstop	-0.010	-0.044	-0.001
			Distance^2	(0.018)	(0.016)	(0.019)
			Connecting	0.681	0.661	0.675
			Distance	(0.083)	(0.096)	(0.091)
			Connecting	-0.028	-0.018	-0.026
			Distance^2	(0.012)	(0.013)	(0.013)
	Std. Dev.	σ_{MC}	Constant	0.164	0.191	0.143
				(0.021)	(0.016)	(0.018)
Carrier Effective	Mean	β_F	Legacy	0.887	0.897	0.855
Fixed Costs			Constant	(0.061)	(0.056)	(0.063)
($1m. units)			LCC	0.957	1.008	0.857
			Constant	(0.109)	(0.118)	(0.100)
			Dom. Hub	-0.058	-0.302	-0.205
			Dummy	(0.127)	(0.157)	(0.193)
			Log	-0.871	-1.000	-0.602
			$\widehat{\text{(Conn. Traff.)}}$	(0.227)	(0.207)	(0.257)
			Intl. Hub	-0.118	-0.144	-0.107
				(0.120)	(0.090)	(0.093)
			Slot Const.	0.568	0.424	0.514
			Airport	(0.094)	(0.099)	(0.085)
	Std. Dev.	σ_F	Constant	0.215	0.275	0.220
				(0.035)	(0.029)	(0.030)
Covariances	Incremental Nonstop Quality			-	0.012	0.018
	& Fixed Cost				(0.010)	(0.010)
	Connecting Quality			-	-	0.006
	& Connecting Marginal Cost					(0.007)

Notes: see notes below Table 3.5. The Log(Predicted Connecting Traffic) variable is zero for routes that do not involve a domestic hub, and for hub routes it is re-scaled with mean 0.52 and standard deviation 0.34.

3.5 Parameter Estimates

The first columns of Tables 3.5 and 3.6 present our baseline estimates. The demand coefficients confirm several expected patterns: all else equal, consumers prefer nonstop service, legacy carriers and carriers with greater originating airport presence. Demand is less elastic on routes with more business travelers.[21] The average own price demand elasticity is 4.25, and the elasticity of demand for air travel (i.e., when all prices rise by the same proportion) is 1.3, consistent with literature averages reported by Gillen et al. (2003). Implied diversion illustrates the preference for nonstop service: in markets with two nonstop carriers and at least one connecting carrier, a price increase by a nonstop carrier leads five times as many passengers, on average, to switch to the other nonstop carrier as switch to connecting carriers.

Marginal costs are lower on LCCs and increase with distance. To illustrate, consider the 3,000 mile round-trip Miami-Minneapolis route. For the named legacy carriers, the expected nonstop marginal cost is \$345, compared to an average of \$367 for (longer-distance) connecting service. Marginal costs for Southwest (and Other LCC) are lower and, for this route, Southwest's expected nonstop and connecting (via Chicago Midway) costs are almost identical (\$303 and \$298 respectively). The expected effective fixed cost of nonstop service is just over \$840,000, but the expectation is lower (\$610,000) for those carriers that choose nonstop service because hub status and connecting traffic can reduce effective fixed costs quite substantially: for example, a one standard deviation increase in connecting traffic offsets almost \$300,000 in fixed costs.

[20] In Roberts and Sweeting (2013) we bootstrap the entire multi-round procedure to calculate standard errors. In the current paper we are bootstrap the final stage, while acknowledging that the choice of g was informed by our initial attempts at estimation. See Li et al. (2018) for Monte Carlo evidence on how varying the gs affects the estimates.

[21] The expected price coefficient (α) for Dayton-Dallas-Fort Worth, which has the highest business index, is -0.34 compared to the cross-market average of -0.57.

3.5.1 Model Fit and the Role of Unobservables

To assess the model fit and the importance of different types of unobserved heterogeneity, we simulate 20 new sets of all of the demand and cost variables for each market from the estimated distributions. Observable variation accounts for the majority of variation in simulated costs: for example, the standard deviation (across all carrier-market simulations) of $F_{i,m}$ is \$301,912, and the standard deviation of $X^F_{i,m}\widehat{\beta_F}$ is \$259,481, so that the unobserved heterogeneity provides only 14% of the variation. Similarly, unobserved heterogeneity accounts for only 3% of the variation in marginal costs and 15% of the variation in the price sensitivity of demand. However, unobserved heterogeneity accounts for 26% of the variation in carriers' connecting quality and 34% of the variation in nonstop quality, while we also find that the random effect in market demand is quite large and statistically significant. These patterns suggest that accounting for selection on demand unobservables may affect our counterfactuals.[22]

We use the 20 sets of draws to assess how well our model predicts observed service choices (discussed here) and variation in prices and market shares across service types (discussed in Appendix B.2.4). We predict a carrier's observed service choice correctly for 87.5% of our draws (with standard error 1.1%). For 82.6% (2.2%) of observations where the majority of our simulations predict nonstop service, the carrier is nonstop in the data. Appendix Table C.1 shows that we accurately predict that carriers will serve most routes from their hubs nonstop: for example, we predict that Delta serves 92.5% (2.3%) of routes from Atlanta nonstop, compared to 96.5% in the data. We are also able to match service decisions at non-hub airports. To illustrate, Table 3.7 reports our service choice predictions for routes with Raleigh-Durham (RDU) as an endpoint. The model predicts the proportion of routes served nonstop accurately for each carrier. The prediction is least accurate for United, as

[22] Li et al. (2018) uses these draws to estimate several linear probability models to investigate how all of the observed and unobserved components of demand and costs affect equilibrium service choices. Consistent with the simpler breakdown presented here, observables explain the vast majority of variation in service choices, with demand unobservables playing a greater role than cost unobservables.

Table 3.7: Model Fit: Predictions of Service Decisions at Raleigh-Durham

	Number of Routes	Mean Presence at Route Endpoints	% Nonstop	
			Data	Simulation
American	44	0.29	22.7%	22.8% (1.6%)
Continental	30	0.14	10.0%	10.0% (1.0%)
Delta	57	0.24	8.7%	14.8% (1.9%)
Northwest	22	0.18	9.1%	11.0% (1.2%)
United	25	0.12	4%	14.4% (1.9%)
US Airways	54	0.12	5.6%	9.4% (2.7%)
Southwest	48	0.30	12.5%	14.5% (4.3%)
Other Low Cost	25	0.08	4%	13.4% (4.9%)

Notes: Predictions from the model calculated based on twenty simulation draws from each market from the relevant estimated distributions.

most of the simulations predict that United should serve Denver and San Francisco nonstop. United has launched nonstop service on both routes since 2006.

3.5.2 Robustness Checks

We now discuss what happens when we relax some of the assumptions imposed on our baseline estimates.

Correlations Between the Unobservables. Our baseline specification imposes that the unobserved components of carrier demand, marginal costs and fixed costs are independent, although the observed variables do imply some strong correlations among these elements of the model.[23] The main reason for excluding them from the model is to reduce the computational burden of estimating additional parameters when we do not find that allowing them improves the fit of the model. The second and third columns of Tables 3.5 and 3.6 present our estimates when we allow for correlations between the unobserved incremental quality of nonstop service and the fixed cost of providing nonstop service, and between connecting quality and connecting marginal costs. The estimated covariances are small, and only one of them is statistically significant at the 10% level.[24]

[23]For example, based on the 20 sets of draws used to examine model fit, the correlation between a carrier's nonstop quality and its fixed costs of nonstop service is -0.56.

[24]When we allow unrestricted correlations we tend to find that our estimator has additional local minima. We have used a grid search on the covariance parameters to confirm that values close to

Reduction in the Number of Moments. We estimate our baseline parameters by fitting 1,384 moments. A large number of moments creates the possibility of bias in finite samples, so we have re-estimated the model, and performed an analysis of model fit and a subset of our counterfactuals, using only the 740 carrier-specific moments. The results are reported in Appendix B.2.5, and we find that they are very similar to the baseline estimates.

Equilibrium Selection. Our baseline estimates assume that service choice decisions are made in a known sequential order. This assumption contrasts with recent literature that has used moment inequalities to estimate discrete choice models allowing for firms to be playing any pure strategy equilibrium in a simultaneous move game (Ciliberto and Tamer (2009), Eizenberg (2014) and Wollmann (2018)). Parameters may not be point identified under this type of weaker assumption. This leads to the question of whether our results would change if we made different assumptions, and we have performed a number of analyses which show that our results are very robust, reflecting several features of the data.

One analysis, described in Appendix B.2.6, extends our estimation methodology to use moment inequalities that allow for either simultaneous service choices or sequential choices with an unknown order (i.e., an assumption more general than the one used in the literature). The coefficients that the minimize the resulting objective function are very similar to our baseline estimates. Consistent with this fact, when we simulate our model, using our baseline estimates, allowing for these alternative timing assumptions, we find that, on average, only 1.017 outcomes can be supported as equilibrium outcomes per market-simulation, i.e., we get the same predicted outcomes whatever timing assumptions we make. The parameters may be point identified from those markets where outcomes are always unique and the moment inequalities become equalities (for example, an outcome with no nonstop carriers, which is the most common outcome in the data, will always be unique).

This finding may seem surprising given the existing literature: for example, there are multiple equilibria in over 95% of market-simulations in some of the spec-

zero minimize the objective function.

ifications considered by Ciliberto and Tamer (2009). The comparable statistic for our estimates is 1.6%. The difference lies in the much greater ability of observed variables to explain service choices, rather than the entry outcomes (defined as a carrier serving more than 20 passengers in each direction in a quarter) that Ciliberto and Tamer model. For a simulation to support more than one outcome as an equilibrium, at least two carriers must find entering/nonstop service to be marginally profitable, in the sense that it is profitable for some choices of rival carriers but not for others (i.e., they do not have dominant service choice strategies). Without estimating the model, an informal method for assessing whether a carrier is likely to be on the margin is to see whether its choice can be predicted based on its observed characteristics and market characteristics. As shown in Appendix B.3, simple probit specifications show that observed service choices are predicted with high probability for the vast majority of market-carriers in our sample. The implied probabilities of nonstop service for two or more carriers are between 0.1 and 0.9 in only 15% of markets (in our simulations, the proportion of draws with multiple equilibrium outcomes is more than twice as high in these markets). In contrast, if we look at entry-type decisions for all carriers that are active at the route endpoints, with no distinction between service types, the predicted probabilities for most carriers lie between 0.4 and 0.7, and 96% of markets have at least two carriers with intermediate predicted entry probabilities, consistent with finding that multiplicity appears to be common when modeling entry decisions.

3.6 Merger Counterfactuals

We now present our counterfactuals. They use the baseline estimates from the first columns of Tables 3.5 and 3.6, but, as discussed in the Introduction, our methodology for conducting counterfactuals could be used even if the model parameters are chosen based on documents or expert testimony. After outlining the mergers that we consider and the assumptions we make about the effects of the merger on the merging firms, we present results when service choices are assumed to be held fixed after the merger. This provides a baseline against which we can compare our predictions when service choices are endogenized.

Mergers Considered. We examine the three legacy mergers completed after our sample and a blocked merger between United and US Airways that was proposed in 2000. In this merger the parties proposed a remedy where a third carrier, American, would commit to provide nonstop service for ten years on several routes where the merging parties were nonstop duopolists. This remedy would have preserved the number of nonstop competitors for passengers and it would have satisfied the likely and timely criteria in the Guidelines. Our model is well-suited to evaluating the Department of Justice's view that it would have been insufficient to restore pre-merger competition.[25] We do not consider the merger between Southwest and Airtran, because Airtran is part of our composite "Other LCC".

Baseline Assumptions about the Merged Firm. Merger simulations require assumptions about what the merger will do to the quality and marginal costs of the merged firm. Throughout we will assume that the two products owned by the merging parties, are replaced by a single product of the merged carrier ("Newco"). Most of our analysis will make a "baseline" assumption that on each route Newco will have the quality and costs of the merging party with the higher average endpoint presence before the merger. However, we report several results where Newco is assumed, instead, to inherit the higher quality and lower cost of the merging parties, which we will label the "best case" assumption.[26]

[25]R. Hewitt Pate, Deputy Assistant Attorney General, discussed the merger and the remedy in a speech, "International Aviation Alliances: Market Turmoil and the Future of Airline Competition", on November 7, 2001, available at: `https://www.justice.gov/atr/department-justice-10` (accessed June 29, 2017): "And this summer, we announced our intent to challenge the United/US Airways merger, the second- and sixth-largest airlines, after concluding that the merger would reduce competition, raise fares, and harm consumers on airline routes throughout the United States and on a number of international routes, including giving United a monopoly or duopoly on nonstop service on over 30 routes. We concluded that ... American Airlines' promise to fly five routes on a nonstop basis [was] inadequate to replace the competitive pressure that a carrier like US Airways brings to the marketplace, and would have substituted regulation for competition on key routes. After our announcement, the parties abandoned their merger plans."

[26]The best case approach parallels what Li and Zhang (2015) assume about valuations and hauling costs in the context of timber auctions. We use the label best case because it tends to increase the profits of the merging parties relative to our baseline assumption.

3.6.1 Predicted Merger Effects Holding Service Types Fixed

Table 3.8 reports results for different groups of markets where we assume that service types stay the same after a merger, as is usually assumed in merger simulations. Setting the nesting and price coefficients equal to their expected values for each market, we infer carrier qualities and marginal costs from observed market shares and prices, and then re-solve for post-merger prices, following Nevo (2000).[27]

The first panel of Table 3.8 reports results for routes where the merging parties are nonstop duopolists when we make the baseline assumption about the merger. All of the considered mergers are expected to raise the merging carriers' average prices (we also take averages across directions), by between 5% and 15% (relative to their average pre-merger prices) and the standard errors for the predictions are small. The parties' market shares are predicted to fall by between 25% and 30% reflecting both the price increases and the elimination of a product. The next rows allow us to examine the profitability of the merger. Even though the decision to merge is taken at the network rather than the route level, it is informative to look at the predicted profitability of a merger that was actually completed to understand whether the assumptions are plausible.[28] While the elimination of a product and the lack of synergies means that variable profits tend to fall, total profits tend to increase because a large fixed cost of nonstop service is eliminated. Connecting rivals also increase their prices, although the magnitude of these changes are small. Consumer surplus, measured in dollars per pre-merger traveler, tends to fall quite significantly.[29]

The second panel shows the results for the same markets under the best case merger assumption. The numbers change in the expected directions: the merged

[27] For comparison, we also use the expected values of the nesting and price parameters when we endogenize service choices. The results for those counterfactuals are almost identical if we do not make this assumption, reflecting the fact that our estimates of the unobserved heterogeneity in these parameters across markets is small.

[28] While we do not do so in this paper, it is also possible to condition the unobservables on the profitability of the merger.

[29] We measure consumer surplus per pre-merger traveler because the markets considered vary quite dramatically in size, and our definitions of market size are imperfect.

Table 3.8: Predicted Effects of Mergers with Service Choices Held Fixed

	Delta/Northwest		United/Continental		American/US Airways		United/US Airways		Average	
	Data	Post	Data	Post	Data	Post	Data	Post	Data	Post
1. Merging Parties Nonstop Duopolists & Merger Eliminates Lower Presence Carrier										
Numb. of Routes	2 routes		4 routes		11 routes		7 routes		24 routes	
Merging Carrier Prices	\$566.39	\$593.20	\$503.75	\$556.17	\$459.13	\$521.15	\$479.32	\$549.49	\$481.40	\$541.25
		(1.17)		(1.57)		(1.79)		(1.44)		(1.55)
Combined Mkt. Share	18.9%	14.3%	29.1%	21.7%	26.9%	18.8%	20.8%	12.9%	24.8%	17.2%
		(0.1)		(0.0)		(0.1)		(0.0)		(0.0)
Combined Variable Profit (\$k)	1,287	1,235	6,112	6,225	4,336	4,006	4,023	3,907	4,287	4,116
	(47)	(43)	(208)	(208)	(201)	(187)	(124)	(104)	(164)	(151)
Combined Fixed Costs (\$k)	689	194	1,143	536	1,564	621	1,248	503	1,321	537
	(108)	(55)	(144)	(66)	(90)	(47)	(100)	(61)	(96)	(51)
Average Rival Prices	\$235.90	\$237.48	\$455.57	\$457.29	\$400.44	\$404.18	\$280.19	\$282.09	\$360.85	\$363.53
		(0.10)		(0.03)		(0.14)		(0.15)		(0.08)
Change in Cons. Surp. Per Traveler	−\$51.36		−\$62.81		−\$64.06		−\$80.03		−\$67.04	
	(1.64)		(2.21)		(2.89)		(2.19)		(2.47)	
2. Merging Parties Nonstop Duopolists & Merged Firm Receives Highest Qualities and Lowest Costs of the Merging Parties										
Merging Carrier Prices	\$566.39	\$598.77	\$503.75	\$558.63	\$459.13	\$513.34	\$479.32	\$537.60	\$481.40	\$535.09
		(1.14)		(1.58)		(2.18)		(1.57)		(1.75)
Combined Mkt. Share	18.9%	15.1%	29.1%	21.9%	26.9%	19.9%	20.8%	14.3%	24.8%	18.2%
		(0.0)		(0.0)		(0.01)		(0.0)		(0.0)
Combined Variable Profit (\$k)	1,287	1,343	6,112	6,359	4,336	4,418	4,023	4,566	4,287	4,528
	(47)	(414)	(208)	(209)	(201)	(162)	(124)	(103)	(164)	(141)
Combined Fixed Costs (\$k)	689	162	1143	375	1,564	565	1,248	446	1,321	465
	(108)	(39)	(144)	(57)	(90)	(39)	(100)	(64)	(96)	(47)
Rival Carrier Prices	\$235.90	\$237.87	\$455.57	\$457.14	\$400.44	\$403.46	\$280.19	\$281.36	\$360.85	\$362.91
		(0.06)		(0.03)		(0.14)		(0.04)		(0.08)
Change in Cons. Surp. Per Traveler	−\$44.88		−\$60.83		−\$56.94		−\$68.25		−\$59.74	
	(1.72)		(2.18)		(3.21)		(2.19)		(2.63)	
3. Alternative Market Structures & Merger Eliminates Lower Presence Carrier										
Merging parties nonstop	\$351.26	\$382.04	\$438.08	\$464.98	\$363.11	\$404.84	\$350.02	\$378.15	\$368.70	\$402.08
with nonstop rivals	2 routes		4 routes		10 routes		10 routes		26 routes	
One party nonstop,	\$472.99	\$524.67	\$502.60	\$513.29	\$447.95	\$478.95	\$443.30	\$462.53	\$458.02	\$486.40
other connecting	91 routes		59 routes		158 routes		163 routes		471 routes	
Both parties connecting	\$433.26	\$444.63	\$487.04	\$486.86	\$464.20	\$457.77	\$484.25	\$479.62	\$466.00	\$465.97
	479 routes		334 routes		471 routes		521 routes		1,805 routes	

Notes: for routes where the merging carriers are nonstop duopolists, standard errors for measures not directly observed in the data are reported in parentheses, and the share, fixed cost and profit numbers are for the merging carriers combined. Prices averaged across directions, and pre-merger prices are averages across carriers. For other pre-merger market structures, the table shows the number of affected routes, and merging carrier prices with no standard errors. All calculations assume that the price and nesting parameters have their expected values for each market. Each merger is considered separately, not cumulatively.

firm is predicted to lose fewer passengers, and its profits increase. However, the magnitude of the changes are quite small: for example, the merged firm's prices increase by 11.2% rather than 12.4% under the baseline assumption. This is because the higher presence carrier, whose characteristics Newco inherits under our baseline assumption, tends to be the carrier with the higher quality, and there tends to be too little variation in implied marginal costs to create substantial differences in the outcomes under different assumptions on most routes.[30]

The third panel reports pre- and post-merger average prices for the merging firms under our baseline merger assumption for different market structures (we do not report standard errors to prevent excessive clutter, but the predictions of average changes remain precise). When the merging parties are both nonstop, but face additional nonstop rivals, predicted price increases are substantial (average 9.1%), and we will consider these markets in later counterfactuals. When one party is nonstop and the other is connecting we tend to predict smaller increases (6.1%), although they are quite large for Delta/Northwest routes where the connecting party often has an unusually high market share. When both parties are connecting we predict small price reductions, which is possible when the higher presence carrier has lower costs because its connecting hub is more conveniently located. Consumer surplus still falls because the disappearance of an option, but the drop is much smaller than for nonstop duopolies (average $4.91 per pre-merger traveler).

3.6.2 Merger Counterfactuals When Rivals' Service Types Can Change

We now present our main counterfactuals where we allow rivals to respond to a merger by changing their service types. For routes where the merging parties are nonstop duopolists, this requires us to predict the demand and marginal cost shocks that rivals would have if they launched nonstop service. Our preferred approach, which accounts for the selection that is implied by our model and which is consistent with the way that merger simulations usually make assumptions about demand and

[30] In contrast, CMT estimate that unobserved carrier quality and costs are more important, and that different merger assumptions change counterfactual predictions quite dramatically.

costs that are consistent with observed pre-merger data, involves conditioning on the service choices observed pre-merger. We explain how this is done, before presenting our results using this approach and comparing these results with alternatives, such as when we assume that rivals' nonstop demand and cost shocks could be new draws from the estimated distributions.

Calculating Conditional Distributions. We call the distributions of demand and costs that are consistent with pre-merger service choices, as well as observed prices and market shares, "conditional distributions".[31] However, one can also interpret them as posteriors if the estimated distributions are treated as priors.

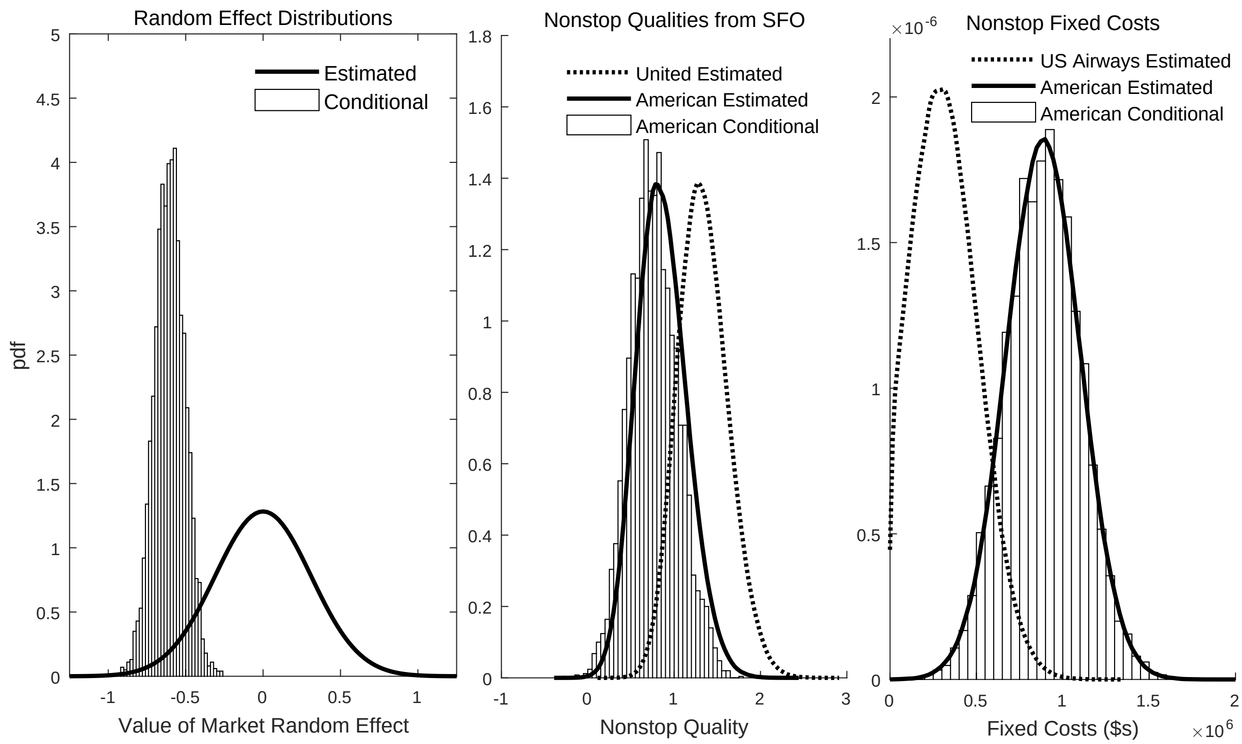
We form the distributions using simulation with the following steps. First, we specify a discrete set of possible values for the market-level demand random effect. For each value, we calculate the qualities and marginal costs implied by observed prices and market shares for the chosen service types. We then take draws of the remaining random components of the model from their estimated distributions and, for each set of draws, we check whether the observed service choices would be an equilibrium outcome of the sequential service choice game, keeping the accepted draws. We weight the accepted draws using the estimated distribution of the random effect, and the density of observed qualities and costs, to form the conditional joint distribution of the random effect, carrier qualities, marginal costs and fixed costs for all of the carriers in the market.[32]

We illustrate the effect of conditioning in Figure 3.1 for the Philadelphia (PHL)-San Francisco (SFO) market, one of the nonstop duopoly markets affected by the United/US Airways merger. The solid line in the left panel shows the estimated density of the demand random effect, while the histogram shows the simulated marginal conditional density (50,000 simulation draws). The conditional distribution has a lower mean, reflecting the fact that the number of observed passen-

[31] We note that one could also choose to condition, for example, on the profitability of the merger, which is an extension we are considering in a separate project.

[32] The acceptance rate drops if more discrete choices are added to the model or we add additional players. This is the primary reason why we moved away from the Li et al. (2015) model where we gave carriers three choices (do not enter, enter connecting, enter nonstop).

Figure 3.1: Selection of Marginal Conditional Distributions for Philadelphia-San Francisco



gers, across all carriers, is relatively low (combined market share is 28.3%, averaged across directions) given the value of the observed covariates, including our market size variable. As a comparison, the mean of the conditional distribution for Las Vegas-Miami, where combined market shares equal 42.5%, is 0.5.

Nonstop quality is the sum of a carrier's connecting quality and the incremental quality of nonstop service. The solid lines in the middle panel show the density of nonstop quality for passengers originating at SFO for United and American based on the estimates. United's expected quality is higher, because of its high presence at SFO. The histogram shows the conditional density for American's nonstop quality. This distribution is similar, but with a slightly lower mean, than the distribution implied by the estimates. The intuition is that given observed shares and prices and the likely value of the random effect, we only need to shift our belief about American's nonstop quality down by a small amount to explain why it chooses connecting service. The third panel shows the marginal densities for the fixed cost

Table 3.9: Predicted Effects of United/US Airways Merger in Four Nonstop Duopoly Markets Where American is a Connecting Competitor using Conditional Distributions for Connecting Carriers' Nonstop Quality and Costs

Service Change Considered	Pre-Merger United/US Airways Price	Exp. Numb. of Rivals Launching Nonstop Service: American	Exp. Numb. of Rivals Launching Nonstop Service: Other Rivals	Post-Merger Merged Carrier Price	Change in Consumer Surplus
Baseline Merger Assumption					
1. Service Types Fixed	$531.97	-	-	$577.72 (0.76)	-$48.07 (1.69)
2. Rivals' Choices Endogenized	$531.97	0.035 (0.023)	0.063 (0.055)	$573.37 (2.36)	-$42.96 (4.88)
Best Case Merger Assumption					
1. Service Types Fixed	$531.97	-	-	$562.82 (0.94)	-$37.76 (1.77)
2. Rivals' Choices Endogenized	$531.97	0.020 (0.015)	0.043 (0.042)	$560.73 (1.96)	-$33.80 (4.00)

Notes: predictions are averages across 1,000 draws from the conditional distributions. In the baseline case, the merger eliminates the carrier with the lowest presence on the route. Standard errors in parentheses based on the same bootstrap estimates used for the parameter estimates. The reported pre-merger price is the average of the merging carriers' prices across directions. Consumer surplus changes measured per pre-merger traveler. For American, the expected number of rivals launching nonstop service is the probability that American launches nonstop service.

of nonstop service for American and US Airways. US Airways has a lower expected effective fixed cost because of its domestic and international hubs at PHL. The estimated and conditional distributions for American's fixed costs look essentially identical.

Predicted Effects of a United/US Airways Merger Using the Conditional Distributions. We now present our predictions of what would have happened after the United/US Airways merger when we endogenize service choices and ensure that our assumptions are consistent with pre-merger choices. We focus on four routes where the merging parties were nonstop duopolists and American provided connecting service, so we can later consider the effects of the American nonstop remedy. We note that it is not unusual for merger analyses to focus on a small number of markets, but below we will consider 17 additional nonstop duopoly routes when we examine the completed mergers.

The upper panel in Table 3.9 presents some summary results under our baseline merger assumption. We expect the merged firm's prices to increase by 8.6% on these routes if service types are held fixed with a significant predicted decline in consumer surplus. These predictions would usually lead an antitrust agency to oppose a merger unless offsetting synergies or repositioning are likely.

The second row reports our predictions when we allow rivals' service types to change after the merger, using 1,000 draws from the conditional distributions for each market. We impose that the merged firm maintains nonstop service, as this is always observed in the data.[33] The connecting rivals re-optimize their service choices, in the order assumed in estimation. The expected number of rivals initiating nonstop service, a measure of the likelihood of repositioning, is small: across the four markets, American (one of the connecting rivals) does so for only 3.5% (s.e. 6.3%) of simulations, leading to the result that, in expectation, the merged carrier's price increases by \$41 (7.8%), so the possibility of repositioning is not sufficient to constrain prices. We also find that the merger is, on average, profitable for the merging firm despite the repositioning that takes place, with its profits increasing by an average of \$279k (s.e. \$78k) per market.

The lower panel performs the same simulations under the best case assumption. This assumption results in smaller predicted price increases and smaller predicted declines in consumer surplus, with less repositioning by rivals. However, as when service types are held fixed, the differences between the predictions, compared to the baseline case, are small, except that the merger now appears to be much more profitable, raising profits by an average of \$1.1m. (s.e. \$85k).

To understand the predictions for the baseline assumption, Table 3.10 provides more detail for the PHL-SFO market. In this market, United, the lower average presence carrier that is assumed to be eliminated by the merger, has a particularly large market share, so that the merger potentially creates a significant opportunity for a connecting carrier that launches nonstop service. The results in the table use 5,000 draws so we can measure different outcomes accurately.

For two-thirds of the draws, no connecting rival launches nonstop service,

[33] This is almost always the equilibrium outcome with conditional distributions, but it is frequently not the predicted outcome when we use alternative distributions, which provides an additional reason why these alternatives are less reasonable.

Table 3.10: Predictions for the Philadelphia-San Francisco Market Allowing for Endogenous Rival Service Choices Following a United/US Airways Merger

Carrier (pre-merger service type, price and share)	No Service Changes 3,267/5,000 Draws		American Nonstop 570/5,000 Draws		Delta Nonstop 483/5,000 Draws	
	Price	Share	Price	Share	Price	Share
US Airways/Newco	$691.53	15.4%	$661.67	14.1%	$661.46	14.0%
(NS, $649.74, 13.0%)	(1.17)	(0.0)	(0.66)	(0.1)	(1.64)	(0.1)
United	-	-	-	-	-	-
(NS, $613.54, 12.1%)						
American	$478.98	1.2%	$554.64	8.1%	$477.30	0.8%
(CON, $476.52, 0.5%)	(0.05)	(0.0)	(9.70)	(0.4)	(0.07)	(0.0)
Delta	$666.89	0.6%	$666.08	0.4%	$550.98	7.9%
(CON,$665.77, 0.3%)	(0.03)	(0.0)	(0.04)	(0.0)	(8.74)	(0.5)
Northwest	$307.35	3.5%	$302.51	2.4%	$302.47	2.4%
(CON, $300.60,1.9%)	(0.18)	(0.0)	(0.23)	(0.1)	(0.23)	(0.1)
Other LCC	$377.27	1.1%	$375.82	0.7%	$375.80	0.7%
(CON,$375.27,0.6%)	(0.06)	(0.0)	(0.07)	(0.0)	(0.07)	(0.0)

Notes: predictions are averages from 5,000 draws from the conditional distributions. Standard errors in parentheses based on the same bootstrap estimates used for the parameter estimates. The merger assumed to eliminate United (lower presence carrier). NS denotes nonstop and CON denotes connecting pre-merger.

and merged carrier's price increases by 9.5% (from the pre-merger average) and its market share falls by 38%. The non-merging carriers, with small shares pre-merger, increase their prices slightly and double their combined market share. Reflecting the loss of a large carrier, consumer surplus falls by an average of $72.91 per pre-merger traveler.

The remaining columns show what happens when one of American or Delta launch nonstop service, which are the most common outcomes involving repositioning (for 0.9% of draws more than one rival launches nonstop service). The increased competition reduces (but does not eliminate) the equilibrium price increase for US Airways, but the new nonstop carrier usually has a market share that is smaller than United's prior to the merger, causing consumer surplus to fall by around $30 per pre-merger traveler in both cases. This route provides an example where there can be multiple equilibrium outcomes depending on timing assumptions about service choices. For example, there are 27 (out of 5,000) draws where either American launching nonstop service or Delta launching nonstop service (but not both) are equilibrium outcomes. However, the different outcomes typically have very similar

Table 3.11: Predicted Effects of United/US Airways Merger in Four Nonstop Duopoly Markets Under the Baseline Merger Assumption Using Different Assumptions About the Nonstop Quality and Costs of Rivals, And Allowing for the American Service Remedy

Service Change Considered	Pre-Merger United/US Airways Price	Exp. Numb. of Rivals Launching Nonstop Service American	Others	Post-Merger Merged Carrier Price	Change in Consumer Surplus
1. No Service Changes	\$531.97	-	-	\$577.72	-\$48.07
Allow Rival Service Changes					
Counterfactuals Computed Using					
2. Conditional Distns.	\$531.97	0.035	0.063	\$573.37	-\$42.96
3. Estimated Distns.	\$531.97	0.190	0.325	\$559.56	-\$16.22
4. Connecting Carriers' Nonstop Same as Average Merging Parties	\$531.97	0.678	1.915	\$531.79	+\$62.36
American Nonstop Remedy Allowing Rival Service Changes					
5. Conditional Distns.	\$531.97	1	0.030	\$566.34	-\$31.29
6. Estimated Distns.	\$531.97	1	0.253	\$556.18	-\$3.98
7. Connecting Carriers' Nonstop Same as Average of Merging Parties	\$531.97	1	1.883	\$529.90	+\$68.55

Notes: predictions with endogenous service choices are averages from 1,000 draws from the appropriate distributions. The merger is assumed to eliminate the carrier with the lowest presence on the route. Implementation of rows 3 and 4 explained in the text. Standard errors not reported (referenced where relevant in the text).

welfare implications (the average within-draw-across-outcome standard deviation in the US Airways price is \$3). Repositioning by rivals, when it happens, does tend to make the merger unprofitable for this route: for example, the merged firm's profits fall by \$920k when American becomes nonstop.[34]

Predicted Effects Using Alternative Assumptions About Rival Qualities. It is natural to ask whether we would find different results if we did not use conditional distributions. We consider two alternatives, presenting the results for the four United/US Airways nonstop duopoly routes in rows 3 and 4 of the upper panel of Table 3.11. To save space, we do not report standard errors in the remaining tables, but they are of similar magnitude to those reported earlier and we will note in the text where any discussed changes are not statistically significant.

The first alternative (row 3) uses new draws from the estimated cost and in-

[34] We have also calculated what happens under the best case assumption. In this case, there is no repositioning for 78% of draws (rather than 65%), US Airways price increases by an average of 4.3% (rather than 6.4%) when there is no repositioning and the merger is only marginal unprofitable when repositioning occurs (e.g., profits fall by \$106k when American becomes nonstop).

cremental nonstop quality distributions for the nonstop qualities and costs of the connecting carriers. We therefore account for differences in the observable characteristics of different carriers, but do not account for the additional information in pre-merger service choices. The second alternative (row 4) assumes that if any connecting rival becomes nonstop then it would have the average quality and marginal costs of the merging nonstop carriers and draw its fixed cost from a distribution that has a mean equal to average of the means for the merging carriers. This approach ignores observable differences between carriers, but it might be viewed as being consistent with the logic of *Waste Management* and the Department of Transportation's decisions if clear barriers to repositioning by rivals could not be identified. In both cases, we continue to draw the random effect from its conditional distribution and we use the qualities and marginal costs for observed service types that are implied by observed prices and market shares, so that we can isolate the effects that arise from making alternative assumptions about how competitive rivals will be if they launch nonstop service.[35]

Compared to our results using the conditional distributions, using the estimated distributions significantly increases the probability that rivals will launch nonstop service (the expected number of nonstop launches is 0.52, rather than 0.1), leading to a smaller expected price increase and a smaller and statistically insignificant decrease in consumer surplus of \$16.22 per pre-merger traveler (s.e. \$11.22). Using the estimated distributions also makes the merger appear to be unprofitable: average profits are predicted to fall by \$105k (s.e. \$150k), whereas they increase by \$279k (s.e. \$78k) when we use the conditional distributions.

Assuming that connecting carriers can offer nonstop service on similar terms to the merging parties leads to a prediction that, on average, 2.6 of them would launch nonstop service[36] and that, because consumers prefer nonstop service, consumer

[35] An additional rationale for using the conditional distribution of the random effect is that the random effect is partly intended to address imperfections in our definition of market size. In a merger investigation, the parties and the agencies would likely be able to construct better measures of potential demand in each market.

[36] If we assumed that connecting carriers would be similar to the eliminated carrier, rather than the average of the merging carriers, we would expect 1.5 of them to launch nonstop service.

surplus is predicted to increase after the merger. However, if we use the same assumption to solve for equilibrium outcomes *before the merger*, we would predict that several connecting carriers should have chosen to offer nonstop service (e.g., American's probability of launching nonstop service would be 0.6 pre-merger), which is inconsistent with the observed data. This illustrates the importance of considering whether assumptions about the post-merger competitiveness of repositioning firms, or new entrants, are consistent with their pre-merger choices. The results are similar if we make the best case assumption about the merger: for example, the expected number of carriers launching nonstop service are 0.46 (row 3) and 2.4 (row 4), rather than 0.52 and 2.6.

The Proposed Service Remedy. The results presented so far suggest that when rivals launch nonstop service, the merged carrier can only increase prices by a small amount. This might be interpreted as implying that the proposed American nonstop remedy, which would have maintained the number of nonstop carriers at its pre-merger level, would have been effective. However, this logic implicitly assumes that American's nonstop service would constrain the merged carrier's prices even when it is unprofitable.[37]

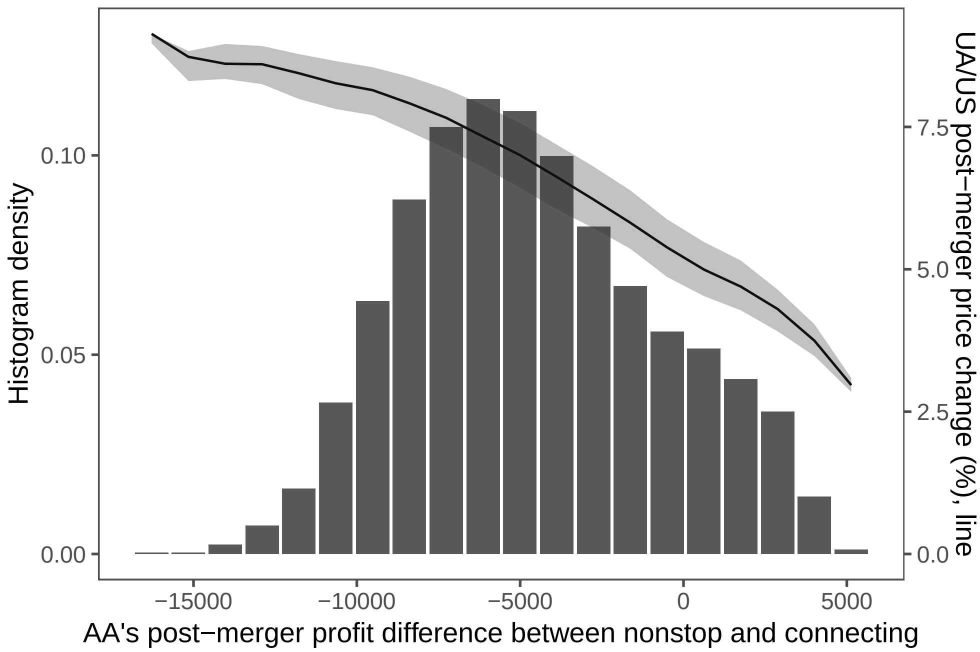
The lower panel of Table 3.11 presents our average predictions for the four routes using the different distributions when we force the merged firm and American to provide nonstop service, but allow other carriers to sequentially re-optimize their service choices. The results clearly indicate that under any of the assumptions, the additional effects of the remedy on the merged firm's expected prices are small, and, when we use the conditional distribution, consumer surplus is still predicted to decline significantly. American's ineffectiveness as a nonstop competitor when its nonstop service is not profitable is also illustrated by how other rival carriers' service decisions are largely unaffected by the remedy.

Figure 3.2(a) helps to explain what is going on. The histogram shows the

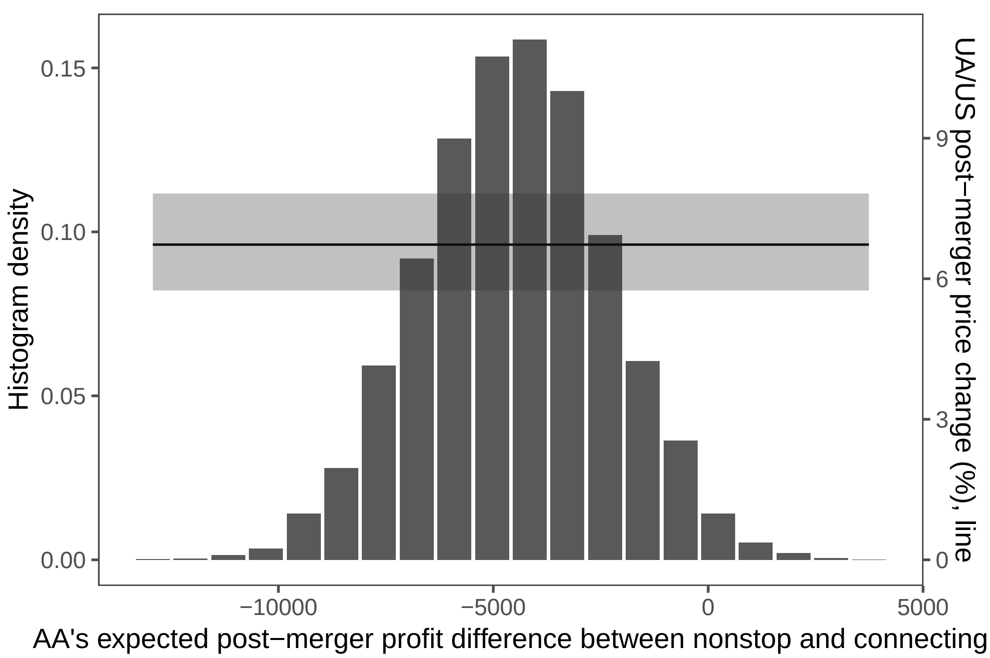
[37]The parties did not claim that nonstop service on the affected routes would be profitable for American: instead the attraction for American was that it would receive a package of assets on the East Coast if the merger was completed.

Figure 3.2: Distribution of American Incremental Profits (in \$00s) from Nonstop Service on PHL-SFO and the Predicted Increase in the Merged Carrier's Price if American Launches Nonstop Service (Relative to Pre-Merger Average Prices) Given American's Profitability. The grey area marks the interquartile range of price outcomes.

(a) Full Information



(b) Limited Information (Expected Profits)



distribution of the difference between nonstop and connecting profits for American on the PHL-SFO route. For simplicity, we draw the figure assuming that American knows no other connecting carriers will launch nonstop service. The line on the figure shows the median simulated post-merger price increase for US Airways (relative to the average of United's and US Airways's pre-merger prices) when we force American to provide nonstop service given this level of profitability (the shaded area indicates the interquartile range generated by our simulations). There is a monotonic relationship between American's profitability and its effectiveness at reducing increases in the US Airways's prices, and there is only a really significant constraining effect on those prices when nonstop service is at least close to being profitable for American.

To illustrate the effects of our assumption that demand and cost shocks are known when making service choices ("full information"), Figure 3.2(b) shows the same figure assuming that American has no information about its quality or marginal cost unobservables when making its service choice (for comparability we assume American does know its fixed costs and the qualities and costs of other carriers). The variance of the (expected) profit distribution is reduced, as it now reflects only the distribution of fixed costs. As fixed costs will not affect the prices that carriers set, there is no link between the level of profit that American expects when it launches nonstop service and how much this will constrain the profits of the merging firm.[38]

Predicted Effects of Completed Legacy Mergers on Nonstop Duopoly Routes. The upper panel of Table 3.12 summarizes our baseline merger assumption predictions for repositioning and post-merger prices for 17 routes where legacy carriers merging after our data were nonstop duopolists, under our different assumptions about the nonstop quality and costs of connecting carriers.

The qualitative patterns are very similar to Table 3.11, although magnitudes vary across mergers reflecting differences in conditions across routes. When we use our preferred conditional distributions, an average of 0.18 rivals are predicted to

[38] An analyst's assumptions about the nature of any link may matter, for example, when interpreting documents that discuss the likely business plans of rivals.

Table 3.12: Predicted Price and Service Changes for Subsequent Completed Mergers on Routes where Merging Parties are Nonstop Duopolists (Baseline Assumption)

	Delta/Northwest		United/Continental		American/US Airways		Average for Completed Mergers	
	Price	Exp. Numb. New Nonstop	Price	Exp. Numb. New Nonstop	Price	Exp. Numb. New Nonstop	Price	Exp. Numb. New Nonstop
Pre-merger	\$566.39	-	\$503.75	-	\$459.13	-	\$482.25	-
Post-Merger								
Service Types Fixed	\$593.20	-	\$556.17	-	\$521.15	-	\$537.86	-
Allow Rival Service Changes								
Connecting Rivals Nonstop Quality and Costs Drawn from:								
Conditional Distributions	\$590.34	0.07	\$547.65	0.14	\$511.33	0.21	\$529.17	0.18
Estimated Distributions	\$584.20	0.19	\$534.08	0.35	\$488.45	0.73	\$510.45	0.57
Average of Merging Parties	\$573.83	0.93	\$454.36	2.62	\$460.25	2.10	\$472.23	2.08
Number of Routes	2		4		11		17	

Table 3.13: Predicted Price and Service Changes Where Merging Parties and at Least One Rival are Nonstop

	Delta/Northwest		United/Continental		American/US Airways		United/US Airways		Average	
	Price	Δ in # Of NS Rivals	Price	Δ in # Of NS Rivals	Price	Δ in # Of NS Rivals	Price	Δ in # Of NS Rivals	Price	Δ in # Of NS Rivals
Pre-merger	\$351.26	-	\$438.08	-	\$363.11	-	\$350.02	-	\$377.51	-
Post-Merger										
Service Types Fixed	\$382.04	-	\$464.98	-	\$404.84	-	\$378.15	-	\$412.27	-
Allow Rival Service Changes										
Connecting Rivals Nonstop Quality and Costs Drawn from:										
Conditional Distributions	\$378.90	0.16	\$464.86	0.01	\$404.41	0.03	\$377.24	0.05	\$411.07	0.06
Estimated Distributions	\$386.40	-0.51	\$466.18	-0.03	\$403.55	-0.27	\$375.17	-0.11	\$413.33	-0.28
Average of Merging Parties	\$374.37	0.66	\$455.64	0.61	\$398.85	-0.03	\$367.68	0.48	\$404.95	0.34
Number of Routes	2		4		10		10		26	

Notes: see notes to Table 3.11. All predictions make the baseline merger assumption and, when service types are endogenous, use 1,000 draws from the relevant distribution. Pre-merger prices are averages across the merging parties. Standard errors not reported.

launch nonstop service on each affected route, and the merged carriers' prices are predicted to increase by an average of just under 10%, which is only 2 percentage points smaller than if service types are held fixed. Using the estimated distributions we predict more than three times as much repositioning by rivals and smaller, although still economically significant, price increases.[39] If we assume that connecting carriers could provide nonstop service with similar quality and costs to the merging parties, we predict that the mergers would have no anti-competitive effects.

It is natural to compare these predicted changes with what we observe actually happening after these mergers, although we note that the set of routes do not coincide exactly due to changes in market structure between 2006 and when the mergers were completed. As discussed in Section 3.3, rivals initiated nonstop service in four out of sixteen nonstop duopoly routes within two years and the merging firms increased their prices by 11% when no rivals initiated service. These empirical patterns are consistent with our predictions when we use preferred conditional distributions.[40] Our conditional distribution results also predict that the merging carriers' market shares should fall by an average of 30%, which is similar to the changes that we observe when we look at local traffic (i.e., passengers only flying the segment itself). While the sample sizes are too small to claim that the close match proves that our approach is correct, we view the pattern as highly suggestive, and it stands in contrast to earlier results (e.g., Peters (2006)) that structural models perform poorly at predicting the outcomes of airline mergers.

Mergers in Markets with Nonstop Competition. Mergers that reduce the number of nonstop competitors from 3 to 2 may also generate significant competition concerns. Table 3.13 presents summary results where the merging parties have at least one non-merging nonstop rival (there is one market with two nonstop rivals pre-

[39] Under the best case merger assumption we predict two-and-a-half times as much repositioning using the estimated distributions, so that the comparisons we make below to repositioning in the data still hold.

[40] It is also the case that we observe the most nonstop launches after the American/US Airways merger and none after Delta/Northwest, the same ordering as in our predictions. However, the sample sizes are too small to interpret this pattern as providing more than anecdotal support.

merger). When simulating counterfactuals, we assume that the merged firm will be nonstop and make the same assumptions about connecting rivals that we have made previously. However, we also now endogenize the service choice of the nonstop rival(s). For this carrier its nonstop quality and marginal costs are observed, but we need to make assumptions about the quality and marginal costs of its connecting service, and its fixed costs of providing nonstop service.[41]

When we use conditional distributions, we predict that the nonstop rival(s) will always continue to provide nonstop service and that connecting carriers will rarely introduce nonstop service. As a result, predicted price changes are almost identical to those where service types are assumed fixed. This is consistent with our earlier results. However, differences emerge for the other assumptions, because it becomes likely that the nonstop rival, which is usually a quite effective nonstop competitor, may cease nonstop service and this type of repositioning can lead to price increases. For example, a nonstop rival ceases nonstop service for around one-third of simulations in the results reported in the bottom ("Average of Merging Parties") row of the table. As a result, we now predict significant price increases under all three approaches, and the largest predicted prices increases and the greatest probability of post-merger nonstop monopoly are when we use the estimated distributions. Therefore while the intuition that the conditional distributions will tend to predict the largest prices increases when nonstop duopolists merge is fairly clear, there are additional nuances for other market structures that are relevant for merger analysis.

3.7 Conclusion

We have developed a model of endogenous service choices and price competition in airline markets, assuming that carriers have full information about demand and marginal costs when they make their service choices. In this framework, car-

[41] In the case where we assume that connecting rivals would have the same nonstop quality as the merging parties, we use the observed nonstop quality and marginal costs for the nonstop rival(s), and draw its (their) connecting qualities and marginal costs, and fixed costs, from the estimated distributions.

riers will tend to choose the service type in which they are most competitive, and this naturally has implications for how likely they will be to change their service types in response to a change in their competitive environment, such as when two rivals merge. While it is unlikely to be the right assumption for all industries, we believe the full information assumption is the natural one to use when trying to predict product repositioning by experienced market participants, and when trying to understand whether repositioning will sustainably limit market power after a merger.

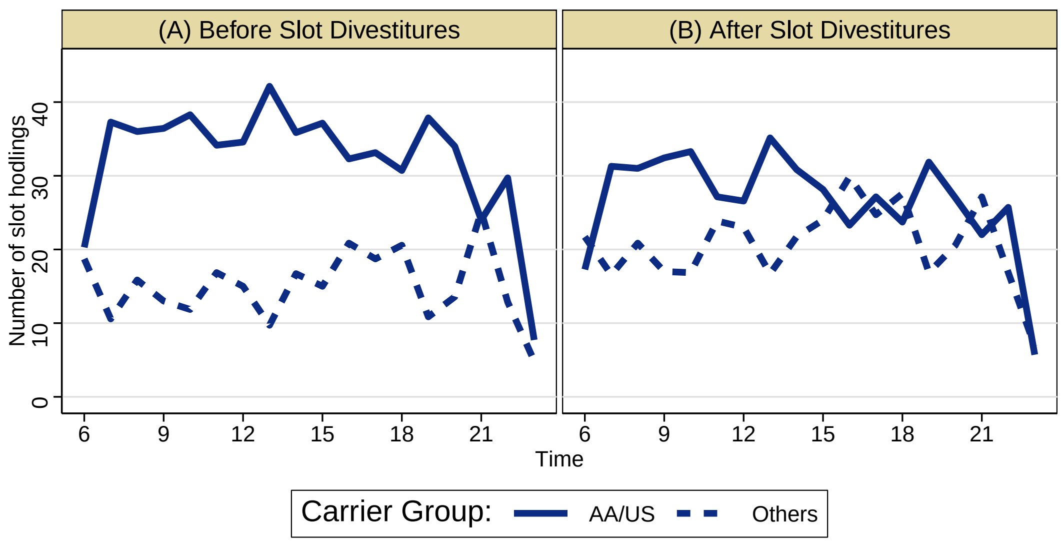
We make two contributions. First, we show how a full information model can be estimated without an excessive computational burden. This is a significant result for the academic literature, as researchers have often chosen to estimate models where firms do not have any information on the realization of demand and marginal cost shocks when entry or positioning decisions are made in order to avoid the computational burden that is perceived to be involved with estimating entry and pricing games simultaneously.

Our second contribution comes from performing a set of counterfactuals which try to systematically assess the likelihood and sufficiency of repositioning as suggested by the *Horizontal Merger Guidelines*. We show how to account for the selection on unobserved demand and marginal cost shocks that is implied by the model, and we find that doing so is important. When we take selection into account we predict that rivals are much less likely to launch nonstop service when nonstop duopolists merge than if we ignore selection, and we predict larger average price increases and significant decreases in consumer surplus. We find that our predictions are consistent with what has been observed after actual airline mergers only when we account for selection. These results are important both for academic research, where we are not aware of this type of conditioning being used previously, and for the analysis of mergers at antitrust agencies, as it is still desirable to report the results of merger simulations and other counterfactuals even when parameters are taken from documents, expert testimony or simple calibrations, rather being estimated.

Appendix A: Appendix for Chapter 1 and 2

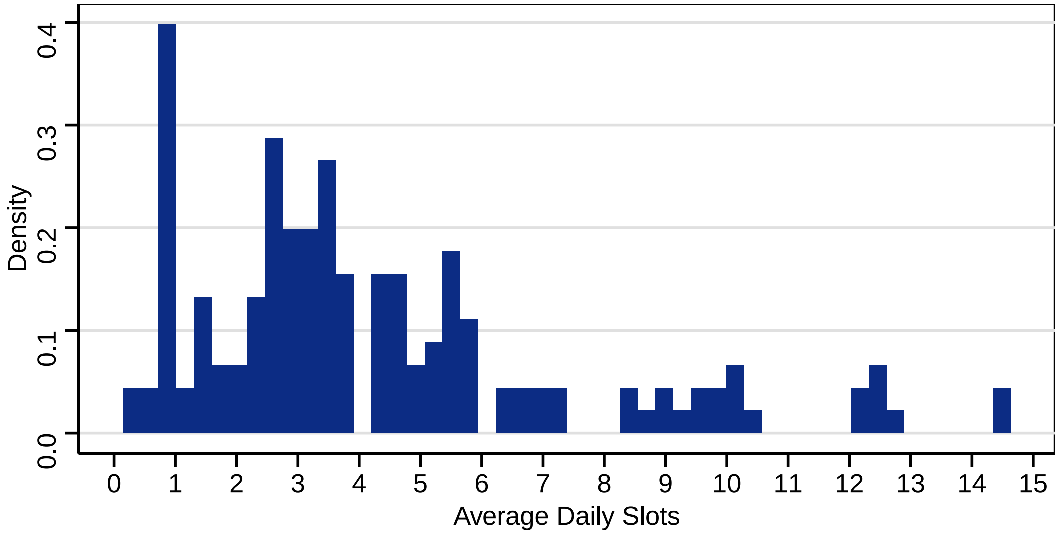
A.1 Figures and Tables

Figure A.1: Hourly Slot Holdings By Carrier Type Before/After Slot Divestitures At DCA



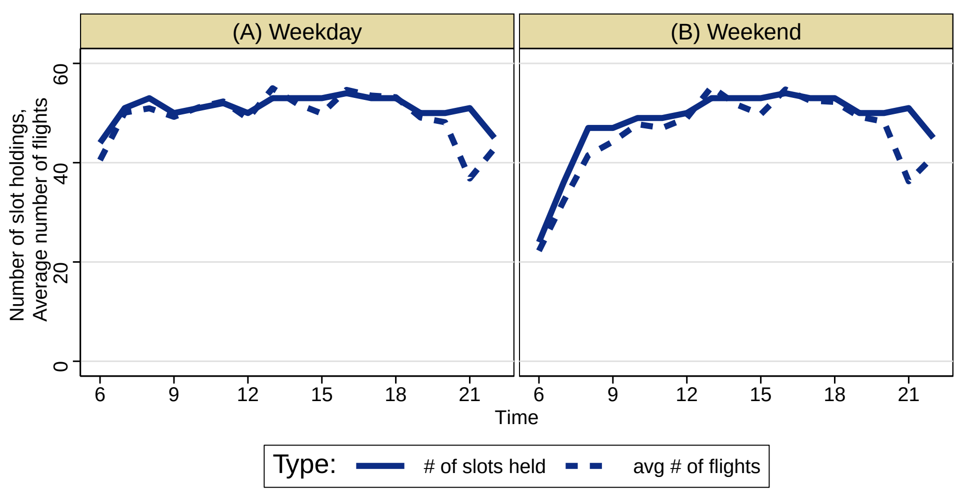
Note: The figures show the number of slot holdings of merging firms (marked as solid line) and other carriers (marked as dotted line) before and after the slot divestitures at DCA. The information on slot holdings is extracted from the Slot Administration page of the Federal Aviation Administration website.

Figure A.2: Histogram of Average Daily Slots Assigned on Segments at DCA (2013Q2)



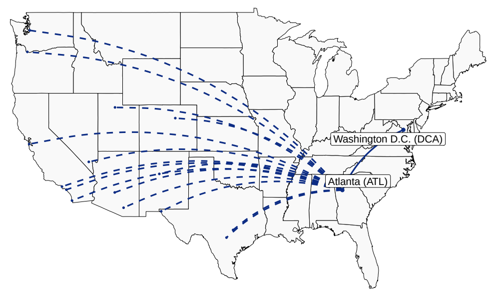
Note: This histogram is based on the average daily slots of DCA flight segments in 2013Q2 (n=156).

Figure A.3: Number of Slot Holdings and Average Number of Flight Operations at DCA (2018Q2)

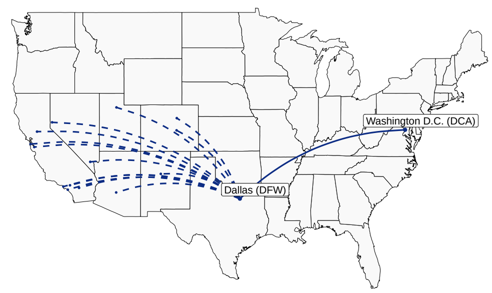


Note: The number of slots held by any commercial carrier in each time bin (one hour block) as of June 2018 is displayed in a solid line, and the average number of scheduled flights in each time bin (operated by any carriers) is displayed in a dashed line. The information on slot holdings is extracted from the Slot Administration page of the Federal Aviation Administration website, and the information on the average number of flight operations is based on the Marketing Carrier On-Time Performance Data from Bureau of Transportation Statistics.

Figure A.4: Illustration of Composite Connecting Products



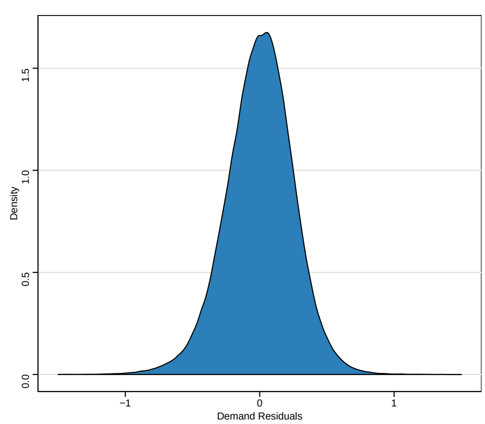
(a) DL's Composite Product



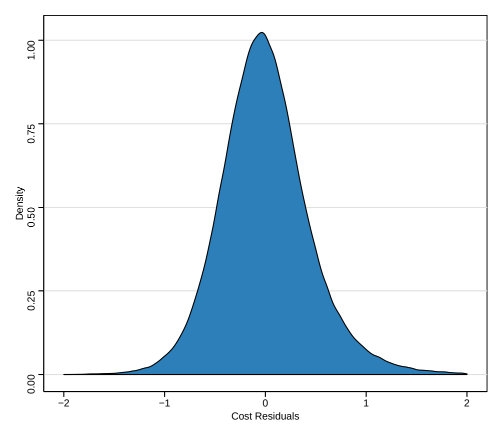
(b) AA's Composite Product

Note: The first panel shows 14 different itineraries (products) offered by Delta when connecting at Atlanta (ATL) to go to DCA. The nonstop distances of the corresponding markets of those itineraries are beyond the perimeter rule threshold (1,250 miles), while (DCA→ATL)$_{DL}$ is within the perimeter rule. I combine those 14 products into a single composite product in order to take into account their small but non-negligible effect on the load factor of (DCA→ATL)$_{DL}$. Analogously, the second panel shows a set of connecting products offered by American connecting at Dallas (DFW). To generate a moderate level of market competition, I assume that the two composite products are in the same market.

Figure A.5: Empirical Distribution of Demand and Marginal Cost Residuals



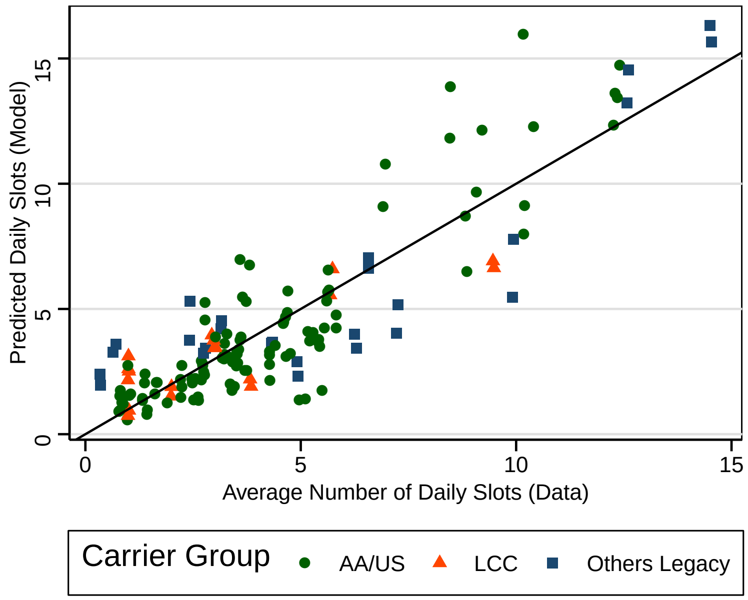
(a) Demand Residuals ($\hat{\xi}$)



(b) Marginal Cost Residuals ($\hat{\omega}$)

Note: The empirical distributions of demand residuals (left) and marginal cost residuals (right) are reported (Airport-Airport pair baseline assumption). One standard deviation of demand and marginal cost residuals are equal to \$74.23 and \$25.35, respectively. In addition, note that the average marginal cost is computed as \$73.46.

Figure A.6: Average Number of Daily Slots (Data and Model Prediction)



Note: This scatter plot compares the average number of daily slots from the data (on the x-axis) with the average number of daily slots from the model prediction (on the y-axis). A 45 degree line is marked as a solid black line.

A.2 Second Stage Supplements

A.2.1 Derivations

In this section, I present the technical details of how to derive the matrix-form version of the price FOC (1.13) from (1.12). Consider two products j and l offered by carrier f in market m and m', respectively. Then, taking the derivatives of the marginal cost $c_{lm'}$ with respect to p_{jm} from (1.7) yields the following:

$$\frac{\partial c_{lm'}}{\partial p_{jm}} = \begin{cases} \sum_{s \in \mathcal{S}_{fk}} \gamma_2 \nu \Big(\dfrac{Q_s}{z_s K_s} \Big)^{\nu} \dfrac{1}{Q_s} \frac{\partial q_{km}}{\partial p_{jm}} & \text{if } \exists k \text{ s.t. } k \in \mathcal{J}_{mf} \text{ and } k \in \mathcal{J}_f(\mathcal{S}_{fl}) \\ 0 & \text{otherwise} \end{cases} \tag{A.1}$$

Table A.1: Regression Results of Airplane Size

	Dependent variable:		
	Airplane Size		
	(1)	(2)	(3)
Distance (1,000 miles)	43.326***	41.659***	20.157***
	(4.055)	(4.145)	(3.183)
Distance^2	$-$3.385**	$-$2.631*	0.041
	(1.517)	(1.573)	(1.197)
International Hub	21.840***	22.622***	
	(2.240)	(2.248)	
Slot-Controlled (All)		$-$8.460***	
		(2.002)	
Origin-Carrier F.E.?	No	No	Yes
Dest-Carrier F.E.?	No	No	Yes
Observations	34,631	34,631	34,631
Adjusted R^2	0.478	0.483	0.833
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.2: Regression Results of Load Factors from Unavailable Products

	Dependent variable:		
	Load Factor from Unavailable Products		
	(1)	(2)	(3)
Distance (1,000 miles)	$-$0.068***	$-$0.080***	$-$0.058***
	(0.004)	(0.004)	(0.003)
Distance^2	0.025***	0.029***	0.019***
	(0.001)	(0.001)	(0.001)
International Hub		0.059***	
		(0.002)	
Origin-Carrier F.E.?	No	No	Yes
Dest-Carrier F.E.?	No	No	Yes
Observations	34,631	34,631	34,631
Adjusted R^2	0.388	0.402	0.671
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A.3: First Stage Results of Marginal Cost Estimation

	(1) Baseline	(2) Baseline	(3) Frequency in Demand	(4) Frequency in Demand
Distance	0.050***	0.454***	0.063***	0.511***
	(0.002)	(0.015)	(0.002)	(0.016)
Distance sq.	−0.016***	−0.143***	−0.021***	−0.160***
	(0.001)	(0.005)	(0.001)	(0.005)
Slot Constraint	−0.008***	−0.133***	−0.010***	−0.155***
	(0.001)	(0.005)	(0.001)	(0.006)
Slot Constraint X LCC	0.007***	0.122***	0.010***	0.143***
	(0.002)	(0.015)	(0.002)	(0.017)
Hub	0.012***	0.108***	0.015***	0.121***
	(0.0004)	(0.003)	(0.001)	(0.004)
# NS in Neighbor Mkt on Seg 1	0.003***	0.022***	0.003***	0.024***
	(0.0001)	(0.001)	(0.0002)	(0.001)
LCC in Neighbor Mkt on Seg 1	0.003***	0.035***	0.004***	0.039***
	(0.0003)	(0.003)	(0.0004)	(0.003)
# NS in Neighbor Mkt on Seg 2	0.003***	0.031***	0.004***	0.035***
	(0.0001)	(0.001)	(0.0002)	(0.001)
LCC in Neighbor Mkt on Seg 2	0.001***	0.027***	0.001***	0.032***
	(0.0004)	(0.003)	(0.0004)	(0.003)
Nonstop	−1.071***	−1.229***	−1.087***	−1.216***
	(0.001)	(0.009)	(0.001)	(0.010)
O-D Pair (Airport or City)	Airport	Airport	Airport	Airport
Observations	358,880	358,880	358,880	358,880
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.4: Airport Codes and Names

Code	Airport Name	City
AGS	Augusta Regional At Bush Field	Bush Field
BDL	Bradley Intl' Airport	Windsor Locks
BHM	Birmingham-Shuttlesworth Intl' Airport	Birmingham
BNA	Nashville Intl' Airport	Nashville
BOS	General Edward Lawrence Logan Intl' Airport	Boston
CAK	Akron Canton Regional Airport	Akron
CHS	Charleston Air Force Base-Intl' Airport	Charleston
CLT	Charlotte Douglas Intl' Airport	Charlotte
CMH	John Glenn Columbus Intl' Airport	Columbus
DAY	James M Cox Dayton Intl' Airport	Dayton
DSM	Des Moines Intl' Airport	Des Moines
FLL	Fort Lauderdale Hollywood Intl' Airport	Fort Lauderdale
GSP	Greenville Spartanburg Intl' Airport	Greenville
IND	Indianapolis Intl' Airport	Indianapolis
JAN	Jackson-Medgar Wiley Evers Intl' Airport	Jackson
JAX	Jacksonville Intl' Airport	Jacksonville
MCI	Kansas City Intl' Airport	Kansas City
MCO	Orlando Intl' Airport	Orlando
MIA	Miami Intl' Airport	Miami
MSP	Minneapolis-St Paul Intl'/Wold-Chamberlain Airport	Minneapolis
MSY	Louis Armstrong New Orleans Intl' Airport	New Orleans
MYR	Myrtle Beach Intl' Airport	Myrtle Beach
OMA	Eppley Airfield	Omaha
PBI	Palm Beach Intl' Airport	West Palm Beach
PNS	Pensacola Regional Airport	Pensacola
PVD	Theodore Francis Green State Airport	Providence
PWM	Portland Intl' Jetport Airport	Portland
ROC	Greater Rochester Intl' Airport	Rochester
RSW	Southwest Florida Intl' Airport	Fort Myers
SAV	Savannah Hilton Head Intl' Airport	Savannah
SRQ	Sarasota Bradenton Intl' Airport	Sarasota
TLH	Tallahassee Regional Airport	Tallahassee
TPA	Tampa Intl' Airport	Tampa
TYS	McGhee Tyson Airport	Knoxville

Table A.5: List of New Flight Segments from DCA from the Data

Carrier	New Segment from DCA
Southwest	**FLL**, **TPA**, **BNA**, **MSY**, MCI, **PVD**, **CMH**, **IND**, OMA, MDW
JetBlue	**PBI**, **BDL**, **JAX**, RSW, CHS

This table lists the set of flight segments that Southwest and JetBlue did not provide nonstop services in 2013 (pre-merger) but did in 2016 (post-merger and post-divestiture). A flight segment is in bold face if the model predicts the new flight segment.

Table A.6: Logit Model Results of Entry Decision by Southwest and JetBlue

	Dependent variable:
	entered
Variable Profit Change (ΔVP)	1.215**
	(0.477)
Presence (non-DCA)	9.600***
	(2.588)
Constant	−5.982***
	(1.412)
Observations	94
Log Likelihood	−22.790
Akaike Inf. Crit.	51.580
Note:	*p<0.1; **p<0.05; ***p<0.01

Table A.7: Difference-in-Differences (DiD) Regression Results of Airplane Size

	Airplane Size			
	(1)	(2)	(3)	(4)
Post X NewAA		0.923	1.427	0.457
		(2.897)	(4.048)	(4.147)
Post	1.341	0.477	−1.021	1.921
	(1.211)	(2.598)	(3.631)	(3.717)
NewAA		−25.027***	−24.200***	−25.872***
		(2.068)	(2.884)	(2.967)
Distance	54.625***	52.166***	51.072***	53.340***
	(1.454)	(1.211)	(1.673)	(1.755)
Constant	43.734***	70.198***	69.997***	70.390***
	(1.208)	(2.073)	(2.898)	(2.968)
DiD Used?	No	Yes	Yes	Yes
Pre-merger Year?	2012-2013	2012-2013	2013	2012
Post-merger Year?	2015-2016	2015-2016	2015	2016
Observations	1,830	2,276	1,147	1,129
Adjusted R^2	0.436	0.517	0.513	0.521
Note:				*p<0.1; **p<0.05; ***p<0.01

Then, the last term of (1.12), $\sum_{l\in\mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'}$, can be expressed as follows:

$$\begin{aligned}
\sum_{l\in\mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'} &= \sum_{k\in\mathcal{J}_{mf}} \sum_{s\in\mathcal{S}_{fk}} \sum_{l\in\mathcal{J}_f(\{s\})} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \frac{1}{Q_s} \frac{\partial q_{km}}{\partial p_{jm}} q_{lm'} \\
&= \sum_{k\in\mathcal{J}_{mf}} \sum_{s\in\mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \frac{1}{Q_s} \frac{\partial q_{km}}{\partial p_{jm}} \sum_{l\in\mathcal{J}_f(\{s\})} q_{lm'} \\
&= \sum_{k\in\mathcal{J}_{mf}} \sum_{s\in\mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \frac{\sum_{l\in\mathcal{J}_f(\{s\})} q_{lm'}}{Q_s} \frac{\partial q_{km}}{\partial p_{jm}} \qquad \text{(A.2)} \\
&= \sum_{k\in\mathcal{J}_{mf}} \sum_{s\in\mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \Big(\frac{Q_s}{Q_s}\Big) \frac{\partial q_{km}}{\partial p_{jm}}. \qquad \text{(From (1.8))}
\end{aligned}$$

Then,

$$\begin{aligned}
\frac{dVP_f}{dp_{jm}} &= q_{jm} + \sum_{k\in\mathcal{J}_{mf}} (p_{km} - c_{km}) \frac{\partial q_{km}}{\partial p_{jm}} - \sum_{l\in\mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'} \\
&= q_{jm} + \sum_{k\in\mathcal{J}_{mf}} \Big(p_{km} - c_{km} - \sum_{s\in\mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu}\Big) \frac{\partial q_{km}}{\partial p_{jm}} = 0 \qquad \text{(A.3)}
\end{aligned}$$

When we stack all the products in market m in a vector form, we can rewrite expression (A.8) as

$$\mathbf{q_m} + \mathbf{\Omega_m}(\mathbf{p_m} - \mathbf{c_m} - \frac{\mathbf{dc_m}}{\mathbf{dQ}}) = 0, \qquad \text{(A.4)}$$

where $\mathbf{\Omega_m}$ is the element-wise multiplication of the response matrix defined in (1.14) and $\frac{\mathbf{dc_m}}{\mathbf{dQ}}$ is a vector with jth element

$$\Big[\frac{\mathbf{dc_m}}{\mathbf{dQ}}\Big]_j = \sum_{s\in\mathcal{S}_{fj}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu}. \qquad \text{(A.5)}$$

A.2.2 Missing Products in Data

To precisely estimate the parameters of a load factor and to solve the model using a realistic load factor value, it is crucial to take into account all types of passengers on a segment to. However, not all the products are included in the ticket-level data (DB1B). One example is an international itinerary ticket that contains a domestic flight segment (e.g. a flight ticket from Washington, D.C. (DCA) to Seoul, Korea (ICN) connecting at Detroit, Michigan (DTW), operated by American Airlines). Any tickets including international segments are not in the ticket-level data used in this paper. Another example is a set of tickets to/from small airports that are outside of the top 100 airports based on passenger boardings. Those connecting flights starting from the small airports that contain a DCA flight segment are not in my sample, while passengers from those flights affect the load factor of the DCA segments.

When there are missing products in the data, we can decompose the total number of passengers on flight segment s into two parts—1) a group of passengers for which we have product-level information in the data, and 2) those for whom we do not have product-level information:

$$Q_s = \underbrace{\sum_{j \in \mathcal{J}(\{s\})} q_{jm}}_{\text{Product Available in Data}} + \underbrace{\widetilde{Q_s}}_{\text{Not Available}}. \tag{A.6}$$

Derivations When There Are Missing Products

With this decomposition, we will have slightly different formulas for $\dfrac{\mathbf{dc_m}}{\mathbf{dQ}}$ in (1.15) and (1.19). Basically, we replace $\sum_{l \in \mathcal{J}_f(\{s\})} q_{lm}$ in (A.2) with (A.6) to obtain a new formula:

$$\sum_{l \in \mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'} = \sum_{k \in \mathcal{J}_{mf}} \sum_{s \in \mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \Big(\frac{Q_s - \widetilde{Q_s}}{Q_s}\Big) \frac{\partial q_{km}}{\partial p_{jm}}. \tag{A.7}$$

Then,

$$\begin{aligned} \frac{dVP_f}{dp_{jm}} &= q_{jm} + \sum_{k \in \mathcal{J}_{mf}} (p_{km} - c_{km}) \frac{\partial q_{km}}{\partial p_{jm}} - \sum_{l \in \mathcal{J}_f(\mathcal{S}_f)} \frac{\partial c_{lm'}}{\partial p_{jm}} q_{lm'} \\ &= q_{jm} + \sum_{k \in \mathcal{J}_{mf}} \Big(p_{km} - c_{km} - \sum_{s \in \mathcal{S}_{fk}} \gamma_2 \nu \Big(\frac{Q_s}{z_s K_s}\Big)^{\nu} \Big(\frac{Q_s - \widetilde{Q_s}}{Q_s}\Big)\Big) \frac{\partial q_{km}}{\partial p_{jm}} = 0. \end{aligned} \tag{A.8}$$

Then, $\dfrac{\mathbf{dc_m}}{\mathbf{dQ}}$ is a vector with the jth element

$$[\frac{\mathbf{dc_m}}{\mathbf{dQ}}]_j = \sum_{s \in \mathcal{S}_{fj}} \gamma_2 \nu (\frac{Q_s}{z_s K_s})^{\nu} (\frac{Q_s - \widetilde{Q_s}}{Q_s}), \tag{A.9}$$

where $\widetilde{Q_s}$ denotes the number of passengers from products that are not shown in the ticket-level data. Fortunately, we can observe the total number of passengers at a segment level from the T-100 flight segment-level data (including those not having product information). I leverage this information to obtain the proportion of the load factor on s originating from those products not available in the data, and adjust the load factor when solving the model.

Load Factor Gap Prediction

The fraction of load factor on a new segment coming from unavailable products, $\widetilde{Q_{fs}}$ in (A.6), is predicted. To do so, I first construct the number of passengers on a segment based on T-100 and based on DB1B, respectively. Then, I calculate the load factor gap between the two by their difference divided by the available seats on the segment. I regress this variable on segment specific characteristics such as distance, distance squared, and the international hub dummy. As in the airplane size prediction, I include origin-carrier pairs and destination-carrier pairs fixed effects in the regression. The regression result is reported in Table A.2 in the Appendix, and I use coefficients in column (3) to predict the load factor gap on a new segment. This predicted load factor gap will be added whenever the load factor on a flight segment needs to be calculated in the model solving process.

A.3 Counterfactual Supplements

A.3.1 Marginally Profitable Segments Prediction

I construct the likelihood of new entry in the following way. First, among counterfactual flight segments to/from DCA on which Southwest and JetBlue did not operate any services in the second quarter of 2013 (pre-merger), I identify those new segments on which they initiated nonstop services in the second quarter of 2016 (post-merger), and construct a dummy variable for the entry decisions. Then, I regress the entry decision made by them on the marginal variable profit change due to the newly added segment (ΔVP described in Assumption 1) and the carrier's presence at the non-DCA endpoint. Using the estimated logit coefficient, reported in Table A.6, I predict the likelihood of entry for all counterfactual segments of Southwest, JetBlue, Delta, and United. Analogously, a list of marginally profitable routes for NewAA can be obtained by removing each of its pre-merger existing segments from its network, and calculating their likelihood by using the same estimated logit coefficient. Finally, I sort the segments from the most likely marginally profitable to the least, and Table 2.1 shows the top ten airports that each carrier is likely to enter/exit.

A.3.2 Post-merger Airplane Size

By using the difference-in-differences methodology, I examine if the merged firm systematically changed its segment-specific airplane size after the merger. To do so, I select the flight segments to/from DCA where the merged firm (treatment group) and other legacy carriers (control group) consistently provided nonstop services from 2012 to 2016. The regression results are shown in Table A.7. There is no evidence that the merged firm substantially changed its airplane size at DCA after the merger (column 1) and that ii) the merged firm's segment-level airplane size change is systematically different from that of other legacy carriers' after the merger (column 2). This result is robust under different pre/post merger time horizons (column 3 and 4).

A.3.3 Heuristic Algorithm

Algorithm 1 shows how the "Heuristic Search" works in my model. Let $\widetilde{\mathcal{S}^0_{f+}}$ and $\widetilde{\mathcal{S}^0_{f-}}$ be the set of marginally profitable segments that carrier f can add to its

Algorithm 1: Flight Segment Choice Equilibrium Using Heuristic Search

set $n \longleftarrow 0$;
repeat
  $n \longleftarrow n+1$;
  $\Pi_f^{old*} \longleftarrow \Pi_f(\mathcal{S}_f^{n-1}, \mathcal{S}_{-f}^{n-1}), \qquad \forall f \in \mathcal{F}$;
  $\mathcal{S}_f^n \longleftarrow \mathcal{S}_f^{n-1}$, $\widetilde{\mathcal{S}_{f+}^n} \longleftarrow \widetilde{\mathcal{S}_{f+}^{n-1}}$, and $\widetilde{\mathcal{S}_{f-}^n} \longleftarrow \widetilde{\mathcal{S}_{f-}^{n-1}} \qquad \forall f \in \mathcal{F}$;
  for $k \in \{1, 2, ..., K\}$ **do**
    $f \longleftarrow f_k$ where $f_k \in \mathcal{F}$;
    $\Pi_f^{new} \longleftarrow \Pi_f(\mathcal{S}_f^n, \mathcal{S}_{-f}^n)$;
    repeat
      $\Pi_f^{old} \longleftarrow \Pi_f^{new}$;
      Pick $\mathcal{T}_-^* = \arg\max_{\mathcal{T}} \Pi_f(\mathcal{S}_f^n - \mathcal{T}, \mathcal{S}_{-f})$ where $\mathcal{T} \subset \widetilde{\mathcal{S}_{f-}^n}$ and $|\mathcal{T}| \leq 1$;
      Pick $\mathcal{T}_+^* = \arg\max_{\mathcal{T}} \Pi_f(\mathcal{S}_f^n \cup \mathcal{T}, \mathcal{S}_{-f})$ where $\mathcal{T} \subset \widetilde{\mathcal{S}_{f+}^n}$ and $|\mathcal{T}| \leq 1$;
      Denote $\mathcal{T}^*$ one of $(\mathcal{T}_-^*, \mathcal{T}_+^*)$ that gives the higher profit to f ;
      if $\mathcal{T}^* = \mathcal{T}_-^*$ **then**
        $\mathcal{S}_f^n \longleftarrow \mathcal{S}_f^n - \mathcal{T}^*$, $\widetilde{\mathcal{S}_{f-}^n} \longleftarrow \widetilde{\mathcal{S}_{f-}^n} - \mathcal{T}^*$, and $\widetilde{\mathcal{S}_{f+}^n} \longleftarrow \widetilde{\mathcal{S}_{f+}^n} \cup \mathcal{T}^*$;
      else
        $\mathcal{S}_f^n \longleftarrow \mathcal{S}_f^n \cup \mathcal{T}^*$, $\widetilde{\mathcal{S}_{f-}^n} \longleftarrow \widetilde{\mathcal{S}_{f-}^n} \cup \mathcal{T}^*$, and $\widetilde{\mathcal{S}_{f+}^n} \longleftarrow \widetilde{\mathcal{S}_{f+}^n} - \mathcal{T}^*$;
      end
      $\Pi_f^{new} \longleftarrow \Pi_f(\mathcal{S}_f^n, \mathcal{S}_{-f}^n)$;
    until $\Pi_f^{new} > \Pi_f^{old}$;
    Update $\mathcal{S}_f^n$ to $\mathcal{S}_{-g}^n$ of firm g (other than f) ;
    $\Pi_f^{new*} \longleftarrow \Pi_f^{new}$
  end
until $\Pi_f^{new*} > \Pi_f^{old*}, \qquad \forall f \in \mathcal{F}$;

network and the set of marginally profitable segments that carrier f can remove from its network at the initial period, respectively. $\widetilde{\mathcal{S}_{f+}^0}$ for carriers other than NewAA will be the list of segments in Table 2.1, while $\widetilde{\mathcal{S}_{f+}^0}$ for NewAA will be empty set. Analogously, $\widetilde{\mathcal{S}_{f-}^0}$ for NewAA will be the list of segments in Table 2.1 and for other carriers, will be the empty set. Let $\mathcal{S}_f^0$ be the set of existing segments that f initially operates. Note that $\widetilde{\mathcal{S}_{f-}^0} \subset \mathcal{S}_f^0$. Let $\mathcal{F}$ be the set of carriers and assume that there is a sequence order of carriers $\mathcal{F} = \{f_1, f_2, ..., f_K\}$ where K is the number of carriers.

Given what other carriers choose in the previous period, firm f chooses either one of the two options—adding a new flight segment or removing an existing segment—that gives the firm the highest profit for each turn, and the firm repeats the process until it reaches the point where its profit is no longer increasing. Given firm f's newly updated flight segments, other firms based on order repeat the same thing. After all carriers update their flight segments in this round, the algorithm checks if the profit under the updated segments is greater than the profit in the previous round. The algorithm repeats the same procedure until it reaches the point at which there are no profitable deviations across all carriers.

A.4 Slot Allocation Models

The baseline model that finds the optimal slot allocation can be extended in two directions. One is to change the order in which the choice variables are chosen, and the second is to assume that both demand and marginal cost are affected by a slot allocation.

A.4.1 Sequential Model

In the baseline model, I assume that a firm *simultaneously* chooses its slot allocation and product prices in the second stage of the model. Alternatively, the firm could choose the slot allocation first, then make product price choices. I call this a sequential model, which actually makes the entry model a three-stage model.

In this sequential model, a slot allocation in the second stage affects product price choices in the third stage. When the carrier excessively allocates its slots to a flight segment, the product costs linked to this slot segment may decline due to the reduced load factor and may give the firm an incentive to reduce prices, which suggests an increase in market competition in markets in which the flight segment is involved. Due to the scarcity of slots, however, the carrier may need to allocate a smaller number of slots to another flight segment. This may lead to a fuller airplane in the segment, and carriers in the markets in which the segment is involved recognize this cost and may set higher prices in those markets. In this model, when setting the optimal slot allocation, carriers recognize that prices are affected by their slot allocation.

A.4.2 Flight Frequency in Demand

In the baseline model, when a slot allocation changes, a firm's variable profit is affected by this change only through the load factors in the firm's marginal cost. However, it is possible to extend the model by allowing product demand to also be affected by the slot allocation. As the demand estimation result in Table 1.4 suggests, passengers prefer a flight product that has more daily departure time options. As the number of daily departures of a product increases in the number of landing slots associated with the product, a change in the number of slots assigned to a flight segment can alter both the demand for and the marginal cost of a product.

Equation (A.10) illustrates how adding a slot to flight segment s can affect the variable profit of carrier f, VP_f:

$$\frac{dVP_f}{dK_s} = \underbrace{\sum_j \frac{\partial VP_f}{\partial q_j}\frac{\partial q_j}{\partial K_s}}_{\Delta VP \text{ via Demand}} + \underbrace{\frac{\partial VP_f}{\partial K_s}}_{\Delta VP \text{ via Supply}} . \tag{A.10}$$

An increase in the number of slots assigned to a flight segment not only has a positive and direct impact on the demand for all the products using the slot but also induces a substitution effect between products of the same carrier within a market, as passengers prefer a more- to less-frequent flight product. On the supply side, adding a slot to a flight segment reduces costs for all products using the slot due to the decrease in the load factor via an increase in the number of available seats on the segment.

To illustrate the change in the variable profit from the demand side, Figure 1.3 presents a simplified carrier airline network. Suppose that carrier f allocates one more slot to the $(\text{DCA}\rightarrow\text{IAH})_f$ flight segment. Then, passengers who fly the DCA-IAH (nonstop) or DCA-IAH-DEN (connecting) products enjoy more departure time options; hence, the slot allocation increases the demand for those products in different markets. However, the marginal increase in demand for the DCA-IAH-DEN product will make some of the passengers in the DCA-DEN market switch to the DCA-IAH-DEN product from other products in the same market.

While this model extension is rich in the sense that it captures both demand and supply responses to a slot allocation, it entails an additional computational burden. In an optimization procedure, a long time is needed to obtain the optimal solution without providing the analytic gradient and/or Hessian of the objective function. The first term in (A.10) makes it challenging to obtain the analytic gradients, as the term is associated with interactions among those products linked through flight segments. I am currently working on this question to increase the computational speed in this model extension.

Appendix B: Appendix for Chapter 3

The model used in the text assumes that carriers know all demand and cost shocks when making service choices. an alternative assumption used in the literature assumes that firms only know the distributions from which these shocks are drawn. In this Appendix we use an example to illustrate the equilibrium effects of different information structures, which have not been clearly identified in the existing literature. The example model is the same as the one in the text except that marginal costs have a simpler structure and we assume that demand and prices are the same in both directions. The reported results use a single set of parameters, although we have found the same qualitative patterns for the alternatives that we have tried.

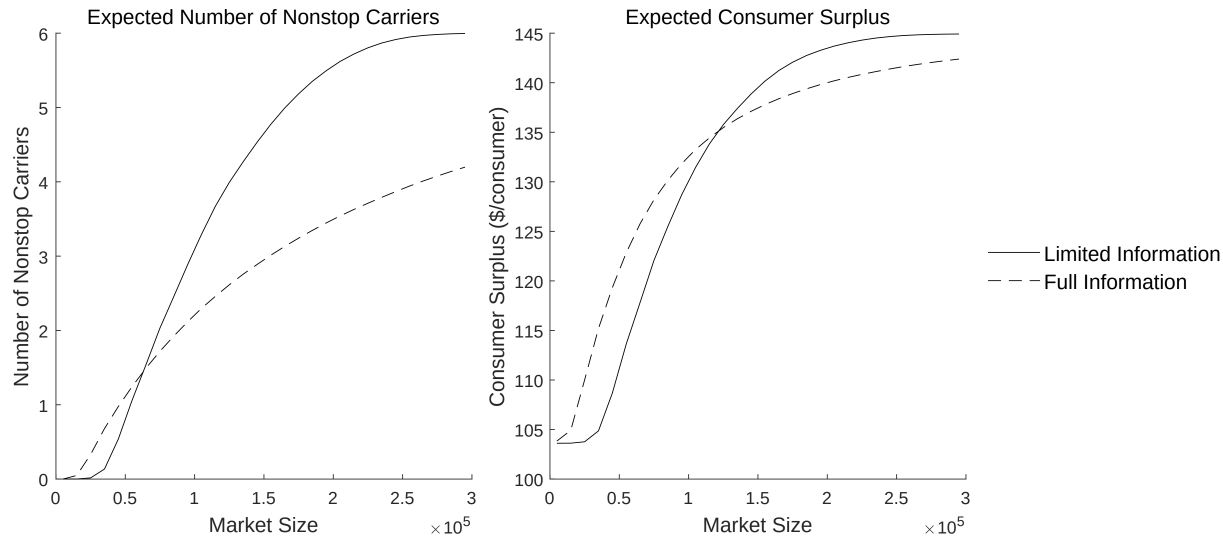
Overview. We consider a single market, although we shall vary its size, with six carriers, A,..,F. In the first stage of the game, the carriers choose whether to provide connecting service or higher-quality nonstop service. Nonstop service requires payment of a fixed cost. Having selected their service types they simultaneously choose prices in the second stage. Demand is determined by a nested logit model, with all carriers in the same nest. The quality of a carrier's service is determined by the sum of a fixed carrier-specific quality component, which will always be known to rivals, a random component and, if it provides nonstop service, a second random component which is truncated to be greater than zero. Marginal costs consist of a common fixed service-specific component and a random component that is common across service types. A carrier's fixed cost is drawn from a normal distribution with a common mean and variance. Service choices are made sequentially, where the carriers with the highest fixed quality move first.

Parameters. The indirect utility for consumer k using carrier i is $u_{ki} = \beta_i - \alpha p_i + \tau\zeta_k + (1-\tau)\varepsilon_{ki}$, with $\tau = 0.7$, $\alpha = 0.5$, and $\beta_i = \beta_i^{CON} + \beta_i^{NS}$ x $\mathcal{I}(i \text{ is nonstop})$. β_i^{CON} is drawn from a normal distribution with standard deviation 0.2 and mean values of 0.6, 0.55, 0.5, 0.45, 0.4 and 0.35 for carriers A to F respectively. The incremental quality of nonstop service, β_i^{NS}, is a draw from a truncated normal distribution with mean 0.3, standard deviation 0.2 and a lower truncation point of 0. The mean utility of not traveling is zero. Carrier marginal costs are \$200 for nonstop service and \$220 for (longer) connecting service, plus a carrier-specific component, common across service types, drawn from a normal distribution with mean zero and standard deviation \$15. Nonstop service requires a carrier to pay a fixed cost that has mean \$600,000 and standard deviation \$125,000.

Information Structures. We compare outcomes under two alternative information structures, although both are "complete information" in the sense that the firms do not have any private information. Under "full information", all draws are known to all carriers throughout the game. Under "limited information", carriers only know the model parameters and the draws of fixed costs (assumed to be known by all carriers) in the first stage, but the demand and marginal cost draws are revealed before prices are chosen. Limited information is the common assumption in the empirical literature on models with entry or product selection and price competition (Draganska et al. (2009), Eizenberg (2014), Wollmann (2018) and Fan and Yang (2018)). We simulate equilibrium outcomes 50,000 times for each of 30 different market sizes, ranging from 5,000 and 295,000.

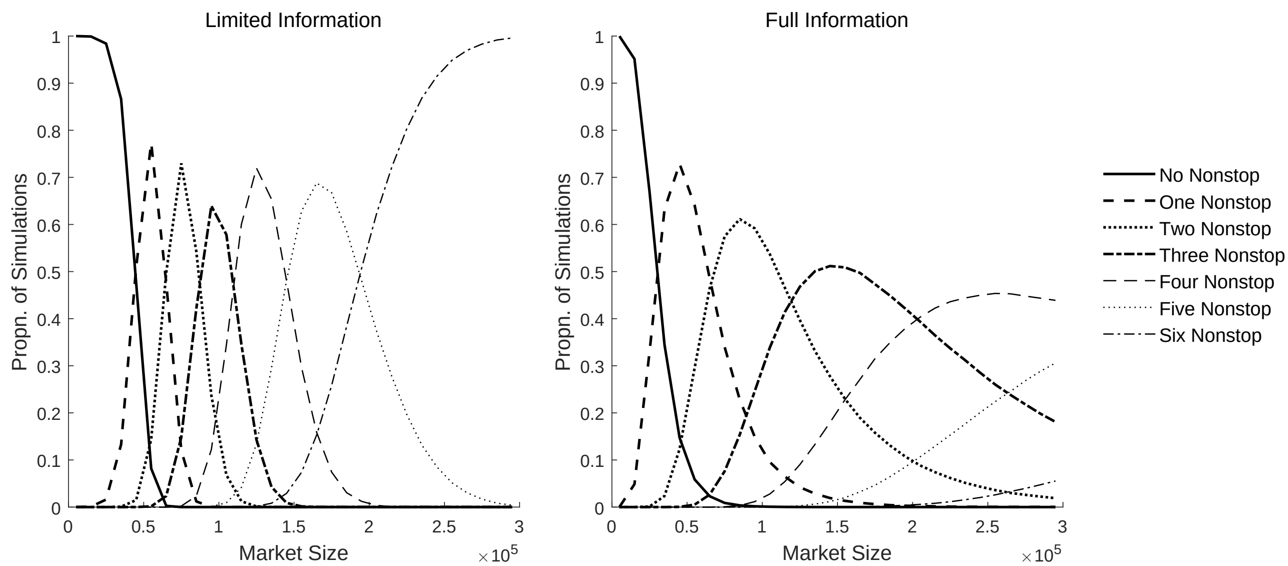
The method for solving the full information model is the same as the one used in the paper. For the limited information model, we approximate the expected profits of each carrier in every possible market configuration by taking 1,000 draws of marginal costs and qualities. We then solve sequential service choice games for each of 50,000 draws of fixed costs, before simulating realizations of the marginal cost and quality draws to compute expected consumer surplus.

Figure B.1: The Relationship Between Market Size, Expected Consumer Surplus and the Expected Number of Nonstop Carriers Under Different Informational Assumptions



Results. Figure B.1 compares the average number of nonstop carriers and consumer surplus in equilibrium. In a small market, nonstop service may only be profitable when a carrier has unusually high nonstop quality or low marginal costs, unless its fixed cost is very low. Knowledge of quality and marginal cost draws can therefore make it more likely that a carrier will be nonstop. Fewer carriers provide nonstop service in larger markets under full information. The intuition comes from the competitiveness of the nonstop rivals that a carrier expects to face. Under full information, a nonstop rival will tend to be a stronger competitor (because it has been selected based on its quality and cost), which lowers the expected nonstop profitability of another carrier considering nonstop service. This reduces the number of nonstop carriers in equilibrium. However, selection also means that nonstop carriers tend to provide better quality products, which raises expected consumer surplus under full information for a given number of nonstop carriers. The example also illustrates the feature that carriers may frequently regret their choices under limited information: for example, for a market size of 55,000, for 48% of the draws where a single carrier chooses to be nonstop, that carrier would have increased its

Figure B.2: The Relationship Between Market Size and Equilibrium Market Structure Under Different Informational Assumptions



(ex-post) profits by only offering connecting service.

Figure B.2 shows that, for a given market size, the *distribution* of the number of nonstop carriers is much tighter under limited information.[1] This feature has implications for what we would predict should happen after a merger if carriers can change their service choices. To illustrate, we consider a market size of 85,000 and collect all sets of draws that result in the two carriers with the highest mean quality components being nonstop duopolists, which is the most common outcome under either information structure. Now suppose that these carriers merge, eliminating the carrier with the smaller market share, and that the remaining carriers can re-optimize their service choices in the same sequential order.[2] Under limited information, the probability that at least one rival carrier will introduce nonstop service after the merger is 0.8, and the expected reduction in consumer surplus fol-

[1]For example, for a market size of 145,000, 97% of simulated outcomes have either three or four nonstop carriers, compared with 69% under full information.

[2]The reader might view it as unreasonable to use the limited information assumption in this case because carriers' pre-merger experience on the route in question would inform them of their quality and costs, even for the type of service that they are not offering. We completely agree, which is one reason why we believe a full information model is the natural model for merger counterfactuals.

lowing the merger is just under \$0.3 million. Under full information, the probability that at least one rival will introduce nonstop service after the merger is 31% lower (0.55) and the expected loss of consumer surplus is almost \$1.15 million.[3] In the limited information case, the merger is also, on average, unprofitable for the merging parties, while it is profitable under full information. Note that if, in either version of the model, we had not accounted for selection (which we did by only using draws in our counterfactuals that could generate the pre-merger market structure that we are interested in), we could also get quite different post-merger predictions. In Section 3.6 of the paper, we show how accounting for selection affects merger counterfactuals using our estimated full information model.

B.1 Data Appendix

This Appendix complements the description of the data in Section 3.3 of the text.

B.1.1 Sample Construction and Variable Definitions

Selection of markets. We use 2,028 airport-pair markets linking the 79 U.S. airports (excluding airports in Alaska and Hawaii) with the most enplanements in Q2 2006. The markets that are excluded meet one or more of the following criteria:

- airport-pairs that are less than 350 miles apart as ground transportation may be very competitive on these routes;
- airport-pairs involving Dallas Love Field, which was subject to Wright Amendment restrictions that severely limited nonstop flights;
- airport-pairs involving New York LaGuardia or Reagan National that would violate the so-called perimeter restrictions that were in effect from these air-

[3]The loss in consumer surplus is greater under full information not only because there is less repositioning but also because the pre-merger market shares of the nonstop carriers, whose merger we are considering, tend to be higher because of selection.

ports[4];

- airport-pairs where more than one carrier that is included in our composite "Other Legacy" or "Other LCC" (low-cost) carriers are nonstop, have more than 20% of non-directional traffic or have more than 25% presence (defined in the text) at either of the endpoint airports. Our rationale is that our assumption that the composite carrier will act as a single player may be especially problematic in these situations[5]; and,

- airport-pairs where, based on our market size definition (explained below), the combined market shares of the carriers are more than 85% or less than 4%.

Seasonality. The second quarter is the busiest quarter for airline travel, and one might be concerned that seasonality affects our measures of passenger flows and service choices, and therefore our estimates. We do not believe that this is a first-order concern for our sample of relatively large markets. The website `http://www.anna.aero` (accessed May 29, 2018) provides a formula for measuring the seasonality of airport demand (SVID) which we have calculated for all of the airports in our sample using monthly T100 data on originating passengers.[6] The website classifies seasonality as "excellent" if SVID is less than 2 or "good" if the SVID is between 2 and 10, on the basis that seasonality is costly for an airline or an airport because it requires changes in schedules. All of the airports in our sample are within these ranges, with the highest (most seasonal) values for Seattle (2.4), New Orleans (2.8), Palm Beach (5.2) and Southwest Florida (9.9). In contrast, a non-sample airport with very seasonal demand, Gunnason-Crested Butte (GUC), has an SVID of 65. Applying SVID on a route-level to quarterly traffic, only one sample route (Minneapolis to Southwest Florida) has an SVID greater than 10 (19), and the 95th percentile is 3.12.

[4]To be precise, we exclude routes involving LaGuardia that are more than 1,500 miles (except Denver) and routes involving Reagan National that are more than 1,250 miles.

[5]An example of the type of route that is excluded is Atlanta-Denver where Airtran and Frontier, which are included in our "Other LCC" category had hubs at the endpoints and both carriers served the route nonstop.

[6]The measure is calculated as $\frac{\sum_{m=1,..,M=12}\left(\frac{100\times \text{Traffic}_{a,m}}{\overline{\text{Traffic}_a}}-100\right)^2}{1000}$.

We reach a similar conclusion if we identify markets which a carrier serves nonstop in our data and in the second quarter of 2005, but which they did not serve nonstop in either Q1 2005 or Q1 2006 (i.e., markets where a carrier's nonstop service may be seasonal). We can only identify two such carrier-markets in our sample (United for San Antonio-San Francisco and Sun Country (part of Other Low Cost) for Indianapolis-Kansas City), out of 8,065 carrier-markets.

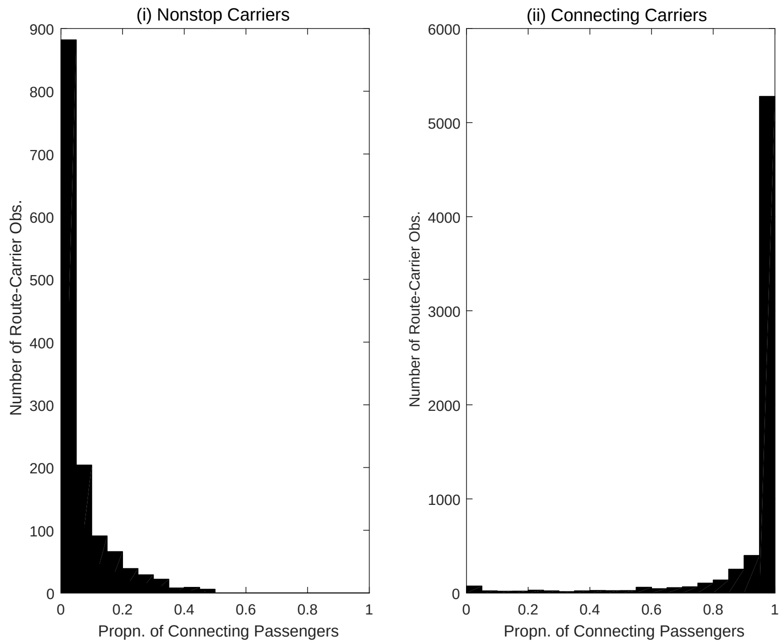
Definition of players, nonstop and connecting service. We are focused on the decision of carriers to provide nonstop service on a route. Before defining any players or outcomes, we drop all passenger itineraries from DB1 that involve prices of less than \$25 or more than \$2000 dollars[7], open-jaw journeys or journeys involving more than one connection in either direction. Our next step is to aggregate smaller players into composite "Other Legacy" and "Other LCC" carriers, in addition to the "named" carriers (American, Continental, Delta, Northwest, Southwest, United and US Airways) that we focus on. Our classification of carriers as low-cost follows Berry and Jia (2010). Based on the number of passengers carried, the largest Other Legacy carrier is Alaska Airlines, and the largest Other LCC carriers are JetBlue and AirTran.

We define the set of players on a given route as those ticketing carriers who achieve at least a 1% share of total travelers (regardless of their originating endpoint) and, based on the assumption that DB1 is a 10% sample, carry at least 200 return passengers per quarter, with a one-way passenger counted as one-half of a return passenger. We define a carrier as providing nonstop service on a route if it, or its regional affiliates, are recorded in the T100 data as having at least 64 nonstop flights in each direction during the quarter and at least 50% of the DB1 passengers that it carries are recorded as not making connections (some of these passengers may be traveling on flights that make a stop but do not require a change of planes). Other players are defined as providing connecting service.

There is some arbitrariness in these thresholds. However, the 64 flight and 50% nonstop thresholds for nonstop service have little effect because almost all

[7]These fare thresholds are halved for one-way trips.

Figure B.1: Proportion of DB1 Passengers Traveling with Connections, Based on the Type of Service



nonstop carriers far exceed these thresholds. For example, Figure B.1 shows that the carriers we define as nonstop typically carry only a small proportion of connecting passengers. For the same reason, we also model nonstop carriers as only providing nonstop service even if some of their passengers fly connecting, although we include the connecting passengers when calculating market shares. On the other hand, our 1% share/200 passenger thresholds do affect the number of connecting carriers. For example, if we instead require players to carry 300 return passengers and have a 2% share, the average number of connecting carriers per market falls by almost one-third as marginal carriers are excluded.

Market Size. Market size is used to define market shares and to calculate counterfactual quantities and profits. Given the role of market size in the identification and estimation of demand and entry-type models, the ideal definition should imply that variation in shares across markets, or across directions, should reflect changes in prices, carrier characteristics and service types, and it should be a good predictor of the number of nonstop firms.

A standard approach in the literature is to use the geometric average of the endpoint MSA populations (e.g., Berry and Jia (2010), Ciliberto and Williams (2014)). However, this performs poorly for airport-pair routes (MSA demand may be split between several airports) and it cannot allow for the possibility that originating demand is systematically different at the endpoints.

We therefore consider an alternative definition based on the estimates of a generalized gravity equation, used previously in Sweeting et al. (ming). The model specifies that the total number of second quarter passengers on a route varies with a linear function of the log of the count of originating and arriving passengers at each of the endpoint airports (measured for the second quarter of the previous year), log route distance and interactions of these lagged passengers flow and distance variables. The corresponding Poisson regression is estimated using data from 2005-2011, including year, origin and destination fixed effects and an interaction between the origin and destination fixed effects and a dummy for long-distance routes, defined as those over 2,300 miles.[8] With the estimates in hand, we calculate the expected number of passengers for each directional market for Q2 2006, based on lagged values of passenger flows in Q2 2005. Our market size measure multiplies this prediction by 3.5.

Two comparisons suggest that our measure provides a superior measure of market size to estimates based on average population. Given that prices and service in each direction on a route tend to be similar we would expect the correlation in the combined market share of all of the carriers to be quite high: using our measure the correlation is 0.86 and using the geometric average population it is 0.56. Consistent with this difference, if one estimates our model using population-based market size measures, there is much greater unobserved heterogeneity in demand than there is in our estimates. CMT, who use a population-based measure, also estimate much more demand heterogeneity than we do.

[8]The individual coefficients are not especially informative because of the interactions, but combining them shows reasonable patterns. For example, the expected number of passengers declines in route distance, increases with both lagged originating traffic at the origin airport, and lagged arriving traffic at the destination.

Table B.1 examines the ability of the different market size variables to predict the number of nonstop carriers on a route using an ordered probit model. Examination of the reported pseudo-R2s shows that our gravity measure has much stronger predictive power, and that when we add population-based variables to a specification with a flexible function of our measure (i.e., going from column (2) to column (5)) the R2 increases by less than 1%. However, because we recognize that our market size measure is still imperfect, we also allow for an additional route-level unobservable that is common to the demand of all carriers, but is unobserved by the researcher.

Prices and Market Shares. As is well-known, airlines use revenue management strategies that result in passengers on the same route paying quite different prices. Even if more detailed data (e.g., on when tickets are purchased) was available, it would likely not be feasible to model these type of strategies within the context of a combined service choice and pricing game. We therefore use the average price as our price measure, but allow for prices and market shares (defined as the number of originating passengers carried divided by market size) to be different in each direction, so that we can capture differences in passenger preferences (possibly reflecting frequent-flyer program membership) across different airports.[9]

Explanatory Variables Reflecting Airline Networks. The legacy carriers in our data operate hub-and-spoke networks. On many medium-sized routes local demand could not generate sufficient variable profits to cover the fixed costs of nonstop service, but nonstop service may be profitable once the value of passengers who will use a nonstop flight as one segment on a longer journey is taken into account. While our structural model captures price competition for passengers traveling only the route itself, we allow for traffic to other destination to reduce the effective fixed cost of providing nonstop service by including three carrier-specific variables in our specification of fixed costs. Two variables are indicators for the principal domestic

[9]Carriers may choose a similar set of ticket prices to use in each direction but revenue management techniques mean that average prices can be significantly different. Fares on contracts that carriers negotiate with the federal government and large employers may also play a role, but there is no data available on how many tickets are sold under these contracts.

Table B.1: Market Size Measures and the Number of Nonstop Carriers

	(1)	(2)	(3)	(4)	(5)
Our Market Size	3.230	11.05			11.04
(/10,000)	(0.110)	(0.440)			(0.482)
Our Market Size^2		-8.933			-8.780
		(0.560)			(0.587)
Our Market Size^3		2.283			2.230
		(0.190)			(0.196)
Geom. Avg. Pop			2.476	10.48	2.125
(/1 m.)			(0.136)	(0.823)	(0.966)
Geom. Avg. Pop^2				-12.98	-4.835
				(1.536)	(1.757)
Geom. Avg. Pop^3				4.977	2.433
				(0.773)	(0.877)
Ordered Probit Cutoffs					
Cutoff 1	0.730	1.596	0.725	1.801	1.813
	(0.0369)	(0.0604)	(0.0460)	(0.113)	(0.126)
Cutoff 2	2.082	3.350	1.722	2.844	3.571
	(0.0563)	(0.0965)	(0.0548)	(0.120)	(0.146)
Cutoff 3	3.915	4.995	2.761	3.890	5.217
	(0.128)	(0.132)	(0.0789)	(0.133)	(0.171)
Cutoff 4	6.987	6.877	4.134	5.181	7.112
	(0.431)	(0.333)	(0.232)	(0.240)	(0.351)
Observations	2,028	2,028	2,028	2,028	2,028
Pseudo-R^2	0.262	0.368	0.0770	0.109	0.371

Notes: coefficients from an ordered probit regression where the dependent variable is the number of nonstop carriers in the non-directional market. "Our market size" measure is the average of our measure of market size across directions. Standard errors in parentheses. Number of observations is equal to the number of markets.

and international hubs of the non-composite carriers. We define domestic hubs as airports where more than 10,000 of the carrier's ticketed passengers made domestic connections in DB1 in Q2 2005 (i.e., one year before our estimation sample). Note that some airports, such as New York's JFK airport for Delta, that are often classified as hubs do not meet our definition because the number of passengers using them for domestic connections is quite small even though the carrier serves many destinations from the airport. International hubs are airports that carriers use to serve a significant number of non-Canadian/Mexican international destinations nonstop. Table B.2 shows the airports counted as hubs for each named carrier.

We also include a continuous measure of the potential connecting traffic that will be served if nonstop service is provided on routes involving a domestic hub. The construction of this variable, as the prediction of a Heckman selection model, is detailed next.

B.1.2 An Ancillary Model of Connecting Traffic

As explained in Section 3.3, we want to allow for the amount of connecting traffic that a carrier can carry when it serves a route nonstop to affect its decision to do so. Connecting traffic is especially important in explaining why a large number of nonstop flights can be supported at domestic hubs in smaller cities, such as Charlotte, NC (a US Airways hub) and Salt Lake City (Delta). While the development of a model where carriers choose their entire network structure is well beyond the scope of the paper, we use a reduced-form model of network flows that fits the data well[10] and which gives us a prediction of how much connecting traffic that a carrier can generate on a route where it does not currently provide nonstop service, taking the service that it provides on other routes as given. We include this prediction in our model of entry as a variable that can reduce the effective fixed

[10]This is true even though we do not make use of additional information on connecting times at different domestic hubs which could potentially improve the within-sample fit of the model, as in Berry and Jia (2010). As well as wanting to avoid excessive complexity, we would face the problem that we would not observe connection times for routes that do not currently have nonstop service on each segment, but which could for alternative service choices considered in our model.

Table B.2: Domestic and International Hubs for Each Named Carrier

Airline	Domestic Hub Airports	International Hub Airports
American	Chicago O'Hare, Dallas-Fort Worth, St. Louis	Chicago O'Hare, Dallas-Fort Worth, New York JFK, Miami, Los Angeles
Continental	Cleveland, Houston Intercontinental	Houston Intercontinental, Newark
Delta	Atlanta, Cincinnati, Salt Lake City	Atlanta, New York JFK
Northwest	Detroit, Memphis, Minneapolis	Detroit, Minneapolis
United	Chicago O'Hare, Denver, Washington Dulles	Chicago O'Hare, San Francisco, Washington Dulles
Southwest	Phoenix, Las Vegas, Chicago Midway, Baltimore	none
US Airways	Charlotte, Philadelphia, Pittsburgh	Charlotte, Philadelphia

cost of providing nonstop service on the route.[11]

Model. We build our prediction of nonstop traffic on a particular segment up from a multinomial logit model of the share of the connecting passengers going from a particular origin to a particular destination (e.g., Raleigh (RDU) to San Francisco (SFO)) who will use a particular carrier-hub combination to make the connection. Specifically,

$$s_{c,i,od} = \frac{\exp(X_{c,i,od}\beta + \xi_{c,i,od})}{1 + \sum_l \sum_k \exp(X_{l,k,o,d}\beta + \xi_{l,k,od})} \tag{B.1}$$

where $X_{c,i,od}$ is a vector of observed characteristics for the connection (c)-carrier (i)-origin (o)- destination (d) combination and $\xi_{c,i,od}$ is an unobserved characteristic. The Xs are functions of variables that we are treating as exogenous such as airport presence, endpoint populations and geography. The outside good is traveling using connecting service via an airport that is not one of the domestic hubs that we identify.[12] Assuming that we have enough connecting passengers that the choice probabilities can be treated as equal to the observed market shares, we could potentially estimate the parameters using the standard estimating equation for aggregate data (Berry 1994):

$$\log(s_{c,i,od}) - \log(s_{0,od}) = X_{c,i,od}\beta + \xi_{c,i,od}. \tag{B.2}$$

However, estimating (B.2) would ignore the selection problem that arises from the fact that some connections may only be available because the carrier will attract a large share of connecting traffic. We therefore introduce an additional probit model, as part of a Heckman selection model, to describe the probability that carrier i does serve the full ocd route,

$$\Pr(i \text{ serves route } ocd) = \Phi\left(W_{i,c,od}\gamma\right). \tag{B.3}$$

[11] We also use the predicted value, not the actual value, on routes where we actually observe nonstop service.

[12] For example, the outside good for Raleigh to San Francisco could involve traveling via Nashville on any carrier (because Nashville is not a domestic hub) or on Delta via Dallas Fort Worth because, during our data, Dallas is not defined as a domestic hub for Delta even though it is for American.

Sample, Included Variables and Exclusion Restrictions. We estimate our model using data from Q2 2005 (one year prior to the data used to estimate our main model) for the top 100 US airports. We use DB1B passengers who (i) travel from their origin to their destination making at least one stop in at least one direction (or their only direction if they go one-way) and no more than one stop in either direction; and, (ii) have only one ticketing carrier for their entire trip. For each direction of the trip, a passenger counts as one-half of a passenger on an origin-connecting-destination pair route (so a passenger traveling RDU-ATL-SFO-CVG-RDU counts as $\frac{1}{2}$ on RDU-ATL-SFO and $\frac{1}{2}$ on RDU-CVG-SFO). Having joined the passenger data to the set of carrier-origin-destination-connecting airport combinations, we then exclude origin-destination routes with less than 25 connecting passengers (adding up across all connecting routes) or any origin-connection or connection-destination segment that is less than 100 miles long.[13] We also drop carrier-origin-destination-connecting airport observations where the carrier (or one of its regional affiliates) is not, based on T100, providing nonstop service on the segments involved in the connection. This gives us a sample of 5,765 origin-destination pairs and 142,506 carrier-origin-destination-hub connecting airport combinations, of which 47,996 are considered to be served in the data.

In $X_{c,i,od}$ (share equation), we include variables designed to measure the attractiveness of the carrier i and the particular ocd connecting route. Specifically, the included variables are carrier i's presence at the origin and its square, its presence at the destination and its square, the interaction between carrier i's origin and destination presence, the distance involved in flying route ocd divided by the nonstop distance between the origin and destination (we call this the 'relative distance' of the connecting route), an indicator for whether route ocd is the shortest route involving a hub, an indicator for whether ocd is the shortest route involving a hub for carrier i and the interaction between these two indicator variables and the relative distance.

[13] Note while we will only use routes of more than 350 miles in the estimation of our main model, we use a shorter cut-off here because we do not want to lose too many passengers who travel more than 350 miles on one segment but less than 350 miles on a second segment.

The logic of our model allows us to define some identifying exclusion restrictions in the form of variables that appear in W but not in X. For example, the size of the populations in Raleigh, Atlanta and San Francisco will affect whether Delta offers service between RDU and ATL and ATL and SFO, but it should not be directly relevant for the choice of whether a traveler who is going from RDU to SFO connects via Atlanta (or a smaller city such as Charlotte), so these population terms can appear in the selection equation for whether nonstop service is offered but not the connecting share equation. In $W_{c,i,od}$ we include origin, destination and connecting airport presence for carrier i; the interactions of origin and connecting airport presence and of destination and connecting airport presence; origin, destination and connecting city populations; the interactions of origin and connecting city populations and of destination and connecting city populations, a count of the number of airports in the origin, destination and connecting cities[14]; indicators for whether either of the origin or destination airports is an airport with limitations on how far planes can fly (LaGuardia and Reagan National) and the interactions of these variables with the distance between the origin or destination (as appropriate) and the connecting airport; indicators for whether the origin or destination airport are slot-constrained. In both $X_{i,c,od}$ and $W_{i,c,od}$ we also include origin, destination and carrier-connecting airport dummies.

Results. We estimate the equations using a one-step Maximum Likelihood procedure where we allow for residuals in (B.2) and (B.3), which are assumed to be normally distributed, to be correlated. However, our predictions are almost identical using a two-step procedure (the correlation in predictions greater than 0.999). The coefficient estimates are in Table B.3, although the many interactions mean that it is not straightforward to interpret the coefficients.

To generate a prediction of the connecting traffic that a carrier will serve if it operates nonstop on particular segment, we proceed as follows. First, holding service on other routes and by other carriers fixed, we use the estimates to calculate

[14]For example, the number is 3 for the airports BWI, DCA and IAD in the Washington DC-Baltimore metro area.

Table B.3: Estimation Coefficients for Ancillary Model of Connecting Traffic

	Connecting Share	Serve Route	$\frac{1}{2}log\frac{1+\rho}{1-\rho}$	$log(std.\ deviation)$
Constant	4.200	-8.712	-0.109	0.308
	(0.338)	(0.823)	(0.0860)	(0.0150)
Presence at Origin Airport	4.135	6.052		
	(0.396)	(1.136)		
Presence at Connecting Airport		11.90		
		(0.721)		
Presence at Destination Airport	2.587	6.094		
	(0.396)	(1.126)		
Origin Presence X Connecting Presence		-5.536		
		(1.311)		
Destin. Presence X Connecting Presence		-5.771		
		(1.303)		
Population of Connecting Airport		-1.20e-07		
		(3.16e-08)		
Origin Population X Origin Presence		-5.09e-08		
		(2.23e-08)		
Destin. Population X Destination Presence		-4.46e-08		
		(2.35e-08)		
Number of Airports Served from Origin		0.543		
		(0.101)		
Number of Airports Served from Destination		0.529		
		(0.0984)		
Origin is Restricted Perimeter Airport		0.0317		
		(0.321)		
Destination is Restricted Perimeter Airport		-0.0865		
		(0.305)		
Origin is Slot Controlled Airport		-1.098		
		(0.321)		
Destination is Slot Controlled Airport		-1.055		
		(0.331)		
Distance: Origin to Connection		-0.00146		
		(0.000128)		
Distance: Connection to Destination		-0.00143		
		(0.000125)		
Origin Restricted X Distance Origin - Connection		0.000569		
		(0.000207)		
Destin. Restricted X Distance Connection - Destin		0.000602		
		(0.000211)		
Relative Distance	-4.657			
	(0.441)			
Most Convenient Own Hub	-0.357			
	(0.192)			
Most Convenient Hub of Any Carrier	-0.574			
	(0.442)			
Origin Presence^2	-2.797			
	(0.429)			
Destination Presence^2	-1.862			
	(0.449)			
Relative Distance^2	0.745			
	(0.129)			
Most Convenient Own Hub X Relative Distance^2	0.479			
	(0.151)			
Most Convenient Hub of Any Carrier X	0.590			
Relative Distance	(0.434)			
Origin Presence X Destination Presence	-5.278			
	(0.513)			
Observations	142,506	-	-	-

Notes: robust standard errors in parentheses.

a predicted value for each carrier's share of traffic on a particular *ocd* route. Second, we multiply this share prediction by the number of connecting travelers on the *od* route to get a predicted number of passengers. Third, we add up across all *oc* and *cd* pairs involving a segment to get our prediction of the number of connecting passengers served if nonstop service is provided. There will obviously be error in this prediction resulting from our failure to account for how the total number of connecting passengers may be affected by service changes and the fact that service decisions will really be made simultaneously across an airline network.

However we find that the estimated model provides quite accurate predictions of how many connecting travelers use different segments, which makes us believe that it should be useful when thinking about the gain to adding some marginal nonstop routes to a network. For the named legacy carriers in our primary model, there is a correlation of 0.96 between the predicted and observed numbers of connecting passengers on segments that are served nonstop. The model also captures some natural geographic variation. For example, for many destinations a connection via Dallas is likely to be more attractive for a passenger originating in Raleigh-Durham (RDU) than a passenger originating in Boston (BOS), while the opposite may hold for Chicago. Our model predicts that American, with hubs in both Dallas (DFW) and Chicago (ORD), should serve 2,247 connecting DB1 passengers on RDU-DFW, 1,213 on RDU-ORD and 376 on RDU-STL (St Louis), which compares with observed numbers of 2,533, 1,197 and 376. On the other hand, from Boston the model predicts that American will serve more connecting traffic via ORD (2,265, observed 2,765) than DFW (2,040, observed 2,364).

B.1.3 An Analysis of Changes to Prices and Service After Airline Mergers Post-2006

We use our model to predict the effects of three legacy carrier mergers that took place after the period of our data (Delta/Northwest merger (closed October 2008), United/Continental (October 2010) and American/US Airways (December

2013)). In this Appendix we describe an analysis of what happened to the prices and quantities of the merging parties and the service decisions of rivals on routes where the merging parties were nonstop duopolists. Based on a fixed service types, one would expect that the merger might create significant market power in these markets. We also consider the Southwest/Airtran merger (May 2011) although we do not perform counterfactuals for that merger as Airtran is part of our composite Other LCC carrier. To perform the analysis, we created a panel dataset that runs from the first quarter of 2001 to the first quarter of 2017 using the same definition of nonstop service, but without aggregating smaller carriers into composite Other Legacy and Other LCC rivals.

B.1.3.1 Frequency of Rivals Launching Nonstop Service

On routes where the merging firms are nonstop duopolists before the merger, the merged firm always maintains nonstop service until the end of our data. We calculate the number of routes where at least one rival carrier, including carriers that were not providing any service prior to the merger, initiated nonstop service within two (or three) years of the merger closing. A two year window is often considered when examining entry and repositioning in merger cases, and was explicitly cited by the Department of Transportation (Keyes (1987)). We will use three years in our analysis of price and quantity changes below as an additional year provides more precision to our estimates which are based on a small number of markets, with only small effects on the point estimates.

We find that no rivals (no rivals) initiated nonstop service within two (three) years on five routes where the merging parties were nonstop duopolists immediately before the closing of the merger for Delta/Northwest. Rivals did initiate nonstop service on one (two) out of five routes for United/Continental, three (four) out of six routes for American/US Airways and one (one) out of seventeen nonstop duopoly routes for Southwest/Airtran. Therefore, the overall rate of rivals initiating nonstop service was five (seven) out of thirty-three routes, or four (six) out of sixteen if we only consider legacy mergers.[15]

One explanation for a low rate of repositioning is that rivals are ill-suited to provide nonstop service on these routes, so that the merging carriers can exercise market power even if the merger does not generate efficiency advantages (higher quality or lower marginal costs). This will be the explanation that we focus on in our counterfactuals. However, an alternative explanation is that it is efficiencies created through the merger make it unattractive for rivals to offer nonstop service. An analysis of changes to price and market shares can give some insights into which of these stores are correct.

B.1.3.2 Changes to the Merging Carriers' Prices and Quantities

We define a treatment group of markets where the merging carriers were nonstop duopolists prior to the merger. We also define a control group of markets where one of the merging carriers is nonstop and the other is either not in the market at all or is at most a quite marginal connecting carrier, with a nondirectional share of traffic of less than 2%. However, we acknowledge that the literature has defined control groups in a number of different ways, with different results (see the literature review in the Introduction), and that to the extent that carriers offer networks, it is implausible that the control markets would be completely unaffected by changes in the treatment markets. We also restrict the control group to only include routes where no carriers initiated new nonstop service after the merger. We define three year pre- and post-merger windows (this provides more power than two year windows, although the pattern of the coefficients are similar using two or three year windows). For Delta/Northwest the windows are Q3 2005-Q2 2008 and Q1 2009-Q4 2011. For United/Continental the windows are Q3 2007-Q2 2010 and Q1 2011-Q4 2013. For American/US Airways the situation is less straightforward as detailed negotiations between the parties, a bankruptcy judge and the Department of Justice were known to be ongoing from at least August 2012. We therefore use windows of

[15] There is no overlap in the routes across these mergers.

Q3 2009-Q2 2012 and Q2 2014-Q1 2017.[16] For Southwest/Airtran we use windows of Q2 2007-Q1 2010 and Q3 2010-Q2 2013.

We use a regression specification

$$y_{imt} = \beta_0 + \beta_1 * \text{Treatment}_{im} * \text{Post-Merger}_{it} + X_{imt}\beta_2 + Q_t\beta_3 + M_{im}\beta_4 + \varepsilon_{imt}$$

where y_{imt} is the outcome variable (the log of the weighted average price or the log of the combined number of local passengers (i.e., passengers just flying the route itself and not making connections to other destinations) on the merging carriers) for merging carrier i in directional airport-pair market m in quarter t, Q_t and M_{im} are quarter and carrier-market dummies and β_1 is the coefficient of interest.[17] m is defined directionally, but we cluster standard errors on the non-directional route. X_{imt} contains dummy controls for the number of competitors (including connecting carriers), distinguishing between legacy and LCC competitors, and one-quarter lagged fuel prices interacted with route nonstop distance and its square. A route is defined to be in the treatment or the control group based on the observed market structure in the last four quarters of the pre-merger window (so to be in the treatment group, for example, both merging carriers must be nonstop in each of these quarters). Note that this means that the treatment samples are different and smaller than those considered for the repositioning analysis above, where we defined duopoly based on the one quarter immediately before the financial closing of the merger. They can also differ from the routes used in our counterfactuals where we will use the market structure from Q2 2006.

The results are presented in Table B.4. We report results for each merger and for the three legacy mergers combined. The upper part of the table presents the results when we only include treatment markets where there is no rival nonstop entry before or during the post-merger window. In the lower panel we only use treatment markets where at least one rival initiated nonstop service after the financial closure of

[16] We exclude two American/US Airways markets where rivals began service between the end of the pre-merger window and the financial closing of the merger from the treatment group.

[17] To be clear, in the pre-merger period we combine the number of passengers on the merging carriers and use their weighted average fare, so there is a single observation per market-quarter.

Table B.4: Price and Quantity Changes After Four Mergers

	(1) All Legacy Mergers	(2) Delta/ Northwest	(3) United/ Continental	(4) American/ US Airways	(5) Southwest/ Airtran
	Routes Where No Rivals Initiate Nonstop Service Post-Merger				
Dep. Var.: Log (Average Fare)					
Treatment X Post-Merger	0.111	0.141	0.084	0.108	0.038
	(0.052)	(0.078)	(0.026)	(0.118)	(0.028)
Dep. Var.: Log (Number of Local Passengers)					
Treatment X Post-Merger	-0.295	-0.230	-0.463	-0.323	-0.073
	(0.078)	(0.134)	(0.169)	(0.117)	(0.091)
Number of Non-Directional Routes:					
Treatment Group	9	3	4	2	4
Control Group	298	107	112	79	185
	Routes Where At Least One Rival Initiated Nonstop Service Post-Merger				
Dep. Var.: Log (Average Fare)					
Treatment X Post-Merger	0.032	-	-0.028	-0.047	-0.229
	(0.045)		(0.105)	(0.028)	(0.027)
Dep. Var.: Log (Number of Local Passengers)					
Treatment X Post-Merger	-0.358	-	-0.696	-0.478	0.376
	(0.077)		(0.378)	(0.074)	(0.110)
Number of Non-Directional Routes:					
Treatment Group	4	-	1	3	1
Control Group	298	107	112	79	185

Notes: an observation is a carrier-directional airport pair, and only observations for the merging carrier(s) are included. Dependent variable is the log of the weighted average of fares or the log of the combined number of local passengers (i.e., not including passengers connecting to other destinations) on the merging carriers. The pre- and post-merger windows are defined in the text. For treatment routes where a rival initiated nonstop service we only use post-merger observations after the rival began nonstop service. Standard errors in parentheses are clustered on the non-directional route.

the merger but before or during the post-period window, and, for these markets, we only include post-merger window observations where this rival service was actually provided.

The results are suggestive, despite the small number of treatment observations. For the legacy mergers the pattern is that prices increase and the number of local passengers falls in the treatment markets when no rivals initiate nonstop service, consistent with an increase in market power and limited synergies from combining service on the treatment routes. The fall in the number of local passengers is large, but this pattern appears to be robust: for example, if we also include a linear time trend for the treatment group markets, to allow for the possibility that demand was falling in the type of markets that are nonstop duopolies, the coefficient is -0.293 with a standard error of 0.092. This is almost identical to the coefficient of -0.295 reported in Table B.4, column (1). On the other hand, in markets where rival nonstop service is initiated there is no clear pattern of price increases. The number of passengers declines in these markets, presumably due to competition from the new nonstop carrier.

The pattern is different for Southwest/Airtran, although we note that we have fewer treatment routes than the sixteen routes that were nonstop duopolies immediately before the merger because, in a number of markets, a legacy carrier stopped its nonstop service during the pre-merger window once both Southwest and Airtran were nonstop. There is no statistically significant price increase on the nonstop duopoly routes when Southwest and Airtran merge and there is no statistically significant decline in the number of passengers. This result suggests that this LCC merger may have generated route-level synergies.

B.2 Estimation and Robustness Checks

This Appendix provides additional detail on how we solve the model, the performance of our estimation algorithm and the robustness of our estimates. Appendix B.2.1 explains how we solve the model. Appendices B.2.2-B.2.5 analyze aspects of the performance of the estimation algorithm in more detail, including the fit of the model and the robustness of the results to reducing the number of moments. Appendix B.2.6 presents estimation results using moment inequalities. The reader is referred to Li et al. (2018) for details of a Monte Carlo procedure that illustrates the good performance of our estimation procedures, under our baseline assumption and using inequalities.

B.2.1 Solving the Model

Our baseline assumption is that service choices are made sequentially in a known order. For a given set of service choices on a given route, we can solve for a unique Bertrand Nash pricing in each direction by solving the system of first-order conditions. One approach for solving the service choice game would be to compute equilibrium variable profits for each possible service choice combination and then apply backwards induction. However, we are able to speed up solving the game, by 80% or more, by selectively *growing the game tree forward*.

To do so, we first calculate whether the first mover would earn positive profits as a nonstop carrier if it were the only carrier in the market, given its fixed cost.[18] If not, then we do not need to consider any of the branches where it provides nonstop service, immediately eliminating half of the game tree from consideration. If it is profitable, then we need to consider both branches. We then turn to the second carrier, and ask the same question, for each of the first carrier branches that remain under consideration, and we only keep the nonstop branch for the second carrier if nonstop service yields it (i.e., the second carrier) positive profits. Once this has

[18] To be clear, this is not the same as testing whether nonstop service is more profitable than connecting service.

Figure C.1: Shape of the Objective Function Around the Estimated Parameters For the Parameter Estimates in Column (1) of Tables 3.5 and 3.6 (black dot marks the estimated coefficient value)

been done for all carriers, we can solve backwards to find the unique subgame perfect equilibrium using the resulting tree, which usually has many fewer branches than the full game tree.

B.2.2 Performance of the Estimation Algorithm For the Baseline Estimates

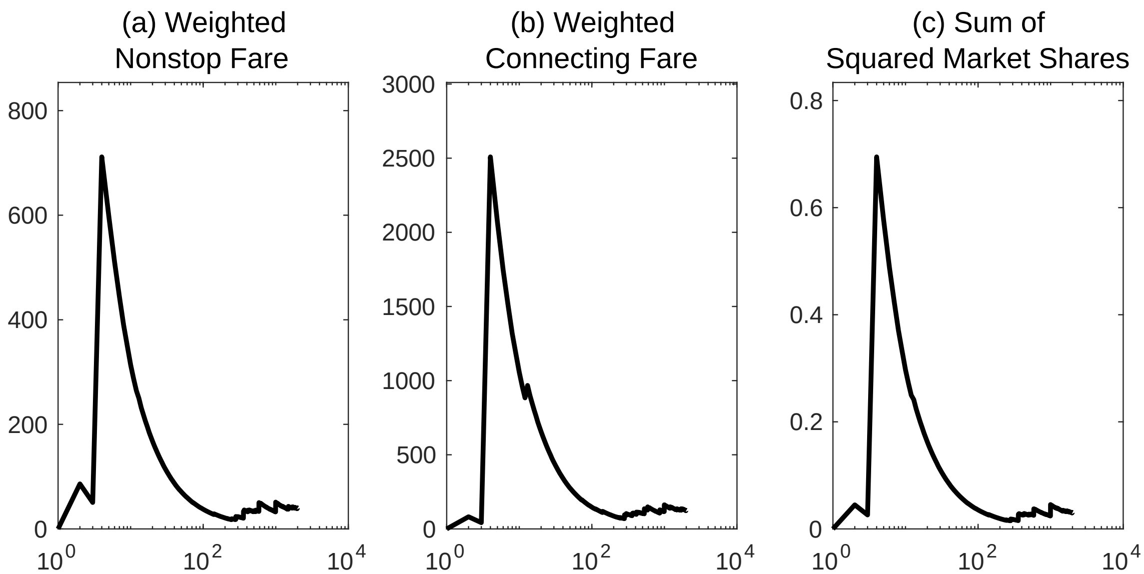
The use of importance sampling during estimation has two benefits: it greatly reduces the computational burden and it generates a smooth objective function. As noted in the text, the first step of our estimation routine (solving 2,000 simulated games for each market) takes less than two days on a small cluster, while estimation of the parameters takes around one day on a desktop or laptop computer without any parallelization. Figure C.1 illustrates the second property, showing the shape of the objective function when we vary each parameter around its estimated value, holding the other parameters fixed. While these pictures certainly should not be interpreted as strong evidence that there is a global minimum in multiple dimensions, it is comforting that the objective function is convex in almost all dimensions.

B.2.3 Variance of the Moments

For an importance sample estimate of a moment to be consistent the variance of $y(\theta_{ms}, X_m)\frac{f(\theta_{ms}|X_m,\Gamma)}{g(\theta_{ms}|X_m)}$ must be finite (Geweke (1989)). One informal way to assess this property in an application (Koopman et al. (2009)) is to plot how an estimate of the *sample variance* changes with S, and, in particular, to see how 'jumpy' the variance plot is as S increases. The intuition is that if the true variance is infinite, the estimated sample variance is likely to continue to jump wildly as S rises.

Figure C.2 shows these estimates of the sample variance for the moments associated with three market-level outcomes, namely the weighted nonstop fare,

Figure C.2: Sample Variance of Three Moments as the Number of Simulation Draws is Increased (logarithm of the number of draws on the x-axis)



the weighted connecting fare and the quantity-based sum of squared market shares for the carriers in the market, based on the estimated parameters. The number of simulations is on the x-axis (log scale) and the variance of $\frac{1}{M}\sum y(\theta_{ms}, X_m)\frac{f(\theta_{ms}|X_m,\Gamma)}{g(\theta_{ms})}$ across simulations $s = 1, .., S$ is on the y-axis. Relative to examples in Koopman et al. (2009), the jumps in the estimated sample variance are quite small for $S > 500$. In our application we are using $S = 1,000$.

B.2.4 Model Fit

Section 3.5.1 of the text briefly discusses the performance of the model at matching service choices. Table C.1 provides more detail of how well the model predicts service choices for carriers at some of their major hubs. In general, the model matches the fact that hub carriers serve most routes nonstop, although it does unpredict service at both Salt Lake City and Newark.

Table C.2 uses the same draws to show the fit of average prices and shares by type of service and by terciles of the market size distribution. We match average *differences* in market shares and prices across service types very accurately, although

Table C.1: Model Fit: Prediction of Service Choices by Carriers at a Selection of Domestic Hubs

		Number of	% Nonstop	
Airport	Carrier	Routes	Data	Simulation
Atlanta	Delta	57	96.5%	92.5% (2.3%)
Salt Lake City	Delta	65	73.8%	52.9% (4.3%)
Chicago O'Hare	American	53	96.2%	90.2% (2.7%)
Chicago O'Hare	United	57	94.7%	92.4% (2.7%)
Charlotte	US Airways	46	84.7%	77.9% (2.7%)
Denver	United	58	72.4%	73.4% (4.2%)
Newark	Continental	43	86.0%	61.6% (5.0%)
Houston Intercontinental	Continental	55	90.9%	85.4% (4.3%)
Minneapolis	Northwest	62	85.4%	77.7% (6.3%)
Chicago Midway	Southwest	44	72.7%	64.5% (6.0%)

Notes: predictions based on the average of 20 simulated draws for each market using the estimated parameters in column (1) of Tables 3.5 and 3.6. Standard errors based on additional sets of 20 draws for each of the bootstrap estimates used to calculate standard errors in the same tables.

we overpredict the levels of prices and market shares. This partly reflects our use of new draws to assess fit rather than the draws used in estimation, as the estimation draws provide a closer fit to levels as well.

B.2.5 Robustness of the Results to Reducing the Number of Moments

As mentioned in the text, we have repeated our estimation using only the 740 moments that are based on carrier-specific outcomes.

Estimates. Table C.3 shows our estimates from the main text and the estimates when we use the reduced number of moments. Most of the coefficients are very similar, and even where individual coefficients are different they have similar implications. For example, even though the individual coefficients measuring the incremental value of nonstop service change significantly, the implied mean value of the increment falls only from 0.299 to 0.268.

Table C.2: Model Fit: Average Market Shares and Prices (bootstrapped standard errors in parentheses)

			Data	Model Prediction
Average Prices (directions weighted by market shares)	All Markets	Any Service	\$436	\$455 (5)
		Nonstop	\$415	\$436 (8)
		Connecting	\$440	\$458 (5)
	Market Size Groups			
	1st Tercile	Any Service	\$460	\$465 (5)
	2nd Tercile	Any Service	\$442	\$460 (5)
	3rd Tercile	Any Service	\$412	\$441 (5)
Average Carrier Market Shares	All Markets	Any Service	7.1%	8.4% (0.3%)
		Nonstop	17.9%	20.5% (0.9%)
		Connecting	4.9%	5.8% (0.3%)
	Market Size Groups			
	1st Tercile	Nonstop	25.6%	29.8% (2.4%)
		Connecting	8.6%	8.0% (0.4%)
	2nd Tercile	Nonstop	23.1%	26.6% (1.5%)
		Connecting	4.3%	5.5% (0.3%)
	3rd Tercile	Nonstop	15.9%	18.7% (0.8%)
		Connecting	1.8%	3.4% (0.3%)

Notes: see the notes to Table C.1.

Table C.3: Estimates Based on Different Sets of Moments (bootstrapped standard errors in parentheses)

				(1) Text Estimates from (from Table 3.5 and 3.6)		(2) Carrier-Specific Moments Only	
Demand: Market Parameters							
Random Effect	Std. D.	σ_{RE}	Constant	0.311	(0.138)	0.377	(0.142)
Nesting Parameter	Mean	β_{τ}	Constant	0.645	(0.012)	0.641	(0.013)
	Std. D.	σ_{τ}	Constant	0.042	(0.010)	0.029	(0.008)
Demand Slope	Mean	β_{α}	Constant	-0.567	(0.040)	-0.591	(0.036)
(price in $100 units)			Business Index	0.349	(0.110)	0.400	(0.101)
	Std. D.	σ_{α}	Constant	0.015	(0.010)	0.013	(0.008)
Demand: Carrier Qualities							
Carrier Quality for	Mean	β_{CON}	Legacy Constant	0.376	(0.054)	0.332	(0.049)
Connecting Service			LCC Constant	0.237	(0.094)	0.187	(0.094)
			Presence	0.845	(0.130)	0.910	(0.154)
	Std. D.	σ_{CON}	Constant	0.195	(0.025)	0.199	(0.030)
Incremental Quality	Mean	β_{NS}	Constant	0.258	(0.235)	0.000	(0.210)
of Nonstop Service			Distance	-0.025	(0.034)	-0.001	(0.039)
			Business Index	0.247	(0.494)	0.653	(0.483)
	Std. D.	σ_{NS}	Constant	0.278	(0.038)	0.334	(0.051)
Costs							
Carrier Marginal Cost	Mean	β_{MC}	Legacy Constant	1.802	(0.168)	1.713	(0.137)
(units are $100)			LCC Constant	1.383	(0.194)	1.210	(0.135)
			Conn. X Legacy	0.100	(0.229)	0.107	(0.230)
			Conn. X LCC	-0.165	(0.291)	-0.150	(0.264)
			Conn. X Other Leg.	-0.270	(0.680)	-0.226	(0.147)
			Conn. X Other LCC	0.124	(0.156)	0.217	(0.151)
			Nonstop Dist.	0.579	(0.117)	0.654	(0.096)
			Nonstop Dist.^{2}	-0.010	(0.018)	-0.024	(0.016)
			Conn. Distance	0.681	(0.083)	0.732	(0.099)
			Conn. Distance^2	-0.028	(0.012)	-0.034	(0.012)
	Std. D.	σ_{MC}	Constant	0.164	(0.021)	0.153	(0.015)
Carrier Fixed Cost	Mean	β_F	Legacy Constant	0.887	(0.061)	0.878	(0.062)
(units are $1 million)			LCC Constant	0.957	(0.109)	0.923	(0.113)
			Dom. Hub Dummy	-0.058	(0.127)	0.000	(0.207)
			$\widehat{\text{Connecting Traffic}}$	-0.871	(0.227)	-0.761	(0.281)
			Intl. Hub	-0.118	(0.120)	-0.355	(0.142)
			Slot Const. Airport	0.568	(0.094)	0.530	(0.095)
	Std. Dev.	σ_F	Constant	0.215	(0.035)	0.223	(0.036)

Note: standard errors in parentheses based on a bootstrap where markets are re-sampled and simulations are drawn from a pool of 2,000 draws for each selected market.

Table C.4: Model Fit: Average Market Shares and Prices Based on Different Sets of Moments

			Data	Model Predictions: Text Estimates (Table C.2)	Model Predictions: Carrier Moments
Average Prices (directions weighted by market shares)	All Markets	Any Service	\$436	\$455	\$455
		Nonstop	\$415	\$436	\$442
		Connecting	\$440	\$458	\$459
	Market Size Groups				
	1st Tercile	Any Service	\$460	\$465	\$466
	2nd Tercile	Any Service	\$442	\$460	\$461
	3rd Tercile	Any Service	\$412	\$441	\$442
Average Carrier Market Shares	All Markets	Any Service	7.1%	8.4%	8.5%
		Nonstop	17.9%	20.5%	21.5%
		Connecting	4.9%	5.8%	5.5%
	Market Size Groups				
	1st Tercile	Nonstop	25.6%	29.8%	30.4%
		Connecting	8.6%	8.0%	7.9%
	2nd Tercile	Nonstop	23.1%	26.6%	26.4%
		Connecting	4.3%	5.5%	5.2%
	3rd Tercile	Nonstop	15.9%	18.7%	18.7%
		Connecting	1.8%	3.4%	3.1%

Notes: Predictions from the model calculated based on twenty simulation draws from each market from the relevant estimated distributions.

Fit. Table C.4 compares model fit for prices and market shares for the two sets of estimates. The predictions are very similar to each other.

Counterfactuals. Finally, we consider predicted price effects and service changes after a merger between United and US Airways. We compute predictions using the four routes where the United and US Airways were nonstop duopolists and American provided connecting service and the ten routes where United and US Airways were nonstop and there was another nonstop rival. We consider the case where we account for selection by forming conditional distributions, under our baseline merger assumption that the lower presence carrier is removed, so that our results correspond to row 2 of Table 3.9 and the third row of Table 3.13. The results from the text and the estimates using the smaller number of moments are almost identical.

Table C.5: Predicted Effects of a United/US Airways Merger, under the Baseline Merger Assumption, in Four Nonstop Duopoly Markets Based on Different Sets of Moments and the Conditional Distributions

	United/US Airways Nonstop Duopoly Routes		United & US Airways Nonstop with Nonstop Rivals	
	Text Estimates (from Table 3.9)	Carrier Moments	Text Estimates (from Table 3.13)	Carrier Moments
Mean Pre-Merger United/ US Airways Price	\$531.97	\$531.97	\$350.02	\$350.02
Predicted Change in Nonstop Rivals Post-Merger	+0.10	+0.08	+0.05	+0.03
Mean Predicted Post-Merger "New United" Price	\$573.37	\$574.29	\$377.24	\$377.55

B.2.6 Estimation Using Moment Inequalities

Our baseline estimates assume that carriers make service choices in a known sequential order, so that there is a unique equilibrium. An alternative approach is to allow for simultaneous choices, or an unknown order of moves, and estimate parameters based on moment inequalities. We present results based on this approach here.

The form of the inequalities is

$$h(y, X, Z, \Gamma) = \mathbb{E}\left[\begin{matrix} y_m^{data} - \underline{\mathbb{E}(\widehat{y_m(X,\Gamma)})} \\ \\ \overline{\mathbb{E}(\widehat{y_m(X,\Gamma)})} - y_m^{data} \end{matrix} \otimes Z_m\right] \geq 0$$

where y_m^{data} are observed outcomes in the data and Z_m are non-negative instruments. $\underline{\mathbb{E}(\widehat{y_m(X,\Gamma)})}$ and $\overline{\mathbb{E}(\widehat{y_m(X,\Gamma)})}$ are minimum and maximum expected values for y_m given a set of parameters Γ. The minimum and maximum are formed by using the minimum and maximum values of the outcome across different equilibria or across orders for each simulated draw from the importance density. For example, if the outcome is whether firm A is nonstop, the lower bound (minimum) would be formed by assuming that whenever there are equilibrium outcomes where A is **not** nonstop, one of them will be realized, whereas the upper bound (maximum) would be formed by assuming that whenever there are equilibrium outcomes where A is nonstop, one of them is realized. We can also do the same type of calculation of minima and maxima for prices and market shares. If there is a unique outcome the minimum and maximum will be the same. The expected values of the minimum and maximum are calculated by re-weighting the different simulations in the same way that we do when assuming a known sequential order, and we form moments using the same outcomes and interactions that we use for our primary estimates. We note that our use of moment inequalities differs from how it has been used in some entry-type games, such as Eizenberg (2014) and Wollmann (2018), where selection on demand and marginal cost shocks is ruled out by assumption and the moments are based on an equation for fixed costs with an additive structural error.

The objective function that is minimized is

$$Q(\Gamma) = \min_{t \geq 0} [h(\widehat{y, X, Z}, \Gamma) - t] W [h(\widehat{y, X, Z}, \Gamma) - t]$$

where t is a vector equal in length to the vector of moments, which sets equal to zeros the inrqualities that are satisfied. W is a weighting matrix, and, as for the baseline estimates, we use a diagonal weighting matrix, dividing the moments into three groups (service choices, shares and prices). The sum of the diagonal components for each group equals one, with each element scaled so that it is proportional to the inverse of the variance of the moment evaluated at an initial set of estimates, which were calculated using the identity matrix.

Estimates. The ideal procedure for presenting the results of an estimation based on inequalities is to present confidence sets for coefficients because the coefficients may not be point identified. The construction of confidence sets is very difficult with large numbers of parameters and moments, and, as we have emphasized in the text, certain features of the data mean that we expect the parameters to be point identified even when we use inequalities in our setting.[19] Therefore in the right-hand column of Table C.6 we simply present the point estimates that we find minimize the objective function. These estimates are very close to the estimates from the text that are also reported in the table, which we view as confirming the result that we would expect given the nature of the game that we are looking at and the data at hand.

[19] Outcomes where no carrier provides nonstop service (the most common outcome in our data) will always be unique, and a necessary condition for there to be multiple equilibria is that at least two carriers do not have a dominant service strategy. In our setting, in the vast majority of markets there is no more than one carrier with intermediate probabilities of nonstop service based on a simple set of observables, which strongly suggests that multiplicity should be rare. See Appendix B.3.

Table C.6: Coefficient Estimates Based on Inequalities

				(1) Baseline Assumed Seq. Entry		(2) No Eqm. Selection
Demand: Market Parameters						
Random Effect	Std. Dev.	σ_{RE}	Constant	0.311	(0.138)	0.350
Nesting Parameter	Mean	β_τ	Constant	0.645	(0.012)	0.647
	Std. Dev.	σ_τ	Constant	0.042	(0.010)	0.040
Demand Slope	Mean	β_α	Constant	-0.567	(0.040)	-0.568
(price in \$100 units)			Business Index	0.349	(0.110)	0.345
	Std. Dev.	σ_α	Constant	0.015	(0.010)	0.017
Demand: Carrier Qualities						
Carrier Quality for	Mean	β_{CON}	Legacy Constant	0.376	(0.054)	0.368
Connecting Service			LCC Constant	0.237	(0.094)	0.250
			Presence	0.845	(0.130)	0.824
	Std. Dev.	σ_{CON}	Constant	0.195	(0.025)	0.193
Incremental Quality	Mean	β_{NS}	Constant	0.258	(0.235)	0.366
of Nonstop Service			Distance	-0.025	(0.034)	-0.041
			Business Index	0.247	(0.494)	0.227
	Std. Dev.	σ_{NS}	Constant	0.278	(0.038)	0.261
Costs						
Carrier Marginal Cost	Mean	β_{MC}	Legacy Constant	1.802	(0.168)	1.792
(units are \$100)			LCC Constant	1.383	(0.194)	1.331
			Conn. X Legacy	0.100	(0.229)	0.134
			Conn. X LCC	-0.165	(0.291)	-0.077
			Conn. X Other Leg.	-0.270	(0.680)	0.197
			Conn. X Other LCC	0.124	(0.156)	0.164
			Nonstop Distance	0.579	(0.117)	0.589
			Nonstop Distance^2	-0.010	(0.018)	-0.012
			Connecting Distance	0.681	(0.083)	0.654
			Connecting Distance^2	-0.028	(0.012)	-0.024
	Std. Dev.	σ_{MC}	Constant	0.164	(0.021)	0.159
Carrier Fixed Cost	Mean	β_F	Legacy Constant	0.887	(0.061)	0.913
(units are \$1 million)			LCC Constant	0.957	(0.109)	1.015
			Dom. Hub Dummy	-0.058	(0.127)	-0.140
			Log($\widehat{\text{Connecting}}$ Traffic)	-0.871	(0.227)	-0.713
			International Hub	-0.118	(0.120)	-0.168
			Slot Const. Airport	0.568	(0.094)	0.602
	Std. Dev.	σ_F	Constant	0.215	(0.035)	0.198

Notes: standard errors, in parentheses, are based on 100 bootstrap replications where 2,028 markets are sampled with replacement, and we draw a new set of 1,000 simulation draws (taken from a pool of 2,000 draws) for each selected market. The Log(Predicted Connecting Traffic) variable is re-scaled so that for routes out of domestic hubs its mean is 0.52 and its standard deviation is 0.34. Its value is zero for non-hub routes. Distance is measured in thousands of miles.

B.3 Multiple Equilibria, Identification and the Explanatory Power of Observed Variables for Service and Entry Choices

A striking result is that, at the estimated parameters, less than 2% of simulations from our model could support a different equilibrium outcome (i.e., different service choices) if we allowed for simultaneous moves or any alternative sequential order. As a result it is not surprising that our coefficient estimates are very similar when we allow for these alternative possibilities (Appendix B.2.6). Several scholars have commented to us that they find this result surprising given earlier work examining airline entry decisions, notably Berry (1992) and Ciliberto and Tamer (2009), has found that assumptions about the timing of decisions can affect estimates quite dramatically and that it is common for a simultaneous move game to support multiple different outcomes as equilibria (for example, Ciliberto and Tamer find this is true for 95% of their simulations). In this Appendix, we explain why models estimated using service choices and entry decisions, as defined in the existing literature, can differ so much on this dimension.

We define a carrier to be nonstop based on the number of nonstop flights that a carrier has per quarter (at least 64 in each direction to be defined as nonstop) and the proportion of passengers carried that travel direct (at least 50% without a change of planes). Other carriers are connecting. Carriers that provide nonstop service serve many more passengers than connecting carriers: the median nonstop (named) carrier serves over 1,000 round-trip passengers in DB1 (which is a 10% sample), whereas the median connecting carrier serves only 38 round-trip passengers, and, as noted in Appendix B.1 there are few carriers close to the 64 or 50% thresholds.[20] We focus on nonstop carriers as it is reasonable to expect that only carriers that serve large numbers of passengers are likely to have market power, and because in the data, a monopoly nonstop carrier appears able to charge significantly higher prices. As we will show below, observable variables are also able to explain which carriers are likely to offer nonstop service.

[20] The statistics discussed in this paragraph are for the named carriers we use, and not the composite Other Legacy and Other LCC carriers.

In contrast, in Berry (1992) and Ciliberto and Tamer (2009), a carrier is defined as an entrant if it carries, by any type of service, a relatively small number of passengers (for example, 20 in Ciliberto and Tamer (2009)). In the data, there are many carriers with passenger counts that are right around these thresholds: the 25th percentile number of connecting passengers is 14 and the median is 38. Given this pattern and the sampling error in the DB1 sample, it is naturally quite difficult to predict which connecting carriers will be counted as entrants on a particular route.

We illustrate how well our data explains service choices and entry by estimating several probit specifications where the dependent variable are indicators for nonstop service or entry and the explanatory variables are the observed characteristics of the carrier and market characteristics (such as market size). The results are reported in Table D.1.

In the first four columns the dependent variable is equal to one if the carrier is nonstop, and we use the 8,065 carrier-market observations in our data. The regressors in column (1) are observed market characteristics, including the average of our market size measure across directions, and the observable carrier variables that we include in our specification of fixed costs, including our measure of connecting traffic that will be generated if the route is served nonstop. Despite the simplicity of the specification the pseudo-R^2 is 0.52. Column (2) replaces our market size measure with the geometric average population measure that is most commonly used in the literature: the pseudo-R2 decreases to 0.45, indicating that this is a poor alternative to our market size measure (a result which is consistent with the results presented in Appendix Table B.1). Column (3) adds measures of the carrier's presence at each endpoint, which we allow to affect demand, to the first specification, and the pseudo-R^2 increases to 0.65. In column (4) we include interactions between a number of the variables in the specification (as noted beneath the table) as well as measures of the number of rival carriers, and we find the pseudo-R^2 increases to 0.72.

In column (5) we consider instead the decision to enter a market (i.e., to provide either type of service) among the carriers that provide service (to any destination) at both airport endpoints and use a specification similar to column (3).

Figure D.1: Predicted Probabilities of Carrier Service Choices (based on Table D.1, column (3)) and Entry Decisions (based on Table D.1, column (5))

This is the type of binary outcome modeled in in Berry (1992), Ciliberto and Tamer (2009) and Ciliberto et al. (2018). The pseudo-R^2 is *much* lower (0.136).

What is the implication of these results for whether our model should be expected to support multiple equilibrium outcomes? A game with binary discrete choices can only support multiple outcomes if the more profitable option depends on what other players do for at least two of the players (i.e., at least two players do not have a dominant strategy). Intuitively, players are much less likely to be on the margin between different options when observed variables (that do not reflect what their rivals choose) strongly predict what their service choices will be. The service choice and entry models are clearly very different in this regard.

To illustrate, Figure D.1(a), shows the distribution of predicted probabilities for a carrier providing nonstop service using 40 bins based on column (3). We observe that the predicted probabilities are concentrated either very close to zero or very close to one. Defining intermediate as predicted probabilities between 0.05 and 0.95 based on the column (3) estimates, there are 482 markets (less than 24% of the total) where two or more carriers have intermediate nonstop service probabilities (using thresholds of 0.1 and 0.9, 302 markets would have at least two carriers with intermediate probabilities). In contrast, the predicted probabilities for entry choices, shown in Figure D.1(b) (based on column (5)), lie mainly in the range from 0.2 to 0.8, and 96% of markets have two or more carriers with intermediate entry probabilities. When we perform the exercise of counting how many different outcomes our parameter estimates can support under different timing assumptions, discussed in Section 3.5.2, we can see the connection between the predicted probabilities of nonstop service in these simple regressions and the multiplicity of equilibrium outcomes: the probability of a simulation draw for one of the 482 intermediate probability markets supporting multiple outcomes is two-and-half times as high as for the remaining markets.

Table D.1: Probit Models of Carrier Service Choice and Entry Decisions

	(1)	(2)	(3)	(4)	(5)
Dep. Var.	Nonstop	Nonstop	Nonstop	Nonstop	Enter
Low Cost Carrier	0.808	0.782	0.537	1.681	0.514
	(0.0516)	(0.0476)	(0.0685)	(0.395)	(0.0376)
Slot Constr. Airport	0.587	0.724	0.541	0.232	-0.207
	(0.0961)	(0.0927)	(0.112)	(0.132)	(0.0650)
Carrier Intl. Hub	0.946	0.836	0.0385	-0.165	0.158
	(0.0748)	(0.0738)	(0.0894)	(0.113)	(0.0801)
Carrier Dom. Hub	-6.161	-6.942	-6.578	-34.24	-3.740
	(0.647)	(0.623)	(0.648)	(47.37)	(0.627)
Carrier Pred. Connecting	1.355	1.464	1.160	5.701	0.611
Traffic Measure	(0.107)	(0.104)	(0.108)	(7.932)	(0.106)
Route Business Index	-0.663	-1.364	0.198	0.670	-0.126
	(0.293)	(0.268)	(0.348)	(0.387)	(0.142)
Our Market Size	1.595		2.019	-0.176	-0.0552
/10,000	(0.0649)		(0.0828)	(0.671)	(0.0405)
Geom. Avg. Pop.		0.0122			
/10,000		(0.00112)			
Carrier Max.			3.543	4.334	1.622
Endpoint Presence			(0.144)	(0.626)	(0.109)
Carrier Min.			1.916	6.814	4.424
Endpoint Presence			(0.276)	(2.510)	(0.266)
Number Rival				-0.167	
Carriers in Market				(0.0237)	
Number Rival Low Cost				0.167	
Carriers in Market				(0.0663)	
Constant	-2.065	-1.581	-3.930	-4.131	-0.312
	(0.127)	(0.115)	(0.177)	(0.387)	(0.0662)
Variable interactions	N	N	N	Y	N
Observations	8,065	8,065	8,065	8,065	12,550
Pseudo-R2	0.522	0.450	0.653	0.726	0.134

Notes: standard errors in parentheses. Observations in columns (1)-(4) are the carrier-market observations that are included in our estimation dataset. Our Market Size is the average of our market size estimate across directions. Geom. Avg. Pop. is the geometric average of the MSA endpoint populations, a popular alternative measure of market size. We measure carrier presence (the number of routes served nonstop by the carrier out of the total number of routes served nonstop by any carrier) at the carrier-airport level and include the higher and lower values separately in the regressions. Observations in column (5) include the observations in our estimation dataset plus observations for carrier-markets where the carrier provides some service at both endpoints but does not meet our criteria for being a competitor on the route in question. The interactions that are included in column (5) are between LCC, domestic hub, the predicted connecting traffic, market size and the two presence measures.

The service choice probit results also have implications for the identification of the model. As discussed in Section 3.4, one argument for why the demand and marginal cost parameters are point identified is that there are a large number of markets and carriers for which observed covariates essentially determine their service choices so that there should be (almost) no selection on unobservable demand or marginal cost shocks when they make these choices. Based on the column (3) estimates, 58% of market-carriers predicted nonstop service probabilities are less than 0.01 or more than 0.99, meaning that we have a large number of observations where conventional identification arguments for the demand and marginal cost equations should apply.

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