Repositioning and Market Power After Airline Mergers

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July 2018

Abstract

We estimate a model of airline route competition in which carriers first choose what type of service (nonstop or connecting) to offer and then choose prices. We assume that carriers have full information about all demand and cost unobservables when they make service choices, so that the carriers choosing a particular type of service will be selected. Our model can be estimated without an excessive computational burden and we use it to simulate the effects of proposed and completed mergers. We show how accounting for selection substantially lowers the probability that rivals will reposition their products after a merger and, in markets where the merging carriers are nonstop duopolists, it raises post-merger prices. Predictions that account for selection are consistent with what has been observed after completed mergers. We also consider a proposed merger remedy that would have preserved nonstop competition without necessarily limiting market power.

Keywords: product repositioning, market power, endogenous market structure, selection, horizontal mergers, remedies, discrete choice games, multiple equilibria, airlines.

JEL Codes: C31, C35, C54, L4, L13, L93

*Corresponding author, sweeting@econ.umd.edu, who conducted some of this research during a five-month spell as an Academic Visitor at the US Department of Justice, whose hospitality is warmly acknowledged, although the paper does not reflect the views, opinions or practice of the Department. We thank a number of seminar and conference participants and especially Fiona Scott Morton for very useful comments. The research has been supported by NSF Grant SES-1260876. Earlier versions of this paper were circulated as "Airline Mergers and the Potential Entry Defense" and "Endogenous and Selective Service Choices After Airline Mergers". Peichun Wang provided excellent research assistance during an early phase of the project. The usual disclaimer applies.

1 Introduction

It has long been recognized that the market power created by a horizontal merger may be limited by rival firms entering a market or, when products are differentiated, repositioning their products to compete more directly with those of the merging firms. In the 1980s and early 1990s, several court decisions, such as *Waste Management*, *Baker Hughes* and *Syufy*[1], articulated the view that entry or repositioning would "trump" (Baker (1996)) anti-competitive concerns if they would be no more difficult for rivals than they had been for the merging firms. Based on this type of reasoning, the Department of Transportation also approved many airline mergers in the 1980s (Werden, Joskow, and Johnson (1991)).

From an economist's perspective, this approach was flawed because it did not ask whether rivals would find entry or repositioning profitable and whether entry or repositioning would keep prices at pre-merger levels if they happened. In response, the 1992 *Horizontal Merger Guidelines*, and all subsequent revisions, laid out the criteria that entry or repositioning would need to be shown to be "timely, likely and sufficient" to prevent prices from rising (Shapiro (2010), p. 65). While most economists would accept these criteria, they are rarely analyzed rigorously or quantitatively, even though upwards pricing pressure calculations and merger simulations are widely used to quantify price changes taking the set of products as given. Instead, as in the 1980s, expert testimony and both agency and court decisions tend to focus on possible barriers to entry or repositioning without making connections to their profitability or effects on prices.[2]

In this paper, we develop an empirical model of airline markets which integrates product positioning (a choice of whether to provide nonstop or connecting service), and price-setting, and we use it to quantify post-merger price increases when repositioning by rivals is possible. Our model has a standard two-stage structure where carriers first choose what type of service to provide and then choose prices. However, unlike most of the existing literature, we assume that *carriers know all of the demand and marginal cost shocks that will affect second-stage prices, market shares, and profits throughout the game*, which we will label the "full information" assumption.[3] As a

[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 Entertainments*, 903 F.2d 659, 661 (9th Cir. 1990).

[2] For example, Coate (2008), based on a review of internal FTC memoranda, found that the agency's conclusions about the likelihood of entry lacked a "solid foundation" in the evidence, while Kirkwood and Zerbe (2009) found that only one out of thirty-five reviewed court opinions after the 1992 *Guidelines* reviewed the criteria systematically.

[3] In contrast, a model where some unobservable components of product qualities or costs are only revealed

result, the carriers that choose a particular service will be selected based on quality and cost shocks that the econometrician does not observe. We view the full information assumption as being the natural one to use when trying to predict how experienced market participants will respond to a merger, especially when what we really want to know is whether repositioning will constrain market power for several years after a merger is completed.

Our counterfactuals pay particular attention to how our predictions about the likelihood and sufficiency of post-merger repositioning change when we account for the selection required to rationalize the pre-merger market structure as an equilibrium. Testifying experts often argue, without reference to formal analysis, that the fact that rivals do not currently compete directly with the merging firms should make a court skeptical that they will do so after a merger, even if no major entry barriers can be identified (Baker (1996), p. 364).[4] Our analysis assesses the quantitative importance of this intuition.

We make at least two significant contributions. The first contribution is that we show how to estimate a full information model without an excessive computational burden. This is important because limited information has often been assumed on the grounds of econometric and computational convenience. We reduce the computational burden by approximating the moments predicted by our model using importance sampling, following Ackerberg (2009). This approach also provides us with a smooth objective function even though service choices are discrete. We also show that the commonly perceived problem that a given set of parameters may support multiple equilibrium outcomes is a relatively minor concern in our setting.

Our second, and more important, contribution comes from our detailed investigation of how predicted post-merger service and price changes depend on pre-merger market structures as well as whether and how the researcher accounts for selection. Consistent with a common focus in airline mergers, we are particularly interested in markets where the merging parties are nonstop duopolists, a definition which, throughout the paper, unless otherwise stated, includes markets where other carriers provide connecting service.[5] On these routes, the probability that rival

after service choices have been made will be described as "limited information". Both types of model can have "complete information" in the sense that all firms have the same information when service choices are made.

[4] As one very recent example of this type of argument: when asked, under cross-examination, about why he concluded that Chevron Marine would not expand in markets for marine chemicals without identifying the entry barriers that it would face, FTC testifying expert Aviv Nevo argued that "If it's so easy for them to do it, why aren't they selling more?" (*FTC v. Wilhelmsen et al.*, "Merging Marine Supply Cos. Blast FTC Expert's Assumptions", https://www.law360.com/articles/1049537/merging-marine-supply-cos-blast-ftc-expert-s-assumptions (downloaded June 28, 2018)).

[5] See the Department of Justice's 2013 Competitive Impact statement on the American Airlines/US Airways

carriers will initiate nonstop service in response to a merger falls, and predicted post-merger prices rise, when we account for selection.

However, it is not the case that new rival nonstop service is sufficient to eliminate anticompetitive effects. We illustrate this by considering a remedy that was proposed when United Airlines and US Airways attempted to merge in 2000. During that case, American Airlines offered to commit to providing nonstop service on several routes where the parties were nonstop duopolists. Under this remedy the number of nonstop competitors would not have fallen, and, when selection is completely ignored, this remedy can appear as an effective way to prevent prices from increasing.[6] However, when we account for selection, and recognize that American is likely to be an ineffective competitor when it provides nonstop service only because of its commitment under the remedy, we predict that, on average, the merged United's prices would increase by 6.5%, or by almost as much as without the remedy (7.8%) when the probability that any rival would have initiated nonstop service would have been low. In addition, we consider several mergers that were consummated after the period of our data.

We also compute counterfactual predictions when we only account for selection on observables and when we assume that carriers providing connecting service before the merger would have similar nonstop qualities and costs as the nonstop merging parties. This second assumption might be made by an expert for the parties in the absence of widely-accepted barriers to entry or repositioning. We show that these alternative assumptions can lead to predicted probabilities that rivals will reposition their products that are several times greater than probabilities that fully account for selection. When we account for selection on observables we get qualitatively similar predicted price changes to those that we get when we fully account for selection, although the difference in the magnitude of predicted prices changes varies with the merger that is being considered (for example, predictions of 6.0% (observable selection) vs. 7.8% (full selection) for the United/US Airways merger with no remedy, and predictions of 6.4% vs. 11.4% for an American/US Airways merger). We find that our predictions come closest to predicting what has been observed after actual mergers when we account for both types of selection.

Before discussing the related literature, we note three limitations of our analysis. First,

merger, https://www.justice.gov/atr/case-document/competitive-impact-statement-219 (accessed June 26, 2017), and the US Government Accountability Office's 2010 report on the United Airlines/Continental Airlines merger, http://www.gao.gov/new.items/d10778t.pdf (accessed June 26, 2017).

[6] American did not claim that it would be profitable to serve these routes nonstop, but it expected to benefit from the completion of the transaction by acquiring United assets on the east coast.

our model is static rather than dynamic. Our static focus is consistent with the short-run focus of a typical merger analysis (Carlton (2004)), but we cannot speak to exactly how quickly repositioning will happen and, in the long run, changes to the structure of airline networks, which we treat as fixed, may have large effects on welfare. Second, we focus only on post-merger repositioning and do not formally consider new entry into a market by carriers who are not in the market at all. An earlier version of this paper (Li, Mazur, Roberts, and Sweeting (2015)) estimated a model where carriers could choose whether to provide no service, connecting service or nonstop service. The estimated coefficients were consistent with those presented in the current paper, but the greater number of unobservables made it computationally prohibitive to do rigorous counterfactuals for a large number of markets. However, the reader should recgonize that our approach could be used to model binary entry decisions, and perform merger counterfactuals, in any market with a well-defined set of potential entrants (see Appendix C.7 for an illustration). Third, we do not model choices of route-level capacity or schedules, so that we may attribute some differences to carrier heterogeneity when they really reflect strategic scheduling choices. For this reason, we focus on a service remedy for a particular set of routes that was proposed, but rejected, as part of the United/US Airways merger. We are addressing the effectiveness of slot divestitures, which affect carrier capacities at different airports, using a different model in ongoing work.

Section 2 uses a computational example that motivates our use of a full information model of service choices. Section 3 describes the cross-sectional data that we use for estimation and an analysis, using a panel dataset, of what happened after later mergers. Section 4 details the model, while Section 5 describes estimation. Section 6 presents the parameter estimates, the fit of the model and quantifies the roles of observables and unobservables in driving equilibrium service choices. Section 7 presents our analysis of merger counterfactuals. Section 8 concludes. The Appendices, which contain more details of the data and estimation, are intended for online publication.

Related Literature

Ashenfelter, Hosken, and Weinberg (2014) summarize the literature on the effects of consummated airline mergers on route-level prices. Several papers have found that prices increased significantly after mergers approved by the Department of Transportation before 1989, although these results depend on the chosen time-window and control group.[7] Hüschelrath and Müller (2014) and Hüschelrath and Müller (2015) identify short-run price increases of as much as 10% after more recent mergers, suggesting that they have also increased market power, although Israel, Keating, Rubinfeld, and Willig (2013) and Carlton, Israel, MacSwain, and Orlov (forthcoming) suggest that merger-related improvements to carriers' networks may have increased consumers' willingness to pay. A literature has also alleged price collusion or coordination between the largest carriers in recent years (Ciliberto and Williams (2014), Azar, Schmalz, and Tecu (forthcoming)). Our model assumes non-cooperative behavior and we estimate our model using data from 2006. Surprisingly, the existing literature has not provided a systematic analysis of post-merger entry or repositioning by rival carriers, or how effective these types of supply-side reactions have been at constraining prices in any industry.[8]

Our modeling is closely related to the literature on estimating discrete choice games. Most of the early literature (*inter alia* Bresnahan and Reiss (1991), Bresnahan and Reiss (1990), Mazzeo (2002), Seim (2006) and, considering airline markets, Berry (1992) and Ciliberto and Tamer (2009)) estimated reduced-form payoff functions without modeling consumer demand or pricing. Subsequent work has tried to integrate models of entry and equilibrium price competition. A common approach, for example, Draganska, Mazzeo, and Seim (2009), Eizenberg (2014), Wollmann (2018) and Fan and Yang (2016), rules out selection on unobserved demand or marginal cost shocks by assuming that firms have no information on the realized values of these shocks when entry or service choices are made.[9] This type of "limited information" assumption allows demand and marginal cost functions to be estimated separately from the entry game. However, it means that some firms may regret their choices, which is unsatisfactory if the data is to be interpreted as reflecting an industry in steady-state equilibrium. We will suggest that it can also

[7]For example, several papers have measured the effects of the 1986 Northwest/Republic and TWA/Ozark mergers, both of which involved mergers of carriers that had hubs at the same airports. Borenstein (1990) estimated that these mergers increased prices, on routes where both carriers had provided service and no other carriers were active, by 6.7% and -5.8% (i.e., a decrease) respectively. Werden, Joskow, and Johnson (1991) provide evidence that prices rose after both mergers, although only slightly in the case of TWA/Ozark. Peters (2009) finds that prices increased after both mergers, but by more after TWA/Ozark. Morrison (1996) finds that prices fell after Northwest/Republic in the short-run but increased in the long-run, with the opposite effect in TWA/Ozark.

[8]Hüschelrath and Müller (2015) provides an analysis of entry in airline routes but without tying entry closely to pre-merger market structures. Boberg and Woodbury (2009) claims that repositioning is frequent in consumer product markets without a clear connection to mergers or pricing.

[9]Fan (2013) examines how mergers may affect continuous measures of quality, as well as price. Continuous choices can be analyzed by re-solving first-order conditions for a given set of competitors assuming that unobservables remain the same after a merger.

lead to misleading predictions about what will happen after a merger.[10]

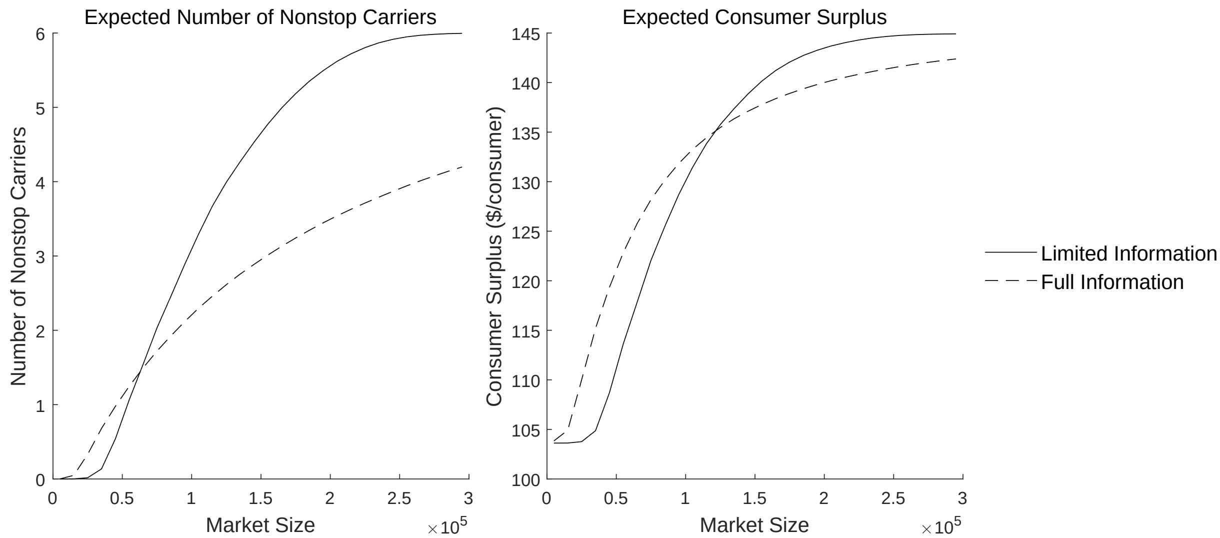
The most closely related papers are the airline papers of Reiss and Spiller (1989) and Ciliberto, Murry, and Tamer (2016) (CMT, hereafter). Reiss and Spiller estimate a full information model of service choice and subsequent price competition, and they "recognize that entry introduces a selection bias in equations explaining fares or quantities." (p. S201). They limit the computational burden by assuming that carriers are symmetric, conditional on service choices, and that there is at most one nonstop carrier. CMT, who developed their paper contemporaneously with ours, estimate a full information model where carriers decide whether to enter airline markets, with no distinction between nonstop and connecting service, and then compete on prices. There are, however, important and informative differences between the papers. CMT use a simulation-based Nested Fixed Point (NFXP) estimation algorithm and construct an objective function based on inequalities to allow for any pure strategy equilibrium of a simultaneous move entry game to be played. The resulting objective function is discontinuous, and the computational burden is addressed by limiting consideration to at most six players and using a simulated annealing minimization algorithm on a supercomputer. Our approach has a much lower computational burden and it should therefore be more accessible to researchers and practitioners, even though, for a fixed number of simulations, the approximation implies some reduction in econometric efficiency. We are also focused on how accounting for selection affects predictions of what rivals will do after mergers, motivated by how the consideration of repositioning often does not follow what is laid out in the merger *Guidelines*.

2 Equilibrium Service Choices Under Full and Limited Information: An Example

In this paper we will assume that carriers have full information when making service choices. In this section we present an example that illustrates how a full information model can generate significantly different outcomes to a limited information model, suggesting that, if we believe that the full information model is more reasonable, it is likely worth the additional effort required to estimate it. As far as we are aware, the differences in the predictions of these models have not been discussed in the existing literature. We describe the model informally, with the exact

[10] In the dynamic games literature, Sweeting (2013) and Jeziorski (2015) also separate estimation into stages, by making timing assumptions about when innovations in product qualities occur.

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



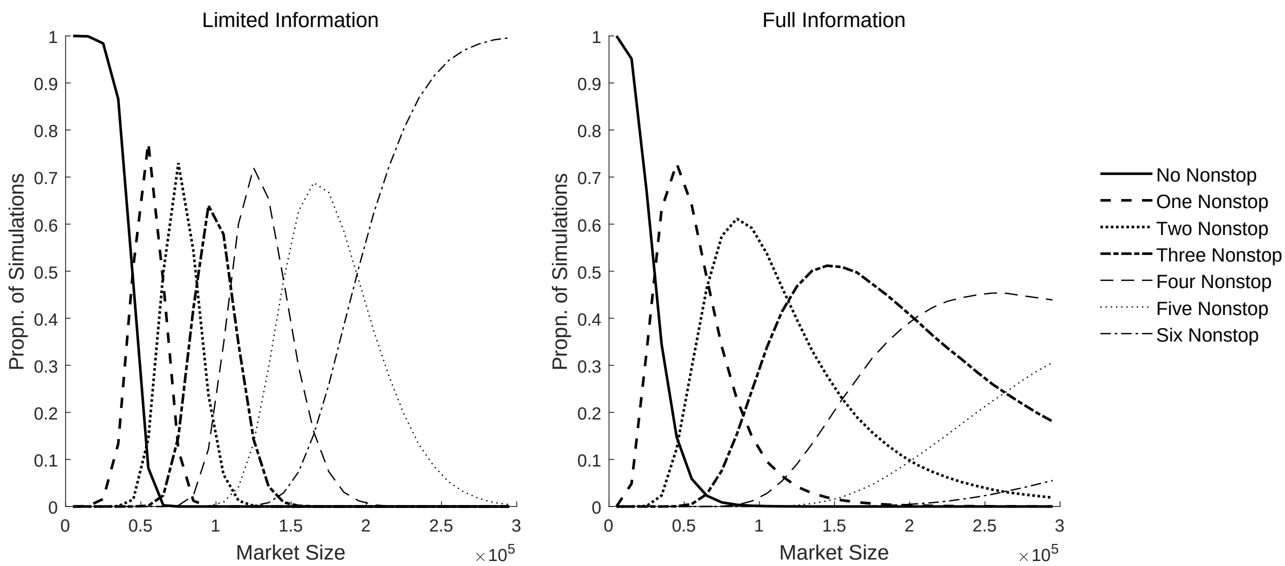
parameter values listed in Appendix A.

We consider a single market, although we shall vary its size, with six carriers. The carriers choose whether to provide connecting or higher-quality nonstop service, which requires payment of a fixed cost, and having selected their service types they simultaneously choose prices. Demand is determined by a one-level 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, 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.

We compare outcomes under two information structures. Under full information, all draws are known to all carriers throughout the game. Under limited information, only the fixed components of qualities and marginal costs as well as realized fixed costs are known (also to all carriers) in the first stage, but the remaining quality and cost draws are revealed before prices are chosen. We simulate equilibrium outcomes 50,000 times for each of 30 different market sizes, ranging from 5,000 to 295,000.

Figure 1 compares the average number of nonstop carriers and consumer surplus in equilib-

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



rium. 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. However, full information reduces the number of nonstop carriers in larger markets. 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 (more selected), which lowers the expected nonstop profitability of another carrier considering nonstop service and 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 can regret their choices under limited information: for example, for a market size of 55,000, for 48% of the draws where a single carrier is nonstop, that carrier would have increased its (ex-post) profits by offering connecting service.

Figure 2 shows that, for a given market size, the *distribution* of the number of nonstop carriers is much tighter under limited information.[11] This pattern has implications for what we would predict should happen after a merger if carriers can change their service choices. To

[11] 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.

illustrate, we consider a market size of 85,000 and collect all sets of draws that result in the two carriers with the highest fixed 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.[12] 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 following the merger is just under $300,000. 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.[13] Unlike the limited information case, the merger is also, on average, profitable for the merging parties. Note that if, in either version of the model, we had not accounted for selection, which we are doing by using only those draws that led the highest quality firms to be nonstop duopolists, we could also get quite different post-merger predictions. In Section 7, we show how accounting for selection affects merger counterfactuals using our estimated full information model.

3 Data and Empirical Setting

In this section we describe our data and the results of an analysis of what happened to prices and service changes after three of the legacy carrier mergers that we will consider as counterfactuals in Section 7. Full details are in Appendix B. Legacy carriers are carriers that were founded prior to airline deregulation in 1978. They typically operate through hub-and-spoke networks and have higher operating costs than low-cost carriers (LCCs) which were founded, or began to provide interstate service, after deregulation.

Market Selection and Carriers. We estimate our model using a cross-section of data from the second quarter of 2006, for 2,028 airport-pair markets linking the 79 busiest US airports in the lower 48 states. Excluded routes include those where nonstop service was limited by

[12]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. We completely agree, which is one reason why we believe a full information model is the natural model for merger counterfactuals.

[13]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.

regulation and routes of less than 350 miles where ground transportation is likely attractive. We use relatively old data so that we can make predictions about subsequent mergers and we can avoid later years where carriers have been alleged to behave cooperatively. The second quarter is the busiest quarter for airline travel, but, as explained in the Appendix, there is no clear seasonal pattern to demand or service choices for the routes in our sample.

We measure quarterly quantities and prices for ticketing carriers, based on the itineraries in the Department of Transportation's DB1 database. Flights recorded in the monthly T100 data are aggregated to quarters and are attributed to ticketing carriers even if performed by regional affiliates. We model seven named carriers, American Airlines, Continental Airlines, Delta Air Lines, Northwest Airlines, Southwest Airlines (an LCC), United Airlines and US Airways, aggregating other ticketing carriers into composite "Other Legacy" (primarily Alaska Airlines) and "Other LCC" (such as JetBlue and Frontier) carriers, so that there is a maximum of nine carriers in any market. Our classification of carriers as LCCs follows Berry and Jia (2010).

Service Types, Market Shares and Prices. In DB1 it is common for a carrier to show up with a small number of passengers on a given route. For example, over 30% of carrier-route observations have less than 20 passengers (reflecting around 200 actual passengers given that DB1 is a 10% sample) and most of these carriers should not be viewed as significant competitors. We therefore restrict our definition of the competitors to include only those carriers with at least 20 return passengers in DB1 and at least a 1% share of passengers.[14] We define a carrier as providing nonstop service on a route if it has at least 64 nonstop flights (5 flights per week) in each direction (T100) and at least 50% of its DB1 passengers do not make connections. The remaining carriers are defined as providing connecting service. The number of nonstop carriers is not sensitive to the 64 flight and 50% thresholds as almost all nonstop carriers far exceed these thresholds (for instance, 80% of our nonstop carriers have less than 10% of passengers making connections). For this reason, we also choose to model a nonstop carrier as only providing a single (nonstop) product. Nonstop carriers tend to have many more passengers than connecting carriers: in DB1, the median nonstop carrier has 1,013 passengers compared to 34 passengers for the median connecting carrier.

As shown in Table 1, there is an average of four carriers in each market. Long distance markets with many plausible connecting routes, such as Orlando-Seattle, tend to have the most

[14] Throughout the paper, a one-way passenger is counted as one-half of a round-trip passenger.

Table 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	6.2
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	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
$\geq$ 1 Endpoint is a Domestic Hub	8,065	0.13	0.33	0	1
$\geq$ 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	8664	7940	2347	52,726

Table 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

carriers. The average number of nonstop carriers is 0.67 and Table 2 shows the distribution of the number of nonstop competitors. Most markets have no nonstop carriers, but the majority of passengers are in markets with two or three nonstop competitors, and these markets will be our focus in Section 7. 163 of the 277 nonstop duopoly routes are legacy carrier duopolies. Most of these routes connect large cities or hub airports, but non-hub pairs such as Boston-Raleigh and Columbus-Tampa are also duopolies. 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.

We model demand and pricing in each direction on each route, to capture the fact that consumer preferences can vary across endpoints because, for example, of frequent-flyer program membership. We allow for preferences to vary with a carrier's *presence* at the origin, where presence is defined by the proportion of routes that the carrier serves nonstop out of the airport out of the routes (including routes that are not in our sample) served nonstop by any carrier.[15] A carrier's market share in a particular direction is defined by the total number of passengers that it carries, regardless of service type, divided by a measure of market size. Appendix B describes how we define market size using the predicted values from a gravity model. We measure a carrier's price using the average return price in DB1. We also allow the price sensitivity of demand and the value of nonstop service to vary with a route-level *business index* measure of the proportion of business travelers on the route, based on data provided by Severin Borenstein (Borenstein (2010)).

The data suggests that nonstop service is a higher quality product and that it affects competition. Nonstop fares are \$43 higher than connecting fares and the average market share of a nonstop carrier is 18% (based on our definition of market size) compared to 4.9% for a connecting carrier (and recall that we have excluded small connecting carriers). The presence of a nonstop carrier is associated with connecting fares falling by \$10, controlling for route characteristics, while a second nonstop carrier is associated with a \$40 reduction in nonstop fares and a \$30 reduction in connecting fares.[16] Consistent with LCCs having lower costs, and possibly lower quality, their fares are on average \$70 lower than those of legacy carriers.

Network Variables. We model route-level competition but we include a number of variables, in addition to the effect of presence on demand, to capture how carriers may find it profitable to serve route segments nonstop partly because this will generate connecting traffic for other destinations in their networks. Specifically we allow the effective fixed cost of nonstop service to vary with whether the endpoints include one of the carrier's domestic or international hubs, and a continuous estimate of the amount of domestic connecting traffic that a carrier will generate by serving a route from a domestic hub nonstop. This estimate comes from a reduced-form model of

[15] A reduced-form analysis indicates that the effects of presence can be large. 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 market shares across the endpoints by 1.3 percentage points (or 20% of the average directional share). Differences in origin presence also have statistically significant, although smaller, effects on differences in average fares.

[16] These estimated differences come from regressions of a carrier's weighted (across directions) average fare on 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.

connecting passenger flows, estimated using data from one year before our sample, where we use a Heckman selection approach to account for the fact that a route may only be served nonstop when connecting traffic is unusually high.[17]

What Happened To Service and Prices After Legacy Mergers? We will use our model to predict what happens to prices and rivals' service choices after mergers, including three legacy carrier mergers (Delta/Northwest (closed October 2008), United/Continental (October 2010) and American/US Airways (December 2013)) that took place after our estimation sample. To give context to these predictions, and the assumptions on which they are based, we analyze what happened after these mergers. Appendix B.3 describes the analysis, which uses a panel dataset that runs from 2001 to 2017, in detail. We summarize the results here.

The first result is that we do not typically observe rivals initiating nonstop service on routes where the merging parties were nonstop duopolists (other carriers may provide connecting service). Specifically within two years of the merger closing, which is a common length of time to consider in merger analysis, another carrier initiates nonstop service on zero out of five routes for Delta/Northwest, one out of five routes for United/Continental and three out of six routes for American/US Airways. The merging firm always maintains nonstop service on these routes. We also observe the same pattern after the Southwest/Airtran low-cost carrier merger (May 2011), where there were sixteen nonstop duopoly routes immediately before the merger and new nonstop service was initiated on only one of them.[18]

One explanation for this pattern is that rivals are ill-suited to providing nonstop service on these routes, so that the merging carriers can exercise market power without repositioning taking place, but an alternative explanation is that the merger allows the merging parties to improve their quality or lower their costs in a way that makes new nonstop service by rivals unprofitable. We examine what happens to the merged carriers' prices and quantities to distinguish these possibilities. Specifically we consider a treatment group of markets where the merging carriers were nonstop duopolists for at least the last four quarters of a three-year pre-merger window

[17]The model, exclusion restrictions and estimates are detailed in Appendix B.2. We recognize that the construction of this variable is not completely consistent with our main model where nonstop service is the equilibrium outcome of a multi-carrier game. However, it helps to explain variation in service choices, and we view it as approximating the type of non-strategic model that a carrier might use to predict connecting passenger flows on new routes.

[18]There is no overlap in the routes across these mergers. Two out of the 32 routes experienced new nonstop service in the third year after the merger.

and compare changes in the merged carrier's prices on these routes to changes in the merged carrier's prices on a group of comparison/control routes where one of the merging parties was nonstop and the other was either completely absent or it only provided connecting service and had, at most, a 2% share of route traffic. We expect that the effects of market power or synergies from combining nonstop services on the same route would be significant for the treatment routes, but not for the control routes. Our regressions use observations from three-year pre-merger and post-merger windows, and control for changes in fuel prices (interacted with route distance) and the number of connecting competitors.

For the legacy carrier mergers, we find that on those pre-merger nonstop duopoly routes where, after the merger, no rivals initiated nonstop service, the merged firm's average prices increased by around 10% compared to the control group. The number of local passengers (i.e., passengers only flying the route itself) carried by the merging parties also falls significantly, by between 20% and 35%. On routes where rivals do initiate nonstop service before the end of the three year period, we do not observe significant price changes relative to the control group, although the merging parties still lose market share on these routes, presumably because of the increased competition. While we are conscious of the fact that research has shown that the estimated impact of earlier airline mergers depends on how the control group is defined and that different papers have also estimated a range of price effects for the mergers in our sample (e.g., Carlton, Israel, MacSwain, and Orlov (forthcoming) argue that prices fell, while Hüschelrath and Müller (2015) find that prices increased), we interpret these results as suggesting that legacy carrier mergers tend to be associated with increased market power without large route-specific synergies on nonstop duopoly routes. This will be reflected in our counterfactuals where we will assume that a merger eliminates a carrier without generating synergies.[19] We could, however, repeat our analysis with any synergy that one wanted to consider.

[19] We observe that there are no significant price increases, and no statistically significant declines in traffic, on nonstop duopoly routes after the Southwest/Airtran LCC merger even when rivals do not initiate nonstop service. This LCC merger may therefore have led to synergies. We do not consider this merger in our counterfactuals as Airtran is a member of our composite Other LCC carrier, which also contains other carriers on some of the affected routes.

4 Model

Consistent with the existing literature, we focus on carriers' strategic decisions at the route-market level (see Mazur (2016) for an exception). Consider a particular market, m, connecting two airports A and B. Denote the players by $i = 1, ..., I_m$. The carriers play a two-stage game. In the first stage they decide whether to provide nonstop or connecting service (i.e., the choice is binary, but unlike most of the entry literature, either choice implies some level of service), where nonstop service is associated with the payment of a fixed cost. This choice is non-directional. In the second stage, carriers choose prices on each directional route.

4.1 Second Stage: Post-Entry Price Competition

We assume that, given service choices, carriers play two static, simultaneous Bertrand Nash pricing games for passengers originating at each endpoint. Demand at each endpoint is described by a nested logit model. For customer k originating at endpoint A, the indirect utility for a return-trip on carrier i is

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

where $p_{im}^{A\to B}$ is the price charged by carrier i for a return trip from A to B, given the type of service that it offers. The first term represents carrier quality associated with the type of service that it offers (CON for connecting and NS for nonstop),

$$\beta_{im}^{A\to B} = \beta_{im}^{CON,A\to B} + \beta_{im}^{NS} \text{ x } \mathcal{I}(i \text{ is nonstop})$$

where

$$\beta_{im}^{CON,A\to B} \sim N(X_{im}^{CON}\beta_{CON}, \sigma_{CON}^2)$$

and

$$\beta_{im}^{NS} \sim TRN(X_{im}^{NS}\beta_{NS}, \sigma_{NS}^2, 0, \infty)$$

so that quality can depend on observed characteristics, such as the type of carrier (legacy vs. LCC) and route characteristics, but it also depends on a random component 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 perceived quality of nonstop service will always be greater than that of connecting service on the same carrier. To apply our estimation procedure we will impose some additional restrictions on supports, as described in Appendix C. The price coefficient and nesting parameters are also allowed to be 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 assume that α_m and τ_m are the same across directions for the same route, as we have found that this allows us to match the pattern that differences in average prices across directions on the same route tend to be fairly small even though they vary in a systematic way with differences in endpoint presence (see footnote 15).

ν_m is a market-specific random effect that is designed to capture the fact that in some markets there are more travelers in both directions, relative to our chosen definition of market size, than can be rationalized with independent quality heterogeneity across carriers. We assume that ν_m is normally distributed with mean zero and variance σ_{RE}^2. $\varepsilon_{kim}^{A \to B}$ is a standard logit error for consumer k and carrier i.

Each carrier has a marginal cost of carrying a passenger. Specifically we assume that

$$c_{im} \sim N(X_{im}^{MC} \beta_{MC}, \sigma_{MC}^2)$$

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 use the nonstop distance, whereas for connecting service we use the distance via the connecting carrier's closest domestic hub.[20] The marginal cost is non-directional as the representative traveler is assumed to make a round-trip.

The marginal cost specification is restrictive in two ways. First, the random component of marginal costs does not vary with the service choice, which is different to what we assumed about quality. Second, our data gives us two directional average prices and two directional market shares for each carrier, while here we are allowing for two directional quality unobservables and a single marginal cost unobservable so we cannot rationalize every realization of market shares and prices in the data. We have adopted these restrictions after finding that a model with independent, directional marginal cost draws fit the data less well.

[20]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.

Equilibrium prices will be unique under our assumptions of nested logit demand, linear marginal costs and single product firms (Mizuno (2003)). We can use these prices to calculate variable profits in each direction, $\pi_m^{A \to B}(s)$, as a function of a vector of carrier service types, s, and realized draws for costs and qualities. We define market-level variable profits as $\pi_m(s) = \pi_m^{A \to B}(s) + \pi_m^{B \to A}(s)$, as service choices are assumed to be the same in both directions.

4.2 First Stage: Service Type Selection

In the first stage carriers choose whether to commit to the fixed costs associated with nonstop service, which would include the opportunity costs of allocating planes and gate capacity to the route. If not, they provide connecting service. For our baseline estimation, we model carriers as making their service choices *sequentially* in order of their average presence at the endpoints. Their realized profits in the full game are therefore

$$\pi_{im}(s) - F_{im} \text{ x } \mathcal{I}(i \text{ is nonstop in } m) \tag{2}$$

where F_{im} is a fixed cost draw associated with providing nonstop service. We assume that

$$F_{im} \sim TRN(X_{im}^F \beta_F, \sigma_F^2, 0, \infty)$$

where X_{im}^F includes several airport and carrier network characteristics, including proxies for the connecting traffic going to, or coming from, other airports that the carrier can serve when it is nonstop. As we have already emphasized, we assume that all of the market-level and carrier-level demand, marginal cost and fixed cost draws are known, by all carriers, when service choices are made.[21]

[21] While we believe that a full information model is the natural model to apply to cross-sectional data, especially when the model is to be used for merger counterfactuals, one may ask whether there is additional evidence for the selection that this framework implies. Two types of evidence are suggestive. First, we have examined how long the named carriers in our sample maintain nonstop service on routes where they initiated nonstop service, for reasons other than mergers, after Q1 2001 but before 2006. If carriers cannot predict their nonstop profits accurately we might expect to observe many periods of brief experimentation. However, on average, nonstop service is maintained for 27 quarters which seems to us a substantial length of time given that our sample period contains the Great Recession and the years after 9/11 when the industry was not profitable. Second, we have estimated a number of Heckman selection-style specifications as intuitive tests of whether, as selection would suggest, carriers that surprisingly offer nonstop service also tend to have surprisingly high nonstop quality in an estimated demand model. Across a range of specifications we have found (usually statistically significant) evidence of positive selection. However, we are not aware of a general test for full information in the context of a game where full information implies that carriers know the qualities and costs of *all carriers*.

As the assumption of a known sequential order may be unattractive, we will show that our estimates are robust to allowing for outcomes to be generated from any pure strategy equilibrium in a simultaneous move game *or* a subgame perfect Nash equilibrium in a sequential move game with any order of moves.

4.3 Solving the Model

Conditional on s, we solve for equilibrium prices, market shares and profits by solving the system of pricing first-order conditions in the usual way. One way to solve for the subgame perfect Nash equilibrium in the sequential first stage of the model is by using backwards induction on a game tree with all possible outcomes as branches. However, we reduce the game tree by selectively *growing it forward*. To be precise, we first calculate whether it would be profitable for the first mover to operate as a nonstop carrier if it were the only carrier in the market, given its F.[22] If not, then we do not even 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 keep both of the initial 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 positive profits. Once this has been done for all carriers, we can solve backwards to find the unique subgame perfect equilibrium using the resulting tree, which often has only a small fraction of the branches of the full tree that one would normally use for backwards induction.

In our game the benefits from this selective growing of the game tree are useful but not necessary for our approach to be feasible. Indeed, we use a more standard approach when we calculate all of the pure strategy Nash equilibria in a simultaneous move game. However, if we were to allow for more choices or more carriers, then this type of approach may be necessary for estimation to be feasible.

[22]To be clear, here we are testing whether the monopoly profits from providing nonstop service are positive, which is a necessary condition for this service choice ever to be optimal, not whether it is more profitable than providing connecting service.

5 Estimation

The selection implied by the full information model means that we have to jointly estimate the demand and marginal cost functions and the service choice model.[23] In this section we briefly describe our estimation method for the baseline case where we assume a known order of entry. Appendix C contains full details for the baseline case and the alternative case where we allow for simultaneous service choices or an unknown order of moves, Monte Carlo evidence on the performance of the algorithm in both cases, and evidence on the robustness of the results to reducing the number of moments.

Objective Function and Moments. We estimate the parameters of our combined entry-and-price competition model by minimizing a simulated method of moments objective function, $m(\Gamma)'Wm(\Gamma)$, where W is a weighting matrix. $m(\Gamma)$ is a vector of moments where each element has the form $\frac{1}{2{,}028}\sum_{m=1}^{m=2{,}028}\left(y_m^{data} - \widehat{E_m(y|\Gamma)}\right)Z_m$, where subscript ms represent markets. Γ are the parameters that we want to estimate, i.e., the βs and σs from the model described in the previous section, y_m are observed outcomes and $E_m(y|\Gamma)$ are the expected values of the outcomes given the parameters and observed covariates.

Our reported results are based on using 1,384 moments, which reflect carrier service choices, carrier prices and carrier market shares, together with market-level outcomes such as the square of the number of nonstop carriers and the sum of squared market shares. The number of moments is large compared to the number of markets (2,028) and the number of carrier-market-direction (16,130) observations. In Appendix C.5 we show that we get similar coefficients, fit and counterfactuals using a subset of 740 moments. We use a diagonal weighting matrix which places equal weight on the price, share and service-type moments, and, within each of these groups, the weight on a particular moment is based on the reciprocal of the variance estimated using the identity matrix in place of W.[24]

Two-Step Estimation Using Importance Sampling. A simulation-based NFXP routine, as used, for example, by CMT, would require many simulated games to be solved for each market

[23] In our setting, the essential problem with trying to estimate demand on its own is that the expected value of the unobserved component of the incremental quality of nonstop service will vary in a highly nonlinear way with the observed and unobserved characteristics of all carriers.

[24] The sum of the values on the diagonal of the weighting matrix equals 1 for each of the three groups of moments. We choose not to use the inverse of the full covariance matrix of the moments because, with a large number of moments relative to the number of markets, we cannot claim that our estimates of the full variance-covariance matrix would be consistent.

whenever any parameter in Γ changes. This creates a very large computational burden and the resulting objective function will be discontinuous due to the discrete nature of simulated service choices. This limits the number of carriers or covariates that can be included in the model. Instead, we follow Ackerberg (2009) by using importance sampling to approximate the value of the moments predicted by the model.[25] Suppose that we want to calculate the expected value of a particular outcome, $E_m(y|\Gamma)$. Denoting a realization of all market and carrier-level draws as a vector θ_m, and its probability density function as $f(\theta_m|X_m, \Gamma)$,

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

where $y(\theta_m, X_m)$ is the unique equilibrium outcome given our baseline assumptions. This integral cannot be calculated analytically. However, 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. 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 Γ, approximating $E_m(y)$ using

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

where we only need to recalculate $f(\theta_{ms}|X_m, \Gamma)$ when the parameters change ($g(\theta_{ms}|X_m)$ can be calculated at the start of the estimation procedure). A major benefit is that $\widehat{E_m(y|\Gamma)}$ will be a smooth function of Γ even when the outcome of interest, such as a service choice, is discrete. For our reported estimates, we take 2,000 draws for each market, using 1,000 in estimation and drawing from the full pool of 2,000 when estimating standard errors using a bootstrap where we resample markets. Solving 2,000 games for each market takes a couple of days on a medium-sized cluster, while the estimation of the parameters takes around one day on a laptop or desktop

[25] Our application is most similar to Ackerberg's Example 2, although that example assumes an integer quantity-setting game and that the researcher would only observe integer quantities, not quantities, prices and product-type choices.

computer without any parallelization.

This approach assumes that $g(\theta_m|X_m)$ and $f(\theta_m|X_m,\Gamma)$ have the same support, and that this support does not depend on Γ. Therefore they have to be chosen by the researcher, and we describe our choices, where we aim to include all plausible values, in Appendix C.1. The use of wide supports, including areas where $f(\theta_m|X_m,\Gamma)$ may be almost zero, may reduce the accuracy of the approximation and potentially lead to an inconsistent estimate of the moment (Geweke (1989)). We examine this issue in Appendix C.4.

Identification. While our parametric assumptions, including the independence of demand, marginal cost and fixed cost unobservables, help to identify the parameters, the main intuition for identification is that we are making exclusion restrictions for our mean utility, marginal cost and fixed cost equations.[26] For example, carrier endpoint presence is assumed to only affect the preferences of consumers originating at that endpoint, with no direct effect on marginal costs or fixed costs. Route distance, which can vary across routes and across carriers depending on the location of their domestic hubs, is allowed to affect marginal costs, but not demand (our gravity-based market size measure accounts for the effect of distance on demand prior to estimation) or fixed costs. Domestic and international hub status, slot constraints and our continuous measure of generated connecting traffic affect the fixed cost of nonstop service but not demand or marginal costs. Our measure of connecting traffic may be especially valuable because when its value is very large (for example, between two of a carrier's domestic hubs), the carrier should be almost certain to offer nonstop service and there should be almost no selection on the draw of incremental nonstop quality.

6 Parameter Estimates

In this section we present our parameter estimates, assess the model's fit and quantify the importance of different types of selection in explaining service choices. Appendix C contains additional results on the performance of the estimation algorithm and on the robustness of the estimates to reducing the number of moments.

[26] We do allow for a correlation in demand across carriers via the market-level random effect. MacKay and Miller (2018) discuss how an assumption that demand and marginal cost shocks are independent can aid identification, even in the absence of exclusion restrictions. As we make exclusion restrictions, we could allow for correlations but our experience is that the objective function can have several local minima when we allow for unrestricted correlations.

6.1 Estimates with Known Order of Entry

The parameter estimates given our assumed order of entry are presented in column (1) of Table 3.

Demand Parameters. The estimated demand parameters imply that demand on business routes is less elastic (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), and that most substitution when a carrier's price increases is to other carriers rather than the outside good. The average (absolute value) own-price demand elasticity is 4.25, and the elasticity of demand for air travel (i.e., the change when all prices are increased by the same proportion) is 1.29.[27] There is relatively little unobserved cross-market heterogeneity in the price or nesting coefficients, but there is significant cross-market heterogeneity in the level of demand, as indicated by the standard deviation on the random effect.

The remaining demand parameters indicate that customers prefer carriers with a higher presence at their originating airport, which is also consistent with the earlier literature. The point estimates imply that preference for nonstop service is stronger on shorter routes and routes with a higher business index, although these coefficients are not statistically significant. Legacy carriers are estimated to give higher utility, all else equal, than low-cost carriers.

Marginal Cost Parameters. We allow a fairly rich specification for observable marginal costs, in order to explain differences in prices across routes and carriers. The coefficients indicate that legacy carriers have higher marginal costs for both nonstop and connecting service, and that distance increases nonstop and connecting costs in a similar way. For a legacy carrier, the average marginal cost of providing nonstop service on the Miami-Minneapolis route, which is roughly 3,000 miles round-trip, is \$345, compared to \$367 for connecting service. Marginal costs for Southwest are lower and, for this route, its expected nonstop and connecting (via Chicago Midway) costs are almost identical (\$303 and \$298 respectively). Estimated unobserved heterogeneity in marginal costs is quite small, with an estimated standard deviation of \$16.

Fixed Cost Parameters. The expected fixed cost for nonstop service is around \$841,000, although the expected value for those carriers that choose nonstop service is \$610,000, as estimated

[27] This estimate is consistent with the existing literature: for example, Gillen, Morrison, and Stewart (2003) report a median elasticity of 1.33 across 85 airline demand studies, and Berry and Jia (2010) estimate an elasticity of 1.67 using a much more disaggregated demand model and data from 2006.

Table 3: Coefficient Estimates (bootstrapped standard errors in parentheses)

				(1) Assumed Order of 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.

costs are lower from domestic and international hubs, especially on routes where nonstop service will generate more domestic connecting traffic to other destinations. Estimated unobserved heterogeneity in fixed costs is also relatively small (standard deviation of $215,000).

6.2 Estimates Without a Known Order of Entry

The assumption that there is a known sequential order of entry is helpful because it guarantees a unique equilibrium outcome for a given set of draws. However, the assumption is not necessary and several researchers have argued that estimates will be sensitive to equilibrium selection assumptions if, without them, several different outcomes could be supported as equilibria (for example, Ciliberto and Tamer (2009) report that their estimates imply multiple equilibria in over 90% of their market-simulations). Column (2) of Table 3 reports the point estimates when we minimize an objective function based on moment inequalities, allowing for the observed outcome to be the outcome associated with any pure strategy Nash equilibrium in a simultaneous service choice game or the subgame perfect Nash equilibrium in a sequential game with any order of moves. Appendix C.6 explains how the estimation approach described in Section 5 is extended for this case.

We find that the inequality-based objective function is minimized by a unique set of parameters even though we are using inequalities. The parameters are also very similar to those in column (1), with the exception of some of the marginal cost coefficients which also had large standard errors in column (1). This result reflects the fact that the parameters in column (1) typically only support a single equilibrium outcome even when we consider the more general service choice model. Table 4 illustrates this point by reporting the average number of different outcomes that can be supported as equilibria for markets with different numbers of carriers: the average is 1.017 per simulation and 98.4% of draws support only a single outcome.[28] We view this result as reflecting the fact that differences in the included carrier- and market-specific variables are able to explain much of the variation in which carriers provide nonstop service.

[28] A natural step would be to evaluate whether the coefficients in column (1) are within the confidence sets for the inequality estimator. However, this is not a straightforward task when the number of moments is large and the approach of Chernozhukov, Chetverikov, and Kato (2016), which is designed to work in this case, cannot easily be adapted to handle the case where some inequalities are violated, quite significantly, at the estimated parameters.

Table 4: Number of Outcomes Supported as Pure Strategy, Simultaneous Move Nash Equilibria or Subgame Perfect Nash Equilibria in a Sequential Move Game Given the Estimated Parameters

Number of Carriers	1	2	3	4	5	6	7	8	9	All
Number of Markets	141	304	416	413	342	228	136	46	2	2,028
Average Numb. of Eqm. Outcomes Per Simulation Draw	1	1.004	1.014	1.019	1.025	1.022	1.028	1.037	1.042	1.017

Notes: table reports the average number of outcomes that can be supported as equilibria in either simultaneous or sequential service choice games when we simulate 2,000 draws for each market in our data using the estimated parameters in column (1) of Table 3.

6.3 Model Fit

We now assess how well the model predicts service choices (see Appendix C.3 for some statistics on prices and market shares). Establishing that the model provides accurate in-sample predictions would be critical if any counterfactual predictions were going to be presented as evidence in a merger investigation. We simulate 20 new sets of demand and cost draws for each market from the estimated distributions and solve for equilibrium outcomes. We calculate standard errors for our predictions using additional sets of 20 draws based on each of the bootstrap estimates that were used to calculate standard errors in Table 3.

Our success rate at predicting a carrier's service choice is 87.5% (standard error 1.1%). This involves correctly predicting 91.7% (1.0%) of decisions to provide connecting service and 67.1% (2.8%) of decisions to provide nonstop service. For 82.6% (2.2%) of market-carrier observations where the majority of our simulations predict nonstop service, we observe the carrier actually providing nonstop service in the data.

Table 5 shows the performance of our model at predicting service at a number of hubs for the hub carrier. While we predict less nonstop service by Delta in Salt Lake City and Continental at Newark than they actually provide, the fit is generally impressive. We do even better at many non-hub airports. Table 6 shows the percentage of routes out of Raleigh-Durham served nonstop by each carrier (the number of routes varies across carriers depending on the airports that they serve nonstop or via connections). Both the percentage (reported in the table) and the identity of routes served nonstop is predicted very accurately for the largest nonstop carriers, American

Table 5: Model Fit: Prediction of Service Choices by Carriers at a Selection of Domestic Hubs

Airport	Carrier	Number of Routes	% Nonstop Data	% Nonstop 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 based on the estimated parameters in column (1) of Table 3. Standard errors based on additional sets of 20 draws for each of the bootstrap estimates used to report standard errors in the same table.

Table 6: Model Fit: Predictions of Service Decisions at Raleigh-Durham

	Number of Routes	Mean Presence at Route Endpoints	% Nonstop Data	% Nonstop 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: see notes to Table 5.

and Southwest. The largest difference between the prediction and the data is for United, as most simulations predict that United would serve its hubs in Denver and San Francisco nonstop. These routes were actually added by United after 2006. Delta, whose service is also overpredicted, has also subsequently increased its nonstop service at RDU.

6.4 Quantifying the Types of Selection Implied by the Estimates

Our model allows unobserved components of demand and marginal costs to affect carriers' service choices, in contrast to limited information models but, for policy analysis, it is also natural to want observed covariates to explain most of the variation. To quantify how different components affect service choices we estimate linear probability models using the same 20 sets of draws for each market where the dependent variable is a dummy for whether a carrier provides nonstop service and the observed and unobserved components of demand and cost for that carrier are regressors.[29] We rescale the continuous explanatory variables to have mean zero and standard deviation one, so that it is easier to compare the coefficients when variables have different units.

Table 7 shows seven specifications. Column (1) has only market-level regressors. Higher and less elastic demand make nonstop service more likely, and a one standard deviation change in (observed) market size has a much larger effect on service choices than one standard deviation changes in the random effect, nesting or price parameters. In column (2) we include the components of the carrier's own qualities and costs that are based on observed variables. These five variables increase the adjusted R^2 from 0.23 to 0.43, and they indicate that higher quality, lower nonstop marginal costs and, especially, lower fixed costs raise the probability of nonstop service.[30] Column (3) adds the unobserved components of carriers' quality and cost draws. This raises the adjusted R^2 by a further 0.1 (23%), which can be interpreted as a very rough measure of the relative importance of carrier unobservables in determining service choices. Column (4) adds dummies for the carrier's position in the move order and the number of carriers that are players in the game. Consistent with almost all simulations having a single equilibrium outcome regardless of the move order, the adjusted R^2 and most coefficients change only slightly. The remaining specifications include either market, market-simulation or market-carrier fixed effects so that the coefficients are identified from cross-carrier or cross-simulation variation within markets and coefficients on variables that only vary across markets are not identified.

We see two important patterns in the coefficients. First, observed variation in demand and costs explains much of the variation in service choices, as measured by the changes in R^2. This highlights one of the benefits of our estimation method which allows many covariates to be included. Second, among the different unobservables that enter the model, variation in the incremental quality of a carrier's nonstop service has the largest effect on service choices. Recall

[29] Our model implies non-linear relationships between the characteristics of all carriers and service choices, but we view the estimated coefficients in this linear specification as being informative about the relative importance of different variables. Probit or logit models give similar implications.

[30] Recall that an increase in connecting quality also increases nonstop quality, so that coefficients on nonstop quality measure the effects of incremental nonstop quality. The coefficient on observed nonstop quality has an unexpected negative sign and this may reflect a non-linear effect.

Table 7: Determinants of Nonstop Service at the Estimated Parameters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Size	0.183***	0.152***	0.154***	0.160***			
	(0.006)	(0.005)	(0.005)	(0.005)			
Market Random	0.021***	0.021***	0.021***	0.021***	0.022***		0.022***
Effect	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Nesting	-0.003***	-0.002***	-0.003***	-0.003***	-0.003***		-0.003***
Parameter	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Price	0.033***	0.023**	0.025***	0.042***	-645.709		-639.643
Parameter	(0.003)	(0.009)	(0.009)	(0.009)	(1,271.633)		(1,293.485)
Components of Carrier Quality							
Obs. Connecting		0.080***	0.078***	0.091***	0.019***	0.019***	
		(0.020)	(0.019)	(0.019)	(0.003)	(0.004)	
Unobs. Connecting			-0.049***	-0.049***	-0.049***	-0.050***	-0.049***
			(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Obs. Nonstop		-0.021	-0.018	-0.052***			
		(0.019)	(0.018)	(0.018)			
Unobs. Nonstop			0.094***	0.094***	0.094***	0.105***	0.094***
			(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Components of Carrier Marginal Cost							
Obs. Connecting		0.011	0.010	0.149***	0.135***	0.133***	
		(0.030)	(0.029)	(0.031)	(0.029)	(0.033)	
Obs. Nonstop		-0.086**	-0.089**	-0.238***	-0.220***	-0.218***	
		(0.042)	(0.041)	(0.042)	(0.040)	(0.045)	
Unobs. MC			-0.027***	-0.027***	-0.027***	-0.030***	-0.027***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Components of Carrier Fixed Cost							
Observed		-0.124***	-0.134***	-0.126***	-0.158***	-0.158***	
		(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	
Unobserved			-0.048***	-0.048***	-0.049***	-0.051***	-0.044***
			(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Carrier Position in Move Order							
2nd				-0.054***	-0.048***	-0.047***	
				(0.005)	(0.005)	(0.005)	
3rd				-0.091***	-0.085***	-0.084***	
				(0.006)	(0.006)	(0.007)	
4th				-0.105***	-0.102***	-0.101***	
				(0.007)	(0.006)	(0.007)	
5th				-0.107***	-0.106***	-0.106***	
				(0.007)	(0.007)	(0.008)	
6th				-0.102***	-0.102***	-0.102***	
				(0.008)	(0.007)	(0.008)	
7th				-0.105***	-0.108***	-0.107***	
				(0.009)	(0.008)	(0.009)	
8th				-0.110***	-0.115***	-0.114***	
				(0.014)	(0.013)	(0.015)	
9th				-0.096***	-0.102***	-0.099***	
				(0.008)	(0.007)	(0.009)	
Fixed Effects	-	-	-	Number of Carriers	Market	Market-Simulation	Market-Carrier
Observations	161,300	161,300	161,300	161,300	161,300	161,300	161,300
Adjusted R^2	0.230	0.427	0.521	0.528	0.588	0.550	0.632

Notes: estimates from linear probability models using 20 sets of draws from the estimated parameters for each market. Observations are at the carrier-market-simulation level and the dependent variable is a dummy for whether the carrier provides nonstop service. Standard errors in parentheses. ***, ** and * indicate statistical significance at 10%, 5% and 1% levels.

that the unobserved components of qualities and marginal costs would only be revealed after service choices had been made in a limited information model.

7 Merger Counterfactuals

We now use our estimated model to perform merger counterfactuals, focusing on whether changes in rivals' service choices are able and likely to constrain the market power of merging firms, and how these predictions depend on the types of selection that we allow for. We consider the three legacy mergers (Delta/Northwest, United/Continental and American/US Airways) that were completed after 2006, and a merger between United and US Airways that was proposed in 2000, but blocked. This latter merger is of interest because of a proposed remedy where American offered to commit to providing nonstop service, for ten years, on five routes where the merging parties were nonstop duopolists.[31]

Throughout we make the simple assumption that a merger simply eliminates one of the merging carriers and that the surviving "Newco" carrier has the quality and marginal costs of the merging party with the highest average presence at the route endpoints.[32] We could consider many alternative assumptions, including allowing for synergies on either the demand-side or the cost-side. These alternatives might have the effect of making a merger seem more beneficial or making new nonstop service by rivals less profitable. We do not do so for two reasons. First, we are already going to consider a large number of cases so that considering additional scenarios would make the presentation difficult to follow. Second, our simple assumptions produce results that are broadly consistent with what we observe, on average, on nonstop duopoly routes after the three mergers that took place after 2006 (Section 3 and Appendix B.3).

[31] 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 United's proposal to divest assets at Reagan National Airport and American Airlines' promise to fly five routes on a nonstop basis were 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."

[32] While eliminating a product tends to reduce the profitability of a merger, the mergers that we consider are profitable on most routes if they are assumed to eliminate one of the fixed costs and no rivals initiate nonstop service.

7.1 Effects of Mergers Holding Service Types Fixed

Table 8 shows predicted price effects on four types of routes when service types, qualities and marginal costs are held fixed at the levels implied by pre-merger market shares and prices, as is typically done in merger simulations (Nevo (2000)). The reported pre-merger price is the average price paid by consumers traveling on the merging parties in our data. To calculate post-merger prices, we fix the nesting and price coefficients at their mean values for each market (recall these parameters have small estimated variances).[33] To ensure comparability, we will also fix these coefficients in the analysis of endogenous service choices which follows. The types of route reflect whether the merging carriers are providing nonstop or connecting service in our Q2 2006 data.

The predicted price changes vary systematically with the types of service offered by the merging carriers, supporting our distinction between nonstop and connecting service. While there is heterogeneity in the predicted changes across routes and mergers, we predict that mergers between nonstop duopolists would raise the merged carrier's prices by an average of 12.4%. The average price increase when the parties are nonstop and there is another nonstop rival is still substantial, 9.1%, but average price increases are smaller when one or both merging parties offer connecting service.[34] When the merging carriers both offer connecting service we predict no price increases on average, because, even though competition is reduced, average prices may fall if the carrier that we assume survives the merger has a lower marginal cost than its partner. We have also calculated changes in consumer surplus. If nonstop duopolists merge, consumer surplus is expected to decline by an average of $35.09 per pre-merger traveler, whereas on routes where the parties are both connecting it is only expected to fall by $4.91.

7.2 Merger Counterfactuals When Rivals' Service Types Can Change

We now describe counterfactuals where rival service choices can change after a merger. These counterfactuals provide the main insights of our paper. We proceed by describing how we form conditional distributions for carrier qualities and costs to account for selection, and we show

[33]When we invert back from prices and market shares, we get a predicted marginal cost in each direction, whereas our model assumes that the marginal cost is the same in both directions. We therefore use the average of the two directional marginal costs, which are usually very close to each other, when performing counterfactuals.

[34]The predicted patterns are different for the Delta/Northwest merger, where the parties tend to have a significantly higher combined market share when one of them is nonstop and the other is connecting than is the case for the other mergers.

Table 8: Price Effects of Mergers with Service Type Choices Held Fixed

	Delta/Northwest		United/Continental		American/US Airways		United/US Airways		Average	
Merging parties are	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
Nonstop	\$566.39	\$593.20	\$503.75	\$556.17	\$459.13	\$521.15	\$479.32	\$549.49	\$481.40	\$541.25
duopolists	2 routes	+4.7%	4 routes	+10.4%	11 routes	+13.5%	7 routes	+14.6%	24 routes	+12.4%
Nonstop with	\$351.26	\$382.04	\$438.08	\$464.98	\$363.11	\$404.84	\$350.02	\$378.15	\$368.70	\$402.08
nonstop rivals	2 routes	+8.8%	4 routes	+6.1%	10 routes	+11.5%	10 routes	+8.0%	26 routes	+9.1%
Nonstop and	\$472.99	\$524.67	\$502.60	\$513.29	\$447.95	\$478.95	\$443.30	\$462.53	\$458.02	\$486.40
connecting	91 routes	+10.9%	59 routes	+2.1%	158 routes	+6.9%	163 routes	+4.3%	471 routes	+6.2%
Both connecting	\$433.26	\$444.63	\$487.04	\$486.86	\$464.20	\$457.77	\$484.25	\$479.62	\$466.00	\$465.97
	479 routes	+2.6%	334 routes	0.0%	471 routes	-1.4%	521 routes	-1.0%	1,805 routes	+0.0%

Notes: for each type of route and each merger the table shows the number of affected routes, the pre-merger average price on the merging parties, the predicted post-merger price of the merged carrier given the parameter estimates (with the price and nesting coefficients held at their mean values for the market) and the percentage price change.

how using these distributions affects an analysis of the United/US Airways merger in nonstop duopoly markets and the analysis of the proposed remedy. We then present the predictions for completed legacy mergers and for markets with three or more nonstop carriers before a merger, where the effects of accounting for selection are subtly different.

Conditional Distributions. Given our model, the natural way to perform counterfactuals in a particular market is to use values of the random components of our model that are consistent with both our estimates and the prices, market shares and service choices that are observed in this market in the data. The random components include carrier qualities and costs for the type of service that is not chosen. We will call these distributions "conditional distributions", although we could also label them as posterior distributions if we interpret the estimated distributions as providing a prior.

We use simulation to form the conditional distributions. We begin by specifying a grid of possible values for the market-level random effect. For each grid point, we calculate the qualities and marginal costs implied by observed prices and market shares for the service types that each carrier offers. We then take draws of the remaining stochastic components of the model from their estimated distributions and, for each set of draws, we check whether the observed service choices would be the equilibrium outcome of the sequential service choice game, collecting those draws that satisfy this requirement. We then combine the distributions of the accepted draws with the estimated distribution of the random effect to form our conditional joint distribution of the random effect, carrier qualities and both types of cost for all of the carriers in the market.[35]

As an example of the output from this process, we consider the market Philadelphia (PHL)-San Francisco (SFO) which is one of the United/US Airways nonstop duopoly markets where American offered to initiate nonstop service. Figure 3 shows simulated marginal conditional densities (50,000 draws) for the market random effect, the nonstop quality of American originating at SFO, and American's fixed cost for providing nonstop service. The solid line in the random effect plot shows the density of the random effect given the parameter estimates, while the histogram shows the conditional density. The conditional random effect has a lower mean, reflecting the fact that, in this market, the number of observed travelers, on any carrier, and the number of nonstop carriers is lower than we might have predicted based on observed market

[35]This process becomes more burdensome when we add draws to the model. This is the main reason why we moved away from the Li, Mazur, Roberts, and Sweeting (2015) model where carriers could also choose not to enter the market at all.

Figure 3: Selection of Marginal Conditional Distributions for Philadelphia-San Francisco

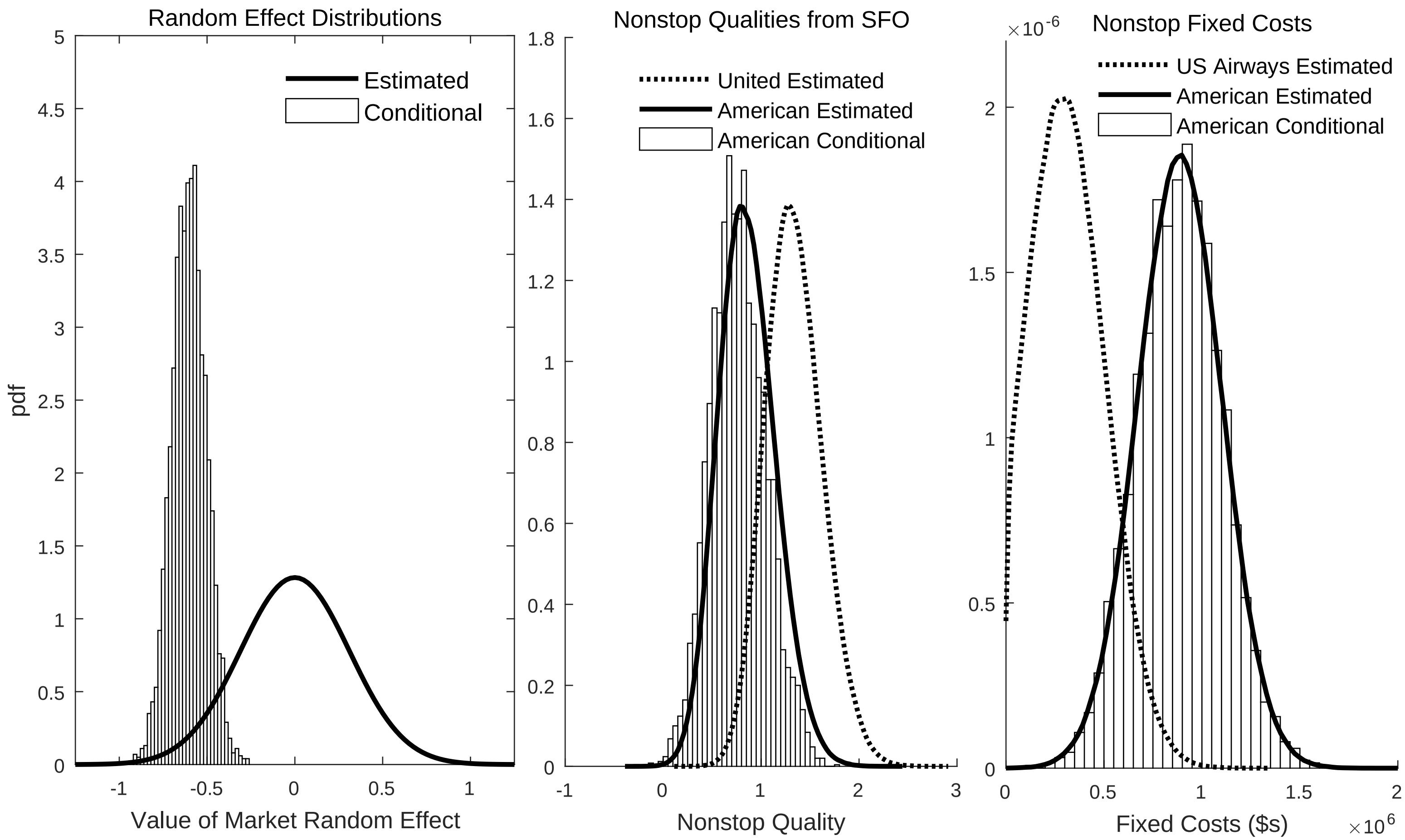


Table 9: Predicted Effects of United/US Airways Merger in Four Nonstop Duopoly Markets Affected By the Proposed Remedy

Selection/Service Change Considered	Mean Pre-Merger United/US Airways Price	Expected # of Rivals Initiating Nonstop Service: American	Expected # of Rivals Initiating Nonstop Service: Other Rivals	Expected Post-Merger "New United" Price
1. No Service Change	\$531.97	-	-	\$577.72 (+8.6%)
Allow Rival Service Changes				
Counterfactuals Computed Using				
2. Conditional Distns.	\$531.97	0.035	0.063	\$573.37 (+7.8%)
3. Estimated Distns.	\$531.97	0.148	0.298	\$563.73 (+6.0%)
4. Connecting Carriers' Nonstop Same As Merging Parties	\$531.97	0.645	1.938	\$531.77 (-0.0%)
American Nonstop Remedy Allowing Rival Service Changes				
Counterfactuals Computed Using				
5. Conditional Distns.	\$531.97	1	0.030	\$566.34 (+6.5%)
6. Estimated Distns.	\$531.97	1	0.253	\$556.18 (+4.6%)
7. Connecting Carriers' Nonstop Same As Merging Parties	\$531.97	1	1.820	\$529.73 (-0.4%)

Notes: predictions based on point estimates of the parameters from column (1) of Table 3 and, where relevant, 1,000 draws from the appropriate distributions. Predictions in rows 2-7 use the conditional distribution of the market random effect. The predictions in rows 4 and 7 assume that a connecting carrier would have the same nonstop quality and marginal cost, and the same mean fixed cost, as the average of the merging carriers if it provided nonstop service.

and carrier characteristics, including our market size estimate. For the nonstop quality figure[36], the lines show the distribution of nonstop quality implied by the estimates for American and United. United's higher expected quality reflects the fact that United has a high presence at SFO. In this dimension, the conditional distribution for American's nonstop quality is close, but slightly lower, than the distribution implied by the estimates: given what we observe in this market, we do not need to believe that American had an unexpectedly low nonstop quality draw to explain why it does not serve the market nonstop. Similarly, we see in the fixed cost figure that conditioning on the observed outcome does not make us noticeably more pessimistic about American's fixed cost. US Airways, which was nonstop, has a much lower expected fixed cost because of its domestic and international hubs at PHL.

[36]Nonstop quality is the sum of a carrier's connecting quality and the incremental quality of nonstop service. In this figure we are showing the densities of the sum of these draws.

Predicted Effects of a United/US Airways Merger and the Proposed Remedy. We now present our predictions of what would have happened after the United/US Airways merger. We focus on four routes where the merging parties were nonstop duopolists and American provided connecting service, so we can consider the effects of the American nonstop remedy. Row 1 of Table 9 shows that we predict that the merged firm's prices would increase by an average of 8.6% on these routes if service types are held fixed. This level of price increase would usual trigger concern in a merger investigation, and would lead an agency to evaluate whether it would be offset by either merger-specific synergies or post-merger entry or repositioning.

Row 2 of Table 9 reports our predictions when we allow rivals' service types to change after the merger, averaging across 1,000 draws from our joint conditional distribution on each route. We assume that the merged firm maintains nonstop service, as this is what we always observe (this is also the equilibrium outcome for almost all of the conditional draws), but we allow rivals to re-optimize their service types in the same order that we assumed for estimation (for PHL-SFO this means that American chooses first). We now predict that the merged carrier's price increases by \$41 (7.8%) on average, which is only slightly smaller than the prediction with fixed service types. The small size of the change can be explained by the fact that the average number of rival carriers (including American) predicted to begin nonstop service is only 0.1. The probability that American itself initiates nonstop service is 0.035.

A natural question is whether we would make similar predictions if we did not use draws from the conditional distribution. We therefore repeat the counterfactuals using draws from the estimated distributions, which account for observable carrier characteristics, for fixed costs and the types of service that are not offered. 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. Our reason for using the conditional distribution of the random effect is that we included the random effect to overcome the imperfections in our definition of market size and we believe that the agencies and parties in a merger investigation would have better measures of potential demand. In row 3 of Table 9 we see that the probability that rivals initiate nonstop service quadruples (the expected number of new nonstop rivals is 0.45, rather than 0.1), but that the predicted price increase is only 23% smaller than in row 2 (6.0% rather than 7.8%).

In row 4 we report what an analyst would predict if she assumed that the connecting carriers could provide nonstop service on the same terms as the merging parties. This is the type of assumption that an expert for the merging parties might suggest in the absence of clearly identified barriers to entry or repositioning. Specifically, we assume that, on each route, connecting rivals would have the mean nonstop quality and mean nonstop marginal costs of the merging carriers and draw their fixed costs from a distribution with a mean equal to the average of the merging carriers. We make the same assumptions about the market random effect and qualities and costs for the type of service that we observe being provided, as in rows 2 and 3.

We now predict that 2.6 carriers would initiate nonstop service, and that, on average, the merged firm's prices would be no higher than before the merger.[37] However, when we predict that a carrier will reposition we would also typically predict that the carrier would have provided nonstop service *before* the merger given these assumptions (for example, this is true for over 90% of draws where we predict American would want to offer nonstop service). Therefore these results highlight both the importance of accounting for observed and unobserved asymmetries between firms in their competitive "match" to particular markets but also how it will often be difficult to rationalize observed pre-merger choices when this accounting is not done.

In rows 2-4 there is a negative correlation between the predicted number of rival carriers initiating nonstop service and the predicted post-merger price increase. Does this imply that the proposed American nonstop remedy, which would have maintained the number of nonstop carriers at its pre-merger level, would have prevented the merged carrier from raising prices? We investigate this in rows 5-7 where we use exactly the same draws as we used in rows 2-4 but we force American to provide nonstop service even if it is not profitable (see footnote 6). In each case, rival carriers know that both the new United and American will provide nonstop service when they make their service choices. The results clearly show that American's nonstop service would not have greatly constrained the new United's market power: in rows 5 and 6 the predicted price increase is only 1.3-1.4 percentage points lower than in rows 2 and 3. The fact that American is not an effective competitor when it only provides nonstop service because of the remedy is also illustrated by the fact that American's certain entry causes only a small drop in the expected number of other rival carriers initiating nonstop service, especially when

[37]An alternative assumption is that other carriers would have the same nonstop quality, marginal cost and fixed cost distribution as the lower presence merging carrier i.e., the carrier that we treat as being eliminated after the merger. In this case, we predict that 1.5 carriers would initiate nonstop service and that, on average, the merged firm's price would increase by $16 or just under 3%.

we account for selection.

The Predicted Effects of Completed Legacy Mergers. We repeat the analysis in the upper part of Table 9 for the three legacy carrier mergers that took place after our sample period. We analyze the mergers separately, rather than cumulatively, as our main purpose is to understand the robustness of the relationships between price changes, service changes and selection.

Table 10 presents predictions of service and price changes in markets where the merging parties are nonstop duopolists. In each case we report the mean predicted post-merger price for the merged carrier and the expected number of new carriers that should initiate nonstop service. The basic patterns are similar to Table 9, although there are some differences across the mergers: when we use the conditional distributions, which fully account for selection, we predict that new nonstop service is unlikely and that price increases will be similar to the case where service types are fixed; if we assume that a connecting carrier could offer nonstop service on the same terms as the merged firm, new nonstop service is very likely and prices should not increase; and, when we use the estimated distributions, which account for selection on observables, the expected number of new nonstop carriers trebles while the reduction in the predicted price increase depends on the merger being considered (it falls by almost 50% for American/US Airways and 25% for Delta/Northwest).

We can also compare the predictions to what we described as happening after these mergers were completed (Section 3), with the caveat that the set of routes being considered do not exactly coincide. Nonstop service was initiated by rival carriers in four out of sixteen nonstop duopoly markets within two years of these mergers: our predictions are closest to this rate when we use the conditional distributions. It is also noticeable that the price increases observed on nonstop duopoly routes with no new nonstop service by rivals (11%, relative to a control group) are similar to those predicted by the model, and the same is true for the predicted decreases in the market shares of the merged firm (both around 30%). This contrasts with negative conclusions about the performance of merger simulation models when used to predict outcomes from earlier airline mergers (Peters (2009)), although this may partly reflect conflicting estimates of what actually happened to prices after these mergers (see footnote 7).

In Table 11 we perform a similar analysis for routes where the merging parties are nonstop and there was at least one nonstop rival prior to the merger (in only one case is there more than one nonstop rival). In these markets, we assume that, after the merger, the merged Newco

Table 10: Predicted Price and Service Changes in Mergers Following the Sample Period on Routes where Merging Parties are Nonstop Duopolists

	Delta/Northwest		United/Continental		American/US Airways		Average for Completed Mergers	
	Price	Numb. New Nonstop	Price	Numb. New Nonstop	Price	Numb. New Nonstop	Price	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	-
	+4.7%		+10.4%		+13.5%		+11.5%	
Allow Rival Service Changes								
Counterfactuals Computed Using:								
Conditional Distributions	$590.34	0.07	$547.65	0.14	$511.33	0.21	$529.17	0.18
	+4.2%		+8.7%		+11.4%		+9.7%	
Estimated Distributions	$584.20	0.19	$534.08	0.35	$488.45	0.73	$510.45	0.57
	+3.1%		+6.0%		+6.4%		+5.8%	
Connecting Carriers' Nonstop Same as Merging Parties	$573.83	0.93	$454.36	2.62	$460.25	2.10	$472.23	2.08
	+1.3%		-9.8%		+0.2%		-2.1%	
Number of Routes	2		4		11		17	

Notes: see notes to Table 9.

Table 11: Price Effects of Mergers Where Both Merging Parties and at Least One Rival Carrier Provide Nonstop Service

	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	-
	+8.1%		+6.1%		+11.5%		+8.0%		+9.1%	
Allow Rival Service Changes										
Counterfactuals Computed Using:										
Conditional Distributions	\$378.90	0.16	\$464.86	0.01	\$404.41	0.03	\$377.24	0.05	\$411.07	0.06
	+7.9%		+6.1%		+11.4%		+7.8%		+8.9%	
Estimated Distributions	\$386.40	-0.51	\$466.18	-0.03	\$403.55	-0.27	\$375.17	-0.11	\$413.33	-0.28
	+10.0%		+6.4%		+11.1%		+7.2%		+9.5%	
Connecting Carriers' Nonstop Same as Merging Parties	\$374.37	0.66	\$455.64	0.61	\$398.85	-0.03	\$367.68	0.48	\$404.95	0.34
	+6.6%		+4.0%		+9.8%		+5.0%		+7.3%	
Number of Routes	2		4		10		10		26	

Notes: see notes to Table 9.

is nonstop but, when we endogenize service choices, we allow the pre-merger nonstop rival to switch to connecting service. We include United/US Airways nonstop routes in this analysis as we did not consider these markets in our previous analysis of that merger.

When we use the conditional distributions, we predict that all non-merging nonstop rivals will maintain nonstop service, that there is a small probability that a rival carrier will add nonstop service and that the merger will likely result in the merged carrier raising its price significantly. When we assume that any connecting carrier could provide nonstop service on the same terms as the merging carriers, we predict that, on average, one connecting carrier would begin nonstop service, but that the existing nonstop rival would drop nonstop service in one-third of our simulations. Combining these offsetting changes, we still predict that prices will increase significantly, which was not true for nonstop duopoly routes. When we use the estimated distributions, we predict an overall decline in the number of nonstop rivals to the merged firm and, on average, the largest price increases. Therefore the duopoly result that the prediction that accounts for observed selection lies between our other predictions depends on the market structure being considered.[38]

8 Conclusions

We have estimated a model of endogenous service choices and price competition in airline markets. Our model assumes that carriers have full information about demand and marginal cost shocks when they choose whether to provide nonstop service. In this framework, the carriers providing nonstop service will be selected based on how competitive their nonstop service will be. We view the full information assumption as the natural one to make when analyzing product repositioning by firms that are experienced industry participants, and we have illustrated how it can affect equilibrium outcomes and the predicted effects of mergers. Our full information model can be estimated without an excessive computational burden, making this approach potentially accessible to a wide-range of academics and practitioners.

Our merger counterfactuals show that assumptions about how competitive rivals will be if they reposition their products can determine how concerned one will be about post-merger

[38]The intuition is that favorable unobservables, such as a low realized fixed cost, are often required to rationalize why a third carrier finds it profitable to offer nonstop service.

market power. If one assumes that rivals can offer repositioned products with similar quality and costs to those provided by the merging firms, one will tend to predict that one or more rivals will reposition their products after a merger and, at least in the nonstop duopoly case, that mergers will not increase prices. On the other hand, when one accounts for observable differences between firms and the selection implicit in their pre-merger choices, repositioning will appear to be far less likely and predicted price increases will be similar to those predicted by a simulation where repositioning is not allowed. These price increases can be substantial when the merging firms are close competitors.

Even when the computational burden is low, economic experts may be reluctant to place too much weight on formal merger simulations when evaluating horizontal mergers because of the limited time that is usually available. However, we view our analysis, which reflects the logic of the merger *Guidelines*, as still shedding valuable light on how any post-merger scenarios suggested by an economic expert should be evaluated. For example, if the expert assumes that a repositioning competitor, or a new entrant, will be as competitive as one of the merging parties then they should have to explain why this is consistent with no repositioning or entry taking place before the merger, and why the informational assumptions that would tend to rationalize this type of "no selection" assumption are plausible. Industry experts could also be asked to testify as to how accurately firms can predict their market shares or costs prior to providing a product, as this will indicate whether the type of selection analyzed here needs to be accounted for when a particular merger is reviewed.

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APPENDICES TO "SERVICE CHOICES AND MARKET POWER AFTER AIRLINE MERGERS" FOR ONLINE PUBLICATION

A Details of the Example Comparing the Limited and Full Information Models

Section 2 compares market outcomes and the effects of a merger under models that assume that carrier have either full or limited information about quality and marginal cost unobservables when they make service choices. In this Appendix we provide full details of the parameterization of these models.

The core model is a stylized version of the model estimated in the paper, although we do not allow for the fact that a single route serves two markets for passengers originating at different endpoints. There is one market with six carriers, A,..,F, who choose to offer either connecting or nonstop service, with nonstop service having higher quality. Demand has a nested logit structure, where all carriers are in a single 'travel' nest, and 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. The game has two stages. Carriers make service choices in alphabetical (i.e., expected quality) sequential order in the first stage, and simultaneously choose prices in the second stage.

We compare outcomes under two information structures. 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 (these are also known to all carriers) in the first stage, but all draws are revealed before prices are chosen. 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 described in the text. 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.

B Data Appendix

This appendix complements the description of the data in Section 3 of the text.

B.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 airports[39];
- 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[40]; 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

[39] 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.

[40] 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.

of the airports in our sample using monthly T100 data on originating passengers.[41] 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.

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 nonstop entry appears to 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[42], 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.

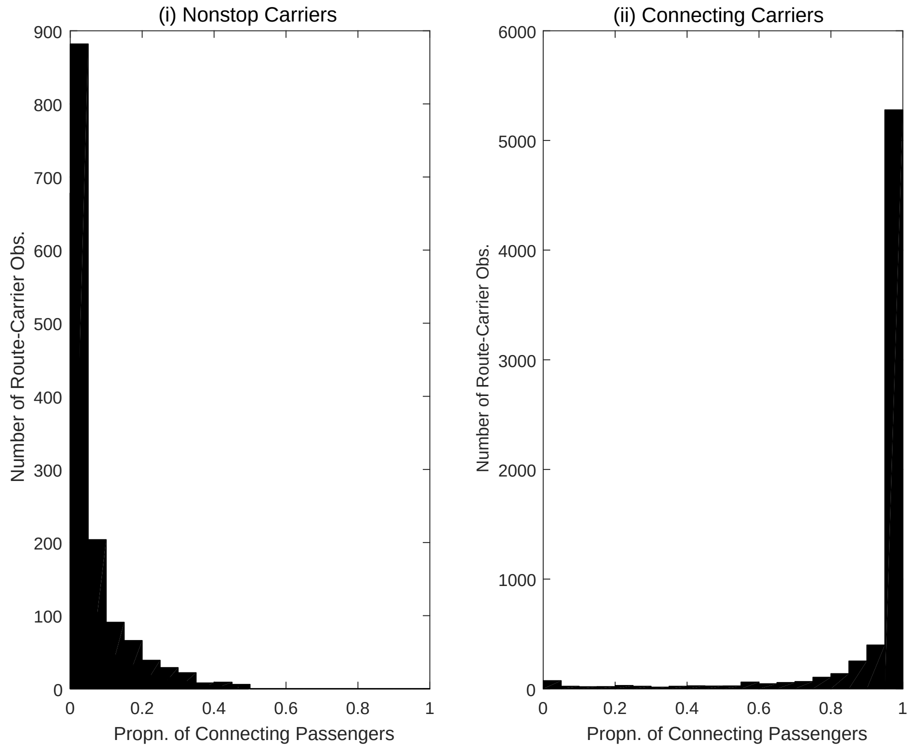
We define the set of players on a given route as those ticketing carriers who achieve at least a 1% share of total travelers (regardless of their originating endpoint) and, based on the assumption that DB1 is a 10% sample, carry at least 200 return passengers per quarter, with a one-way passenger counted 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 nonstop carriers far exceed these thresholds. For example, Figure B.1 shows that the carriers we define as nonstop typically

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

[42] 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



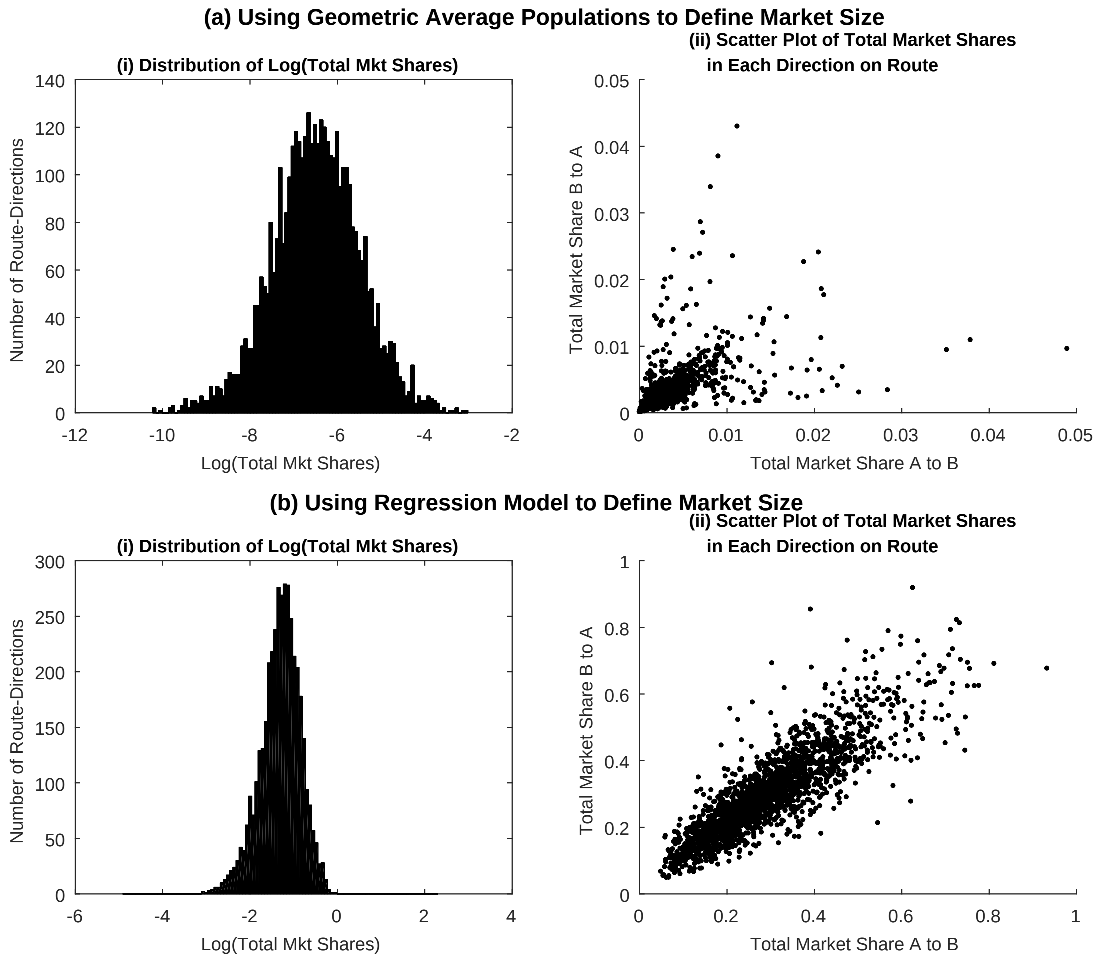
carry only a small proportion of connecting passengers. For the same reason, we also model nonstop carriers as only providing nonstop service even if some of their passengers fly connecting, although we include the connecting passengers when calculating market shares. On the other hand, our 1% share/200 passenger thresholds do affect the number of connecting carriers. For example, if we instead required 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. As in many settings where discrete choice demand models are estimated, the definition of market size is important but not straightforward. Ideally, variation in market shares across carriers and markets should reflect variation in prices, carrier characteristics and service types rather than variation in how many people consider flying on a particular route which is what the market size measure should be capturing.

A common approach is to use the geometric average of endpoint populations as the measure of market size (e.g., Berry and Jia (2010), Ciliberto and Williams (2014)).[43] However, as illustrated in the left-hand panel of Figure B.2(a), using this measure results in considerable heterogeneity in (the natural log of) total market shares (i.e., summing across all carriers) across routes. It also

[43] Reiss and Spiller (1989) use the minimum endpoint population as their market size measure.

Figure B.2: Market Size Measures and their Impact on Market Shares



leads to significant variation in the proportion of the market traveling in each direction on many routes even though the services offered by the carriers are usually very similar in both directions (right-hand panel). This is a problem as we model competition on directional routes.

We address these issues in two ways. First, conditional on our market size measure, our estimated demand model allows for a route-level random effect, unobserved to the econometrician but known to the carriers. This random effect is common to all carriers and all types of service, and it can explain why more people travel on some routes holding service, prices and observed variables constant. Second, we define market size using the regression-based gravity model of Silva and Tenreyro (2006) where the log of the number of passengers traveling on a directional route is projected onto a set of interactions between the total number of originating and destination passengers (i.e., aggregating across all carriers and routes) at the endpoint airports and the nonstop distance between the airports. We multiply the predicted traveler number by 3.5 so that, on average, the combined market share of all carriers is just under 30%. Figure B.2(b) repeats the figures in Figure B.2(a) using this new definition, and the distribution of the log of total market shares and the relationship between total market shares in each direction display much more limited heterogeneity.

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.[44]

Explanatory Variables Reflecting Airline Networks. The legacy carriers in our data operate hub-and-spoke networks. On many medium-sized routes nonstop service may be profitable only because it allows a large number of passengers who use the route as one segment of a longer trip to be served. While our structural model captures price competition for passengers traveling only the route itself, we allow for connecting traffic to reduce the effective fixed cost of providing non-stop service by including three carrier-specific variables in our specification of fixed costs. Two variables are indicators for the principal domestic 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 limited 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.1 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 in Appendix B.2.

B.2 An Ancillary Model of Connecting Traffic

As explained in Section 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

[44] 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, which may be significantly below list prices, may also play a role, but there is no data available on how many tickets are sold under these contracts.

Table B.1: 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

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), Memphis (Northwest) 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[45] 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 or opportunity cost of providing nonstop service on the route.[46]

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,

$$s_{c,i,od} = \frac{\exp(X_{c,i,od}\beta + \xi_{c,i,od})}{1 + \sum_l \sum_k \exp(X_{l,k,o,d}\beta + \xi_{l,k,od})} \tag{3}$$

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.[47] 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):

$$\log(s_{c,i,od}) - \log(s_{0,od}) = X_{c,i,od}\beta + \xi_{c,i,od}. \tag{4}$$

However, estimating (4) 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

[45] 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.

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

[47] 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.

model, to describe the probability that carrier i does serve the full ocd route,

$$\Pr(i \text{ serves route } ocd) = \Phi\left(W_{i,c,od}\gamma\right). \tag{5}$$

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.[48] 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.

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

[48] 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.

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[49]; 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 (4) and (5), 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.2, 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 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 network decisions will really be made simultaneously.

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, 1213 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

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

Table B.2: 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 * Connecting Presence		-5.536***		
		(1.311)		
Destin. Presence * Connecting Presence		-5.771***		
		(1.303)		
Population of Connecting Airport		-1.20e-07***		
		(3.16e-08)		
Origin Population * Origin Presence		-5.09e-08**		
		(2.23e-08)		
Destin. Population * 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 * Distance Origin - Connection		0.000569***		
		(0.000207)		
Destin. Restricted * 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 * Relative Distance^2	0.479***			
	(0.151)			
Most Convenient Hub of Any Carrier *	0.590			
Relative Distance	(0.434)			
Origin Presence * Destination Presence	-5.278***			
	(0.513)			
Observations	142,506	-	-	-

Notes: robust standard errors in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

(2265, observed 2765) than DFW (2040, observed 2364).

B.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.3.1 Frequency of Rivals Introducing 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 calculated 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 years of the merger closing, which is window that is often considered when examining whether there will be timely entry or repositioning after a merger. We find that no rivals initiated nonstop service 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 out of five routes for United/Continental, three out of six routes for American/US Airways and one out of sixteen nonstop duopoly routes for Southwest/Airtran. Therefore, the overall rate of rivals initiating nonstop service was five out of thirty-two, or four out of sixteen if we only consider legacy mergers.[50]

One explanation for this pattern is that rivals are ill-suited to provide nonstop service on these routes, so that the merging carriers can exercise market power. This will be the explanation that we focus on in our counterfactuals. However, an alternative explanation is that the merger allows the merging carriers to improve their quality or lower their costs in a way that makes new nonstop service by rivals unprofitable. We examine what happens to the merged carrier's prices and quantities to try to distinguish these possibilities.

[50] There is no overlap in the routes across these mergers. Two out of the 32 routes experienced new nonstop service in the third year after the merger.

B.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%.[51] 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. 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 Q3 2009-Q2 2012 and Q2 2014-Q1 2017.[52] 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 total 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.[53] 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

[51] As mentioned in footnote 7 in the Introduction, the literature on airline mergers has found that results can be sensitive to the definition of the control group (for example, should prices be compared across routes for the merging carriers or across carriers?). More broadly, one should also recognize that because airlines provide networks where many passengers make connections, the routes in the treatment and control groups will interact meaning that we cannot have an ideal experiment.

[52] 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.

[53] 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.

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.3. 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 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. 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.

Table B.3: 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*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*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*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*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 weighted average of fares or 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. *,**,*** indicate significance at the 10%, 5% and 1% significance levels.

C Estimation

This Appendix provides additional information on the algorithm that we use to estimate our model. Appendix C.1 lays out the details for our baseline specification where we assume that carriers make service choices in a known order. Appendices C.2-C.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 C.6 explains how we estimate our model using moment inequalities when we do not impose a known order of moves. Appendix C.7 provides Monte Carlo evidence that the baseline and inequality estimators work well for a simplified model.

C.1 Moments, Supports and Starting Values

Estimation involves a two-step procedure, where the first step involves solving a large number of simulated games and the second step estimates the parameters by minimizing a simulated method of moments objective function. We describe the procedure for our preferred specification, with a sequential order of moves in the service choice game, here.

The second step objective function is

$$m(\Gamma)'Wm(\Gamma)$$

where W is a weighting matrix. $m(\Gamma)$ is a vector of moments where each element has the form $\frac{1}{2{,}028}\sum_{m=1}^{m=2{,}028}\left(y_m^{data}-\widehat{E_m(y|\Gamma)}\right)Z_m$, where subscript ms represent markets. y_m^{data} are observed outcomes and Z_m are observed exogenous variables.

As described in the main text, $\widehat{E_m(y|\Gamma)}$ is approximated using importance sampling. In the first step of the procedure, we solve for the unique equilibrium outcomes for a given set of S draws of the demand and cost draws θ_m, drawn from importance densities $g(\theta|X_m)$. When estimating the parameters in the second step, we calculate

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

To apply this approach, we need to specify, before estimation, the support of each of the θ draws and to choose the importance density g. To generate the reported results, we use the supports and truncated densities listed in Table C.1. The supports were chosen to be broad in the sense that they contain all of the values that were likely to be relevant, although we restrict the support for the nesting parameter after we found local minima with implausibly high or low mean values of τ when we allowed a full range of between 0 and 1. The assumed range of τ is consistent with most values in the literature (for example, Berry and Jia (2010) and Ciliberto

Table C.1: 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	$\beta_{im}^{CON,A\rightarrow B}$	[-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.

and Williams (2014) report estimates between 0.62 and 0.77, albeit with a different definition of market size). Draws from the gs are taken independently for each market, carrier and type of draw, although the market random effect induces correlation in demand across carriers in a given market.

To choose the mean and standard deviation parameters of the g densities, we initially attempted to match (by eye) a small number of price, market share and entry moments to make sure that our model could capture the main patterns in the data. This led to the "initial" parameterization reported in the notes to the Table C.1, where we tried to allow for sufficiently large standard deviations that, during estimation, there would be enough draws covering a wide range of qualities and costs that the mean coefficients could move significantly if this allowed the estimated model to achieve a better fit. We then ran a couple of rounds of our estimation routine to identify the parameters that we use to create the draws for the final round of estimation whose results we report. While the estimator can be consistent for any set of gs that give finite variances, Ackerberg (2009) recommends using a multi-round estimation procedure to improve efficiency.[54] We take 2,000 sets of draws from the gs for each market. 1,000 sets are used in the

[54] A formal iterated procedure was used by Roberts and Sweeting (2013) in estimating a model of selective entry for auctions, where the standard errors were bootstrapped to account for this multi-stage estimation procedure. To implement this bootstrapping approach, to account for what happens in the early iterations, in the current

estimation (i.e., $S = 1,000$), with the full sets of 2,000 being used as a pool of draws that we use when performing a non-parametric bootstrap to calculate standard errors.

We use a large number (1,384) of moments in estimation. Table C.2 presents a cross-tab describing the interactions that we use between observed outcomes and exogenous variables. There are two types of outcomes: market-specific and carrier-specific, and for each of these types, we are interested in prices, market shares and service choices. For example, market-specific outcomes include weighted average connecting and nonstop prices in each direction. Carrier-specific outcomes include the carrier's price in each direction, its market share in each direction and whether it provides nonstop service. The exogenous Z variables can be divided into three groups: market-level variables, variables that are specific to a single carrier, and variables that measure the characteristics of the other carriers that are in the market (e.g., Delta's presence at each of the endpoint airports when we are looking at an outcome that involves United's price or service choice).

We recognize that this is a large number of moments given the number of markets in our sample. In Appendix C.5 we show that the coefficient estimates are quite similar, and, more importantly, the fit of our model and our counterfactual predictions are very similar when we only use the 740 carrier-specific moments.

We use a diagonal weighting matrix (W) with equal weight on the price, share and service-type moments, and, within each of these groups, the weight on a particular moment is based on the reciprocal of the variance based on initial estimates that use the identity matrix as the weighting matrix.[55] We choose not to use the inverse of the full covariance matrix of the moments because, with a large number of moments relative to the number of markets, we cannot claim that we can estimate the full variance-covariance matrix consistently, and, in practice, the coefficient estimates are less stable if an estimate of the full-covariance matrix is used.

C.2 Performance of the Estimation Algorithm For the Baseline Estimates

There are two important reasons for using importance sampling when estimating our model: 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 around 2 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 shows the

setting would create a large computational burden, so we instead present our results as being conditional on the final round g, while acknowledging that the choice of g was informed by our initial attempts at estimation. See Appendix C.7 for a discussion of how using different gs affect the estimates in a Monte Carlo.

[55]The sum of the values on the diagonal of the weighting matrix equals 1 for each of the three groups of moments.

Table C.2: Moments Used in Estimation

Exogenous Variables (Z)	Market Specific (y_M) Endogenous Outcomes 7 outcomes	Carrier Specific (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.

Table C.3: 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%)

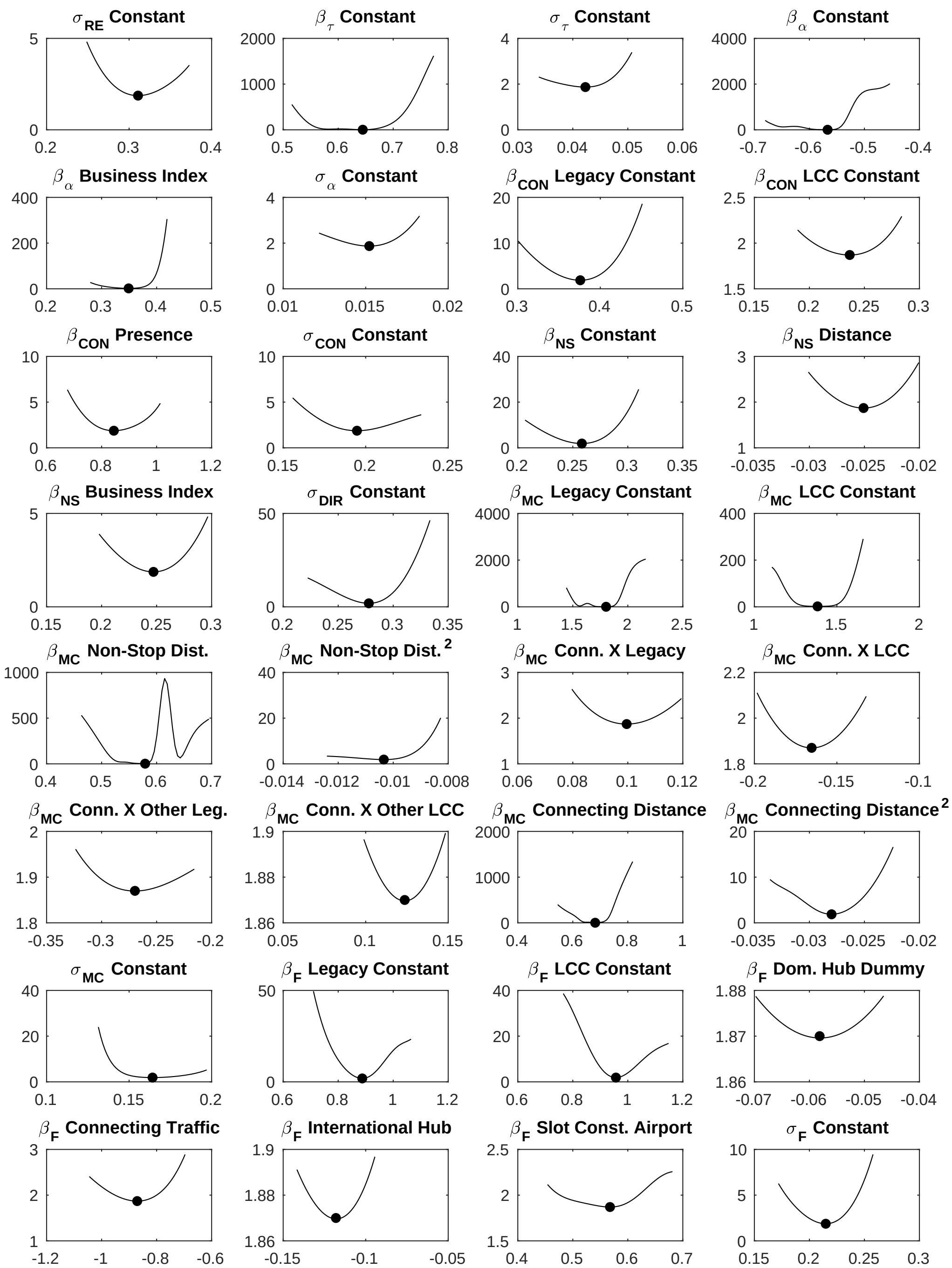
Notes: Predictions from the model calculated based on twenty simulation draws from each market from the estimated distributions. Standard errors in parentheses come from generating additional sets of twenty draws from each of the bootstrap sample estimates used to report standard errors in Table 3.

shape of the continuous objective function when we vary the parameters one-at-a-time around their estimated values. While these pictures do not show the shape of the objective function in multiple dimensions, they illustrate the smoothness of the objective function and provide some grounds for optimism that a global minimum has been found. We have also verified that restarting the estimation at different starting points produces estimates that are very similar to those reported in the Table 3.

C.3 Model Fit: Prices and Market Shares

Section 6.3 of the main text describes how well the estimated model predicts carriers' service choices, based on twenty sets of draws for each market. Here we report the fit of prices and market shares using the same draws based on the estimated parameters from column (1) of Table 3. Table C.3 shows average reported prices and shares by type of service and by terciles of the market size distribution.

Figure C.1: Shape of the Objective Function Around the Estimated Parameters For the Parameter Estimates in Column (1) of Table 3 (black dot marks the estimated value)



We match average *differences* in market shares and prices across service types very accurately, although we overpredict the levels of prices and market shares.[56] These cross-carrier averages mask some differences at the carrier-level. For example, the observed and (predicted) prices for United's nonstop and connecting services are \$479 (\$472) and \$436 (\$445) so the match is very close, whereas for Delta the comparisons are \$498 (\$453) and \$448 (\$466).

C.4 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, Shephard, and Creal (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 will 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, 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, Shephard, and Creal (2009), the jumps in the estimated sample variance are quite small for $S > 500$. In our application we are using $S = 1,000$.

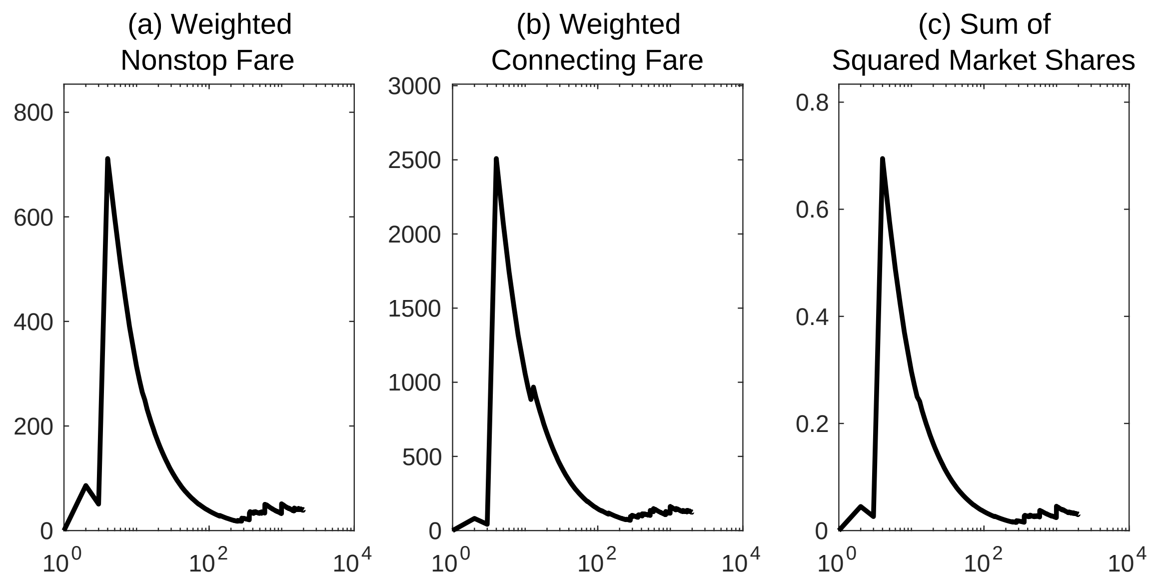
C.5 Robustness of the Results to Reducing the Number of Moments

In our reported results the number of moments (1,384) is large compared to the number of markets (2,028), the number of carrier-markets ($8,065$) and the number of carrier-market-directions (16,130) in the sample. We have therefore checked whether reducing the number of moments significantly affects our estimates, and, more importantly, our conclusions about post-merger service choices and market power. Here we present the results when we exclude all 644 moments based on market-specific outcomes, which are non-linear functions (e.g., the sum of squared carrier market shares) of the outcomes that appear in the carrier-specific moments. This leaves us with 740 carrier-specific moments.

Estimates. Table C.4 shows our baseline estimates and the estimates when we use the reduced number of moments. Most of the coefficients are very similar to our baseline estimates, and even where they are different they have similar implications. For example, the implied mean value

[56] The difference in the level of predicted average prices partly reflects the fact that here we are analyzing fit using a new set of simulation draws, not the importance sample draws that we used to predict prices during estimation, where, on average, we match the levels of average prices more accurately.

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)



of the distribution of incremental nonstop quality is 0.299 in the baseline and 0.268 with fewer moments, although it is more sensitive to the market's business index in the latter case.

Fit. Table C.5 compares model fit for prices and market shares for the baseline (repeating Table C.3) and these new point estimates. The predictions are very similar, and no more different to the data than the baseline.

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 full selection by forming posteriors, so that our results correspond to row 2 of Table 9 and the third row of Table 11. The results based on the baseline estimates and the estimates using the smaller number of moments are almost identical.

Table C.4: Baseline Coefficient Estimates and Estimates Based on Different Sets of Moments (bootstrapped standard errors in parentheses)

				(1) Baseline (from Table 3)		(2) Carrier-Specific Moments Only	
Demand: Market Parameters							
Random Effect	Std. Dev.	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. Dev.	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. Dev.	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. Dev.	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. Dev.	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)
			Connecting Distance	0.681	(0.083)	0.732	(0.099)
			Connecting Distance^2	-0.028	(0.012)	-0.034	(0.012)
	Std. Dev.	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)
			International 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 resampled and simulations are drawn from a pool of 2,000 draws for each selected market.

Table C.5: Model Fit: Average Market Shares and Prices Based on Different Sets of Moments

				Model Predictions	
			Data	Baseline (Table C.3)	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.

Table C.6: Predicted Effects of a United/US Airways Merger 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	
	Baseline (from Table 9)	Carrier Moments	Baseline (from Table 11)	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 (+7.8%)	$574.29 (+8.0%)	$377.24 (+7.8%)	$377.55 (+7.9%)

C.6 Estimation Using Moment Inequalities

Our baseline estimates assume that carriers play a sequential service choice game. However we also present estimated coefficients based on moment inequality estimation where we allow for the observed outcome to be associated with any pure strategy equilibrium in a simultaneous move game or a a subgame perfect Nash equilibrium in a sequential move game with any order of moves. Estimation is based on moment inequalities of the form

$$\mathbb{E}(m(y,X,Z,\Gamma)) = \mathbb{E}\begin{bmatrix} y_m^{data} - \underline{\mathbb{E}(\widehat{y_m(X,\Gamma)})} \\ \\ \overline{\mathbb{E}(\widehat{y_m(X,\Gamma)})} - y_m^{data} \end{bmatrix} \otimes Z_m \geq 0$$

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, and these are calculated using importance sampling where, for each set of draws, we now calculate the minimum and maximum values of the outcome across different equilibria. For example, suppose that 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.[57] The instruments are the same as for the baseline estimation.

The objective function that is minimized is

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

where t is a vector equal in length to the vector of moments, and it sets equal to zero those moment inequalities which hold so that they do not contribute to the objective function. 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.

[57] Because only a subset of outcomes, or combinations of outcomes, are considered when forming moments, estimates based on these inequalities will not be sharp.

C.7 Monte Carlo

We present the results of several Monte Carlo exercises that examine the performance of our 'Simulated Method of Moments with Importance Sampling' estimator when applied to a model of airline entry. To make the Monte Carlo exercises computationally feasible, we use a slightly simpler model by reducing the number of covariates and using a binary choice of whether or not to enter a market rather than a service choice decision. However, compared with many Monte Carlos, the number of parameters that we estimate is still large, illustrating that we can accurately estimate many parameters using our approach.

C.7.1 Model

All of the Monte Carlo exercises are based on the same economic model.

Industry Participants. At the industry level, there are six carriers, A, B, C, D, E and F. A, B, C and D are 'legacy' carriers ($LEG_i = 1$) whereas E and F are low-cost carriers ($LCC_i = 1$). A carrier's legacy/low-cost status can affect both its demand and costs.

Potential Entrants. We create datasets with observations from either 500 or 1,000 independent local markets, which one can think of as airport-pairs. For each market, we first draw the number of potential entrants (2, 3 or 4 with equal probability), and then randomly choose which of the six carriers will be potential entrants.

Demand, Costs and Market and Carrier Characteristics. Each carrier has a demand quality and a marginal cost (which does not depend on quality if it enters). Carrier i's quality, $\beta^D_{i,m}$, is a draw from a truncated normal distribution

$$\beta^D_{i,m} \sim TRN(\underset{0.2}{\beta^{D,LEG}} LEG_i + \underset{0}{\beta^{D,LCC}} LCC_i + \underset{0.3}{\beta^D_1} X^D_{i,m} \text{ x } LEG_i, \underset{0.2}{\sigma^D}, -2, 10)$$

where the terms in parentheses are the mean, the standard deviation and the lower and upper truncation points respectively. The numbers beneath the Greek parameters are their true values. Carrier i's marginal cost, $c_{i,m}$, is also drawn from a truncated normal

$$c_{i,m} \sim TRN(\underset{0}{\gamma^{C,LEG}} LEG_i + \underset{-0.5}{\gamma^{C,LCC}} LCC_i + \underset{0.5}{\gamma^C_1} X^C_m, \underset{0.2}{\sigma^C}, 0, 6).$$

Each carrier also has a truncated normal fixed cost, $F_{i,m}$, that is paid if it enters the market

$$F_{i,m} \sim TRN(\underset{7500}{\theta^F_1} + \underset{1000}{\theta^F_2} X^F_{i,m} + \underset{5000}{\theta^F_3} X^F_m, \underset{2500}{\sigma^F}, 0, 30000).$$

As shown in these equations, demand and cost depend on a combination of observed market and carrier characteristics. Carrier characteristics include the carrier's type (legacy/LCC), the demand shifter $X^D_{i,m}$ (which we loosely interpret as the carrier's presence at the endpoints, and we assume that this only affects demand for legacy carriers, reflecting their greater use of frequent-flyer programs), and the carrier-specific fixed cost shifter $X_{i,m}^F$. $X_{i,m}^D$ and $X_{i,m}^F$ are drawn from independent $U[0,1]$ distributions. Market characteristics, X_m^C (which we interpret as distance) and X_m^F (which we interpret as a measure of airport congestion), affect marginal costs and entry costs. X_m^C is drawn from a $U[1,6]$ distribution. X_m^F is drawn from a $U[0,1]$ distribution.

We also allow for some additional unobserved market-level heterogeneity that affects demand. Specifically, a consumer j's indirect utility for traveling on carrier i is

$$u_{i,j,m} = \beta_{i,m}^D + \eta_m - \alpha_m p_{im} + \lambda_m \zeta_{j,m} + (1 - \lambda_m)\varepsilon_{i,j,m}$$

where there is cross-market unobserved heterogeneity in the level of demand through a market random effect, η_m, the price sensitivity parameter, α_m, and the nesting parameter, λ_m. $\varepsilon_{i,j,m}$ is the standard Type I extreme value logit error. We make the following distributional assumptions:

$$\begin{aligned} \eta_m &\sim TRN(0, \underset{0.5}{\sigma^\eta}, -2, 2) \\ \alpha_m &\sim TRN(\underset{0.45}{\mu^\alpha}, \underset{0.1}{\sigma^\alpha}, 0.15, 0.75) \\ \lambda_m &\sim TRN(\underset{0.7}{\mu^\lambda}, \underset{0.1}{\sigma^\lambda}, 0.5, 0.9) \end{aligned}$$

where setting the mean of the random effect to zero is a normalization as we included separate mean quality coefficients for legacy and LCC carriers. Market size is assumed to be observed, and is drawn from a uniform distribution on the interval 10,000 to 100,000.

Order of Entry We study Monte Carlos under different assumptions on the equilibrium being played and what the researcher knows about equilibrium selection. In each case there is complete information and carriers set prices simultaneously once entry decisions have been made. We assume that the true model is that there is sequential entry. Legacy carriers are assumed to move first, ordered by $X_{i,m}^D$ (highest moves first), followed by low-cost carriers who are ordered randomly. The firms know the order. Firms enter when they expect their profits from entering to be greater than zero. Given the specification of the entry game, and the fact that there will be a unique equilibrium in any of the pricing games that follow entry[58], the game will have a unique subgame perfect Nash equilibrium.

C.7.2 Summary Statistics

We briefly summarize some of the patterns that emerge when we simulate outcomes for 2,000 markets given these parameters. 15.1% of the markets have no entrants, while 51.8%, 28.0%,

[58]This follows from Mizuno (2003) due to the assumptions that demand has a nested logit structure, each firm produces a single product and marginal costs are non-decreasing with quantity.

4.6% and 0.5% of markets have one, two, three and four entrants respectively. In 11.7% of markets, all of the potential entrants enter. 48.8% and 26.0% of legacy and LCC potential entrants enter respectively, which partly reflects the demand advantage of legacy carriers, but also their first mover advantage in the entry game. Variation in market size and the demand parameters α (price coefficient), λ (nesting coefficient) and η (market demand random effect) have sensible effects on entry. Moving from the lowest to the highest tercile of market size increases the average number of entering firms from 0.7 to 1.7. Similarly, going from the lowest to the highest tercile of $-\alpha$ (demand become less price sensitive), λ (carriers become closer substitutes) and η (market demand increases) changes the average number of entrants from 1.4 to 2.0, from 2.0 to 1.4 and from 1.5 to 1.9 respectively. There are both direct and indirect (via entry) effects on prices. For example, going from the lowest to the highest tercile of $-\alpha$ increases average prices, from 3.2 to 3.8, consistent with demand becoming less elastic, but it also increases the standard deviation of prices, from 1.0 to 1.4, because prices will tend to fall if more entry occurs. We also observe the standard deviation of prices increasing with λ (1.1 to 1.5). This reflects the fact that, because entering carriers will be closer substitutes when the nesting parameter is large, there will be a greater spread between monopoly and duopoly prices. Observed market marginal cost and fixed cost shifters also affect both price and entry outcomes. For example, going from the lowest to the highest tercile of the marginal cost shifter (X_m^C) increases average prices from 2.7 to 4.6, while reducing the number of entrants from 1.9 to 1.6. For the market fixed cost shifter (X_m^F) moving from the lowest to the highest tercile reduces expected entry from 1.9 to 1.6 carriers, and because of the reduced entry, average prices increase from 3.4 to 3.7.

C.7.3 Monte Carlo Exercises

There are 17 parameters, $\Gamma = \{\beta^{D,LEG}, \beta^{D,LCC}, \beta_1^D, \sigma^D, \gamma^{C,LEG}, \gamma^{C,LCC}, \gamma^C, \sigma^C, \theta_1^F, \theta_2^F, \theta_3^F, \sigma^F, \sigma^\eta$, μ^α, σ^α, μ^λ, $\sigma^\lambda\}$, to be estimated. Label the true parameters Γ_0. We present results for three Monte Carlo exercises below.

Monte Carlo Exercise 1: Estimation When the True Distributions Are Used To Form the Importance Sampling Density & Known Order of Entry. Recall that an importance sampling estimate of the expected value for a particular outcome h_m in market m, $\widehat{E(h_m)}$, is calculated as

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

where, in our setting, θ_{ms} is a vector of draws for the market-level parameters and demand and cost draws for all of the potential entrant carriers, f is the density of these draws given parameters Γ', g is the importance density from which θ_{ms} is drawn, and $y(X_m, \theta_{ms})$ is the value of the outcome of interest given observed market characteristics and θ_{ms} (e.g., a dummy for whether firm A enters, or the combined market share of entrants).

In the first exercise, we use the true distribution as the importance density, i.e., $g(\theta_{ms}|X_m) \equiv f(\theta_{ms}|x_{m,}\Gamma_0)$. While this estimator is generally infeasible, it is the efficient estimator in the sense that the variance of the importance sampling estimate of each expected outcome is minimized. It therefore provides a benchmark against which we can compare other results.

To perform this exercise, we first create one hundred datasets, each with 1,000 markets. We perform the estimation using 1,000 importance sampling draws per market.[59] We use the following observed outcomes in estimation: the entry decision (represented by a 0/1 dummy), the price and the market share of each of the firms (A-F)[60], and three market outcomes: the average transaction price (i.e., the average price of the entrants weighted by their market shares), the sum of squared market shares for the entering carriers[61] and the square of the number of entrants.

These outcome measures are then interacted with several observed variables to create moments for estimation. Market-level variables include a constant, market size, X_m^C, X_m^F and the number of LCC potential entrants. Carrier-level variables are $X_{i,m}^D$, $X_{i,m}^F$ and the average of these variables for *other* potential entrants, although we do not use $X_{i,m}^D$ for the LCC carriers as, by assumption, it does not affect their demand or their entry order. We then create moments by interacting market outcomes with the market-level variables and the carrier variables for each of the six carriers, and the carrier outcomes with the market level variables and the carrier variables for that firm. This gives us a total of 237 moments for estimation. We weight these moments by the inverse of their variances (evaluated at the true parameters, which, recall, we are using to form the importance densities) in forming the objective function.[62]

Column (1) of Table C.7 reports the mean and standard deviation of the parameters estimated for the one hundred repetitions. For all of the parameters that determine mean qualities or costs, the mean estimated value is close to the true value, indicating that there is no systematic bias. For the standard deviation parameters, there is some evidence of a downward bias for the market demand slope and nesting parameters, although if we interpret the standard deviations as standard errors the differences of the estimated means from the true values of these parameters would not be statistically significant.

[59] We first create the data and 2,000 draws for 2,000 different markets. Given that the importance density is the true density of the parameters, this effectively involves doing 2,001 sets of draws, and arbitrarily calling the first set 'data'. We then create the one hundred datasets. For each dataset, we draw 1,000 markets from the sample of 2,000 without replacement and, for each of the drawn markets, taking a sample of one thousand draws, without replacement, from the 2,000 that were created for that market.

[60] Obviously, if a carrier is not a potential entrant in a particular market these outcomes will be zero.

[61] For this calculation, market shares are defined allowing for some consumers to purchase the outside good so this is not the same as the HHI.

[62] We found that in practice the estimator performed more reliably from a wider range of starting values when we used a diagonal weighting matrix rather than the usual inverse covariance matrix of the moments.

Table C.7: Monte Carlo Results with Known Order of Entry

			(1)	(2)	(3)
		IS Density:	Same As True Distribution	50% Increase in Std. Devs.	Same As True Distribution
		# of Mkts.:	1000	1000	500
		# of IS Draws:	1000	1000	1000
		True Values			
Market Demand	Std. Dev.	0.5	0.496	0.462	0.485
Random Effect	(σ^{η})		(0.073)	(0.151)	(0.108)
Mkt Demand Slope	Mean	-0.45	-0.420	-0.429	-0.424
	(μ^{α})		(0.024)	(0.026)	(0.025)
	Std. Dev.	0.1	0.039	0.080	0.060
	(σ^{α})		(0.039)	(0.056)	(0.051)
Nesting Parameter	Mean	0.7	0.694	0.691	0.704
	(μ^{λ})		(0.033)	(0.035)	(0.036)
	Std. Dev.	0.1	0.049	0.063	0.052
	(σ^{θ})		(0.039)	(0.033)	(0.038)
Carrier Quality	Legacy	0.2	0.188	0.195	0.192
	($\beta^{D,LEG}$)		(0.064)	(0.103)	(0.063)
	LCC	0	0.001	-0.028	0.006
	($\beta^{D,LCC}$)		(0.064)	(0.087)	(0.061)
	$X^D_{i,m} * LEG_i$	0.3	0.296	0.289	0.292
	(β^D_1)		(0.067)	(0.142)	(0.097)
	Std. Dev.	0.2	0.175	0.211	0.168
	(σ^D)		(0.043)	(0.064)	(0.051)
Carrier Marginal	Legacy Constant	0	0.040	0.034	0.056
Cost	($\gamma^{C,LEG}$)		(0.111)	(0.133)	(0.112)
	LCC Constant	-0.5	-0.500	-0.479	-0.475
	($\gamma^{C,LCC}$)		(0.135)	(0.141)	(0.137)
	X^C_m	0.5	0.498	0.479	0.491
	(γ^C)		(0.034)	(0.047)	(0.039)
	Std. Dev.	0.2	0.218	0.164	0.196
	(σ^C)		(0.069)	(0.081)	(0.060)
Carrier Fixed	Constant	0.75	0.741	0.735	0.729
Cost	($\theta^F_1/10,000$)		(0.096)	(0.131)	(0.108)
	$X^F_{i,m}$	0.1	0.110	0.118	0.105
	($\theta^F_2/10,000$)		(0.081)	(0.166)	(0.100)
	X^F_m	0.5	0.557	0.578	0.561
	($\theta^F_3/10,000$)		(0.126)	(0.163)	(0.160)
	Std. Dev.	0.25	0.206	0.238	0.219
	($\sigma^F/10,000$)		(0.065)	(0.084)	(0.063)

Notes: Reported numbers are the mean estimates of each parameter across 100 repetitions, with the standard deviations reported in parentheses.

Table C.8: Illustrative Counterfactual: The Effects of Increasing the Fixed Entry Costs of Legacy Carriers Using Parameters Estimated Using IS Distributions that are the Same as True Distribution of the Parameters and 1,000 Markets

Change in ...	Using True Parameters	Mean (Std. Dev.) Prediction Across MC Repetitions
Total Number of Entrants	-0.335	-0.332
		(0.0254)
Number of Legacy Entrants	-0.493	-0.478
		(0.0332)
Number of LCC Entrants	+0.158	+0.145
		(0.0241)
Total Market Share	-0.054	-0.053
		(0.003)
Average Price (conditional on at least one firm entering)	+0.228	+0.219
		(0.056)

Another way of assessing the accuracy of the Monte Carlo estimates is by looking at how accurately we are able to predict how market outcomes would change in response to a change in the market environment. As an illustration we consider an increase in mean fixed costs of all legacy carriers by 10,000 (taking their mean fixed cost from 10,500 to 20,500). The fixed costs of LCC carriers are not affected. The first column of Table C.8 reports the expected changes in entry, the cumulative market share of entering carriers and average prices under the true parameters.[63] As expected, fewer legacy carriers enter, while there is some increased entry by LCCs. The reduction in entry causes weighted average prices to rise and the number of travelers to fall.[64] The second column reports the mean changes and standard deviations (in parentheses) across the 100 Monte Carlo repetitions.[65] We can see that the Monte Carlo counterfactuals predict the true effects accurately, with small standard deviations.[66]

Column (3) of Table C.7 shows the results when there are only 500 markets, rather than 1,000, in each of the datasets (we continue to use 1,000 importance draws for each market). In this case, the standard deviation of the parameter estimates increase, but only by a relatively

[63]We use the outcomes for the 2,000 markets in our "data", and then re-compute outcomes increasing the fixed costs of legacy carriers but leaving the other draws unchanged.

[64]Average prices are only calculated for markets where entry occurs, so average prices are calculated for the subset of markets where entry occurs before the increase in fixed costs.

[65]To isolate the effects of using different parameters, we use the same percentile for each parameter draw as in our "data" for each market, before calculating predicted outcomes with and without the increase in legacy carrier fixed costs. So, for example, suppose that in market 17 (out of 2,000), α_m was drawn from the 43rd percentile of the true distribution that has (untruncated) mean -0.45 and standard deviation 0.1. When we are considering a Monte Carlo repetition where the estimates of the mean and standard deviation of α are -0.6 and 0.2, we would use the 43rd percentile draw from this distribution.

[66]The standard deviation for the predicted change in prices is larger simply because differences in predictions of entry, either with or without the change in fixed costs, can have a large effect on prices. However, the mean prediction is close to the true value.

small amount, while the means remain very close to the true values of the parameters. We also note that with either 500 or 1,000 markets, estimation is quite quick: each optimization takes less than four hours even when we rely on numerical derivatives. We also get similar Monte Carlo results when starting each optimization at parameters that are significantly perturbed from their true values.[67]

Monte Carlo Exercise 2: Estimation When Wider Distributions Are Used To Form the Importance Sampling Density & Known Order of Entry Our second exercise considers the case where we use an importance distribution that is more dispersed than the true parameters. This reflects the fact that in practice we do not know what the true parameters are and that, when estimating unknown parameters, it makes sense to use an importance distribution that will contain some draws that will still have reasonable density when the parameters are changed. As an illustration, we therefore repeat the first exercise, but the importance distributions are formed by increasing all of the standard deviation parameters by 50%. The mean parameters remain unchanged. Column (2) of Table C.7 reports the results when each dataset contains 1,000 markets. The mean estimates continue to be very close to the true parameter values. The standard deviations increase for most parameters, as one might expect, but the magnitude of the increases are fairly small.

Monte Carlo Exercise 3: Estimation When the Econometrician Only Knows that a Pure Strategy Nash Equilibrium is Played Our third exercise considers estimation when we relax the assumption that entry decisions are made in a known sequential order. Instead, we follow the strand of the literature (most notably, Ciliberto and Tamer (2009)) that has based estimation on moment inequalities formed under the assumption that firms play some pure strategy Nash equilibrium in a simultaneous move game.[68] The idea is that, as long as the set of equilibrium outcomes (i.e., entry decisions, prices and market shares) can be enumerated, one can use the set to calculate lower and upper bound predictions for moments of the data, and then, in estimation, search for the parameters that make inequalities based on these lower and upper bounds hold.

We keep the same assumptions on the set of potential entrants, demand and costs as in the previous exercises. The change is that now we assume that the potential entrants make entry decisions simultaneously and that they play a complete information, pure strategy Nash

[67] This comment comes with the caveat that in a small number of cases when we start with perturbed parameters, a parameter drifted to some very extreme value (e.g. an estimated mean of the untruncated distribution of the nesting parameter λ of -9.96, whereas only values of λ between 0 and 1 can be rationalized if consumers maximize their utility) in which case we rejected the repetition and added a new repetition. We only drop estimates that are truly extreme as in this example. We also observed examples where μ^{α} drifted to extreme values.

[68] In our application we also allow for the observed outcome to be the equilibrium outcome in a sequential move game with any order.

equilibrium (as competition always reduces profits, at least one pure strategy Nash equilibrium will exist). With at most six potential entrants it is straightforward to find all of the pure strategy Nash equilibria for a given draw of all of the cost and demand shocks. When creating our data, we choose an equilibrium randomly if more than one equilibrium exists for a given set of draws. Given the assumed parameters, there are multiple equilibrium outcomes in 24.2% of the 2,000 sample data markets. In most cases, the equilibria differ only in the identity of entrants rather than the number of firms that enter.

The details of estimation are explained in Appendix C.6 and we follow Exercise 1 in using the true distributions of the parameters when taking our importance sample draws. The one difference to what we do in the text is that we restrict ourselves to examining pure strategy equilibria in a simultaneous move game, rather than also allowing for sequential move games with any order.

There are now many papers that propose approaches for inference for moment inequality models (for example, Chernozhukov, Hong, and Tamer (2007) Rosen (2008), Andrews and Soares (2010), Andrews and Barwick (2012), Andrews and Shi (2013), Pakes, Porter, Ho, and Ishii (2015)), and these methods often involve a significant amount of simulation making them somewhat impractical for a Monte Carlo where the procedure would have to be repeated multiple times. For our example, we therefore restrict ourselves to minimizing the objective function and reporting the means and standard deviations (across Monte Carlo runs) of the objective function-minimizing parameters. While asymptotically the objective function should be equal to zero at the true parameters (all of the inequalities satisfied), in practice we always found that the objective function was minimized slightly above zero by a unique set of parameters (the mean minimized value is 0.0026, with a standard deviation of 0.001 across our Monte Carlo runs).[69] Table C.9 reports the Monte Carlo results, using 1,000 markets and 1,000 IS draws for each market in each Monte Carlo run.[70]

Comparing the results to those from column (1) of Table C.7 (which used the same number of observation and the same distribution to generate the importance sample draws), we see that the estimator performs almost as well, with all of the mean parameters close to their true values with the exception of the standard deviation of the carrier quality which is underestimated. The standard deviations of the estimated parameters also remain similar. Of course, it is possible that estimates would become less accurate if we assumed parameters that generated multiple equilibria in a higher proportion of markets.

One of the advantages of using importance sampling, with or without equilibrium selection, is that the objective function is smooth, so that we can use derivatives to find the minimum.

[69] As before we use the inverse of the variance of the moments, evaluated at the true parameters, as the weighting matrix.

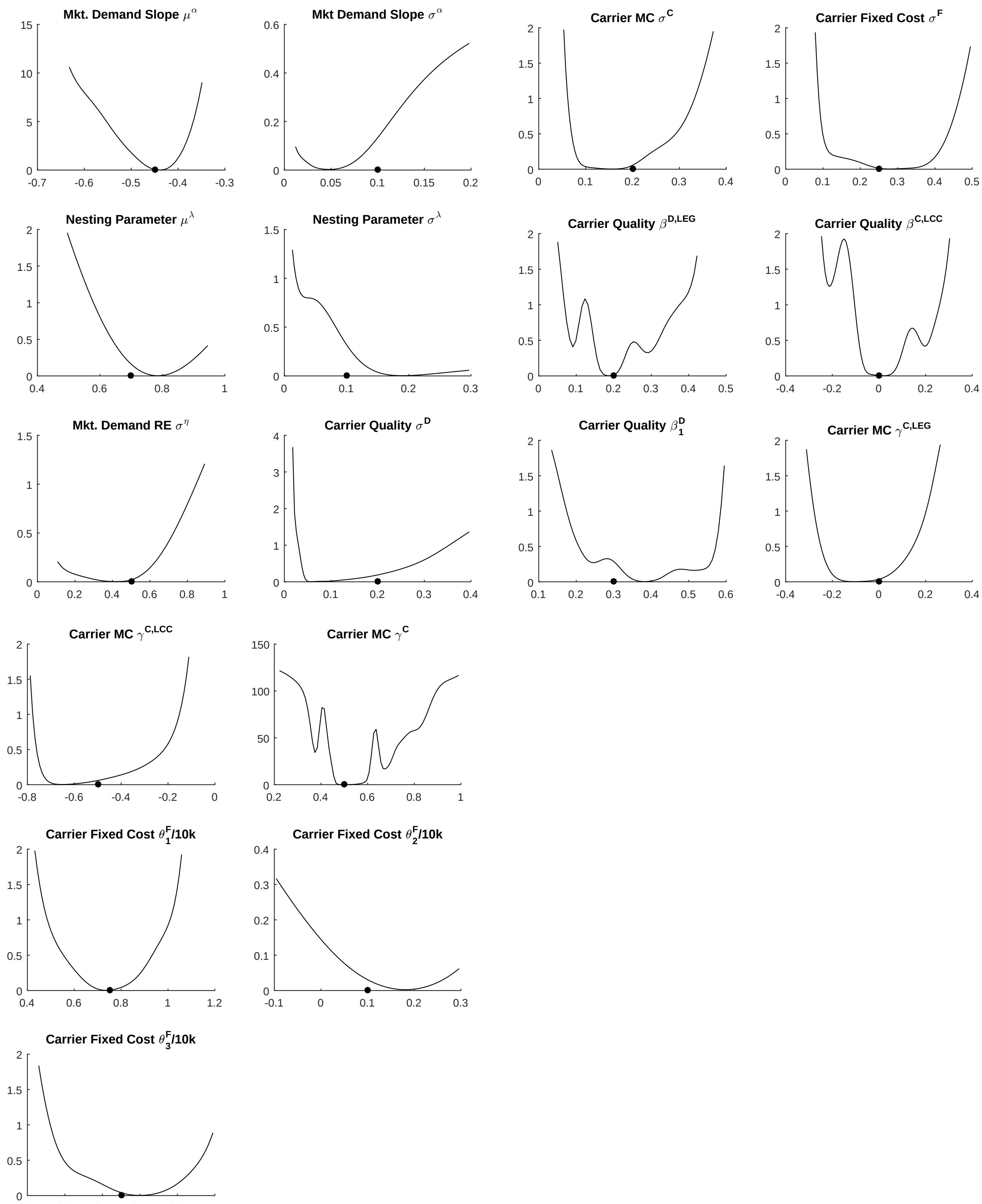
[70] As in Exercise 1 we initially create a sample of 2,000 markets and 2,000 IS draws for each market, and then randomly sample from these sets when creating datasets for each Monte Carlo run.

Table C.9: Monte Carlo Results with Unknown Equilibrium Selection in a Simultaneous Move Game

Parameters		True Value	Estimated Value Mean (Std. Dev.)
Market Demand Random Effect	Std. Dev. (σ^{η})	0.5	0.472
			(0.078)
Market Demand Slope	Mean (μ^{α})	-0.45	-0.422
			(0.020)
	Std. Dev. (σ^{α})	0.1	0.072
			(0.037)
Nesting Parameter	Mean (μ^{λ})	0.7	0.744
			(0.057)
	Std. Dev. (σ^{λ})	0.1	0.113
			(0.085)
Carrier Quality	Legacy constant ($\beta^{D,LEG}$)	0.2	0.191
			(0.081)
	LCC constant ($\beta^{D,LCC}$)	0	0.004
			(0.066)
	$X^D_{i,m} * LEG_i$ (β^D_1)	0.3	0.281
			(0.121)
	Std. Dev. (σ^D)	0.2	0.091
			(0.036)
Carrier Marginal Cost	Legacy constant ($\gamma^{C,LEG}$)	0	-0.020
			(0.127)
	LCC constant ($\gamma^{C,LCC}$)	-0.5	-0.562
			(0.126)
	X^C_m	0.5	0.488
			(0.032)
	Std. Dev. (σ^C)	0.2	0.189
			(0.059)
Carrier Fixed Cost	Constant ($\theta^F_1/10,000$)	0.75	0.696
			(0.104)
	$X^F_{i,m}$ ($\theta^F_2/10,000$)	0.1	0.213
			(0.147)
	X^F_m ($\theta^F_3/10,000$)	0.5	0.586
			(0.109)
	Std. Dev. ($\sigma^F/10,000$)	0.25	0.204
			(0.060)

Notes: Reported numbers are the mean estimates of each parameter across 100 repetitions, with the standard deviations reported in parentheses.

Figure C.3: Shape of the Objective Function Based on Inequalities Around the Estimated Parameters for the First Monte Carlo Run (black dot marks the true value of the parameter)



In Figure C.3 we examine the shape of the objective function using moment inequalities based on the first Monte Carlo run when we change each of the parameters in turn. The black dot on each horizontal axis marks the true value of the parameter. On the other hand, for three parameters (γ^C, $\beta^{D,LEG}$, $\beta^{D,LCC}$) it is also clear that there are multiple local minima even when we are only changing a single parameter at a time. The fact that the objective function can have multiple local minima makes the second feature of the importance sampling approach, the ability to calculate the value of the objective function quickly, without having to re-solve a large number of games, particularly valuable because it allows the estimation routine to be restarted multiple times.