Appendices for Endogenous and Selective Service Choices After Airline Mergers

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APPENDICES

A Data Construction

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

Selection of markets. We use 2,028 airport-pair markets linking the 79 U.S. airports (excluding 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[1];
- 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[2]; 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%.

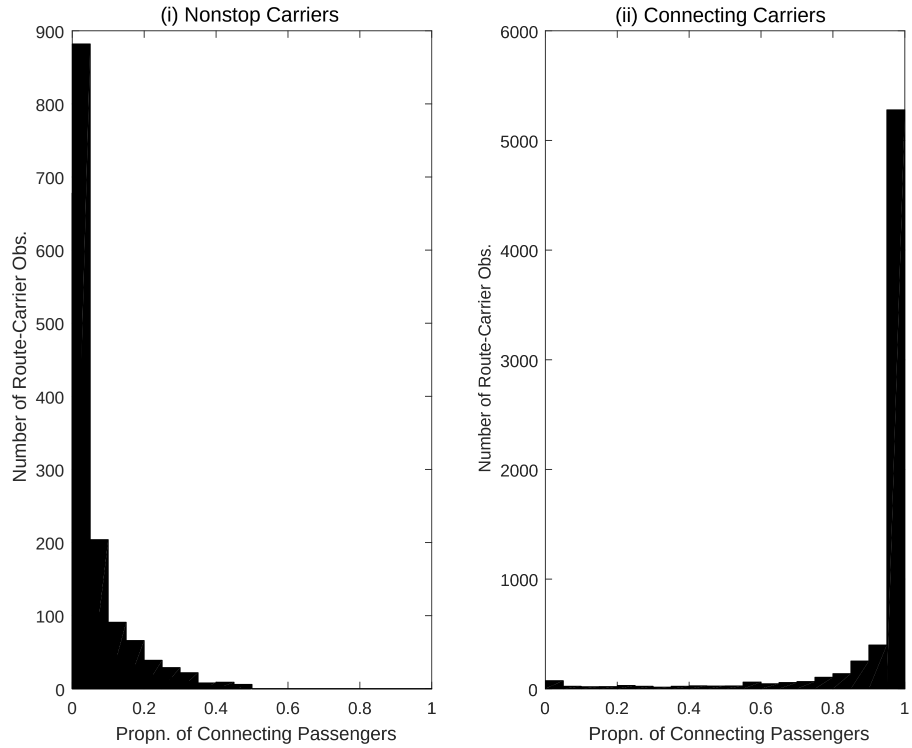
Definition of players, nonstop and connecting service. We are focused on the decision of carriers to provide nonstop service on a route. Before defining any players or outcomes, we drop all passenger itineraries from DB1 that involve prices of less than \$25 or more than \$2000 dollars[3], open-jaw journeys 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

[1] 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.

[2] 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.

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

Figure A.2: Proportion of DB1 Passengers Traveling with Connections, Based on the Type of Service

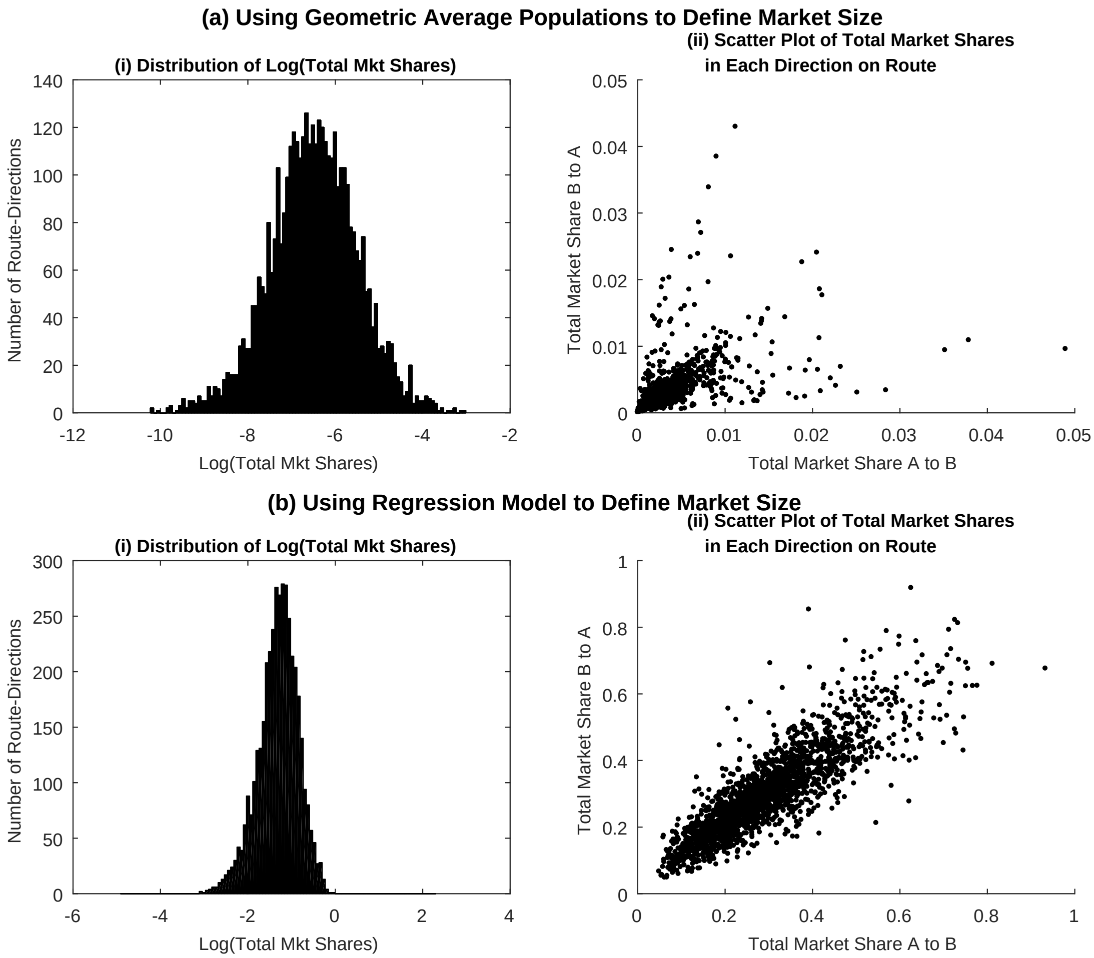


and US Airways) that we focus on. Our classification of carriers as low-cost follows Berry and Jia (2010). Based on the number of passengers carried, the largest Other Legacy carrier is Alaska Airlines, and the largest Other LCC carriers are JetBlue and AirTran.

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 A.2 shows that the carriers we define as nonstop typically carry only a small proportion of connecting passengers. For this reason, we feel able to ignore

Figure A.3: Market Size Measures and their Impact on Market Shares



the fact that carriers may provide both nonstop and connecting service on the same route. 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)).[4] However, as illustrated in the left-hand panel of Figure A.3(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 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 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 then multiply the predicted traveler number by 3.5 so that, on average, the combined market shares of carriers is just under 30%. Figure A.3(b) repeats the figures in Figure A.3(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.[5]

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

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

[5] 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.

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 nonstop 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 destination nonstop. Table A.2 shows the airports counted as hubs for each named carrier.

We also include a continuous measure of the potential connecting traffic that will be served if nonstop service is provided on routes involving a domestic hub. The construction of this variable, as the prediction of a Heckman selection model, is detailed in Appendix A.1.

A.1 An Ancillary Model of Connecting Traffic

As explained in Section 2 of the text, we want to allow for the amount of connecting traffic that a carrier can carry when it serves a route nonstop to affect its decision to do so. Connecting traffic is especially important in explaining why a large number of nonstop flights can be supported at domestic hubs in smaller cities, such as Charlotte, NC (a US Airways hub), 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[6] 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.[7]

Model. We build our prediction of nonstop traffic on a particular segment up from a multi-

[6]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 not 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.

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

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

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

nomial 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,

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

where $X_{c,i,od}$ is a vector of observed characteristics for the connection (c)-carrier (i)-origin (o)-destination (d) combination and $\xi_{c,i,od}$ is an unobserved characteristic. The Xs are functions of variables that we are treating as exogenous such as airport presence, endpoint populations and geography. The outside good is traveling using connecting service via an airport that is not one of the domestic hubs that we identify.[8] 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):

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

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

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

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

[8] 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.

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.[9] 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 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[10]; 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;

[9] 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.

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

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 that are assumed to be normally distributed in both (3) and (2) to be correlated, although our predictions are almost identical using a two-step procedure (correlation in predictions greater than 0.999). The coefficient estimates are in Table A.3, although the many interactions means 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 does a pretty accurate job of predicting how many connecting travelers there are on the segments that airlines fly in 2005. For example, for the identified legacy carriers in our primary model, the correlation between the number of connecting passengers served on one of these segments and the number of passengers the model predicts is 0.96, and the model 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 (2265, observed 2765) than DFW (2040, observed 2364).

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

	Connecting Share	Serve Route	$\frac{1}{2}log\frac{1+\rho}{1-\rho}$	$log(std.\ deviation)$
Constant	4.200***	-8.712***	-0.109	0.308***
	(0.338)	(0.823)	(0.0860)	(0.0150)
Presence at Origin Airport	4.135***	6.052***		
	(0.396)	(1.136)		
Presence at Connecting Airport		11.90***		
		(0.721)		
Presence at Destination Airport	2.587***	6.094***		
	(0.396)	(1.126)		
Origin Presence * 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	-	-	-

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

B Estimation

This Appendix provides additional information on the algorithm that we use to estimate our model. Appendix B.1 lays out the set of moments that are used in our preferred specification. Appendix B.2 explains how we estimate our model when we do not impose a known order of moves. Appendix B.3 provides Monte Carlo evidence that both estimators work well for a simplified model. Appendix B.4 provides some evidence that the algorithm works well when applied to our data.

B.1 Moments

When estimating our preferred specification, we minimize a standard simulated method of moments objective function in the second step

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

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 exogenous observed variables.

We use a large number (1,384) of moments in estimation. To understand how we get to this number, Table B.2 presents a cross-tab describing the interactions that we use between 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).

B.2 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

Table B.2: Moments Used in Estimation

Exogenous Variables	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 (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.

the observed outcome to be associated with any pure strategy equilibrium in a simultaneous move game or a sequential move game with any order of moves. Estimation is based on moment inequalities of the form

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

where y_m^{data} are observed outcomes in the data and Z_m are non-negative instruments. $\underline{\mathbb{E}(\widehat{y_m(X,\Gamma)})}$ and $\overline{\mathbb{E}(\widehat{y_m(X,\Gamma)})}$ are minimum and maximum expected values for y_m given a set of parameters Γ, 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.[11] 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.

B.3 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

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

accurately estimate many parameters using our approach.

B.3.1 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 $X^F_{i,m}$. $X^D_{i,m}$ and $X^F_{i,m}$ are drawn from independent $U[0,1]$ distributions. Market characteristics, X^C_m (which we interpret as distance) and X^F_m (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

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

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 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[12], the game will have a unique subgame perfect Nash equilibrium.

B.3.2 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%,

[12]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.

B.3.3 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.[13] 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)[14], 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[15] 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.[16]

Column (1) of Table B.3 reports the mean and standard deviation of the parameters estimated

[13]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.

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

[15]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.

[16]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.

for the one hundred repetitions. For all of the parameters, the mean estimated value is close to the true value, indicating that there is no systematic bias, and the standard deviations are small enough that, if they were interpreted as standard errors, all of the parameters whose true values are not equal to zero, would be statistically different from zero at the 5% level, with the exception of θ_2^F.

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 B.4 reports the expected changes in entry, the cumulative market share of entering carriers and average prices under the true parameters.[17] 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.[18] The second column reports the mean changes and standard deviations (in parentheses) across the 100 Monte Carlo repetitions.[19] We can see that the Monte Carlo counterfactuals predict the true effects accurately, with small standard deviations.[20]

Column (3) of Table B.3 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 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.[21]

[17] 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.

[18] 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.

[19] 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 43$^{\text{rd}}$ 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 43$^{\text{rd}}$ percentile draw from this distribution.

[20] 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.

[21] 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

Table B.3: 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 Random Effect	Std. Dev. (σ^η)	0.5	0.494	0.473	0.511
			(0.073)	(0.151)	(0.089)
Mkt Demand Slope	Mean (μ^α)	-0.45	-0.421	-0.429	-0.425
			(0.024)	(0.026)	(0.022)
	Std. Dev. (σ^α)	0.1	0.038	0.075	0.051
			(0.039)	(0.056)	(0.044)
Nesting Parameter	Mean (μ^λ)	0.7	0.694	0.689	0.701
			(0.033)	(0.035)	(0.054)
	Std. Dev. (σ^θ)	0.1	0.051	0.062	0.089
			(0.039)	(0.033)	(0.072)
Carrier Quality	Legacy ($\beta^{D,LEG}$)	0.2	0.189	0.190	0.188
			(0.064)	(0.103)	(0.076)
	LCC ($\beta^{D,LCC}$)	0	0.000	-0.031	0.003
			(0.064)	(0.087)	(0.069)
	$X^D_{i,m} * LEG_i$ (β^D_1)	0.3	0.295	0.295	0.293
			(0.067)	(0.142)	(0.097)
	Std. Dev. (σ^D)	0.2	0.176	0.209	0.170
			(0.043)	(0.064)	(0.050)
Carrier Marginal Cost	Legacy Constant ($\gamma^{C,LEG}$)	0	0.031	0.040	0.054
			(0.111)	(0.133)	(0.130)
	LCC Constant ($\gamma^{C,LCC}$)	-0.5	-0.507	-0.470	-0.483
			(0.135)	(0.141)	(0.158)
	X^C_m (γ^C)	0.5	0.500	0.479	0.489
			(0.034)	(0.047)	(0.042)
	Std. Dev. (σ^C)	0.2	0.216	0.169	0.205
			(0.069)	(0.081)	(0.072)
Carrier Fixed Cost	Constant ($\theta^F_1/10,000$)	0.75	0.738	0.725	0.743
			(0.096)	(0.131)	(0.101)
	$X^F_{i,m}$ ($\theta^F_2/10,000$)	0.1	0.110	0.118	0.121
			(0.081)	(0.166)	(0.130)
	X^F_m ($\theta^F_3/10,000$)	0.5	0.556	0.599	0.548
			(0.126)	(0.163)	(0.142)
	Std. Dev. ($\sigma^F/10,000$)	0.25	0.210	0.246	0.209
			(0.065)	(0.084)	(0.086)

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

Table B.4: 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)

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 B.3 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 is 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

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.

strategy Nash equilibrium in a simultaneous move game.[22] 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 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 B.2 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 mean 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).[23]

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

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

Table B.5 reports the Monte Carlo results, using 1,000 markets and 1,000 IS draws for each market in each Monte Carlo run.[24]

Comparing the results to those from column (1) of Table B.3 (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. In Figure B.2 we examine the 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 objective function can have multiple local minima makes the a 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.

B.4 Performance of the Estimation Algorithm Using the Actual Data

In this section we examine two features of the estimator in the context of our application for the case where we assume a known, sequential order of entry (i.e., the estimates in column (1) of Table 3). Figure B.3 shows the 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 is well-behaved in multiple dimensions, there is at least some grounds for optimism that a global minimum has been found.

We also address the question of whether our importance sampling estimator satisfies the condition that the variance of $y(\theta_{ms}, X_m)\frac{f(\theta_{ms}|X_m,\Gamma)}{g(\theta_{ms}|X_m)}$ must be finite, identified by Geweke (1989). One informal way to assess this property in an application (Koopman, Shephard, and Creal

matrix.

[24] 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 B.5: 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 B.2: 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)

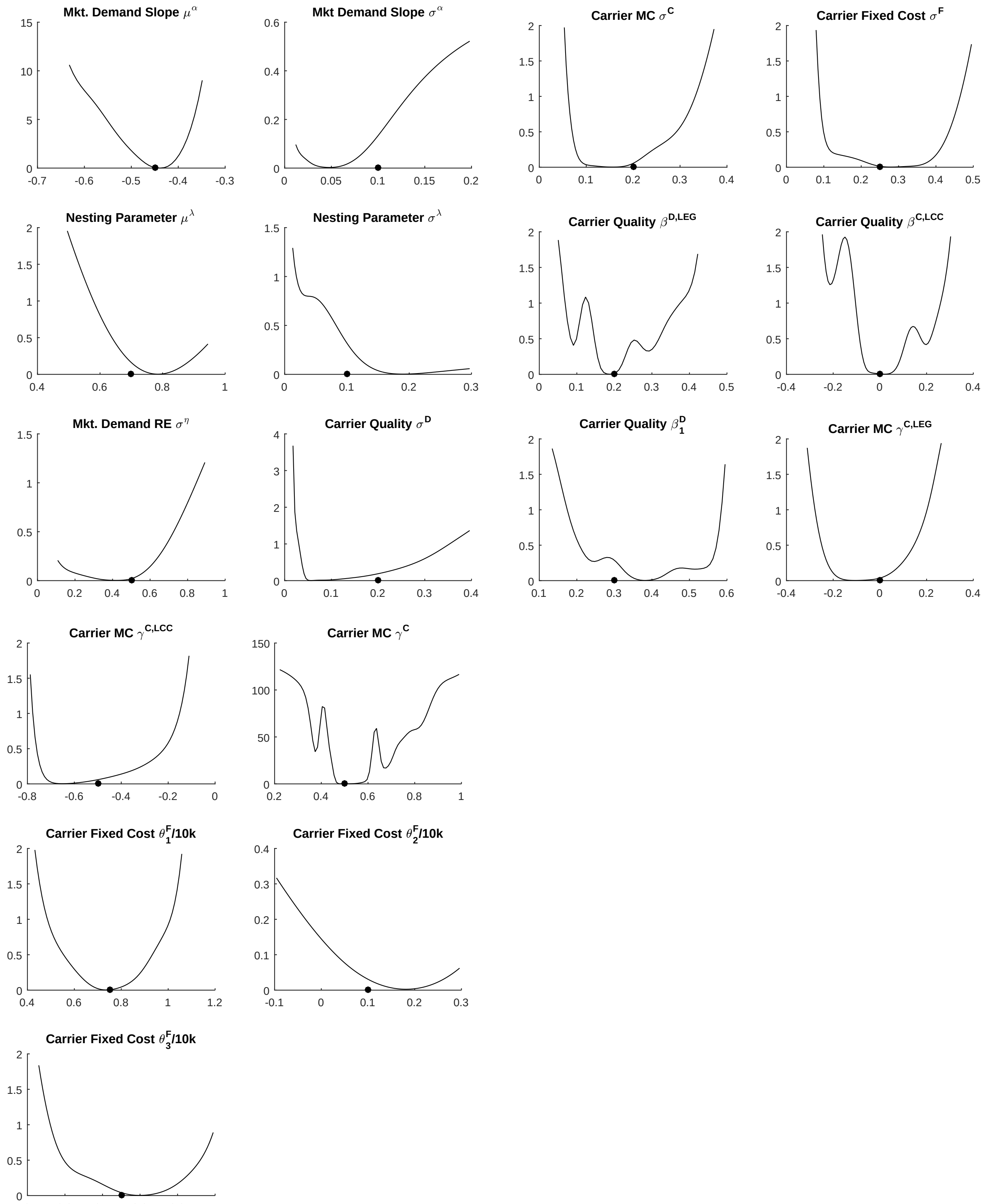


Figure B.3: Shape of the Objective Function Around the Estimated Parameters For the Parameter Estimates in Column (1) of Table 3 (black dot marks the estimated value)

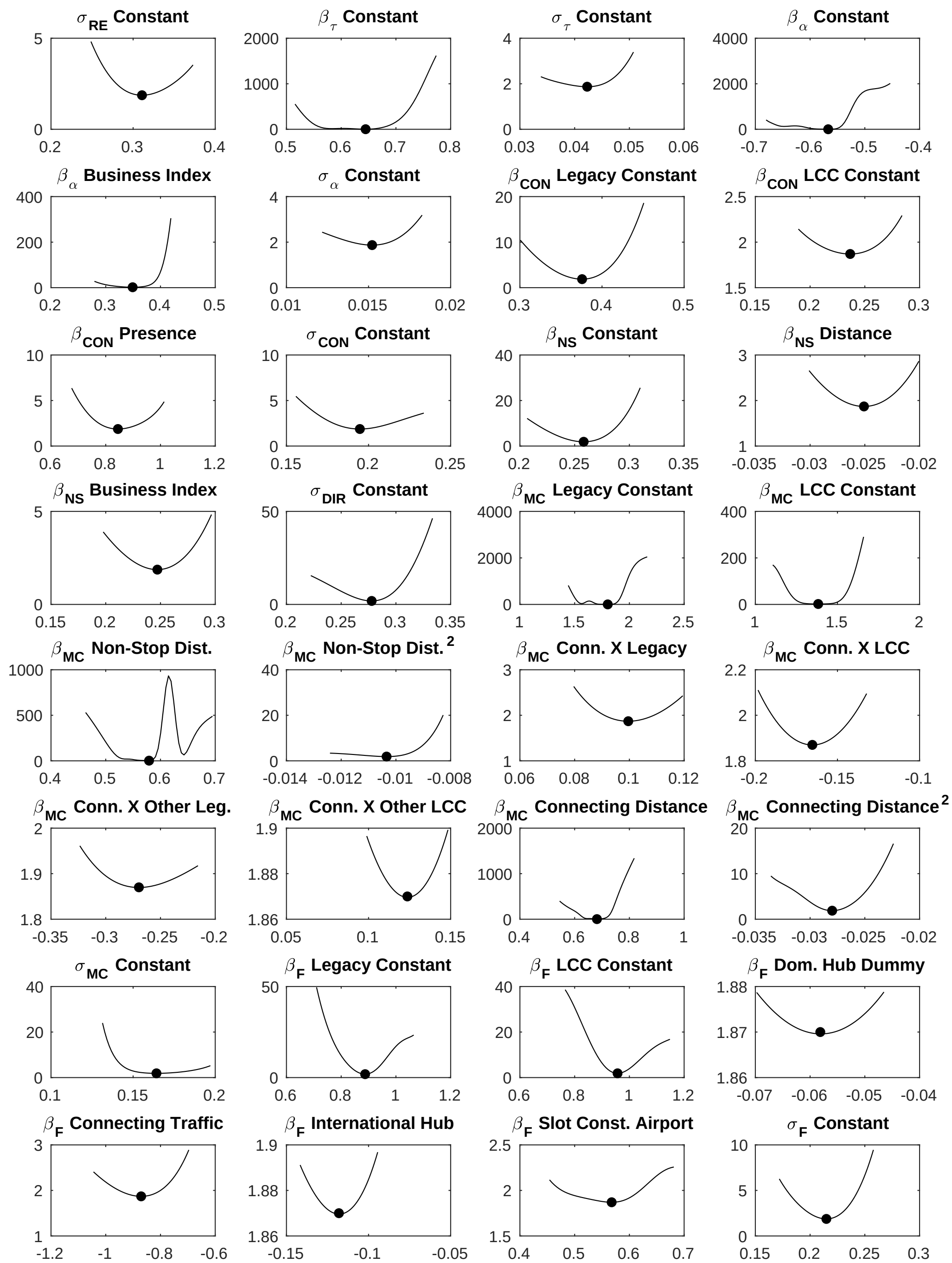
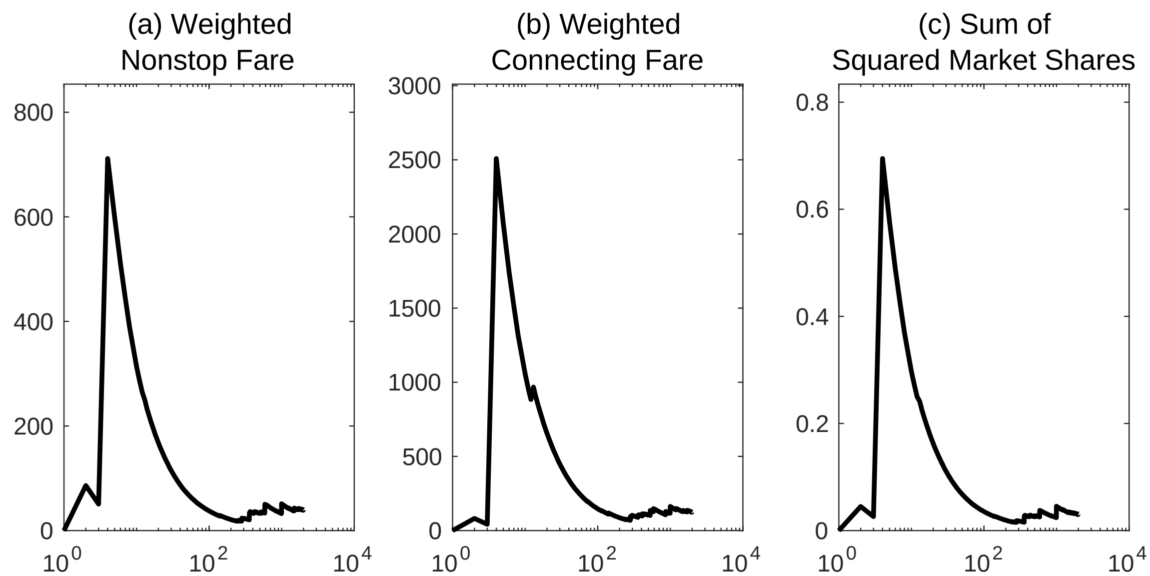


Figure B.4: Sample Variance of Three Moments as the Number of Simulation Draws is Increased (logarithm of the number of draws on the x-axis)



(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 B.4 shows these recursive estimates of the sample variance for the moments associated with the 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, for the estimated parameters. The log of the number of simulations is on the x-axis 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 $S = 1,000$.

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