Airline Mergers and the Potential Entry Defense

Sophia Ying Li* Joe Mazur†
James W. Roberts‡ Andrew Sweeting§

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Abstract

Horizontal mergers may be approved if antitrust authorities believe that new entry would limit any anticompetitive effects. This 'potential entry defense' has led to mergers being approved in concentrated markets in several industries, including airlines. However, entry will be both less likely and less able to constrain market power if the pre-merger entry process already selected the best firms into the market, for example those firms with better product qualities or lower marginal or fixed costs. We estimate a rich empirical entry model allowing for these types of selection using data from airline routes connecting the top 80 airports in the U.S. Our results indicate that selection is important and helps to explain the fact that airline mergers have tended to increase prices without inducing a significant number of new entering firms, even though most of these markets have several potential entrants and, in most cities, entry barriers are relatively low. We also use our model to conduct counterfactual merger analysis. We are in the process of updating the paper to reflect more recent mergers and data.

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*Cornerstone Research, Menlo Park, CA. Contact: sli@cornerstone.com
†Department of Economics, Purdue University. Contact: mazur3@purdue.edu
‡Department of Economics, Duke University and NBER. Contact: j.roberts@duke.edu.
§Department of Economics, University of Maryland and NBER. Contact: sweeting@econ.umd.edu.

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1 Introduction

This paper explores the role of new entry in constraining market power after mergers. In a number of cases, including several involving airlines, mergers that have significantly increased concentration in already concentrated markets have been permitted because it is believed that new entry is sufficiently easy that the merging parties would not find it profitable to significantly raise prices above pre-merger levels. For example, the Department of Transportation approved TWA's 1986 acquisition of Ozark Air Lines based on the argument that new entry would constrain prices (see Nannes (2000)). More recently, in 2011, the Department of Justice supported its decision not to challenge the merger between Southwest and AirTran by citing the possibility of new entry by non-merging parties onto routes previously served by each of the two airlines. Similar 'potential entry defenses' have led to the approval of mergers that would have greatly increased concentration, given the pre-merger market structure, in industries as varied as supermarkets, film processing and oil services in both the United States and Europe (Bergman (2003)). Section 9 of the 2010 Horizontal Merger Guidelines makes clear that a merger can be approved if the authorities believe that, if the merger is anti-competitive, new entry would be likely within a relatively short (1-2 year) time horizon, and sufficient to keep prices at or below pre-merger levels.[1]

As argued by Schmalensee (1987), one should be careful before concluding that mergers will not harm consumers because new entry appears to be easy. In particular, one needs to understand how attractive entry is likely to be to potential entrants who are not already in the market, as these firms may differ in systematic ways from firms already in the market, such as the merging parties. Unfortunately, the possibility that these differences may exist has not been recognized in the existing literature on mergers with entry. For example, Werden and Froeb (1998), Cabral (2003) or Spector (2003), who use static models, or Marino and Zabojnik (2006), who analyze dynamic endogenous merger formation, assume that potential entrants will have similar costs and qualities to the firms that are already in the market. [2]

[1]The Guidelines argue that (p. 28) "a merger is not likely to enhance market power if entry into the market is so easy that the merged firm and its remaining rivals in the market, either unilaterally or collectively, could not profitably raise price or otherwise reduce competition compared to the level that would prevail in the absence of the merger." A standard rule of thumb for the horizon over which such entry is considered is approximately 2 years (McDonald (2005)).

[2]Gowrisankaran (1999) considers a computational dynamic model with endogenous mergers. In his model

A simple example illustrates the effect of this type of assumption. Suppose that there is a set of symmetric potential entrants into an industry, that the nature of competition (e.g., Cournot or Bertrand Nash) implies a unique equilibrium given a number of entrants, and that the level of fixed costs implies that the unique equilibrium number of entrants is N^*. If a merger takes place between two incumbents and does not produce quality or marginal cost improvements (synergies), it is natural to expect that after the merger another firm will enter replacing the lost competitor, so that the number of firms is once again equal to N^*, restoring the pre-merger equilibrium.

On the other hand, suppose that the initial set of potential entrants is heterogeneous (e.g., they have different marginal costs or product qualities). Then most plausible entry processes will likely result in the best firms entering, so that the remaining potential entrants when the merger takes place are relatively weak. If all of the remaining potential entrants have lower quality, or higher marginal or fixed costs than the incumbents, then the merger may not trigger new entry even if there are no synergies. Even if new entry does restore the number of firms in the market to N^*, if these entrants have lower quality or higher marginal costs, prices may be higher in the post-merger equilibrium. An alternative way of viewing the problem is that when potential entrants are weaker than incumbents, anti-competitive mergers, or mergers with only small synergies, are more likely to be profitable, implying that the authorities may need to be more skeptical about the set of mergers that will be proposed when entry is selective [3].

The primary contribution of our paper is to develop an estimable entry model that allows for selection on at least three dimensions (product quality, marginal costs, and entry/fixed costs), which can be used to analyze the effects of both observed and hypothetical mergers on consumer welfare, allowing for additional potential entry. Following the Guidelines, our estimated model can be used to assess the likelihood and sufficiency of post-merger entry. In doing so, we extend the empirical literature that tries to understand and predict the effects

all potential entrants are ex ante identical when they decide to enter, so there is no explicit notion of an entry process that selects the best firms (e.g., those with better product qualities or lower marginal or fixed costs) in the market. However, because firms' characteristics can evolve post entry, and the firms that do best are more likely to survive (i.e., there is selection in the exit process), the potential entrants at the time that the merger takes place will tend to look weaker than the firms currently in the industry.

[3]Bougette et al. (2013) empirically find that after the merger between US Airways and America West in 2005, routes with ex ante greater competition concerns indeed do not show increasing entry.

of mergers, most of which has focused on the case where the set of non-merging competitors and products is held fixed (e.g., Nevo (2000)).

Our second contribution is to provide an empirical analysis of what happens after large mergers in the airline industry, considering both prices and entry. Since the industry's deregulation a large number of mergers have been proposed and consummated. Because markets, defined as city-city or airport-airport routes, are often highly concentrated (with the merging parties as the only competitors on a significant proportion of them), arguments about the viability of new entry have always played a role in analyzing these mergers and their potential anti-competitive effects. In many cases regulators have viewed entry as sufficiently straightforward, at least for the carriers already active at the route's endpoints, that mergers have been approved despite their effects on concentration. In other cases, the perception of higher entry barriers at congested or slot-constrained airports has led to mergers being challenged and prohibited (e.g., United/US Airways) or only approved following significant divestitures of gates and/or slots that other carriers can use to enter (e.g., US Airways/American, United/Continental, or Eastern/Texas Air).[4] However, there has been relatively little explicit focus on the questions of whether potential entrants will be as effective competitors as those firms already in the market, which is surprising given that observed outcomes at the route level are rarely consistent with the idea that all firms are symmetric. We show that our model that allows for asymmetries, which are considered by firms when they decide whether to enter, can explain two observed stylized facts about what happens after mergers. First, prices on the most affected routes tend to rise, a pattern which we show holds after recent mergers. This is consistent with the results in two recent papers, Luo (2013) and Lee (2010), which specifically document the price effect of the Delta/Northwest merger in 2008, as well as with those which have been the subject of previous empirical analysis (Borenstein (1990), Kim and Singal (1993), Peters (2006)). Second, entry, especially by carriers offering non-stop service, is very limited even where slot constraints are absent.

Our model consists of a two-stage game where, in the first stage, a set of carriers decide whether to enter the market and, if they enter, which type of service (direct or connecting)

[4] Snider and Williams (2011) use a regression discontinuity approach to find that prices indeed declined after reducing entry barriers through AIR-21 reform. The decline was mainly driven by the entry of low-cost carriers.

to offer. As both our summary statistics and estimates show, connecting service is usually a poor substitute for direct service, especially on shorter routes. Allowing for this service heterogeneity is important, even though it has often been ignored in the empirical entry literature, because post-merger entry in the markets we look at has usually taken the form of connecting service. In the second stage, the entrants compete on prices given a standard differentiated products demand system. Critically, we allow for firms to differ in their marginal costs and product qualities, based on both observed variables and unobserved heterogeneity, which are features that will affect the profits of other firms in the second-stage competition, as well as fixed costs. We assume that firms know both their own and competitors' costs and qualities when they take their entry decisions, and it is this informational assumption, combined with heterogeneity, that leads to selection in the entry process.

Our specification therefore differs in some important ways from the classic airline entry models of Berry (1992) and Ciliberto and Tamer (2009).[5] In those papers, a firm's payoff from entering is an additively separable function of the carrier's own characteristics, competition effects (reflecting the entry decisions of other firms), and an idiosyncratic error term. In such a specification, the observed or unobserved factors that affect one firm's entry decision do not affect the profitability of other firms, so that it is natural to consider them as factors only affecting entry or fixed costs. On the other hand, it is clear that one needs a lot of heterogeneity in both qualities and marginal costs, which will affect the profitability of other firms, in order to explain the market shares and prices observed in the data. Allowing for heterogeneity in qualities or marginal costs also allows us to explain observed entry patterns without necessarily estimating implausibly high levels of unobserved heterogeneity in fixed or entry costs (for example, one might expect carriers to have similar costs of acquiring additional gate capacity), as has often be found in the empirical entry literature. We also avoid making the assumption that unobserved heterogeneity in qualities or marginal costs are unknown at the time when entry decisions are taken (e.g., Eizenberg, 2011), an assumption that limits the scope for there to be selective entry.

We estimate our model using price, quantity, and entry decision data for the second

[5] There is also a recent airline entry paper, Ciliberto and Zhang (2014), that compares 3 types of repeated static entry models (simultaneous move, sequential move, and sequential move with entry deterrence investments) and finds that the model with entry deterrence investment fits the data best.

quarter of 2005 for airport-airport markets between the 80 largest airports in the United States, as measured by enplanements.[6] We focus on these markets because they cover all the hub-to-hub markets. Hub airport-pair markets have been the focus of concern in recent airline merger cases. For example, all of the markets identified in the United States Government Accountability Office (2010) report on the United/Continental merger as being of most concern linked a United hub with a Continental hub (e.g., Denver and Houston's George Bush Intercontinental), because usually the two hub carriers have a dominant position on the route, such that mergers would tend to result in situations close to monopoly based on pre-merger market shares. In addition, for hub airport-pair markets almost all carriers serve both the endpoints, which is usually how the set of potential entrants who could enter in the short-run are identified in airline markets. One might expect that new entry would provide a constraint on post-merger market power if the potential entrants and the incumbent carriers were approximately symmetric. These markets are therefore very natural ones to think about the types of asymmetry/heterogeneity and selection that our model allows. On the other hand, we do not constrain our sample to only the hub-to-hub markets in order to allow reasonable variation in the number of potential entrants. The number of potential entrants in our sample ranges from two to nine, facilitating the identification of the entry model.[7]

Estimating a combined entry-and-competition model that allows for wide-ranging carrier heterogeneity leads us to use a new estimation methodology. In particular, we build off of earlier and on-going work estimating models of selective entry into first and second price auctions (Bhattacharya et al. (2013); Roberts and Sweeting (2013a,b)) by using a method of simulated moments estimator where importance sampling is used to calculate the moments (a method proposed by Ackerberg (2009)). In practice, this means that we solve a very large number of games for different parameters (in our case, different quality and cost draws for each of the potential entrants) once, and then re-weight the outcomes of these games to calculate the simulated moments when estimating the parameters of the distributions from which the qualities and costs are drawn. Without this type of approach, estimation of a

[6] We are in the process of updating the paper to use more recent data and mergers.

[7] Berry and Tamer (2006) discuss how variation in the number of potential entrants can play an important role in the identification of the parameters in entry models, and previous work such as Berry (1992) and Ciliberto and Tamer (2009) has even used a broader cross-section of medium and large markets, with more variation in the number of potential entrants. We discuss identification in Section 4.1 below.

model with a large number of potential entrants (we allow up to nine by aggregating smaller carriers), multiple product type choices (direct, connecting), and a fully specified model of post-entry competition (required to do interesting counterfactuals) would not be feasible.[8]

While we believe that our model significantly extends the literature on empirical entry models and our understanding of airline mergers, we also acknowledge some of its limitations. First, like most of the existing literature, we do not have an explicit model of airlines' network choice. Aguirregabiria and Ho (2012) explicitly estimate a game of network competition where entry into a city-pair generates profits over all non-stop and one-stop routes among 55 cities in the U.S. that include that city-pair as a segment. They find that the airlines with a small number of connections in an airport have to pay a large entry cost. However, they do not model heterogeneity in qualities and costs among different carriers. Instead, in order to model richer heterogeneity we focus on entry at the route level, conditioning on airlines' presence/network at the endpoints. While not explicitly modeling network competition, we do partly reflect how network considerations affect entry choices by constructing a connecting traffic variable for hub airports and allowing this variable to affect the actual entry/fixed cost for direct service. One might be concerned that the large airport-airport markets that we analyze play a more important role in airline networks than other routes, so that this would be an even greater simplification for us than other authors. The data, however, indicate that this is not the case. For example, on average, 60% of people traveling on planes between hub airports are on journeys that only include this segment, which is almost exactly the same as on other routes.[9]

Second, our model is static. Including the types of persistent asymmetry that we are interested in within a dynamic model is an important direction for future research, but we

[8] Ellickson and Misra (2012) consider a two-step selection correction method for estimating a discrete choice game with selection using outcome data. However, as they note, the viability of this method depends on the outcome equations, such as the grocery store revenue equation that they specify, being a simple linear function. In contrast, Nash equilibrium prices and market shares in a model with differentiated products and standard forms of demand, such as logit, will not be linear.

[9] For domestic travel, the large number of destinations that can be reached from each hub often precludes the need to travel indirectly via another hub. On the other hand, people may travel to another airline's hub in order to travel on their preferred carrier (for example, someone who was flying from Madison, WI to New York might choose to fly via Chicago if they were a United frequent flyer – before the United/Continental merger – and so would have traveled from Chicago to New York, one of the routes in our data), and hub-hub routes do play an important role in airlines international networks, as they may only serve international destinations from a subset of their hubs.

believe that a static model is an appropriate simplification given merger policy's focus on the immediate period following a merger's consummation (usually up to 2 years). During this period of time, for example, the basic hub configurations of the carriers are likely to remain similar, even if the merger leads to some locations losing hub status in the long-run. We interpret our results as being complementary to the analysis of Benkard et al. (2010), who model a dynamic entry game with static price competition, but only allow carriers to choose route entry instead of the type of services they provide once having the network, and again do not try to model the types of selection that interest us.

Third, and perhaps most importantly, we model carriers as choosing prices in the second stage game rather than capacities, flight frequencies, or other quality measures, which are likely to be valued by customers. Therefore, we are not able to measure the effect of mergers on quality provision. There is a growing literature on endogenous product (quality) choice in oligopoly competition (e.g., Fan (2013)). For the airline industry, Lee (2013) models carriers' decisions in a sequential two-stage game, where in the first stage, carriers choose product qualities (e.g., flight frequency and on-time performance, among others), and in the second stage, carriers compete in prices. He finds greater product differentiation for merged firms after merger, which results in smaller price increase compared to that predicted by models without quality choice. Several retrospective studies also document airline mergers' effects on product qualities. Chen and Gayle (2013) use the ratio of nonstop flight distance to the ticket itinerary flight distance between origin and destination as a measure of quality, finding that after a merger this quality decreased in markets with pre-merger competition between the merging parties, and increased in markets without such pre-merger competition. Prince and Simon (2014) find that recent airline mergers improved merging carriers' on-time performance in the long run and did not affect flight cancellation. While it is possible to consider product choices in our model by including an additional stage after entry, our decision not to do so reflects our need to have a second stage game that has a unique solution (guaranteed by our assumptions on demand) that can be found quickly in order to make estimation of the whole game tractable.[10]

[10]The implementation presented below also requires us to have a unique solution in the entry stage as well, leading us to consider a sequential entry game where the researcher knows the order (or at least the probabilistic function that determines the order). It is straightforward, however, to consider alternative entry

Finally, our model only considers one way that potential entry may constrain pricing. In particular, the 'entry-then-price competition' structure of our model implies that having a large set of potential entrants with possibly low entry costs will only constrain prices if entry actually occurs. In contrast, the older contestability literature (e.g., Baumol et al. (1982)) suggested that the existence of the potential entrants could constrain pricing even without actual entry. While the airline industry was seen as a plausible example of contestability in the period immediately following deregulation, it has now been discredited as an accurate description of the way that airline markets work (Borenstein and Rose (2013)).[11] On the other hand, regressions of prices on the number of actual and potential competitors do tend to indicate that prices are lower when there are more potential, as well as actual, entrants (Kwoka and Shumilkina (2010), Gayle and Wu (2013), which also contain many references to the older literature). Gedge et al. (2014) develops a dynamic limit pricing model to explain the stylized fact that incumbent prices are lower when Southwest becomes a potential entrant. In their model the incumbent monopoly has private information on its correlated but not perfectly persistent cost each period, which gives the monopoly incentive to signal its cost by setting a lower price. While our model does not incorporate the signaling game, it can still help rationalize the fact that with more potential entrants, prices are lower. This is because with the type of selection model with carrier heterogeneity that we consider, when there are more potential entrants, it is likely that some will be very efficient, leading to lower equilibrium prices when they enter.

The paper proceeds as follows. Section 2 details the model. Section 3 describes the data used to estimate the model, and presents evidence on what happened to prices and entry on hub-hub routes after the Delta/Northwest (2008) and United/Continental (2010) mergers. Section 4 describes our estimation method and discusses identification. Section 5 presents some initial estimates and discusses some simple counterfactuals that illustrate

orders, and it is also possible to use an approach, akin to the one used in Ciliberto and Tamer (2009), where the researcher is agnostic about the order, resulting in estimated bounds on the parameters. We illustrate this alternative in the paper's appendix.

[11] Former Antitrust Division Assistant Attorney General Joel Klein addressed this issue in a recent speech stating that the contestable market theory "simply does not conform to the facts in a post-deregulation world consisting of hub airports." See page 25 of the Statement Concerning Antitrust Issues in the Airline Industry of former Assistant Attorney General Antitrust Division Joel I. Klein Before The Committee on Commerce, Science, and Transportation, ("Klein Statement") presented on July 27, 2000.

the extent and effects of selection on post-merger predictions. Section 6 concludes. Appendix A presents Monte Carlo studies of alternate estimation approaches based on different equilibrium selection assumptions.

2 Model

We model a two-stage game in which potential entrants, carriers, first decide whether to enter a market and afterwards compete with one another. A market is a non directional airport-pair that provides two directional services, one for each direction. For example between Boston Logan Airport and Charlotte Douglas Airport is one market that provides a directional service from BOS to CLT, and another directional service from CLT to BOS.

In the first stage, each potential entrant observes all demand and cost realizations, defined below, and chooses whether to enter and what type of service to provide. The information assumption allows for entrants to be selected on observed and unobserved variation in qualities and marginal costs, as well as fixed costs, and it is motivated by the fact that the firms that we define as potential entrants are large, sophisticated firms, already operating at both endpoints. These firms should have good information about how well suited other carriers are to the route. [12] There are three entry options: don't entry, enter with direct service or enter with connecting service. Each of this option is non-directional, meaning that if a potential entrant decides to enter a market with direct service, it needs to serve both directions and both with direct service. We assume that each carrier only chooses one of these options, so that a carrier chooses to offer direct service does not offer connecting service. This is a reasonable simplification for the markets in our sample as based on our data (introduced below) if a carrier is counted as offering direct service, over 91% of passengers who choose that carrier fly direct.[13] In the second stage, the entrants pay their entry costs and compete by setting prices in a Bertrand Nash equilibrium for service in each direction. We assume

[12]The ideal model would probably also allow for some aggregate demand or cost shock to be realized after entry decisions are made. However, allowing for these shocks would significantly increase an already large computational burden.

[13]The exceptions come when a carrier begins or ends direct service during a quarter, or for long routes out of airports such as Washington National where there are constraints on how many direct flights can be made to cities beyond a certain geographic distance from the origin.

that the pricing games are independent for the two directions in a market.

A key feature of our model is that we allow for considerable observed and unobserved heterogeneity in costs and product qualities across carriers and markets. This increases the flexibility of our model, allowing us to explain why carriers serving the same route have quite different prices and market shares, and it also facilitates the estimation procedure described below.

We consider a simple one-level nested logit discrete choice demand structure where the nests are 'fly' and 'no fly'. Consumer i's utility from choosing a carrier j offering service type t on market m's direction d is

$$\begin{aligned} u_{ijmtd} = {} & q_{jmd}^{Direct} I(t = Direct) + q_{jmd}^{Connecting} I(t = Indirect) \\ & + RE_m - \alpha_{md} p_{jmtd} + \nu_i^{FLY}(\lambda_{md}) + (1-\lambda_{md})\varepsilon_{ijmtd}. \end{aligned} \tag{1}$$

If a consumer chooses not to fly (the outside good), his utility is normalized to ε_{i0}. q_{jmd} is the carrier quality on the route. For a direct service, q_{jmd}^{Direct}, is the sum of two components. The first component is a carrier specific quality μ_{jd} that is assumed to be $\mu_{jd} \sim N(\beta_{\mu,j}, \sigma_\mu^2)$. The second component is the additional quality ψ_{jmd} enjoyed by consumers through the carrier's presence [14] at the origin of the airport for direction d. We see from the data that carriers with high presence (or a hub at the origin) are more likely to enter a market with direct service and charging a higher price, which indicates that presence generates a positive utility for direct service. Therefore, we assume that $\psi_{jmd} \sim TRN(\beta_\psi Presence_{jmd}, \sigma_\psi^2)$. [15]

For an indirect service, $q_{jmd}^{Connecting}$ is assumed to have lower quality than that from a direct service because consumers dislike connect flights reflected as low market shares for connecting service in the data. Therefore, we subtract a penalty from the direct service quality, and assume that this penalty $\phi_{jm} \sim TRN(\beta_\phi, \sigma_\phi^2)$. In addition, we assume that consumers choosing indirect service does not enjoy the benefit of a high presence of the

[14] Presence of carrier j in airport c is defined as $\frac{\text{number of other cities served by } j \text{ out of c}}{\text{number of other cities served by any carrier out of c}}$

[15] This second component will be 0 for Southwest, aggregated other legacy carriers and aggregated other low cost carriers, as will be defined later. This is reasonable because for the aggregated carriers, the presence is also calculated as the aggregate presence. Therefore it is unclear that they can benefit from the presence. Southwest and these aggregated carriers also do not have frequent flyer programs that other literatures used to explain hub dominance (for example, Lederman (2008)).

carrier at the origin. As a result, $q_{jmd}^{Connecting} = q_{jmd}^{Direct} - \psi_{jmd} - \phi_{jm}$.

RE_m is a market random effect, and we assume that $RE_m \sim N(0, \sigma_{re}^2)$. In the data, there are markets where all entrants have high market shares or low market shares. While the standard errors in quality q's can account for that, it will result in a large estimated standard errors for μ_{jd} that complicates the effect of presence. From simulation exercises, we find that a large standard error in μ_{jd} results in carriers with lower presence enter with higher probability,[16] which is not the case in the data. As a result, this market random effect is needed to explain the high and low total inside market shares while still allowing the model to predict that the carriers with larger presence are more likely to enter holding everything else equal.

The price coefficient, α_{md} can vary across markets and we assume that $\alpha_{md} \sim logN(\beta_\alpha, \sigma_\alpha^2)$ (lognormal). λ_{md} is the nesting parameter and also can differ across markets to reflect varying attractiveness of the outside option to traveling by plane (e.g., other modes of transpiration or not traveling at all) and we assume that $\lambda_{md} \sim TRN(\beta_\lambda, \sigma_\lambda^2, 0.2, 0.95)$ (truncated normal between 0.2 and 0.95). ε_{ijm} is the standard logit error and $\nu_i^{FLY}(\lambda_{md})$ is a constant for i across all products in the flying-nest and is distributed so that $\nu_i^{FLY}(\lambda_{md}) + (1 - \lambda_{md})\varepsilon_{ijm}$ is distributed Type 1 Extreme Value. When $\lambda = 1$, conditional on flying, all consumers will choose the product that generates the highest $q_{jmd}^{Direct} I(t = Direct) + q_{jmd}^{Connecting} I(t = Indirect) - \alpha_{md} p_{jmtd}$. When $\lambda = 0$, $\nu_i^{FLY}(\lambda) = 0$, and utility function becomes a simple logit.

Each carrier has a linear per-passenger marginal cost for each type of service t (direct or connecting), drawn from carrier-type and service-type specific distributions. This marginal cost is nondirectional because factors generally considered affecting marginal cost do no vary by different directions in the same market. We assume that $c_{jm}^t \sim TRN(X_{jm}^c \gamma_{c,\tau(j)}^t, \omega_{c,\tau(j)}^{t2}, 0, 100)$ where X_{jm}^c include a constant term and distance. $\tau(j)$ is an indicator whether carrier j is a legacy carrier or low cost carrier. Fixed costs are drawn from service-type specific distributions and we assume $F_{jm}^t \sim logN(X_{jm}^F \gamma_F^t, \omega_F^{t2}, 0, 100)$. When $t = Direct$, X_{jm}^F includes a constant term and delay measures that potentially increase the entry cost due to congestion

[16] Presence decides the order of movers in the entry game

induced higher entry barrier [17]. It also includes an indicator of whether one of the airports is an international hub. The ability to serve international travelers at an international hub may influence the entry decisions on the route. For example, United's decision in entering the Raleigh-Durham (RDU) - O'Hare Airport (ORD) market with direct service is likely affected by ORD being an international hub for UA so that if enters, UA can transport international travelers from and to RDU through ORD. We assume that when $t = Connecting$, X_{jm} only contains a constant term.

Similar to the idea of including an indicator of an international hub, in addition, we include an additional fixed revenue $C_{jm} \sim logN(X_{jm}^C \gamma_C, \omega_C^2)$ gained from domestic connecting traffic when calculating the total profit from providing a direct service. We see in the data that about 65% of passengers originating in RDU who fly on Delta to Atlanta (ATL) use Atlanta as their connecting stop to go to somewhere else such as SFO. The ability to serve these connecting passengers make it more attractive for Delta to serve directly between RDU and ATL. This additional fixed revenue for direct service from connecting traffic is then subtracted from the fixed cost when calculating total profits in the entry game. X_{jm}^C includes a constant term and a measure of connecting traffic (number of connecting passengers served by the route) for carrier m on route j. For the purpose of our full information entry game, we need to calculate the connecting traffic measure even for potential entrants who are not currently serving the market in the data. We use a simple logit choice model with two-step Heckman selection approach for this prediction. The number of passengers who make one connection to travel from a origin o to destination d pair is given. Each of these passenger make decisions on the carrier and connecting stop. The utility for a passenger i choosing carrier j and connecting stop c such that he travels $o \rightarrow c \rightarrow d$ is

$$u_{cj}^{od} = X_{cj}^{od} + \xi_{cj}^{od} + \epsilon_{cj}^{od}$$

where ϵ_{cj}^{od} is a logit error. The utility of choosing an outside good is normalized to 0. We

[17] Berry and Jia (2010) instead includes delay in the marginal cost.

can then write the share equation as

$$log(s_{cj}^{od}) - log(s_0^{od}) = X_{cj}^{od}\beta + \xi_{cj}^{od}$$

Because the connecting traffic reflected in the data is conditioned on a carrier serving both $o \to c$ and $c \to d$. A selection problem arises because a carrier may chooses to serve these segment when they can generate a large share of connecting traffic. We address this sample selection problem by modeling explicitly the probability of a carrier's entry to both the $o \to c$ and $c \to d$ markets using a probit model:

$$Pr(j \text{ serves both } o \to c \text{ and } c \to d \text{ markets}) = \Phi(W_{cj}^{od})$$

where W_{cj} are characteristics of the origin, connecting stop, and destination cities and airports. Note that only carrier who has a positive connecting traffic measure for the market can have this additional fixed revenue draw if it provides direct service. We assume this additional revenue to be 0 for all connecting service. For a more detailed explanation of the construction of the connecting traffic measure, please refer to Appendix B.

First Stage: Entry

At the beginning of the game there is a set of potential entrants N who are one of two types $\tau \in \{LEG, LCC\}$, with $N = N_{LEG} + N_{LCC}$ and all demand parameters and carrier cost and quality draws are known by all potential entrants (complete information). These potential entrants sequentially make their entry decisions based on the resulting profits. We assume that the carriers with the highest average presence at the endpoints move first. We discuss alternative modeling options of the entry stage below. Note that while we do not explicitly endogenize network choice, we do endogenize each carrier's choice of whether to offer direct or connecting service.

Second Stage: Price Competition

In the second-stage entrants simultaneously set prices in a Bertrand-Nash equilibrium for each direction of the market and make profits:

$$\pi_{jm}^{t} = \left(p_{jm0}^{*} - c_{jm}^{s}\right) M_{jm0} s_{jm0}^{*} + \left(p_{jm1}^{*} - c_{jm}^{s}\right) M_{jm1} s_{jm1}^{*} - F_{jm}^{t} + C_{jm}^{t}, \tag{2}$$

where Ms are market sizes, and 0 and 1 indicate the direction. It is understood that the equilibrium prices and quantities (denoted by an $*$) for firm j in market m that offers service s are functions of all potential entrants' entry actions, qualities and costs. Non-entrants make zero profit.

The sequential structure, together with our demand and cost assumptions, ensures that the game has a unique, pure-strategy equilibrium (Mizuno (2003) proves the uniqueness of the Bertrand Nash price equilibrium for a nested logit model where each firm only has a single product).

3 Data and Evidence on the Effects of Mergers on Prices and Entry

Our data sources are the publicly available Department of Transportation Origin and Destination Survey (DB1B) and Domestic Segment (T-100) database. The DB1B database is a 10% sample of all passenger itineraries, updated quarterly, that includes coupon-specific information, such as the operating carrier, origin and destination airports, number of passengers, prorated market fare, number of market coupons, market miles flown, carrier change indicators and distance, for domestic itineraries. T-100 is a monthly census of all domestic flights broken down by air carrier and origin and destination airports. In this section we describe our variable definitions and summary statistics for the data that we use to estimate the model and also some stylized facts about what happened after two large, recent mergers: Delta/Northwest (2008) and United/Continental (2010).

3.1 Sample and Variable Definitions for Estimation Dataset

To estimate our model we use data from the second quarter of year 2005.[18] In order to facilitate estimation, we limit ourselves to considering the entry decisions of nine carriers. [19] American (AA), Continental (CO), Delta (DL), Northwest (NW), United (UA), USAirways (US) and Southwest (WN) are modeled as individual carriers. Of these, we label the first six as 'legacy' carriers and Southwest as a 'low cost' carrier. The carrier is defined by the 'ticketing carrier' in the DB1B data, so passengers carried by regional affiliates (such as American Eagle or a United Express flight operated by Air Wisconsin) count as if they were carried by the associated larger carrier. Service by all other carriers are aggregated into an 'Other Legacy' carrier (e.g., Alaska Airlines) and an 'Other LCC' carrier (e.g., Frontier, JetBlue, Midwest).

A market is an airport to airport non-directional pair. We model the entry decision to be non-directional, i.e., once a carrier decides to enter the market it will provide service on both directions between the airport pair. Therefore we define entry as carrying at least 200 passengers on a market and serving both directions of the market with at least one flight, in addition to meeting one of the following two criteria: 1) flying at least 1% of total passengers in the market and 2) flying any number of passengers on direct flights both ways. While a carrier can provide both non-stop and connecting service in the same market, we only allow each carrier to choose one type of service in a market in the model. We define a carrier providing non-stop service if 1) greater than 50% of a carrier's passengers on the market are flown on direct flights and 2) based on T100 this carrier flies at least one flight in both directions. While entry decision is non-directional, prices are decided independently for each direction, and are defined as DB1B passenger-weighted average price in a given direction only using the type of service we assign to the carrier. A carrier is counted as potential entrant if it flies at least one flight out of or into both endpoints of the market in DB1B. In addition, all the above definition only uses domestic, economy class tickets with round trip

[18] We consider the second quarter because it has the highest number of passengers flying. We are in the process of updating the paper to reflect more recent data and mergers.

[19] By estimating only a linear profit equation with carriers making only binary {not enter, enter} and symmetric competition effects, Berry (1992) avoids aggregation. However, Ciliberto and Tamer (2009), who also do not model post-entry competition, but do allow for asymmetric competition effects and less restrictive equilibrium selection assumptions, aggregate to six carriers.

faire ranging from $25 to $2000.

We will allow for the presence of the airport at the origin to affect the perceived quality, reflecting the fact that carriers with a hub or focus city at the origin airport are usually believed to command fare premia (Borenstein (1989)). The presence of a carrier is defined as the percentage of total "served" destinations from this airport that are "served" by this carrier. A destination is "served" by an airport if a) this airport has at least one flight to the destination per weekday, b)destination is at least 350 miles away one way, and c) destination is among the top 75 destinations served from the airport by traffic. A destination is "served" by a carrier from an airport if the carrier flies at least one flight to the destination from this airport per weekday.

We restrict our sample to markets between the top 80 airport based on enplanement. We exclude some routes further based on three additional criteria. First, some cities are so close together (e.g., Philadelphia and Washington D.C., or New York and Philadelphia) that there is very little air service, and most travelers would travel by car or train. Therefore, we drop routes where the airports are less than 350 miles apart one way. Second, we drop markets where the combined market shares of carriers who are in the market are extremely high or extremely low. In order to calculate market share, we need to define market size first. Market size is typically defined as the arithmetic or geometric average population in the literature. However, we think it is an inaccurate measure since the number of travelers can be unrelated to the population (e.g., a city being a tourist destination but with small population or two airports in the same city with each only attracting half of the total traffic). Instead we define market size as the predicted value from an poisson regression of the (log of) total passengers in a market in a year on the (logs of) total traffic into the destination city, total traffic out of the origin city and non-stop round-trip distance between the two cities in the last year. [20] We then drop observations for those markets where the combined market shares of the carriers is less than 5% or greater than 80% in any of the quarters. [21] These restrictions leave us with 1986 airport-pair markets.

[20]We use the lag of explanatory variables because prices affect the explanatory variables, and we do not want price to enter the calculation of market share. Interactions among these variables were tried but added very little explanatory power.

[21]Most of the markets with very small combined market shares are pairs of airports in smaller cities (e.g., BNA-CVG). The pairs with very high market shares include SFO-JFK.

Table 1 provides summary statistics. Because our markets are made up of large airports, many carriers especially legacy carriers among the nine we defined are counted as potential entrants on each route. Southwest on the other hand still has not started serving at a few large airports in 2005, for example, airports in Atlanta, Boston, Charlotte, Cincinnati, Denver, New York, Memphis, Minneapolis, or Pittsburgh. However, while there are many potential entrants, on average less than one carrier serve each market with direct service, with almost 60% of carriers that fly direct having a hub at one (or both) of the endpoints [22] of the routes that they serve. 54% of the market have no direct service, and on 30% of markets there is one direct carrier. There are only 60 markets with 3 direct carriers, and almost all of these link the biggest cities such as New York and Los Angeles. Furthermore, we can see that when a carrier has hub status at one or more ends, the probability of direct entry is high. This can be due to the high quality or low cost due to high presence. In addition to the inclusion of positive presence draw in the direct quality as mentioned earlier, this further justifies our inclusion of the connecting traffic revenue [23] in direct fixed cost in the model to match this data feature.

On the other hand, there are many more carriers offering connecting service in each market. On average, 3.5 additional carriers offer connecting service. Connecting service is also associated with very small market shares relative to direct ones, indicating that for many consumers connecting service is a poor substitute to direct service, even though the average prices of the two types of service are comparable. These stark differences in the number of entrants and shares suggest the need to model quality and cost structure between these two types of service differently.

A further reason for distinguishing between direct and connecting service can be seen in Table 2, which shows the number of direct and connecting carriers in each market size and non-stop distance tercile combination. For direct service, the number of carriers supported in equilibrium increases monotonically with market size, which is what one would expect unless there are large economies or diseconomies of distance (and remember that markets that are very close together have been excluded). This clear monotonic pattern has not

[22] Hub here is defined as having at least 50% presence at the airport

[23] Note that connecting traffic revenue can only be positive at hub airports.

been observed in earlier research, such as Ciliberto and Tamer (2009), where direct and connecting service have not been distinguished. The reason why can be seen in the lower part of the table: the number of connecting carriers varies primarily with route distance, which presumably reflects the fact that passengers are more willing to pay the fixed cost of making a connection on trips that are already long, as well as there probably being a greater number of substitute connections that do not involve the passenger straying too far from the non-stop route. On the other hand, connecting entry does not vary much with market size, suggesting that the fixed costs of entering connecting service do not play a key role in determining this aspect of market structure.

3.2 The Effects of the Delta/Northwest and United/Continental Mergers

A body of research has examined the price effects of mergers that took place in the U.S. airline industry in the decade following deregulation, when mergers were rarely challenged and there was rapid consolidation. Borenstein (1990), Kim and Singal (1993) and Peters (2006), among others, provide evidence that mergers resulted in significant price increases (by the merging carriers) on the routes where both of the merging parties competed prior to the merger. For example, the five mergers (Northwest/Republic, TWA/Ozark, Continental/People Express, Delta/Western, US Air/Piedmont) considered in Peters (2006) resulted in price increases of between 7% and 30%. In this section we provide some evidence that the recent Delta/Northwest and United/Continental mergers also resulted in price increases, as well as relatively little entry.

To perform the analysis we form a quarterly panel of price data from the third quarter of 2007 until the third quarter of 2010 (inclusive). For the purposes of this analysis we define markets as directional airport-pairs, and we only consider direct service, so that our price measure is the average price paid by those flying direct round trips (excluding fares less than \$50 and more than \$2000). Rather than just analyzing routes where the carriers overlap, we consider price changes on the routes most affected by the merger based on the definition that (appears) to be used in U.S. Government Accountability United States

Government Accountability Office (2010): the route is a hub-to-hub market served by both of the merging carriers, who accounted for more than 70% of direct traffic in the quarters prior to the merger. The baseline regression specification is

$$\log(\overline{p}_{jmt}) = \beta_0 + \beta_1 * \text{POST-MERGER}_t * \text{AFFECTED ROUTE}_m + FE_t + FE_{j,m} + \varepsilon_{jmt}$$

where $\overline{p}_{jmt}$ is the average price of combined carrier j on route m for non-stop round trip tickets at time t, FE_t are time fixed effects, $FE_{j,m}$ are carrier-route fixed effects, and β_1 is the coefficient of interest. Standard errors are clustered at the route level. As a control group we identify a set of unaffected routes, defined as routes served non-stop by one of the merging carriers with the other providing neither non-stop nor connecting service in the whole year prior to the announcement of the merger. [24] To make interpretation easier, we drop data between the announcement and closing of the transaction. [25] Table 3 shows the estimates of β_1 from two specifications for each merger (standard errors in parentheses).

In the first specification, the regression only uses the prices set by the merging carriers and, prior to merger, $\overline{p_{jmt}}$ is the weighted average price on the merging carriers. The estimated coefficients indicate that the Delta/Northwest merger raised non-stop prices by 8%, and the United/Continental merger by 16%, on the affected routes relative to non-stop prices on unaffected routes. In the second specification, prices set by American and US Airways, two airlines that were not involved in mergers during the time period covered by the data, on unaffected routes are included in the control group, to make sure that these estimates do not simply reflect the merging parties cutting prices on the unaffected routes. The estimated β_1s are very similar.

While prices increase, consistent with the merger enhancing market power, very little entry is induced, suggesting that route-level entry may not be as easy as the authorities assume. On the 17 (non-directional) hub-hub routes affected by these mergers, the only new non-stop entry after the merger was by Southwest between Newark and Denver. [26] On five

[24] These routes will include routes that are not to, or from, hubs, as well as hub-to-hub routes where only one carrier operates.

[25] When we estimate separate effects for this time period, we find effects that have the same sign but are smaller than the post-merger effects.

[26] We define a carrier as entering if it provides service in multiple quarters after the transaction was closed,

routes there was entry with connecting service (e.g., AA providing service from Houston to Denver via Dallas-Fort Worth), but, as our model allows, connecting service may be a poor substitute for non-stop service.

4 Estimation Method

We need to estimate demand, marginal costs, and fixed costs. 35 parameters need to be estimated once we allow for observed and unobserved heterogeneity. A two-stage approach is not feasible because we need to take into account selection in the entry stage to consistently estimate demand and marginal costs. Moreover, the type of nested fixed point approach used by Berry (1992) and Ciliberto and Tamer (2009), where games are re-solved for each market each time one of the parameters is changed, would likely take months or possibly years to converge. [27] Instead we use an estimation approach, simulated method of moments where the predicted moments are approximated using importance sampling, that involves solving a very large number of games only once, and then simply re-weighting them during estimation. The advantage of this approach is that the estimation-stage is relatively quick (e.g., less than a day using analytical derivatives) because it only involves calculating the product of pdfs, and in the solving-stage we can solve a large number of games in parallel on many different cores (we use as many as 600) that do not need to communicate with each other.

Details. We will estimate the β, σ, γ, and ω parameters which describe the distributions of the market- or carrier-specific demand and cost parameters. In what follows we will denote the collection of these parameters by Γ. Joint estimation is required because of entry selection, as, for example, the expected marginal cost of a legacy carrier that chooses to enter non-stop will be greater than $X_{jm}^{c}\gamma_{c,LEG}^{Direct}$, the mean of its distribution.

The procedure has two steps. In the first step, we draws a large number (S) of combination of draws for each market, including the value of α, λ, RE, which are market-level parameters, and values of qs, ψs, ϕs, cs, Fs, and Cs for each carrier (denote the collection of these draws

having not provided service in the year prior to the merger being proposed.

[27] Neither of these papers has an explicit model of second-stage competition, but they still have to impose either a strict equilibrium selection rule and a small number of parameters (Berry) or only consider a small number of firms (Ciliberto and Tamer). Neither paper distinguishes between direct and connecting service, reducing decisions to a simple {entry, no entry} choice.

θ_s) from an importance sampling density $g(\theta|X_{jm})$. X_{jm} is understood in this context to include all of the observable covariates included in the model's specification. Then for each realized θ_s, we solve the entry game. This can be done in parallel on a large computing cluster. The game is solved using the assumed order of entry (i.e., that the carriers move in order of their average presence at the endpoints) and information on the unique predicted equilibrium outcome (e.g., entry decisions, prices and market shares) is stored.

In the second step, the parameters Γ are estimated using a simulated method of moments estimator, where the value of each moment is calculated by appropriately re-weighting the outcomes from the games solved in the first step. For example, consider an outcome $f_m(\theta)$ (e.g., the number of direct entrants in market m) and a guess of the parameters $\widehat{\Gamma}$. We approximate $E[f_m(\theta)|\widehat{\Gamma}]$ using:

$$E[f_m(\theta)|\widehat{\Gamma}] \approx \frac{1}{S}\sum f_{ms}(\theta_s)\frac{\varphi(\theta_s|X_{jm},\widehat{\Gamma})}{g(\theta_s|X_{jm})} \tag{3}$$

where $\varphi(\theta_s|X_{jm},\widehat{\Gamma})$ is the value of the density for a particular draw θ_s given the observed covariates, all of the parametric distributions assumed in the model and the guess $\widehat{\Gamma}$, and $f_{ms}(\theta_s)$ is the relevant outcome from game s simulated in the first step. When we change $\widehat{\Gamma}$, $E[f_m(\theta)|\widehat{\Gamma}]$ can be calculated without re-solving any games; all that is required is a re-computation of $\varphi(\theta_s|X_{jm},\widehat{\Gamma})$ based on the new guess of $\widehat{\Gamma}$.

The moments f_m that we seek to match are (i) each firm's entry decisions interacted with average presence at end points and its square term; (ii) each firm's market shares and prices at each direction of the market interacted with presence at the origin; (iii) all the above interacting with one of six market size (small/medium/large, defined by terciles) and distance (short/long, defined as round trip distance of 2500 miles) combinations; (iv) indicators of whether the average total inside share at both directions is below 20%, between 20% and 40%, between 40% and 60%; (iv) and indicators of whether the absolute difference between total inside shares at both directions is between 0 and 2.5%, and between 2.5% and 5%.

Ackerberg (2009) suggests the importance sampling approach for estimating complicated static or dynamic decision problems or games. A key assumption that the procedure requires is that the supports of the θ parameters do not depend on the parameters to be estimated. This is true in our case as we either specify unbounded supports (e.g., for qualities), natural truncated supports (e.g., non-negative marginal costs) or we impose the same arbitrary support on both the true parameter distributions and the importance sampling distributions (for example, that the nesting parameter λ_m must lie between 0.2 and 0.95, because values that are very close to 1 can complicate the solution of the model in some markets). Estimates using this approach are more accurate when S, the number of simulation draws, is large and the importance sample densities are similar to the 'true' densities from which the parameters are drawn. In estimating the model, we currently use $S = 1000$.[28] We use importance sampling densities that have the same distributional form (e.g., truncated normal, lognormal) that we assume the true parameters have, and we tried to pick parameters for the densities such that the predicted prices, shares, and entry patterns were approximately consistent with what is shown in the data , and it is also consistent with the estimates of demand, marginal costs and substitution patterns reported in recent airline papers such as Berry and Jia (2010), and variances large enough that all parameters that seemed plausible would have non-negative probability.

4.1 Identification

The full parametric structure of our model and our equilibrium assumptions are imposed during estimation, but there are several sources of plausibly exogenous variation that help to identify the parameters of interest. For example, there is cross-market variation in the number of potential entrants and their characteristics (such as presence and whether they are low-cost) should identify the mean price coefficients in the demand system. The mean of nesting parameter is identified from the variation of total inside share as the number of entrants changes [29]. In practice, the estimate of the mean nesting parameter varies when

[28]Roberts and Sweeting (2013a) present Monte Carlo evidence for a Simulated Maximum Likelihood estimator. Monte Carlo studies in Appendix A suggest that estimates can be unbiased using S as low as 5.

[29]Implementation of the estimation method requires us to allow for unobserved heterogeneity in carrier costs and qualities and the market-demand parameters α and λ. Based on intuitive identification arguments, identification of heterogeneity in α and λ seems likely to be particularly reliant on functional form (at least given the limited time-dimension of our panel), although, as explained below, there are features of the data that should provide information on the heterogeneity in costs and qualities.

there is a change in the specification or the starting value, indicating that there is not enough variation in the cross-sectional data [30] to identify the nesting parameter. This result is not surprising, as we can see from other work. For example, estimates the same nesting parameter in Berry and Jia (2010) range from 0.69 to 0.83 across different specifications, again using cross-sectional data.[31] Therefore, instead of attempting to get an estimate of the nesting parameter with a very large standard error, we fix the nesting parameter value at 0.45, 0.65, and 0.85 in the importance sampling simulation and estimation, and compare the counterfactual results generated from these different values.[32] These three values cover a reasonable range for the nesting parameter estimated in the previous literature and our reduced form analysis with no entry.

The distributions of total inside shares and the differences between the highest share and second highest share identify the heterogeneity of the market random effect. The amount of entry, conditional on a set of potential entrants and their characteristics, will identify the mean level of fixed costs and revenue from connecting traffic. Unobserved heterogeneity in marginal costs and qualities will be identified from the joint distribution of market shares and prices, controlling for observables. For example, if qualities are heterogeneous and marginal costs are common, then equilibrium prices and market shares will be positively correlated, whereas if qualities are common and marginal costs are heterogeneous they would be negatively correlated. The distribution of fixed costs will be partly identified from how realized qualities and costs change as market size varies. For example, if all firms have the same fixed costs, then in small markets, which can only support one or two carriers, we would expect to see the firms with the highest qualities or lowest marginal costs as entrants, with weaker firms entering when we consider larger markets. On the other hand, if fixed costs are very heterogeneous we will be relatively more likely to see small markets served by some weaker firms, and strong competitors being amongst the additional entrants in larger markets. With a similar argument, the heterogeneity in connecting traffic revenue is identified.

[30] We are only using 2005 data.
[31] See Table 3 in Berry and Jia (2010).
[32] This is an approach frequently used in the empirical literature. See the discounting factor in Rust (1987).

4.2 Aside on Weakening the Known Move Order Assumption

Our current results assume a particular order of moves (highest average presence moves first) that is known to the econometrician. We have considered two possible ways to weaken this assumption. The first approach is to assume that the order of entry is probabilistic (although the exact order is known to all firms when they take their entry decisions), depending on factors such as cost, qualities and presence. In this case, it is possible to estimate the probabilistic function determining the order as part of estimation. The second approach is to be agnostic about the entry order, either by assuming that there is a sequential order of entry but that it is unknown to the econometrician, or that there is simultaneous entry but only pure strategy equilibria are played. [33] In both cases, an estimation procedure that roughly follows Ciliberto and Tamer (2009), in the sense of constructing upper and lower bounds on the moments (still using importance sampling), can be used. We have performed Monte Carlo experiments with these approaches, constructing confidence sets using the S1 criterion for critical values described in Andrews and Soares (2010), and have found them to work well as long as the number of parameters is not too large. In fact, the bounds on each parameter tend to be quite close together because, once quality and cost heterogeneity, and a specific model of competition is allowed for, it is unusual for more than one or two outcomes to be supported as different equilibria or by different orders. For the same reason, when we try to estimate a probabilistic order of entry we find that the estimates of the factors that determine the order tend to be very imprecise.

5 Estimation Results and Implications for the P.E.D.

Tables 4 and 5 presents estimates of the model parameters (for demand and cost, respectively). The estimates imply plausible elasticities for many quantities of economic interest. For example, on a monopoly market such as the one between Cincinnati (CVG) and Manch-

[33] Given the assumed form of competition, a pure strategy equilibrium can be shown to exist in the entry game, although mixed strategy equilibria could exist as well. As carriers have three choices there may be outcomes in the sequential game that could not be supported as pure strategy Nash equilibria in the sequential game. However, in both cases it is actually quite easy to calculate which outcomes could be supported by some order or by some set of pure strategies.

ester (MHT), Delta's mean own price elasticity is low at -0.83; Atlanta (ATL) to Dallas (DFW) market has 3 entrants, the mean own price elasticity for American Airline is -2.5; Atlanta (ATL) to San Francisco (SFO) has 6 entrants, the own price elasticity for United is -5.87. Consumers like high airport presence while dislike connecting service. Marginal costs average $355 dollars for legacy carriers and $327 for low-cost carriers for a 2461 mile route (the average distance for all markets in the data), increasing by approximately $55-90 per 1,000 miles for both carrier types. So for a 2,000 mile trip our estimated marginal costs are approximately $0.17 (direct) or $0.15 (indirect) per mile for legacy carriers and $0.15 (direct) or $0.13 (indirect) /mile for low-cost carriers. These numbers are comparable to the $0.16 and $0.11 per available seat mile of total operating expenses reported by legacy and low-cost carriers, respectively, on DOT form 41 in 2008. International hub and delay parameters in the fixed costs are not significant. The estimated average per-quarter fixed costs are around $1,313,456 for direct service without connecting traffic and $38,184 for indirect service. Connecting revenue is estimated to be around $604,996, which is nearly half of the direct fixed costs. The variances of α is estimated to be very small.

The estimates also imply that there is considerable unobserved heterogeneity in carrier qualities and costs, as well as some observed heterogeneity. Given the structure of our model, this implies that there will be selection. The following example illustrates what selection will produce in the data, and how it may affect merger counterfactuals.

Consider the George Bush Intercontinental (IAH) to Denver International (DEN) market. It was one of the markets directly affected by the UA/CO merger. In Q2 2005, CO (IAH hub), UA (DEN hub), and F9 provided non-stop service while AA provided connecting service, although there were five other potential entrants. Table 6 compares the marginal costs and quality component of quality implied by the observed prices and quantities for entering carriers and the unconditional (on entry) marginal costs and quality. First of all, we use the first order condition of profit function and match the model predicted shares to the observed shares in order to back out the implied marginal cost and implied $q_{jmd} + RE_m$ component in the utility function. The distribution of RE_m still needs to be calculated in order to back out the implied quality q. We use simulation to do so. We give the actual entrants the implied marginal costs and $q_{jmd} + RE_m$, and draw the marginal costs, q_{jmd}, and

RE_m for the non entering potential entrants according to the estimated distribution using the estimated parameters. We then collect 200 set of draws that support the observed market structure (meaning the non entering potential entrants in the data indeed do not enter with their simulated draws in the entry game), and calculate the mean of the RE_m from these 200 sets to be -0.6984 and standard deviation to be 0.3290. Since non entrants and entrants share the same RE_m, we then use this implied mean of RE to back out the implied q for all potential entrants. The unconditional marginal cost and q on the other hand are calculated for these service for each potential entrant based on the estimated model parameters (i.e., where we do not condition on the observed entry decisions) [34].

The table illustrates two types of selection. First, looking at the unconditional mean qualities, the model predicts that, because of their lower presence at IAH and DEN legacy carriers other than CO and UA would be less attractive to customers. Low cost carrier also has lower marginal cost compared to the legacy carriers, which gives aggregate low cost carrier ZZ advantage to enter the market. Second, relative to their unconditional means, the observed entrants have favorable quality and cost draws conditional on their service type, consistent with there also being selection on the unobserved part of these dimensions. Both types of selection will tend to make entry less likely and less effective at constraining prices if two incumbents merge.

To see this, consider the UA/CO merger. Out of many possible assumptions, we assume that the merged firm would inherit the higher of CO and UA's quality and the lower of CO and UA's cost draws in each direction, while ZZ would keep its pre-merger quality and cost of non-stop service and AA would keep its pre-merger quality and cost of connecting service. Table 7 shows that a simple counterfactual of this merger with no entry, the model predicts that the average price paid would increase by \$23 or 6.5%, and a resulting \$2.36 million loss in consumer welfare. We can, of course, also use our model to examine what would happen for different types of merger synergies and to test, using post-merger data, whether there is evidence for these in the data.

Now suppose that we allow for additional entry to occur. We will compare results from

[34] These values are calculated based on the mean values of α for the IAH-DEN market. The estimated variances of these parameters are not large, so drawing other values gives similar conclusions.

entry with selection to entry with no selection. Since the market random effect RE_m also plays a part in the selection process, but not related to the idea of our paper with respect to selection in quality and marginal cost, we conduct the following analysis by fixing RE_m at its posterior mean -0.6984 as mentioned above. To do entry with selection, we first compute the distribution of qualities and marginal and fixed costs for each type of service, using simulation by drawing from the estimated distributions, for the non-entrant carriers conditional on the fact that they chose not to enter before the merger, given the implied quality and marginal cost draws of the entrants and an assumed move order according to the average presence of these potential carriers. Because they chose not to enter, these conditional quality and cost distributions will be less favorable for the non-entrants than their unconditional counterparts. We then allow the pre-merger non-entrants to choose to enter using the above order when CO and UA are merged, again keeping the entry decision and service type for ZZ and AA fixed. Given our estimates, we predict that new non-stop entry will happen with low probability (1.5%), and connecting entry with probability 35.32%. However, even when non-stop entry occurs, prices always remain above pre-merger levels because the new entrants will have lower quality or higher costs than UA and CO did prior to the merger. We can see from the table, these new entrants are only able to bring down the price increase by little, and the resulting average price is still above the 5% rule-of-thumb-increase that the Guidelines suggest for problematic merger.

If we ignored selection, we would come to different conclusions. To illustrate, we assumed that the non-entrants had the same qualities for non-stop service as the average of implied qualities of the original entrants (CO, UA, AA and ZZ) which is similar to the assumption in the theory literature. We continue to use conditional marginal and fixed cost distributions for the non-entering firms (re-calculated so that they still do not want to enter before the merger). In this case, we would predict that at least one new carrier would enter non-stop with probability 14.85%, which is significantly higher than the 1% we get with selective entry. These additional new entrants bring down the expected average price such that the price increase compared to before merger is 3.94%. This price increase is now below the 5% rule-of-thumb-increase. In Table 7 we also show the results when the marginal costs instead of qualities for the non entrants are non selective, setting them to be the average implied marginal costs of the original entrants and follow the some procedure. The result is consistent with the results from no selection on the qualities but with a smaller magnitude in change of prices from entry with selection.

6 Conclusion

In this paper we develop an estimable model of airline route markets that is designed to allow us to answer the important policy question of whether new entry would constrain the exercise of market power after mergers. This question is particularly important in the hub-to-hub markets that we look at because there are usually only two carriers that provide direct service on the route, even though a lot of people travel on them. The key feature of our model is that the entry process is selective, so that the firms with better product quality or lower marginal costs, as well as lower fixed costs, are more likely to enter. Allowing for quality and marginal cost asymmetry enables us to consider both the likelihood of new entry and its sufficiency in constraining post-merger prices to be close to pre-merger levels. The Horizontal Merger Guidelines require that both likelihood and sufficiency are considered, but the existing theoretical and empirical literature, which assumes that potential entrants must be similar to incumbents, is only really appropriate for exploring the likelihood of entry, and even then is likely to be biased in favor of saying that entry will constrain post-merger market power.

Table 1: Summary Statistics for 2005 Airport-airport Sample.

Variable	Obs.	Mean	Std. Deviation	10th Percentile	90th Percentile
Potential Entrants	1,986	7.710	1.215	6	9
LCC	1,986	1.469	0.692	0	2
LEG	1,986	6.241	0.965	5	7
Entrants	1,986	4.252	1.911	2	7
Direct	1,986	0.660	0.823	0	2
Connecting	1,986	3.498	1.983	1	6
Hub Status	15,313	0.0761	0.265	0	0
If fly direct	1,311	0.596	0.491	0	1
Fare ($100)					
Direct	1,311	3.876	1.113	2.456	5.374
Connecting	6,948	4.063	0.891	2.927	5.207
Market Share					
Direct	1,311	0.180	0.111	0.0635	0.323
Connecting	6,948	0.0477	0.0515	0.00685	0.109
Probability of Direct Entry if					
Has hub on at least one end	1,166	0.671	0.470	0	1
Has hub on both ends	27	1	0	1	1

Note: An observation is a nondirectional airport pair. Fare and market share are the average across both directions for each carrier in each market. See text for variable definitions.

Table 2: Market Structure by Market Size (average of each direction) and Non-stop Distance Terciles Based on 2005 airport-airport sample.

		Mkt Size Tercile		
Direct Entrants		Small	Medium	Large
	Short	0.18	0.74	1.59
Distance Tercile	Medium	0.04	0.45	1.43
	Long	0.02	0.24	1.24
Connecting Entrants				
	Short	2.78	2.67	1.74
Distance Tercile	Medium	3.30	4.18	3.42
	Long	3.64	5.52	5.41

Table 3: Estimated Price Changes After the DL/NW and UA/CO Mergers.

Dependent Variable	Control Group	Fixed Effects	DL/NW β_1	UA/CO β_1
(1) Prices of merging carriers	Merging Carriers on Unaffected Non-Stop Routes	Quarter Route	0.084 (0.029)	0.154 (0.023)
(2) Prices of merging carriers	Merging Carriers & AA, US on Unaffected Non-Stop Routes	Quarter Carrier-Route	0.069 (0.028)	0.184 (0.020)

Table 4: Estimates of Demand Parameters.

		Estimate	Standard Error
Carrier Quality			
$\beta_{\mu,j}$	AA-US Fixed Effect	0.5610	0.0852
	WN Fixed Effect	0.8377	0.1160
	Other LEG Fixed Effect	0.2365	0.1202
	Other LCC Fixed Effect	0.6200	0.1114
σ_{μ}		0.5579	0.0577
Presence Effect			
β_{ψ}	Presence	1.4406	0.2090
σ_{ψ}		0.4047	0.0499
Market Random Effect			
σ_{re}		0.5250	0.1860
Connecting Penalty			
β_{ϕ}	Constant	0.3863	0.0922
σ_{ϕ}		0.3984	0.0633
Price Coefficient			
β_{α}	Constant	0.4550	0.0895
σ_{α}		0.0326	0.1545
Nesting Parameter (Not Estimated)		0.6500	

Table 5: Estimates of Cost Parameters.

		Estimate	Standard Error
Marginal Cost			
Legacy, Direct			
$\gamma_{c,\tau(j)}$	Constant	2.0608	0.1821
	Distance	0.7096	0.0616
$\sigma_{c,\tau(j)}$		0.4404	0.0699
Legacy, Indirect			
$\gamma_{c,\tau(j)}$	Constant	2.1723	0.1935
	Distance	0.4550	0.0661
$\sigma_{c,\tau(j)}$		0.4545	0.0601
Low Cost, Direct			
$\gamma_{c,\tau(j)}$	Constant	0.2586	0.5040
	Distance	1.2053	0.1921
$\sigma_{c,\tau(j)}$		0.4602	0.1580
Low Cost, Indirect			
$\gamma_{c,\tau(j)}$	Constant	1.8114	0.1267
	Distance	0.6176	0.0453
$\sigma_{c,\tau(j)}$		0.2045	0.0423
Fixed Cost			
Direct			
$\gamma_{F,\tau(j)}$	Constant	13134.5594	1143.5425
	Interntional Hub	1251.9702	785.5771
	Delay	-5099.9983	6544.7673
$\sigma_{F,\tau(j)}$		4719116.2389	762023.9825
Indrect			
$\gamma_{F,\tau(j)}$		381.8359	11.2845
$\sigma_{F,\tau(j)}$		3197.2333	1258.6987
Connecting Traffic Revenue			
γ_C	Constant	6049.9594	1292.7018
	Connect Traffic	-0.3152	1.4487
σ_C		331123.1796	1957304.0891

Table 6: Implied Carrier Qualities and Marginal Costs for IAH to DEN.

				Quality (average of two directions)			MC		
	Service Type	Mean Price	No. of Passengers	Implied	Unconditional Direct	Unconditional Indirect	Implied	Unconditional Direct	Unconditional Indirect
American AA	Indirect	$295	620	0.531	0.911	0.055	2.175	3.283	2.954
Continental CO	Direct	$368	32270	2.216	1.453	0.055	2.084	3.283	2.954
Delta DL	No entry	-		-	0.905	0.055	-	3.283	2.954
Northwest NW	No entry	-		-	0.907	0.055	-	3.283	2.954
United UA	Direct	$352	12655	1.828	1.427	0.055	2.546	3.283	2.954
US Airways US	No entry	-		-	0.908	0.055	-	3.283	2.954
Southwest WN	No entry	-		-	0.838	0.331	-	2.336	2.878
Other Legacy YY	No entry	-		-	0.237	-0.270	-	3.283	2.954
Other Low cost ZZ	Direct	$328	8655	1.595	0.620	0.114	2.388	2.336	2.878

Table 7: UA/CO Merger

	Before Merger	After Merger			
		no entry	entry with selection	entry with no selection	
				MC	Quality
Direct entry probability	-	-	1.49%	6.93%	14.85%
Other entry probability	-	-	35.32%	31.68%	34.65%
Average Prices of original entrants	3.56	3.79	3.76	3.73	3.70
Average Prices of all entrants	-	-	3.78	3.76	3.72
Consumer welfare	$16,719,208	$14,356,898	$14,450,680	$14,573,165	$14,794,473
Average price percentage increase	-	6.46%	5.65%	4.84%	3.94%

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A Monte Carlo Studies of Alternative Equilibrium Selection Methods

In this appendix we present several Monte Carlo studies of the estimation procedure outlined in Section 4 for different equilibrium selection approaches. To simplify things they are performed on a model with fewer parameters, albeit one with a richer nesting structure. In this model there is no distinction between direct and indirect entry but carriers continue to be distinguished by whether they are an LEG or LCC. In this model there is a two-level nesting structure for demand. The highest level of nest is the fly/don't fly decision. The next level of nest, conditional on choosing to fly, is whether to fly a LEG or LCC carrier.

As discussed in Section 4, we considered two weaker assumptions about the order in which potential entrants move. The first approach assumes that the order of entry, which affects the equilibrium outcome in the sequential move game, is probabilistic (although the exact order is known to all firms when they take their entry decisions) and depends on firm characteristics. In this case, it is possible to estimate the probabilistic function determining the order as part of estimation.

The other approach is to be agnostic about the entry order, either by assuming that there is a sequential order of entry but that it is unknown to the econometrician, or that there is simultaneous entry but only pure strategy equilibria are played. This approach builds on Ciliberto and Tamer (2009). For a given simulated value of structural parameters, θ_s, we can solve for all of the equilibria of the entry game. For this value of parameters, across all of these equilibria we can compute outcomes of the game that will form the moments that we are interested in matching. This set of outcomes will have an upper and lower value, which we denote $f^{UB}_{ms}(\theta_{ms})$, and $f^{LB}_{ms}(\theta_{ms})$, respectively. We then can approximate the moments in the data as in Equation (3):

$$E[f^{UB}_m(\theta)|\widehat{\Gamma}] \approx \frac{1}{S}\sum f^{UB}_{ms}(\theta_s)\frac{\phi(\theta_s|X_m,\widehat{\Gamma})}{g(\theta_s|X_{jm})} \tag{4}$$

$$E[f^{LB}_m(\theta)|\widehat{\Gamma}] \approx \frac{1}{S}\sum f^{LB}_{ms}(\theta_s)\frac{\phi(\theta_s|X_m,\widehat{\Gamma})}{g(\theta_s|X_{jm})} \tag{5}$$

This approach differs from Ciliberto and Tamer (2009) in that they need to re-solve for all equilibria each time that they change one of the parameters. We calculate confidence sets using the method of generalized moment selection in Andrews and Soares (2010) and use their S1 criterion with an asymptotic approach to calculating critical values.[35]

To perform the Monte Carlo studies below, we consider data where markets differ according to size and the set of potential entrants. All markets have 6 potential entrants, either 4 LEG and 2 LCC or 2 LEG and 4 LCC, and the market size is defined as either 100 or 150. In each market we observe the set of entrants, equilibrium prices and market shares. We specify 11 moments to match for each type of market based on number of entrants, market shares and prices of each type of entrant.

Table 8 reports the results of three Monte Carlo experiments of this model that differ in their equilibrium selection assumptions. In the first column, the order of entry in the data is random and we assume that this is known to the researcher. This is the assumption most akin to what we do when we estimate our model above. In the second column legacy carriers are more likely to move first according to a probabilistic order selection function where the probability that a firm j is chosen to be next in the order when there are K firms remaining is given by a logit function $\frac{\exp(LEG_j \Psi^{ORDER})}{\sum_{k=1}^{K} \exp(LEG_k \Psi^{ORDER})}$, where LEG_j is an indicator for whether carrier j is a LEG firm, and we estimate the strength of this effect (Ψ^{ORDER}), although the importance sample draws assume a random order. In the final column the entry order in the data is random, but we only assume that a pure strategy equilibrium is played. In this case, for a given parameter vector, we solve for all of the pure strategy equilibria and use the set of equilibria to form lower and upper bounds for each moment (in some cases they will be the same number). We use the S1 criterion for critical values described in Andrews and Soares (2010)'s Generalized Moment Selection procedure to estimate lower and upper bounds for the confidence set for each parameter, which are the numbers reported in the table.[36] The estimation method accurately recovers the structural taste and cost parameters in each of the three specifications. The fact that the bounds on each parameter in the third

[35] There recently has been a good deal of research on constructing confidence sets for partially identified parameters in moment (in)equality models (e.g. Imbens and Manski (2004), Chernozhukov et al. (2007), Bugni (2010)).

[36] We calculate these bounds by searching for the lowest and highest values of the particular parameter where the value of an objective function is less than a critical value.

experiment are close together reflects the fact that it is unusual for more than one or two outcomes to be supported as different equilibria or by different orders. For the same reason, we find that the estimates of the factors that determine the order tend to be very imprecise in the second column.

B Construction of the Connecting Traffic Variable

While we do not try to model an airline's decision about how to configure its entire network, we do need to account for the fact that connecting traffic may influence route-level entry decisions. For example, 65.3% of the passengers orginating in Raleigh-Durham (RDU) who fly on Delta to Atlanta do not have Atlanta as their final destination, but instead go onto cities such as San Francisco. The ability to serve these passengers will make it more attractive for Delta to provide direct service between RDU and ATL. The ability to serve connecting passengers is likely to be particularly important when considering routes into hub airports that are in smaller cities, such as Charlotte, NC.

We view the development of a fully structural model where passengers make choices over the complete range of possible connections as beyond the scope of this paper. Instead we proceed by developing a more 'reduced-form' model of how many people connecting passengers fly on a particular carrier-route segment (e.g., DL on RDU-ATL) out of those taking connections on a longer origin-destination pair (e.g., DL on RDU-SFO), taking into account that the set of carrier-route segments that we observe being served will be a selected sample, by using a two-step Heckman selection approach. We then aggregate up over the carrier origin-destination pairs that use a particular segment (e.g., DL on RDU-SFO and DL on RDU-LAX) to get a prediction of how many connecting passengers will be served if DL flies the segment RDU-ATL. It turns out that we are able to predict how many people use a particular segment as part of a connecting service very well, and our model allows us to make predictions about how many connecting passengers would be served on a segment that we do not currently observe in the data.[37] Of course, this does not tell us

[37] This is true even though our model does not use additional information that will affect connecting choices such as the time between flights.

how valuable these passengers are to the carrier because we do not know a carrier's expected marginal profit of serving a connecting passenger. We can however estimate the value of these connecting passengers when estimating the route-level entry model, using the predicted number of passengers as a covariate.

Model

We take the number of passengers who travel connecting for a given origin-destination pair as given, and instead focus on the connecting airport through which they decide to travel.[38] We assume that from the set of routes that are available for one-stop connections, their choices of which one to choose are made according to a simple logit choice model. The market share s_{cj} of a carrier (c)-connection (j) that is available will be

$$s_{cj} = \frac{\exp(X_{cj}\beta + \xi_{cj})}{1 + \sum_l \sum_k \exp(X_{lk}\beta + \xi_{lk})} \tag{6}$$

where (l, k) are other available carrier-connections and X_{cj} are observed carrier-connection characteristics and ξ_{cj} is an unobserved component, and we are normalizing the $X\beta$ for one of the possible choices to be zero.[39] The outside choice (choice 0) that we will use is the aggregation of all possible carrier-connections that are not makde using a hub (we will define what carrier-airport combinations we consider to be hubs below): for example, travelling from JFK to ATL via RDU on Delta (RDU is not a hub), or travelling from RDU to DFW via ATL on American. In this case we can define

$$\log(s_{cj}) - \log(s_0) = X_{cj}\beta + \xi_j \tag{7}$$

[38] We will only use passengers who make one connection in any direction to estimate our model (allowing for the fact that they might not use the same connecting airport if they connect both ways). FACT ON SIZE OF FLOW. Note that this is not inconsistent with our route level model. For example, when we are looking at the RDU-ATL route market we take into account the fact that entry and pricing decisions on that route will affect how many people fly indirectly between these airports. However, when looking at this route we will take the number of people who fly indirectly between RDU and SFO as given, in the same way that we are treating airport presence (determined by entry decisions on other routes) as given. As a robustness check we can also estimate our connecting entry model using earlier quarters of data and show that our results are similar.

[39] As we do not have prices in this model, we will not try to give it a utility interpretation, although it will be affected by things such as travel distance that will indirectly affect utility.

We could estimate equation (7) directly by OLS if we assumed that $E(\xi_j|X_j) = 0$. For X_js we use are variables that we are treating as exogenous (in this case, airport presence variables and functions of geography such as distances and populations), but the assumption may still fail because of selection. In particular, a carrier may be more likely to be serving a route where it is likely to have a large share of connecting traffic, and we only observe the market share when a carrier serves the route. We address this issue by modelling the probability that the carrier enters (which will mean it serves both of the segments for the connecting route directly e.g., DL serving both RDU to ATL and ATL to SFO) using a probit, i.e.,

$$\Pr(c \text{ serves route } j) = \Phi\left(W_{cj}\gamma\right) \tag{8}$$

which facilitates estimation using a Heckman procedure where we allow for the residuals in (8) and (7) to be correlated. The results are very similar using a two-step approach (which does not impose that the ξ_js are normally distributed) and a maximum likelihood approach, with the correlation of the predicted values in (7) exceeding 0.999, so we report the more efficient maximum likelihood estimates below.

Considering the logic of our model allows us to define some exclusion restrictions that facilitate identification of this system. For example, whether Delta offers direct service between RDU and ATL and ATL and SFO will largely be driven by factors that are relevant for the choices of consumers who want to travel only these segments but would not necessarily the effect the choices of travellers who are trying to go from RDU to SFO. For example, the size of Raleigh-Durham and Atlanta populations (and their interaction) will increase demand on the RDU-ATL route and so will tend to make entry into that route more likely, but, conditional on entry, the size of neither city's population should necessarily affect whether people going from RDU to SFO decide to fly via Atlanta or a smaller city such as Charlotte. In X_{cj} we include carrier c's presence at the origin and its square, its presence at the destination and its square, the interaction between carrier c's origin and destination presence, the distance involved in flying route j divided by the non-stop distance between the origin and destination (call this the 'relative distance'), an indicator for whether route j is the shortest route involving a hub, an indicator for whether j is the shortest route involving a hub for carrier c and the interaction between these two indicator variables and the relative distance. In W_{cj} we include origin, destinaton and connecting airport presence for carrier c; the interactions of origin and connecting airport presence and of destination and connecting airport presence; origin, destinaton 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[40]; indicators for whether either of the origin or destination airports is an airport with limitations on how far planes can fly (LaGuardia and Washington 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 (LaGuardia, JFK, Newark and Washington National). In both X_{cj} and W_{cj} we also include origin, destination and carrier-connecting airport dummies.

To construct our estimation sample we first construct the set of all possible carrier-origin-destination-connecting airport combinations using the 100 largest airports in the US (based on the number of originating passengers - this set includes all of the airports we use when estimating our full model) and the 14 largest carriers. See Table 9 for examples of these combinations. This involves breaking up the 'other LCC' carrier that we use in our full model into Airtran, Frontier, JetBlue and XX and our 'other legacy' carrier into Alaska Airlines, America West and . As our sample of passengers we identify from the DB1B data 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 both directions; and, (ii) have only one ticketing carrier for their entire trip which is one of the carriers just listed. 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 travelling 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 drop [distance, number of travellers].

As mentioned above, we focus on connections involving hub airports and not connections

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

involving airports that are not hubs. This is just to capture the fact that it is really at hubs that connecting traffic has a potentially important effect on entry and exit decisions. While there are many different ways to define hubs, given our purpose we use the airport-carrier combinations where the carrier connects at least 10,000 of the connecting DB1B passengers that we identified above in our Q2 2005 data. The resulting set of carrier-hubs is defined in the following table:

One point to note is that some airports that are often called 'hubs' do not make this list. Examples would be Newark for Continental (8.1k connecting passengers) and San Francisco for United (8.4k). These carriers do have a large number of flights from these airports, but these flights primarily serve people leaving or visiting the associated large cities rather than connecting onto other domestic flights. Our data does contain people making international connections. In our full model we allow for the number of international connections served from a city to have a separate effect on the profitability of serving domestic routes into an airport.

We define a carrier as being 'present' in an origin-destination-connecting airport triple if it (or its regional affiliates) fly at least one flight per day during the quarter on each of the segments, based on the T100 data, and serves at least some connecting passengers via this connection. We also drop any triple where the connecting airport is less than 100 miles from the origin or the destination (this leaves some relatively close pairs such as Raleigh-Durham and Charlotte in our sample). For estimation, we consider origin-destination pairs which at least 25 passengers travel using connecting service and at least some passengers choose our outside option of connecting via other airports, which 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.

The results of the Heckman selection model estimation are reported below. Standard errors are clustered on the carrier-connecting airport combination, and, for this sample of data, the correlation in the residuals in the two equations is estimated to be statistically insignificant. The signs on the coefficients on the other variables generally make sense when they are significant. For example, shorter connecting routes are more popular than longer ones, as are connecting routes served by carriers that have large presence at the origin or destination. Routes are more likely to be served when the carrier has a large presence at the origin, destination and the connecting airport.

Our model predicts values of $X\beta$ for carrier-origin-destination-connecting airport combinations. However, as an input to our model we are interested in how well the model predicts the amount of traffic that a carrier will have when it offers direct service between an airport and a hub (for example, between RDU and Atlanta, where passengers may be going from RDU to a large number of possible destinations or going from anyone of a large number of originating airports to RDU). When we aggregate up to this level, the estimated model does a pretty accurate job of predicting how many people travle giving the set of routes that airlines currently fly. For the identified legacy carriers (AA, CO, DL, NW, UA, US), 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. The model also does a good job of predicting some of the variation created by geography. For example, the model predicts that AA should serve 2,247 connecting passengers on RDU-DFW, 1213 on RDU-ORD and 376 on RDU-STL, which compares with observed numbers of 2,533, 1197 and 376. On the other hand, from Boston the model correctly predicts that AA will serve more connecting traffic via ORD (2265, observed 2765) than DFW (2040, observed 2364).

Table 8: Monte Carlo Results for Different Assumptions on Entry Order

Parameter/ (Distribution Family)	Truth	Random Eqm. Selection	Parametric Eqm. Selection	Assume Pure Strat. Eqm.
LEG Marginal Cost ($LogN$)	{Mean, Var.} ={0.4, 0.01}	{0.40, 0.01} (0.01) (0.002)	{0.40, 0.01} (0.008) (0.002)	{[0.39,0.41], [0.008,0.012]} {[0.003,0.003], [0.001,0.001]}
LCC Marginal Cost ($LogN$)	{Mean, Var.} ={0.2, 0.01}	{0.20, 0.01} (0.01) (0.004)	{0.20, 0.01} (0.01) (0.003)	{[0.19,0.21], [0.007,0.013]} {[0.003,0.003], [0.001,0.001]}
LEG Fixed Cost ($LogN$)	{Mean, Var.} ={3.0, 0.25}	{3.02, 0.26} (0.12) (0.09)	{3.01, 0.25} (0.11) (0.08)	{[2.92,3.07], [0.011,0.722]} {[0.024,0.013], [0.002,0.104]}
LCC Fixed Cost ($LogN$)	{Mean, Var.} ={2.0, 0.25}	{1.99, 0.24} (0.11) (0.10)	{2.01, 0.24} (0.11) (0.08)	{[1.95,2.05], [0.02,0.65]} {[0.018,0.012], [0.019,0.086]}
LEG Quality, β^{LEG} (N)	{Mean, S.D.} ={1.5, 0.4}	{1.52, 0.37} (0.07) (0.07)	{1.50, 0.39} (0.06) (0.07)	{[1.47,1.53], [0.32,0.46]} {[0.005,0.008], [0.029,0.015]}
LCC Quality, β^{LCC} (N)	{Mean, S.D.} ={0.5, 0.4}	{0.51, 0.40} (0.06) (0.06)	{0.49, 0.40} (0.04) (0.06)	{[0.48,0.53], [0.34,0.45]} {[0.005,0.006], [0.021,0.013]}
Price Sensitivity, α (LN)	{Mean, Var.} ={3.0, 0.25}	{3.03, 0.25} (0.11) (0.05)	{2.99, 0.25} (0.12) (0.05)	{[2.97,3.03], [0.21,0.29]} {[0.01,0.01], [0.01,0.01]}
{Fly, No Fly} Nest, γ_1 (TRN)	{Mean, S.D.} ={0.8, 0.03}	{0.80, 0.03} (0.02) (0.01)	{0.80, 0.03} (0.02) (0.01)	{[0.78,0.82], [0.001,0.058]} {[0.004,0.006], [0.0003,0.011]}
$\{LEG, LCC\}$ Nest, γ_2 (TRN)	{Mean, S.D.} ={0.4, 0.03}	{0.40, 0.03} (0.01) (0.01)	{0.40, 0.03} (0.01) (0.01)	{[0.39,0.41], [0.001,0.057]} {[0.003,0.002], [0.001,0.009]}
Ψ^{ORDER}	1.0	N/A	0.74 (0.46)	N/A

Note: The random order and parametric equilibrium approaches use 1000 obs. with 5 sims/obs. When we only assume that pure strategy equilibria are played, we use 5000 obs. with 5 sims/obs. The first two columns of estimates give the mean and standard deviation (in parentheses) of the estimates across 100 replications. The last column gives the mean and standard deviation of the upper and lower bound for each parameter across 10 replications.

Table 9: Examples of Airport-Airline Pairs

Airline	**Airports Defined As Hub For Airline**
American (AA)	Dallas-Fort Worth (DFW, 104.4k), Chicago O'Hare (ORD, 51.8k), St. Louis (STL, 11.3k)
Continental (CO)	Houston Intercontinental (IAH, 61.3k), Cleveland (CLE, 11.2k)
Delta (DL)	Atlanta (ATL, 167.7k), Cincinnati (CVG, 69.4k), Salt Lake City (SLC, 32.0k)
Frontier (F9)	Denver (DEN, 17.8k)
Independence Air (DH)	Washington Dulles (IAD, 19.7k)
Airtran (FL)	Atlanta (ATL, 32.4k)
America West (HP)	Phoenix (PHX, 50.2k), Las Vegas (LAS, 12.5k)
Northwest (NW)	Detroit (DTW, 67.4k), Minneapolis (MSP, 69.7k), Memphis (MEM, 29.8k)
United (UA)	Chicago O'Hare (ORD, 67.4k), Denver (DEN, 53.8k), Washington Dulles (18.1k)
Southwest (WN)	Phoenix (PHX, 18.0k), Las Vegas (LAS, 15.0k), Chicago Midway (14.8k), Baltimore (BWI, 13.3k)
US Airways (US)	Charlotte (CLT, 76.9k), Philadelphia (PHL, 32.1k), Pittsburgh (PIT, 13.5k)