# Market Structure and Competition in Airline Markets *

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**Abstract**

We provide an econometric framework for estimating a game of simultaneous entry and pricing decisions in oligopolistic markets while allowing for correlations between unobserved fixed costs, marginal costs, and demand shocks. Firms' decisions to enter a market are based on whether they will realize positive profits from entry. We use our framework to quantitatively account for this *selection problem* in the pricing stage. We estimate this model using cross-sectional data from the US airline industry. We find that not accounting for endogenous entry leads to overestimation of demand elasticities. This, in turn, leads to biased markups, which has implications for the policy evaluation of market power. Our methodology allows us to study how firms optimally decide entry/exit decision in response to a change in policy. We simulate a merger between American and US Airways and we find that the post-merger market structure and prices depend crucially on how we model the characteristics of the post-merger firm as a function of the pre-merger firms' characteristics. Overall, the merged firm has a strong incentive to enter new markets; the merged firm faces a stronger threat of entry from rival legacy carriers, as opposed to low cost carriers; and, post-merger entry mitigates the adverse effects of increased concentration.

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# 1 Introduction

We estimate a simultaneous, static, complete information game where economic agents make both discrete and continuous choices. We study airlines that strategically decide whether to enter into a market *and* the prices they charge if they enter. Our aim is to provide a framework for combining both entry and pricing into one empirical model that allows us: i) to account for selection of firms into serving a market (or account for endogeneity of product characteristics) and, more importantly, ii) to allow for market structure to adjust as a response to counterfactuals, such as mergers.

Generally, firms self-select into markets that best match their observable and unobservable characteristics. For example, high quality products command higher prices, and it is natural to expect high quality firms to self-select into markets where there is a large fraction of consumers who value high-quality products. Previous work has taken the market structure of the industry, defined as the identity and number of its participants (be they firms or, more generally, products or product characteristics) as exogenous when estimating the parameters of the demand and supply relationships.[1] That is, firms, or products, are assumed to be randomly allocated into markets. This assumption has been necessary to simplify the empirical analysis, but it is not always realistic.

Non-random allocation of firms across markets can lead to self-selection bias in the estimation of the parameters of the demand and cost functions. Existing instrumental variables methods that account for endogeneity of prices do not resolve this selection problem in general.[2] Potentially biased estimates of the demand and cost functions can then lead to mis-measuring demand elasticities, and consequently market power. This is problematic because correctly measuring market power and welfare is crucial for the application of antitrust policies and for a full understanding of the competitiveness of an industry. For example, if the bias is such that we infer firms to have more market power than they actually have, the antitrust authorities may block the merger of two firms that would improve total welfare,

[1] See (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995) and the large subsequent literature in IO that uses this methodology.

[2] This point was previously made by Olley and Pakes (1996) for the estimation of production functions.

possibly by reducing an excessive number of products in the market. Importantly, allowing for entry (or product variety) to change as a response say to a merger is important as usually when a firm (or product) exits, it is likely that other firms may now find it profitable to enter (or new products to be available). Our empirical framework allows for such adjustments.

More generally, our model can also be viewed as a multi-agent version of the classic selection model (Gronau, 1974; Heckman, 1976, 1979). In the classic selection model, a decision maker decides whether to enter the market (e.g. work), and is paid a wage conditional on working. When estimating wage regressions, the selection problem deals with the fact that the sample is selected from a population of workers who found it "profitable to work." Here, firms (e.g. airlines) decide whether to enter a market and then, conditional on entry, they choose prices. Our econometric model accounts for this selection when estimating demand and supply equations, as in the single-agent selection model.

Our model consists of the following conditions: i) entry inequalities that require that, in equilibrium, a firm must be making non-negative profit in each market that it serves; ii) demand equations derived from a discrete choice model of consumer behavior; iii) pricing first-order-conditions, which can be formally derived under the postulated firm conduct. We allow for all firm decisions to depend upon market- and firm-specific random variables (structural errors) that are observed by firms but not the econometrician. In equilibrium firms make entry and pricing decisions such that all three sets of conditions are satisfied.

A set of econometric problems arises when estimating such a model. First, there are multiple equilibria associated with the entry game. Second, prices are endogenous as they are associated with the optimal behavior of firms, which is part of the equilibrium of the model. Finally, the model is nonlinear and so poses a heavy computational burden. We combine the methodology developed by Tamer (2003) and Ciliberto and Tamer (2009) (henceforth CT) for the estimation of complete information, static, discrete entry games with the widely used methods for the estimation of demand and supply relationships in differentiated product markets (see Berry, 1994; Berry, Levinsohn, and Pakes, 1995, henceforth BLP). We simultaneously estimate the parameters of the entry model (the observed fixed costs and the variances of the unobservable components of the fixed costs) and the parameters of the demand and supply relationships.

To estimate the model we use cross-sectional data on the US airline industry.[3] The data are from the second quarter of 2012's Airline Origin and Destination Survey (DB1B). We consider markets between US Metropolitan Statistical Areas (MSAs), which are served by American, Delta, United, USAir, Southwest, and low cost carriers (e.g. Jet Blue). We observe variation in the identity and number of potential entrants across markets.[4] Each firm decides whether or not to enter and chooses the price in that market.[5] The other endogenous variable is the number of passengers transported by each firm. The identification of the three conditions relies on variation in several exogenous explanatory variables, whose selection is supported by a rich and important literature, for example Rosse (1970), Panzar (1979), Bresnahan (1989), and Schmalensee (1989), Brueckner and Spiller (1994), Berry (1990), Ciliberto and Tamer (2009), Berry and Jia (2010), and Ciliberto and Williams (2014).

We begin our empirical analysis by running a standard GMM estimation (see Berry, 1994) on the demand and pricing first order conditions and comparing that to our proposed methodology with exogenous entry. Next, we estimate the model with endogenous entry using our methodology and compare the results with the exogenous entry results. We find that using our methodology and allowing for endogenous entry, the price coefficient in the demand function is estimated to be closer to zero than the case of exogenous entry, and markups are substantially larger. Next, we use our estimated model to simulate the merger of two airlines in our data: American and US Airways.[6] Typical merger analysis involves predicting changes in market power and prices *given* a particular market structure using diversion ratios based on pre-merger market shares, or predictions from static models of product differentiation (see Nevo, 2000). Our methodology allows us to simulate a merger

[3]We also illustrate our methodology by conducting a Monte Carlo exercise, see the Appendix.

[4]A market is defined as a unidirectional pair of an origin and a destination airport, as in Borenstein (1989), Berry and Jia (2010), and Ciliberto and Williams (2014). An airline is considered a potential entrant if it is serving at least one market out of both of the endpoint airports. See the Appendix for more details.

[5]In practice we use the median of the prices observed in a market in a quarter, where each individual price is weighted by the number of passengers on that ticket.

[6]The two firms merged in 2013 after settling with the Department of Justice.

allowing for equilibrium changes to market structure after a merger, which in turn may affect equilibrium prices charged by firms. Market structure reactions to a merger are an important concern for policy makers, such as the DOJ, as they often require entry accommodation by merging firms after the approval of a merger.[7] Our methodology can help policy makers understand in the context of our model how equilibrium entry would change after a merger, which would, in turn, help target tools like the divestiture of airport gates.

There are several findings from the merger analysis, which depend, crucially, on on how we model the characteristics of the post-merger firm as a function of the pre-merger firms' characteristics. We consider three different scenarios. First, we assume that the merged firm takes on the best characteristics, both observed and unobserved, of the two pre-merger firms, and call this the *Best Case Scenario*. In two other cases, we assume that the post-merger firm inherits the average of the observed characteristics of the pre-merger firms, and, either the average of the unobserved (simulated) characteristics (*Average Case Scenario*); or a new random draw of the unobserved characteristics (*Random Case Scenario*).

We find that under all three scenarios there is substantial post-merger entry and exit among the remaining airlines, especially for the surviving merged airline, American Airlines. The results are more complex with respect to prices and welfare. In the *Best Case Scenario*, markets would experience an average price decrease, and an increase in consumer welfare and total industry profits. The welfare gains are explained by price decreases and by increased entry by the new merged firm, especially in markets that were not previously served by any carrier. However, under the other two scenarios, where the post-merger efficiency gains are maintained to be smaller, the average price would increase, and both consumer welfare and profits would decrease.[8]

We find that there is significant heterogeneity in the merger effects across markets. In

[7]For example, in the two most recent large airline mergers (United and American), the DOJ required the merging firms to cede gate access at certain airports to competitors.

[8]Determining the efficiency gains from a merger is a difficult empirical exercise that is at the center of all merger investigations by the federal agencies. In some cases it takes a long time for the efficiencies to be fully realized, and it is not always possible to identify their magnitude. Our approach shows how we can quantify these efficiencies under various plausible assumptions. This should provide a promising approach for future research in antitrust merger research.

markets where American and USAir were in a duopoly and now act as a monopolist, the prices would drop under the *Best Case Scenario*, suggesting that the cost efficiencies are so substantial that upward pricing pressure due to increased concentration is offset by the cost gains. Under the other two scenarios, prices rise, although there is still entry by AA in some markets, and exit by other airlines in some other markets. We also find that the merged firm faces a stronger threat of entry from rival legacy carriers, as opposed to low cost carriers. Under the "Average Case Scenario" and the "Random Case Scenario" we find that the prices would not change when DL or UA enters into the market previously an AA/US duopoly. Prices would rise substantially in the case of the low cost carriers and WN. We find similar results when we consider markets where American was *not present* pre-merger.

Finally, we investigate the effects of the merger in markets originating or ending in DCA, which were of concern for antitrust authorities because both of the merging parties had a very strong incumbent presence. When we maintain that AA experiences large efficiencies, we predict that prices would decrease even though concentration decreases. In the other cases we find that prices would increase slightly along with concentration. In all cases, low-cost carriers are not likely to replace the exiting US Airways, which was a major concern for the DOJ and resulted in landing slot divestitures by the merging party.

There is important work that has estimated static models of competition while allowing for market structure to be endogenous. Reiss and Spiller (1989) estimate an oligopoly model of airline competition but restrict the entry condition to a single entry decision. In contrast, we allow for multiple firms to choose whether or not to serve a market. Cohen and Mazzeo (2007) assume that firms are symmetric within types, as they do not include firm specific observable and unobservable variables. In contrast, we allow for very general forms of heterogeneity across firms. Berry (1999), Draganska, Mazzeo, and Seim (2009), Pakes et al. (2015) (PPHI), and Ho (2008) assume that firms self-select themselves into markets that better match their observable characteristics. In contrast, we focus on the case where firms self-select themselves into markets that better match their observable and *unobservable* characteristics. There are two recent papers that are closely related to ours. Eizenberg (2014) estimates a model of entry and competition in the personal computer industry. Estimation relies on a timing assumption (motivated by PPHI) requiring that firms do not know their own product quality or marginal costs before entry, which limits the amount of selection captured by the model.[9] Similar timing assumptions are made by other papers as well, such Sweeting (2013), Lee (2013), Jeziorksi (2014b), Jeziorksi (2014a) in dynamic empirical games; and Fan (2013) and Fan and Yang (2017) in static games.[10] The other paper that is closely related to ours is Li et al. (2017), who estimate a model of service selection (nonstop vs connecting) and price competition in airline markets, but only consider sequential move equilibria. In addition, Li et al. (2017) do not allow for correlation in the unobservables, which is a key determinant of self-selection that we investigate in this paper.

The paper is organized as follows. Section 2 presents the methodology in detail in the context of a bivariate generalization of the classic selection model, providing the theoretical foundations for the empirical analysis. Section 3 introduces the economic model. Section 4 introduces the airline data, providing some preliminary evidence of self-selection of airlines into markets. Section 5 shows the estimation results and Section 6 presents results and discussion of the merger exercise. Section 7 concludes.

## 2 A Simple Model with Two Firms

We illustrate the inference problem with a simple model of strategic interaction between two firms that is an extension of the classic selection model. Two firms simultaneously make an

[9] If we are willing to make this timing assumption, there would not be a selection on *unobservables*, because the firm would only observe the demand and marginal cost shock after entering. In markets where there is a long lag between the entry/characteristic decision and the pricing decision, such as car manufacturing or computer manufacturing, such timing assumption would seem a reasonable assumption. In the airline industry, firms can enter and exit market quickly, as long as they have access to gates. So the timing assumption is less plausible. Generally, a prudent approach would be to allow for correlation in the unobservables, and if that is non zero, then we could conclude that the timing assumption would be less acceptable.

[10] There is also an empirical literature on auctions (Li and Zheng (2009), Gentry and Li (2014), Roberts and Sweeting (2013), Li and Zhang (2015)) that has relaxed, in static models, the assumption that unobservable payoff shocks are not known at the time entry decisions are taken. However, in contrast to this literature, we allow for multiple, possibly *correlated*, unobservables.

entry/exit decision and, if active, realize some level of a continuous variable. Each firm has complete information about the problem facing the other firm. We first consider a stylized version of this game written in terms of linear link functions. This model is meant to be illustrative, in that it is deliberately parametrized to be close to the classic single agent selection model. This allows for a more transparent comparison between the single vs multi agent model. Section 3 analyzes a full model of entry and pricing.

Consider the following system of inequality conditions,

$$\begin{aligned} y_1 &= 1\left[\delta_2 y_2 + \gamma Z_1 + \nu_1 \geq 0\right], \\ y_2 &= 1\left[\delta_1 y_1 + \gamma Z_2 + \nu_2 \geq 0\right], \\ S_1 &= X_1\beta + \alpha_1 V_1 + \xi_1, \\ S_2 &= X_2\beta + \alpha_2 V_2 + \xi_2 \end{aligned} \tag{1}$$

where $y_j = 1$ if firm $j$ decides to enter a market, and $y_j = 0$ otherwise for $j \in \{1, 2\}$. So $\{1, 2\}$ is the set of *potential* entrants. The endogenous variables are $(y_1, y_2, S_1, S_2, V_1, V_2)$. We observe $(S_1, V_1)$ if and only if $y_1 = 1$ and $(S_2, V_2)$ if and only if $y_2 = 1$. The variables $\mathbf{Z} \equiv (Z_1, Z_2)$ and $\mathbf{X} \equiv (X_1, X_2)$ are exogenous where $(\nu_1, \nu_2, \xi_1, \xi_2)$ are unobserved and are independent of $(\mathbf{Z}, \mathbf{X})$ while the variables $(V_1, V_2)$ are endogenous (such as prices or product characteristics).[11]

The above model is an extension of the classic selection model to cover cases with two decision makers and allows for the possibility of endogenous variables on the rhs (the $V$'s). The key distinction is the presence of simultaneity in the 'participation stage' where decisions are interconnected.

We first make a parametric assumption on the joint distribution of the errors. Let the unobservables have a joint normal distribution,

$$(\nu_1, \nu_2, \xi_1, \xi_2) \sim N(0, \Sigma),$$

where $\Sigma$ is the variance-covariance matrix to be estimated. The off-diagonal entries of the variance-covariance matrix are not generally equal to zero. Such correlation between the

[11]It is simple to allow $\beta$ and $\gamma$ to be different among players, but we maintain this homogeneity for exposition.

unobservables is one source of the selectivity bias.[12]

One reason why we would expect firms to self-select into markets is because the fixed costs of entry are related to the demand and the variable costs. One would expect products of higher quality to be, at the same prices, in higher demand than products of lower quality and also to be more costly to produce. For example, some unforeseen reason (unobserved to the researchers) why a luxury car is more attractive to consumers may also be the reason the car requires more up-front investment and requires greater costs to produce a single unit. This would introduce correlation in the unobservables of the demand, marginal, and fixed costs. Alternatively, the data could be generated by a process similar to the classic selection problem in labor markets: there could exist (unobservably) high ability firms who have lower costs and a more attractive product, just like there might be high ability works who command higher wages and are more likely to receive offers.

Given that the above model is parametric, the only non-standard complications that arise are ones related to multiplicity of equilibria in the underlying game and also endogeneity of the $V$'s. Generally, and given the simultaneous game structure, the system (1) has multiple Nash equilibria in the identity of firms entering into the market. This multiplicity leads to a lack of a well-defined "reduced form" which complicates the inference question. Also, we want to allow for the possibility that the $V$'s are also choice variables (or variables determined in equilibrium).

The data we observe are $(S_1 y_1, V_1 y_1, y_1, S_2 y_2, V_2 y_2, y_2, \mathbf{X}, \mathbf{Z})$ whereby, for example, $S_1$ is observed only when $y_1 = 1$. Given the normality assumption, we link the distribution of the unobservables conditional on the exogenous variables to the distribution of the outcomes to obtain the identified features of the model. The data allow us to estimate the distribution of $(S_1 y_1, V_1 y_1, y_1, S_2 y_2, V_2 y_2, y_2, \mathbf{X}, \mathbf{Z})$; the key to inference is to link this distribution to the one predicted by the model. To illustrate this, consider the observable $(y_1 = 1, y_2 = 0, V_1, S_1, \mathbf{X}, \mathbf{Z})$. For a given value of the parameters, the data allow us to

[12] Also, it is clear that using instrumental variables on the outcome inequality conditions in (1) above does not correct for selectivity in general, since, even though we have $E[\xi_1|X, Z] = 0$, that does not imply that $E[\xi_1|X, Z, y_1 = 1] = 0$.

identify

$$P(S_1 - \alpha_1 V_1 - X_1\beta \leq t_1;\, y_1 = 1, y_2 = 0|X, Z) \tag{2}$$

for all $t_1$. The particular form of the above probability is related to the residuals evaluated at $t_1$ and where we condition on all *exogenous variables* in the model. We elaborate further on this below.[13]

**Remark 1** *It is possible to "ignore" the entry stage and consider only the linear regression parts in (1) above. Then, one could develop methods for dealing with distribution of* $(\xi_1, \xi_2|Z, X, V)$*. For example, under mean independence assumptions, one would have*

$$E[S_1|Z, X, V] = X_1\beta + \alpha_1 V_1 + E[\xi_1|Z, X, V;\, y_1 = 1]$$

*Here, it is possible to leave* $E[\xi_1|Z, X, V;\, y_1 = 1]$ *as an unknown function of* $(Z, X, V)$ *and then use a control function approach for example. In such a model, separating* $(\beta, \alpha_1)$ *from this unknown function (identification of* $(\beta, \alpha_1)$*) requires extra assumptions that are hard to motivate economically (i.e., these assumptions necessarily make implicit restrictions on the entry model).*

To evaluate the probability in (2) above in terms of the model parameters, we first let $(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^U_{(1,0)})$ be the set of $\xi_1$ that are less than $t_1$ when the unobservables $(\nu_1, \nu_2)$ belong to the set $A^U_{(1,0)}$. The set $A^U_{(1,0)}$ is the set where $(1, 0)$ is the unique (pure strategy) Nash equilibrium outcome of the model.

Next, let $\left(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^M_{(1,0)}, d_{(1,0)} = 1\right)$ be the set of $\xi_1$ that are less than $t_1$ when the unobservables $(\nu_1, \nu_2)$ belong to the set $A^M_{(1,0)}$. The set $A^M_{(1,0)}$ is the set where $(1, 0)$ is one among the multiple equilibria outcomes of the model.[14] Let $d_{(1,0)} = 1$ indicate that $(1, 0)$ was selected. The idea here is to try and "match" the distribution of residuals at a given parameter value predicted in the data, with its counterpart predicted by the model using

[13] In the case where we have no endogeneity for example ($\alpha$'s equal to zero), then, one can use on the data side, $P(S_1 \leq t_1; y_1 = 1, y_2 = 0|\mathbf{X}, \mathbf{Z})$ which is equal to the model predicted probability $P(\xi_1 \leq -X_1\beta; y_1 = 1, y_2 = 0|\mathbf{X}, \mathbf{Z})$.

[14] We discuss in Section 3.3 how we handle the situation when there is not an equilibrium in pure-strategies in the entry game.

method of moments. By the law of total probability we have (suppressing the conditioning on $(\mathbf{X}, \mathbf{Z})$):

$$\begin{aligned} P(\xi_1 \leq t_1;\, y_1 = 1; y_2 = 0) &= P\left(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^U_{(1,0)}\right) \\ &+ P(d_{1,0} = 1 \mid \xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^M_{(1,0)})\; P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^M_{(1,0)}\right) \end{aligned} \tag{3}$$

The probability $P(d_{1,0} = 1 \mid \xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^M_{(1,0)})$ above is unknown and represents the equilibrium selection function. A feasible approach to inference, then, is to use the natural (or trivial) upper and lower bounds on this unknown function to get:

$$\begin{aligned} P\left(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^U_{(1,0)}\right) \leq P(\xi_1 \leq t_1;\, y_1 = 1; y_2 = 0) = P(S_1 + \alpha_1 V_1 - X_1\beta \leq t_1;\, y_1 = 1; y_2 = 0) \leq \\ P\left(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^U_{(1,0)}\right) + P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^M_{(1,0)}\right) \end{aligned}$$

The middle part

$$P(S_1 - \alpha_1 V_1 - X_1\beta \leq t_1;\, y_1 = 1; y_2 = 0)$$

can be consistently estimated from the data given a value for $(\alpha_1, \beta, t_1)$. The LHS and RHS contain the following two probabilities

$$P\left(\xi_1 \leq t_1;\, (\nu_1, \nu_2) \in A^U_{(1,0)}\right),\; P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^M_{(1,0)}\right).$$

These can be computed analytically (or via simulations) from the model for a given value of the parameter vector (that includes the covariance matrix of the errors) using the assumption that $(\xi_1, \xi_2, \nu_1, \nu_2)$ has a known distribution up to a finite dimensional parameter (we assume normal) and the fact that the sets $A^M_{(1,0)}$ and $A^U_{(1,0)}$, which depend on regressors and parameters, can be obtained by solving the game given a solution concept (See CT for examples of such sets). For example, for a given value of the unobservables, observables and parameter values, we can solve for the equilibria of the game which determines these sets.

**Remark 2** *Note that we bound the distribution of the* residuals *as opposed to just the distribution of $S_1$ to allow some of the regressors to be endogenous. The conditioning sets in the LHS (and RHS) depend on exogenous covariates only, and hence these probabilities can be easily computed or simulated (for a given value of the parameters).*

The upper and lower bounds on the probability of the event $(S_2 - \alpha_2 V_2 - X_2\beta \leq t_2,\ y_1 = 0, y_2 = 1)$ can similarly be calculated. In addition, in the two player entry game (i.e. $\delta$'s are negative) above with pure strategies, the events $(1,1)$ and $(0,0)$ are uniquely determined, and so

$$P(S_1 - \alpha_1 V_1 - X_1\beta \leq t_1;\ S_2 - \alpha_2 V_2 - X_2\beta \leq t_2; y_1 = 1; y_2 = 1)$$

is equal to (moment equality)

$$P(\xi_1 \leq t_1, \xi_2 \leq t_2, \nu_1 \geq -\delta_2 - \gamma Z_1, \nu_2 \geq -\delta_1 - \gamma Z_2)$$

which can be easily calculated (via simulation for example). We also have:

$$P(y_1 = 0, y_2 = 0) = P(\nu_1 \leq -\gamma Z_1, \nu_2 \leq -\gamma Z_2)$$

To summarize, and for the two-equation selection models, the statistical moment inequality conditions implied by the model at the true parameters are:

$$m^l_{(1,0)}(t_1, \mathbf{Z}; \Sigma) \leq E\left(1\left[S_1 - \alpha_1 V_1 - X_1\beta \leq t_1; y_1 = 1; y_2 = 0\right]\right) \leq m^u_{(1,0)}(t_1, \mathbf{Z}; \Sigma)$$

$$m^l_{(0,1)}(t_2, \mathbf{Z}; \Sigma) \leq E\left(1\left[S_2 - \alpha_2 V_2 - X_2\beta \leq t_2; y_1 = 0; y_2 = 1\right]\right) \leq m^u_{(0,1)}(t_2, \mathbf{Z}; \Sigma)$$

$$E\left(1\left[S_1 - \alpha_1 V_1 - X_1\beta \leq t_1; S_2 - \alpha_2 V_2 - X_2\beta \leq t_2; y_1 = 1; y_2 = 1\right]\right) = m_{(1,1)}(t_1, t_2, \mathbf{Z}; \Sigma)$$

$$E\left(1\left[y_1 = 0; y_2 = 0\right]\right) = m_{(0,0)}(\mathbf{Z}; \Sigma)$$

where

$$\begin{aligned}
m^l_{(1,0)}(t_1, \mathbf{Z}; \Sigma) &= P\left(\xi_1 \leq t_1;\ (\nu_1, \nu_2) \in A^U_{(1,0)}\right) \\
m^u_{(1,0)}(t_1, \mathbf{Z}; \Sigma) &= m^l_{(1,0)}(t_1, \mathbf{Z}; \Sigma) +\ P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^M_{(1,0)}\right) \\
m^l_{(0,1)}(t_2, \mathbf{Z}; \Sigma) &= P\left(\xi_2 \leq t_2;\ (\nu_2, \nu_2) \in A^U_{(0,1)}\right) \\
m^u_{(0,1)}(t_2, \mathbf{Z}; \Sigma) &= m^l_{(0,1)}(t_2, \mathbf{Z}; \Sigma) +\ P\left(\xi_2 \leq t_2; (\nu_1, \nu_2) \in A^M_{(0,1)}\right) \\
m_{(1,1)}(t_1, t_2, \mathbf{Z}; \Sigma) &= P(\xi_1 \leq t_1, \xi_2 \leq t_2, \nu_1 \geq -\delta_2 - \gamma Z_1, \nu_2 \geq -\delta_1 - \gamma Z_2) \\
m_{(0,0)}(\mathbf{Z}; \Sigma) &= P(\nu_1 \leq -\gamma Z_1, \nu_2 \leq -\gamma Z_2)
\end{aligned}$$

Hence, the above can be written as

$$E[\mathbf{G}(\theta, S_1y_1, S_2y_2, V_1y_1, V_2y_2, y_1, y_2; t_1, t_2)|\mathbf{Z}, X] \leq 0 \tag{4}$$

where $\mathbf{G}(.) \in \mathcal{R}^k$.

The last moment, $m_{(0,0)}(\mathbf{Z}; \Sigma)$, is the CT moment when no entrants are in the market. It is an important moment condition for the estimation of the fixed cost parameters. Observe that when $t_1, t_2 \to \infty$, the CMT moments collapse to the CT moments. We thus also add the other CT moments to set of moment conditions that are used in estimation.

We use standard moment inequality methods to conduct inference on the identified parameters. In particular:[15]

**Result 3** *Suppose the above parametric assumptions in model (1) are maintained. In addition, assume that* $(\mathbf{X}, \mathbf{Z}) \perp (\xi_1, \xi_2, \nu_2, \nu_2)$ *where the latter is normally distributed with mean zero and covariance matrix* $\Sigma$. *Then given a large iid data set on* $(y_1, y_2, S_1y_1, V_1y_1, S_2y_2, V_2y_2, \mathbf{X}, \mathbf{Z})$ *the true parameter vector* $\theta = (\delta_1, \delta_2, \alpha_1, \alpha_2, \beta, \gamma, \Sigma)$ *minimizes the nonnegative objective function below to zero:*

$$Q(\theta) = 0 = \int W(\mathbf{X}, \mathbf{Z}) \|\mathbf{G}(\theta, S_1y_1, S_2y_2, V_1y_1, V_2y_2, y_1, y_2)|\mathbf{Z}, X]\|_+ dF_{\mathbf{X},\mathbf{Z}} \tag{5}$$

*for a strictly positive weight function* $W(\mathbf{X}, \mathbf{Z})$.

It is simple to see that the above objective function is zero at the true parameter vector. In addition, if the model is partially identified, this objective function is also zero on all the parameters that belong to the identified set. The above is a standard conditional moment inequality model where we employ discrete valued variables in the conditioning set along with a finite (and small) set of $t$'s.[16].

Clearly, the stylized model above provides intuition about the technical issues involved, but we next link this model to a model of behavior where the decision to enter (or to provide a product) is more explicitly linked to a usual economic condition of profits. This entails specification of costs, demand, and a solution concept.

[15]See the Appendix for more details. See CT for an analogous result and the proof therein.

[16]We discuss the selection of the $t$'s in Appendix B.

# 3 A Model of Entry and Price Competition

## 3.1 The Structural Model

Section 2 above analyzed a stylized model of entry and pricing that used linear approximations to various functions, as it is simpler to explain the inference approach using such a model. We present a fully structural model of entry and pricing and derive formulas for entry thresholds directly from revenue and cost functions. We consider the case of duopoly interaction for simplicity, where two firms must decide, simultaneously, whether to serve a market and the prices they decide to charge given their decision to enter.

The profits of firm 1 if this firm decides to enter is

$$\pi_1 = \left(p_1 - c\left(W_1, \eta_1\right)\right) \mathcal{M} \cdot \tilde{s}_1\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) - F\left(Z_1, \nu_1\right),$$

where

$$\tilde{s}_1\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) = \overbrace{s_1\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right)}^{\text{duopoly demand}} y_2 + \overbrace{s_1\left(p_1, X_1, \xi_1\right)}^{\text{monopoly demand}} \left(1 - y_2\right)$$

is the share of firm 1 which depends on whether firm 2 is in the market, $\mathcal{M}$ is the market size, $c\left(W_1, \eta_1\right)$ is the constant marginal cost for firm 1, $F\left(Z_1, \nu_1\right)$ is the fixed cost of firm 1, and $\mathbf{p} = (p_1, p_2)$. A profit function for firm 2 is specified in the same way.

In addition, we have equilibrium first order conditions that determine prices and shares,

$$\left\{ \begin{array}{l} \left(p_1 - c\left(W_1, \eta_1\right)\right) \partial \tilde{s}_1\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) / \partial p_1 + \tilde{s}_1\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) = 0 \\ \left(p_2 - c\left(W_2, \eta_2\right)\right) \partial \tilde{s}_2\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) / \partial p_2 + \tilde{s}_2\left(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi\right) = 0 \end{array} \right. , \tag{6}$$

which are the first order equilibrium conditions in a simultaneous Nash Bertrand pricing game.

In this model, $y_j = 1$ if firm $j$ decides to enter a market, and $y_j = 0$ otherwise, where $j = 1, 2$ indexes the firms. We impose the following entry condition:

$$y_j = 1 \quad \text{if and only if} \quad \pi_j \geq 0 \quad j = 1, 2$$

There are six endogenous variables: $p_1$, $p_2$, $S_1$, $S_2$, $y_1$, and $y_2$. The observed exogenous variables are $\mathcal{M}$, $\mathbf{W} = (W_1, W_2)$, $\mathbf{Z} = (Z_1, Z_2)$, $\mathbf{X} = (X_1, X_2)$. So, putting these together, we get the following system:

$$\begin{cases} y_1 = 1 \Leftrightarrow \pi_1 = (p_1 - c(W_1, \eta_1)) \mathcal{M} \cdot \tilde{s}_1(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) - F(Z_1, \nu_1) \geq 0, & \text{Entry Conditions} \\ y_2 = 1 \Leftrightarrow \pi_2 = (p_2 - c(W_2, \eta_2)) \mathcal{M} \cdot \tilde{s}_2(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) - F(Z_2, \nu_2) \geq 0, & \\ & \\ S_1 = \tilde{s}_1(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi), & \text{Demand} \\ S_2 = \tilde{s}_2(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi), & \\ & \\ (p_1 - c(W_1, \eta_1)) \partial \tilde{s}_1(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) / \partial p_1 + \tilde{s}_1(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) = 0, & \text{Equilibrium Pricing} \\ (p_2 - c(W_2, \eta_2)) \partial \tilde{s}_2(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) / \partial p_2 + \tilde{s}_2(\mathbf{p}, \mathbf{X}, \mathbf{y}, \xi) = 0, & \end{cases} \tag{7}$$

The first two inequalities are entry conditions that require that in equilibrium a firm that serves a market must be making non-negative profits. The third and fourth equations are demand equations. The fifth and sixth equations are pricing first order conditions. An equilibrium of the model occurs when firms make entry and pricing decisions such that all the six conditions are satisfied. The firm level unobservables that enter into the fixed costs are denoted by $\nu_j$, $j = 1, 2$. The unobservables that enter into the variable costs are denoted by $\eta_j$, $j = 1, 2$ while the unobservables that enter into the demand equations are denoted by $\xi_j$, $j = 1, 2$. The model represented by the set of equations above might have multiple equilibria. Multiplicity arises in the entry decision because there are regions of the observables and unobservables that predict a single firm will enter, but does not predict the identity of the entrant (see Bresnahan and Reiss (1991)). Because we consider single-product firms, there are no multiple equilibria in the pricing game, although in models with richer assumptions on preferences multiple equilibria in pricing could exist. See Caplin and Nalebuff (1991) for uniqueness in the single product simple logit case and Aksoy-Pierson, Allon, and Federgruen (2013) for uniqueness in richer logit-style demand specifications.

It is interesting to compare this system to the ones we studied in Section 2 above and notice the added nonlinearities that are present. Even though the conceptual approach is the same, the inference procedure for this system is computationally more demanding. It is more complex because one needs to *solve for the equilibrium of the full model*, which has six (rather than just four) endogenous variables. On the other hand, one only had to solve for the equilibrium of the entry game in the model (1). The methodology presented in Section (2) can be used to estimate model (7), but now there are *two* unobservables for each firm over which to integrate (the marginal cost and the demand unobservables).

To understand how the model relates to previous work, observe that if we were to estimate a reduced form version of the first two inequalities of the system (7), then that would be akin to the entry game literature (Bresnahan and Reiss, 1990, 1991; Berry, 1992; Mazzeo, 2002; Seim, 2006; Ciliberto and Tamer, 2009). If we were to estimate the third to sixth equation in the system (7), then that would be akin to the demand-supply literature (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995), depending on the specification of the demand system. So, here we join a demand and entry model, while allowing the unobservables of the six conditions to be correlated with each other. This is important, as a model that combines both pricing and entry decisions is able to capture a richer picture of firms' response to policy. For example, the model allows for market structure to adjust optimally after a merger, which may in turn affect prices.

## 3.2 Parameterizing the model

To parametrize the various functions above, we follow Bresnahan (1987) and Berry, Levinsohn, and Pakes (1995), where the unit marginal cost can be written as:

$$\ln c\left(W_j, \eta_j\right) = \varphi_j W_j + \eta_j. \tag{8}$$

As in the entry game literature mentioned above, the fixed costs are

$$\ln F\left(Z_j, \nu_j\right) = \gamma_j Z_j + \nu_j. \tag{9}$$

The demand is derived from a discrete choice model (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995). More specifically, we consider the nested logit model, which is discussed at length in Berry (1994).

In the two goods world that we are considering in this Section, consumers choose among the inside goods $j = 1, 2$ or choose neither one, and we will say in that case that they choose the outside good, indexed with $j = 0$. In our airline example this would include not traveling, or taking another form of transportation. The mean utility from the outside good is normalized to zero. We nest the options into two groups of goods, one that includes all the flight options and one that includes the decision not to fly.[17]

The utility of consumer $i$ from consuming $j$ is

$$\begin{aligned} u_{ij} &= X_j'\beta + \alpha p_j + \xi_j + \upsilon_{ig} + (1-\lambda)\,\epsilon_{ij}, \\ u_{i0} &= \epsilon_{i0}, \end{aligned} \tag{10}$$

where $X_j$ is a vector of product characteristics, $p_j$ is the price, $(\beta, \alpha)$ are the taste parameters, and $\xi_j$ are product characteristics unobserved to the econometrician.

The term $\upsilon_{ig} + (1-\lambda)\epsilon_{ij}$ represents the individual specific unobservables. The term $\upsilon_{ig}$ is common for consumer i across all products that belong to group $g$. We maintain here that the individual specific unobservables follow the distributional assumption that generate the nested logit model (Cardell, 1991). The parameter, $\lambda \in [0, 1]$, governs the substitution patterns between the airline travel nest and the outside good. If $\lambda = 0$ then this is the logit model. We consider the logit model in the Monte Carlo exercise presented in the Section C of the Appendix.

The proportion of consumers who choose to fly is then

$$s_g = \frac{D^{(1-\lambda)}}{1 + D^{(1-\lambda)}},$$

where

$$D = \sum_{j=1}^{J} e^{(X_j'\beta + \alpha p_j + \xi_j)/(1-\lambda)}.$$

Recall that in this section, $J = 2$. In the empirical analysis, $J$ will vary by market, and will take values from 1 to 6.

The probability of a consumer choosing product $j$, conditional on purchasing a product from the air travel nest, is

[17] There is a rich literature on the estimation of demand in airline markets, which allows the choice among airline services to be a function of other factors, such as differences in classes, advance purchase, connecting vs nonstop service, etc. We refer to Lazarev (2013), Williams (2017) for papers that allow for these additional dimensions, but that, on the other hand, abstract from the entry decisions and from oligopoly competition.

$$s_{j/g} \quad = \quad \frac{e^{(X_j'\beta_r+\alpha p_j+\xi_j)/(1-\lambda)}}{D}. \tag{11}$$

Product $j$'s market share is

$$s_j(\mathbf{X},\mathbf{p},\xi,\beta_r,\alpha,\lambda) = \frac{e^{(X_j'\beta+\alpha p_j+\xi_j)/(1-\lambda)}}{D}\frac{D^{(1-\lambda)}}{1+D^{(1-\lambda)}}. \tag{12}$$

Let $E \equiv \{(y_1,..,y_j,..,y_K) : y_j = 1 \text{ or } y_j = 0, \forall 1 \leq j \leq K\}$ denote the set of possible market structures, which contains $2^K$ elements. Let $e \in E$ be an element or a market structure. For example, in the model above where $K = 2$, the set of possible market structures is $E = \{(0,0),(0,1),(1,0),(1,1)\}$. Let $\mathbf{X}^e$, $\mathbf{p}^e$, and $\xi^e$, $N^e$ denote the matrices of, respectively, the exogenous variables, prices, unobservable firm characteristics, and number of firms when the market structure is $e$.

Suppose, for sake of simplicity and just for the next few paragraphs, that $\lambda = 0$, so that the demand is given by the standard logit model. When both firms are in the market, we have:

$$s_j\left(\beta,\alpha,\mathbf{X}^{(1,1)},\mathbf{p}^{(1,1)},\xi^{(1,1)}\right) = \frac{exp(X_j'\beta+\alpha p_j+\xi_j)}{D}$$

where $D = \sum_{j\in J} exp(X_j'\beta+\alpha p_j+\xi_j)$ and $J = \{1,2\}$ indicates the products in the market.[18]

Under the maintained distributional assumptions on $\epsilon$, we can write the following relationship:

$$\ln s_j(\beta,\alpha,\mathbf{X}^e,\mathbf{p}^e,\xi^e) - \ln s_0(\beta,\alpha,\mathbf{X}^e,\mathbf{p}^e,\xi^e) = X_j\beta + \alpha p_j + \xi_j, \tag{13}$$

The markup is then equal to (Berry (1994)):

$$b_j(\mathbf{X}^e,\mathbf{p}^e,\xi^e) = \frac{-1}{\alpha\left[1 - s_j(\beta,\alpha,\mathbf{X}^e,\mathbf{p}^e,\xi^e)\right]}.$$

If we let $\lambda$ free, then, under the maintained distributional assumptions, we can write the following relationship:

$$\ln s_j(\beta,\alpha,\mathbf{X}^e,\mathbf{p}^e,\xi^e) - \ln s_0(\beta,\alpha,\mathbf{X}^e,\mathbf{p}^e,\xi^e) = X_j\beta + \alpha p_j + \lambda \ln s_{j/g} + \xi_j, \tag{14}$$

[18] So, for example, when only one firm is in the market, say firm $j = 1$, then the share equation for $s_j\left(\beta,\alpha,\mathbf{X}^{(1,0)},\mathbf{p}^{(1,0)},\xi^{(1,0)}\right)$ is the same as above, except that $D = 1 + exp(X_1'\beta+\alpha p_1+\xi_1)$.

where $s_{j/g}$ is defined in Equation 11.

Following Berry (1992) and CT, we specify the unobservables that enter into the fixed cost inequality condition, $\eta_{jm}$, as including firm-specific unobserved heterogeneity, $\tilde{\eta}_{jm}$, as well as market specific unobserved heterogeneity, $\eta_m$. $\eta_m$ are unobservables that are market specific and capture, for example, the fact that in market $m$ there are cost shocks that are common across the potential entrants. Thus, we have $\eta_{jm} = \tilde{\eta}_{jm} + \eta_m$. Following Bresnahan [1987] and BLP [1995], the marginal cost and demand unobservables only includes firm-specific heterogeneity.

The unobservables have a joint normal distribution:

$$(\nu_1, \nu_2, \xi_1, \xi_2, \tilde{\eta}_{1m}, \tilde{\eta}_{2m}) \sim N(0, \Sigma) \tag{15}$$

where $\Sigma$ is the variance-covariance matrix to be estimated. Notice that here we do not include $\eta_m$. When we run our simulation exercise, we will draw $\tilde{\eta}_{jm}$ and $\eta_m$ independently from two standard normal distributions. Then, we will apply the Cholesky decomposition to allow for correlations between the demand, marginal cost, and the firm specific fixed cost unobservables. Then, we add the market-specific fixed cost unobservable to the firm-specific fixed cost unobservable.

The off-diagonal terms pick up the correlation between the unobservables that is part of the source of the selection bias in the model. In the empirical implementation of our model, we use the following variance-covariance matrix:

$$\Sigma_m = \begin{bmatrix} \sigma_\xi^2 \cdot I_{Km} & \sigma_{\xi\eta} \cdot I_{Km} & \sigma_{\xi\nu} \cdot I_{Km} \\ \sigma_{\xi\eta} \cdot I_{Km} & \sigma_\eta^2 \cdot I_{Km} & \sigma_{\eta\nu} \cdot I_{Km} \\ \sigma_{\xi\nu} \cdot I_{Km} & \sigma_{\eta\nu} \cdot I_{Km} & \sigma_\nu^2 \cdot I_{Km} \end{bmatrix}.$$

For computational simplicity, this specification restricts the correlations to be the same for each firm. It maintains that the correlation is non-zero only among the unobservables of a firm (within-firm correlation), and not between the unobservables of the $K_m$ firms (between-firm correlation). $I_{Km}$ is a $K_m x K_m$ identity matrix.

Finally, we have normalized the variance of the market-specific unobservable in the fixed cost equation, setting it equal to $\frac{1}{2}$, and we have normalized the variance of the firm-specific unobservable in the same equation, setting it equal to $\frac{1}{2}$. The first one is not identified; the second one is technically identified, but not well, given our limited sample.[19]

## 3.3 Simulation Algorithm

To estimate the parameters of the model we need to predict the market structures and derive distributions of demand and supply unobservables to construct the distance function. This requires the evaluation of a large multidimensional integral, therefore we have constructed an estimation routine that relies heavily on simulation. We solve directly for all equilibria at each iteration in the estimation routine.

The simulation algorithm is presented for the case when there are $K$ potential entrants. We rewrite the model of price and entry competition using the parameterizations above. Here, we write the model in terms of a simple logit demand, although in practice we estimate the nested logit version.

$$\begin{cases} y_j = 1 \Leftrightarrow \pi_j \equiv \left(p_j - \exp\left(\varphi W_j + \eta_j\right)\right) M s_j\left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \exp\left(\gamma Z_j + \nu_j\right) \geq 0, \\ \ln s_j\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \ln s_0\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) = X_j'\beta + \alpha p_j + \xi_j \\ \ln\left[p_j - b_j\left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right)\right] = \varphi W_j + \eta_j, \end{cases}, \tag{16}$$

for $j = 1, ..., K$ and $e \in E$.

We now explain the details of the simulation algorithm that we use.

First, we take $ns$ pseudo-random independent draws from a $3 \times |K|$-variate joint standard normal distribution, where $|K|$ is the cardinality of $K$. Let $r = 1, ..., ns$ index pseudo-random draws. These draws remain unchanged during the minimization. Next, the algorithm uses three steps that we describe below.

Set the candidate parameter value to be $\Theta^0 = \left(\alpha^0, \beta^0, \varphi^0, \gamma^0, \Sigma^0\right)$.

1. We construct the probability distributions for the residuals, which are estimated non-parametrically at each parameter iteration. The steps here do not involve any simu-

[19] We have chosen to set the second one to $\frac{1}{2}$ because that is the value at which the distance function was minimized compared to the case when we set it equal to 1. See Appendix B for more detail.

lations.

(a) Take a market structure $\hat{e} \in E$.

(b) If the market structure in market $m$ is equal to $\hat{e}$, use $\alpha^0$, $\beta^0$, $\varphi^0$ to compute the demand and first order condition residuals $\hat{\xi}_j^{\hat{e}}$ and $\hat{\eta}_j^{\hat{e}}$. These can be done easily using (16) above.

(c) Repeat (b) above for all markets, and then construct $\Pr(\hat{\xi}^{\hat{e}} <= \mathbf{t_D}, \hat{\eta}^{\hat{e}} <= \mathbf{t_S} \mid \mathbf{X}, \mathbf{W}, \mathbf{Z})$, which are joint probability distributions of $\hat{\xi}^{\hat{e}}, \hat{\eta}^{\hat{e}}$ conditional on the values taken by the control variables. $\mathbf{t_D}$ are the t's for the demand residuals, while $\mathbf{t_S}$ are the t's for the supply residuals.[20]

(d) Repeat the steps $1(b)$ and $1(c)$ above for all $\hat{e} \in E$.

2. Next, we construct the probability distributions for the lower and upper bound of the "simulated errors". For each market:

   (a) We simulate random vectors of unobservables $(\nu_r, \xi_r, \eta_r)$ from a multivariate normal density with a given covariance matrix, using the pseudo-random draws described above.

   (b) For each potential market structure $e$ of the $2^{|K|} - 1$ possible ones (excluding the one where no firm enters), we solve the subsystem of the $N^e$ demand equations and $N^e$ first order conditions in (16) for the *equilibrium* prices $\bar{\mathbf{p}}_r^e$ and shares $\bar{\mathbf{s}}_r^e$.[21]

   (c) We compute $2^{|K|} - 1$ *variable* profits.

   (d) We use the candidate parameter $\gamma^0$ and the simulated error $\nu_r$ to compute $2^{|K|} - 1$ fixed costs and *total* profits.

[20] See Section B in the Appendix for details. There is a slight abuse of notation here: the CDF is constructed for a given market structure $\hat{e}$.

[21] For example, if we look at a monopoly of firm $j$ ($|e| = 1$) then the demand $Q_j(p_{jr}, X_{jr}, \xi_{jr}; \beta)$ is readily computed, and the monopoly price, $p_{jr}$, as well. Notice that, given the parametric assumptions (logit model of demand, single product firms), and discussed in the text, there is a unique pure-strategy price equilibrium, conditional on the market structure (Caplin and Nalebuff, 1991; Aksoy-Pierson, Allon, and Federgruen, 2013).

(e) We use the total profits to determine which of the $2^{|K|}$ market structures are *predicted* as equilibria of the full model. If there is a unique equilibrium, say $e^*$, then we collect the simulated errors of the firms that are present in that equilibrium, $\xi_r^{e^*}$ and $\eta_r^{e^*}$. In addition, we collect $\nu_r^{e^*}$ and include them in $A_{e^*}^U$, which was defined in Section (2). If there are multiple equilibria, say $e^*$ and $e^{**}$, then we collect the "simulated errors" of the firms that are present in those equilibria, respectively $\left(\xi_r^{e^*}, \eta_r^{e^*}\right)$ and $\left(\xi_r^{e^{**}}, \eta_r^{e^{**}}\right)$.[22] In addition, we collect $\nu_r^{e^*}$ and $\nu_r^{e^{**}}$ and include them, respectively, in $A_{e^*}^M$ and $A_{e^{**}}^M$, which were also defined in Section (2).

When there is not a pure-strategy equilibrium in the entry game, we know that there exists at least one equilibrium in mixed-strategies. In that case, which happens *very* rarely in our empirical analysis, we proceed as follows. First, we determine the firms for which it is a dominant strategy not to enter. Then, we know that there will be at least one mixed strategy equilibrium where one of the remaining firms assigns a positive probability to the entry decision. Finally, we count this observation-simulation as contributing to the upper bound of the CDF of the simulated errors for all those firms.[23]

(f) We repeat steps 2.a-2.e for all markets and simulations, and then we construct $\Pr\left(\xi_r^e <= \mathbf{t_D}, \eta_r^e <= \mathbf{t_S}; \nu \in A_e^M | \mathbf{X}, \mathbf{W}, \mathbf{Z}\right)$ and $\Pr\left(\xi_r^e, \eta_r^e; \nu \in A_e^U | \mathbf{X}, \mathbf{W}, \mathbf{Z}\right)$.[24]

3. We construct the distance function (5) as in Section (2). The approach we use for inference is similar to the one used in CT, where we use subsampling based methods to construct confidence regions.

Conceptually, the above is a minimum distance procedure that compares the distribution

[22] The set of firms in the two equilibria (if there are multiple equilibria) may not be the same.

[23] For example, suppose that Firm 1 and Firm 2 are the only firms in a market, for a given simulation, for which entry is not a dominated strategy. Then, we maintain that the simulated errors for those two firms, for that simulation in that market, contribute to the upper bound of the CDF.

[24] These CDFs in this setting with two unobservables for each firm are analogous to the ones with just one unobservable per firm on described in Section 2. We use the same $t$'s that we used to construct the CDFs of the residuals.

function from the data (constructed in Part 1 above) to the upper and lower bounds on this distribution predicted by the model (the upper and lower bounds are constructed in part 2). The upper and lower bounds in Part 2) are a result of multiple equilibria while the complication in Part 1) is due to endogeneity.

# 4 Data and Industry Description

We apply our methods to data from the airline industry. This industry is particularly interesting in our setting for two main reasons. First, there is considerable variation in prices and market structure across markets and across carriers, which we expect to be associated with self-selection of carriers into markets. Second, this is an industry where the study of market structure and market power are particularly meaningful because there have been several recent changes in the number and identity of the competitors, with recent mergers among the largest carriers (Delta with Northwest, United with Continental, and American with USAir). Our methods allow us to examine within the context of our model the implications of mergers on equilibrium prices and also on market structure. We start with an examination of our data, and then we provide our estimates.

## 4.1 Market and Carrier Definition

**Data.** We use data from several sources to construct a cross-sectional dataset, where the basic unit of observation is an airline in a market (a *market-carrier*). The main datasets are the second quarter of 2012's *Airline Origin and Destination Survey (DB1B)* and of the *T-100 Domestic Segment Dataset*, the *Aviation Support Tables*, available from the DOT's National Transportation Library. We also use the US Census for the demographic data.[25]

We define a market as a unidirectional trip between two airports, irrespective of intermediate transfer points. The dataset includes the markets between the top 100 US Metropolitan Statistical Areas ranked by their population. We include markets that are *temporarily* not served by any carrier, which are the markets where the number of observed entrants is equal

[25]See Section C of the Appendix for a detailed discussion on the data cleaning and construction.

to zero. There are 8,163 unidirectional markets, and each one is denoted by $m = 1, ..., M$. There are six carriers in the dataset: American, Delta, United, USAir, Southwest, and a low cost type, denoted by `LCC`. The *Low Cost Carrier* type includes Alaska, JetBlue, Frontier, Allegiant, Spirit, Sun Country, Virgin. These firms rarely compete in the same market. The subscript for carriers is $j$, $j \in \{AA, DL, UA, UA, LCC\}$. There are 23,155 market-carrier observations for which we observe prices and shares. There are 710 markets that are not served by any firm.

We denote the number of potential entrants in market $m$ as $K_m$ where $|K_m| \leq 6$. An airline is considered a potential entrant if it is serving at least one market out of both of the endpoint airports.[26]

Tables 1 and 2 present the summary statistics for the distribution of potential and actual entrants in the airline markets. Table 1 shows that American Airlines enters in 39 percent of the markets, although it is a potential entrant in 71 percent of markets. Southwest, on the other hand, is a potential entrant in 64 percent of markets, and enters in 46 percent of the time. So this already shows some interesting heterogeneity in the entry patterns across airlines. Table 2 shows the distribution in the number of potential entrants, and we observe that the large majority of markets have between four and six potential entrants, with less than 2 percent having just one potential entrant.

For each firm in a market there are three endogenous variables: whether or not the firm is in the market, the price that the firm charges in that market, and the number of passengers transported. Following the notation used in the theoretical model, we indicate whether a firm is active in a market as $y_{jm} = 1$, and if it is not active as $y_{jm} = 0$. For example, we set $y_{LCC} = 1$ if at least one of the low cost carriers is active.

Table 3 presents the summary statistics for the variables used in our empirical analysis. For each variable we indicate in the last column whether the variable is used in the entry inequality conditions, demand and marginal cost equations. As in Berry, Carnall, and Spiller

[26] See Goolsbee and Syverson (2008) for an analogous definition. Variation in the identity and number of potential entrants has been shown to help the identification of the parameters of the model (Ciliberto et al., 2010).

Table 1: *Entry Moments*

| | Actual Entry | Potential Entry |
|---|---|---|
| AA | 0.39 | 0.71 |
| DL | 0.73 | 0.95 |
| LCC | 0.18 | 0.46 |
| UA | 0.51 | 0.80 |
| US | 0.49 | 0.87 |
| WN | 0.46 | 0.64 |

Empirical entry probabilities and the percent of markets as a potential entrant, across airlines.

Table 2: *Distribution of Potential Entrants Across Markets*

| | Number of Potential Entrants | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 |
| Percent of Markets | 1.74 | 10.61 | 14.58 | 16.57 | 28.13 | 28.37 |

Distribution of the fraction of markets by number of potential entrants.

(2006), Berry and Jia (2010), and Ciliberto and Williams (2014), market size is the geometric mean of the MSA population of the end-point cities.

The top panel of Table 3 reports the summary statistics for the ticket prices and passengers transported in a quarter. For each airline that is actively serving the market we observe the quarterly mean ticket fare, $p_{jm}$, and the total number of passengers transported in the quarter, $Q_{jm}$. The average value of the mean ticket fare is 242.88 dollars and the average number of passengers transported is $2,602.79$.

**Demand.** Demand is here assumed to be a function of the number of *Origin Presence*, which is defined as the *number* of markets served by an airline out of the origin airport. We maintain that this variable is a proxy of frequent flyer programs: the larger the number of markets that an airline serves out of an airport, the easier is for a traveler to accumulate points, and the more attractive flying on that airline is, *ceteris paribus*. The *Distance* between the origin and destination airports is also a determinant of demand, as shown in previous

Table 3: *Summary Statistics*

| | Mean | Std. Dev. | Min | Max | N | Equation |
|---|---|---|---|---|---|---|
| **Endogenous Variables** | | | | | | |
| Price ($) | 242.88 | 55.25 | 77.13 | 364.00 | 22,445 | Entry, Utility, MC |
| Passengers | 2602.79 | 7042.02 | 90 | 112,120 | 22,445 | Entry, Utility, MC |
| **All Markets** | | | | | | |
| Origin Presence | 100.36 | 71.88 | 0 | 267 | 48,978 | Utility, MC |
| Nonstop Origin | 7.04 | 13.57 | 0 | 127 | 48,978 | Entry |
| Nonstop Destin. | 7.11 | 13.61 | 0 | 127 | 48,978 | Entry |
| Distance (000) | 1.11 | 0.58 | 0.15 | 2.72 | 48,978 | Utility, MC |
| **Markets Served** | | | | | | |
| Origin Presence | 143.23 | 57.91 | 1 | 267 | 22,445 | Utility, MC |
| Nonstop Origin | 10.60 | 16.76 | 0 | 127 | 22,445 | Entry |
| Nonstop Destin. | 10.67 | 16.77 | 0 | 127 | 22,445 | Entry |
| Distance (000) | 1.17 | 0.56 | 0.20 | 2.72 | 22,445 | Utility, MC |

Summary statistics from sample dscribed in the text. Observations from 48,978 potential airline-markets from 8,163 distinct markets. 22,445 airline-markets are active.

studies (Berry, 1990; Berry and Jia, 2010; Ciliberto and Williams, 2014).

The middle and bottom panels of Table 3 report the summary statistics for the exogenous explanatory variables. The middle panel computes the statistics on the whole sample, while the bottom panel computes the statistics only in the markets that are served by at least one airline.

There is clearly selection on observables in our setting. The mean value of *Origin Presence* is 100.36 across all markets, and it is up to 143.23 in markets that are actually served. The mean value of *Distance* is 111 miles (one-way), which is slightly lower than the mean values for active airline-markets, 117 miles.

**Fixed and Marginal Costs in the Airline Industry.**[27] The total costs of serving an airline market consists of three components: airport, flight, and passenger costs.[28]

[27] We thank John Panzar for helpful discussions on how to model costs in the airline industry. See also Panzar (1979).

[28] Other costs are incurred at the aggregate, national, level, and we do not estimate them here (advertising

Airlines must lease gates and hire personnel to enplane and deplane aircrafts at the two endpoints. These *airport* costs do not change with an additional passenger flown on an aircraft, and thus we interpret them as fixed costs. We parameterize fixed costs as functions of *Nonstop Origin*, the number of non-stop routes that an airline serves out of the origin airport, and *Nonstop Destination*, the number of non-stop routes that an airline serves out of the destination airport. The inclusion of these variables is motivated by Brueckner and Spiller (1994) work on economies of density, whereby the larger the network out of an airport, the lower is the market specific fixed cost faced by a firm because the same gate and the same gate personnel can enplane and deplane many flights.

Next, a particular *flight's* costs also enter the marginal cost. This is because these costs depend on the number of flights serving a market, on the size of the planes used, on the fuel costs, and on the wages paid to the pilots and flight attendants. Even with the indivisible nature aircraft capacity and the tendency to allocate these costs to the fixed component, we model these flight costs as a (possibly random) function of the number of passengers transported in a quarter divided by the aircraft capacity. Under such interpretation, the flight costs are variable in the number of passengers transported in a quarter.

Finally, the *accounting* unit costs of transporting a passenger are those associated with issuing tickets, in-flight food and beverages, and insurance and other liability expenses. These costs are very small when compared to the airport and flight specific costs.

Both the flight and passenger costs enter the *economic* opportunity cost of flying a passenger. This is the highest profit that the airline could make off of an alternative trip that uses the same seat on the same plane, possibly as part of a flight connecting two different airports (Elzinga and Mills, 2009).

Returning to the middle and bottom panels of Table 3 we observe that there is selection on these observables as well. The mean value of *Nonstop Origin* is 7.04 in all markets, and 10.60 in markets that were actively served. The magnitudes are analogous for *Nonstop Destination*.

expenditures, for example, are rarely market specific).

The economic marginal cost is not observable (Rosse, 1970; Bresnahan, 1989; Schmalensee, 1989). We parameterize it as a function of *Origin Presence*. The idea is that the opportunity cost is a function of i) the whole network of that carrier that can be reached out of that airport, and ii) of the degree of competition that the carrier faces out of that airport, which is here captured by the size of the network that other airlines have at the origin airport. Given our interpretation of flight costs as entering the variable costs, we also allow the marginal cost to be a function of the non-stop distance, *Distance*, between two airports.

## 4.2 Identification

We begin by discussing the source of exogenous variation in our estimation and how the parameters of the model are identied.

Several variables are omitted in the demand estimation, and their omission could bias the estimation of the price coefficient. For example, we do not include frequency of flights or whether an airline provides connecting or nonstop service between two airports. As mentioned before, quality of airline service is also omitted. All these variables enter in $\xi$. We instrument for price using the exogenous variables for all *potential* rivals. This is similar to the "BLP instruments" (Berry, Levinsohn, and Pakes (1995)) widely used in the literature, and first proposed by Bresnahan (1987).[29] Our approach is slightly different from the standard one because: i) we include every potential entrants' characteristics separately instead of summing or averaging the characteristics in a market; ii) we consider the characteristics of all potential entrants, and not just those of the actual entrants.[30] In addition, the exogenous variables that affect fixed costs, which correlate with equilibrium prices through the entry conditions in our model, will also enter as instruments for the demand estimation.

The fixed cost parameters in the entry inequalities are identified if there is a variable that shifts the fixed cost of one firm without changing the fixed costs of the competitors. This condition is also required to identify the parameters in Ciliberto and Tamer (2009), but in

[29]For example, this approach is also used by Berry and Jia (2010).

[30]Gandhi and Houde (2016) suggest that using firm specific instruments is ideal for identifying demand, but is rarely implementable because in most applications there are too many firms. However, not only do we include firm specific characteristics as instruments, but we also include characteristics of *potential entrants*.

our case this variable should also be excluded from demand and marginal cost. First, we use the carrier's *Nonstop Destination*, the number of nonstop flights from the destination airport. Our choice of this variable as our exclusion restriction is motivated by the observation that passengers only care about the network out of the origin airport when they select and airline, for example because of their ability to accumulate frequent flyer miles over time.[31] In our robustness analysis we have determined that we can also include the carrier's *Nonstop Origin*. Notice that the origin-specific variable, *Nonstop Origin* is the same across markets from the same origin airport. In contrast, the destination variable, *Nonstop Destination*, is not, and this allows for the fixed costs to change across markets from the same airport.

A crucial source of exogenous variation across markets, which reinforces the identification power of the instruments discussed above, is given by the variation in the identity and number of potential entrants across markets, as in Berry (1992). First, the parameters of the exogenous variables in the entry inequalities are *point identified* when there is only one potential entrant because the model would collapse to a classic discrete choice model. Second, the exogenous variables shifting the demand function vary across markets from the same airport. If the exogenous variables in the demand function were the same across all markets from the same airport, then the differences in prices and shares that we observe in those markets would have to be fully explained by the random variables. Instead, the variation is also explained by the variation in the identity of the potential entrants and, consequently, by variation in the attributes of rival products.

Next, we discuss the variation in the data that identifies the variance-covariance matrix. The variance of the unobservable entering the demand function is identified by the variance in (the logarithms of) the odds, which, in turn, are functions of the shares of passengers transported by the airlines. The variance of the unobservables entering in the marginal cost

[31]Berry and Jia (2010) also assume that the variable *Nonstop Destination* is excluded from the demand. However, they assume that this variable enters the marginal cost equation. Earlier, we discussed our assumptions about marginal and fixed costs in our context (whereas Berry and Jia, 2010, do not model fixed costs). We think of marginal costs as the opportunity cost of serving other passengers from the origin airport, and so should include variables relating to the origin airports. As discussed in the text, we think of fixed costs as relating to economies of density (see Brueckner and Spiller, 1994). One way to capture the network density is to consider how many connections happen at the destination airport.

is identified by the variance in the markups charged by the firm, which in turn are functions of the observed prices. The variance in the unobservables entering the entry inequality is identified by the variance in the *variable profits*, which in turn are functions of the observed revenues. Notice that variable profits are expressed in monetary terms, and therefore the fixed cost parameters do not suffer from the standard caveat that they are identified up to a scale. In our analysis, we have found that the variance of the fixed costs is not well identified in practice, and, therefore, we have normalized it as explained in Section 3.2.

Next, we describe how the correlations between the unobservables are identified.[32] The two most important correlations are those that govern the unobserved selection: the correlations of the unobserved fixed cost with the unobserved component of marginal cost and demand. For example, suppose there is a set of firms that share the same observable attributes (i.e., same market type) which implies we predict them to have the same exact revenue conditional on entering the market. If among this set of firms, we observe in the data that firms who enter are more likely to have a lower price (again, holding revenues constant), then we would infer that there is a positive correlation between marginal costs (the reason for the low price) and fixed costs (the reason for entering, holding revenue fixed). If among this group of firms we observe firms who enter are more likely to have higher market shares, then we would infer that there is a negative correlation between unobserved demand (the reason why demand is high) and unobserved fixed costs (low fixed costs being the reason for entering conditional on revenues). More generally, we observe three things in the data: demand, prices, and entry. We use the averages, variances, and covariances between these variables to identify features of the utility function, cost functions (marginal and fixed), and covariances between utility and costs.

[32]Given our assumptions (or lack thereof) on equilibria selection in our model, we do not claim that the parameters of interest are point identified. However, it is useful to generally understand what covariation in the data informs us about the identified set.

# 5 Results

We organize the discussion of the results in two steps. First, we present the results when we estimate demand and supply using the standard GMM method (i.e. Berry, 1994). Next, we estimate demand and supply using our method, but assume that entry is exogenous. Lastly, we present results using our methodology that accounts for firms' entry decisions.

## 5.1 Results with Exogenous Market Structure

In Column 1 of Table 4, we display the results from GMM estimation of a model where the inverted demand is given by a nested logit regression, as in Equation 14.[33] In order to limit the space over which to draw for the minimization procedure, we standardize all the exogenous variables.[34] All the results are as expected and resemble those in previous work, for example Berry and Jia (2010) and Ciliberto and Williams (2014).[35] Starting from the demand estimates, we find the price coefficient to be negative and $\lambda$, the nesting parameter, to be between 0 and 1. The 95% confidence interval for the mean elasticity is [-8.314,-8.249], and the confidence interval for the mean markup is [30.312,30.383]. A larger presence at the origin airport is associated with more demand as in (Berry, 1990), and longer route distance is associated with stronger demand as well. The marginal cost estimates show that the marginal cost is increasing in distance, and decreasing in presence.

Next, we estimate the same exogenous entry model using our methodology. We do this because our methodology requires additional assumptions to those of GMM, such as maintaining the assumption that the unobservables are normally distributed. So estimating the exogenous version using our methodology allows us to (1) examine how close the estimates using these additional assumption are to the standard GMM approach and (2) compare the endogenous market structure version of the model more directly with the exogenous market

[33]We instrument for price and the nest shares using the value of the exogenous data for every firm, regardless of whether they are in the market, including fixed costs which are excluded from supply and demand. So for example, there are six instruments for every element in $X$, $W$, and $Z$.

[34]See Section C in the Appendix for more details.

[35]We also have estimated the GMM model only with the demand moments, and the results were very similar. See Section D in the Appendix.

structure version.

In order to present the results we report superset confidence regions that cover the true parameters with a pre-specified probability, just as we do next when we estimate the model with endogenous selection. Columns 2 and 3 of Table 4 report the cube that contains the confidence region that is defined as the set that contains the parameters that cannot be rejected as the truth with at least 95% probability.[36]

[37] We present the results of this estimation in Column 2 of Table 4. We observe that some coefficients are statistically identical (for example, the price coefficient, most of the coefficients in the marginal cost equation), but few others are different. In future work we hope to relax some of the distributional assumptions made in our current work. The estimate of the median elasticity of demand using our methodology [-9.429, -7.020] is statistically indistinguishable from the the GMM estimates, -8.1247, as is the estimate of markups.

## 5.2 Results with Endogenous Market Structure

Column 3 of Table 4 shows the results when we use the methodology developed in Section 2 and the inverted demand is given by a nested logit as in Equation 14. We allow for the correlation among the unobservables described in Section 3.

We begin by discussing the fit of the model. This consists of comparing the equilibrium market structures, prices, and shares predicted by the model with those observed in the data. This, in turn, consists of comparing predictions and data across markets with different exogenous characteristics. The key idea is to compare predictions and data *market by market*, and then count how many times the predicted market structures, prices, and shares matched those observed in the data, where the number of times is the product of the number of markets times the number of parameters drawn from the set of parameters that are included in the confidence intervals.[38] In practice, we run 200 simulations over 100 parameters, and

[36]This is the approach that was used in CT. See the On-line Supplement to CT and Chernozhukov, Hong, and Tamer (2007) for details.

[37]There are no multiple equilibria in the exogenous selection version of the model, but we report confidence regions for both sets of estimates where we use our methodology.

[38]The parameters are drawn from the confidence intervals presented in Column 3 of Table 4. We have those

Table 4: *Parameter Estimates with Exogenous Market Structure*

| | GMM | Exogenous Entry | Endogenous Entry |
|---|---|---|---|
| **Demand** | | | |
| Constant | -2.064 (0.123) | [ -2.588, -2.180] | [-5.638, -5.560] |
| Distance | 0.336 (0.014) | [ 0.155, 0.394] | [ 0.079, 0.148] |
| Origin Presence | 0.316 (0.012) | [ -0.128, 0.191] | [-0.459, -0.411] |
| LCC | -0.236 (0.048) | [ -2.028, -0.991] | [-1.558, -1.166] |
| WN | 0.277 (0.030) | [ -0.115, 0.575] | [ 0.299, 0.486] |
| Price | -2.364 (0.051) | [ -2.450, -2.290] | [-1.650 -1.633] |
| $\lambda$ | 0.419 (0.051) | [ 0.300, 0.566] | [0.226, 0.238] |
| **Marginal Cost** | | | |
| Constant | 5.364 (0.002) | [ 5.341, 5.394] | [ 5.261, 5.277] |
| Distance | 0.121 (0.001) | [ 0.076, 0.128] | [-0.087, -0.071] |
| Origin Presence | -0.025 (0.002) | [ -0.050, 0.014] | [-0.701, -0.692] |
| Cons LCC | -0.334 (0.007) | [ -0.506, -0.281] | [-0.426, -0.371] |
| Cons WN | -0.145 (0.004) | [ -0.165, -0.038] | [ 0.215, 0.281] |
| **Fixed Cost** | | | |
| Constant | – | – | [-1.353, -1.291] |
| Nonstop Origin | – | – | [-0.393, -0.323] |
| Nonstop Dest. | – | – | [-2.497, -2.434] |
| **Variance-Covariance*** | | | |
| Demand Variance | 1.51 | [1.336,2.852] | [3.939,4.123] |
| Marg. Cost Variance | 0.06 | [0.018, 0.055] | [0.299,0.312] |
| Demand-FC Covariance | – | – | [-0.246,-0.202] |
| Demand-MC Covariance | 0.18 | [0.112, 0.256 | [0.429,0.467] |
| MC-FC Covariance | – | – | [0.246,0.255] |
| **Market Power** | | | |
| Median Elasticity | -8.125 | [-9.429, -7.020] | [-3.985, -3.953] |
| Median Markup | 28.248 | [22.219, 33.006] | [50.825, 51.136] |

Results from estimation of the model presented in Section 3. Column 1: Standard GMM estimation. Column 2: Estimation using the methodology described in Section 2, but holding market structure exogenous. Column 3: Estimation using the methodology described in Section 2. Standard errors in parentheses in Column 1. Columns 2 and 3 contain 95% confidence bounds constructed using the method in Chernozhukov, Hong, and Tamer (2007). Price coefficient multiplied by 100.

* Fixed Cost variance set to 0.5.

compute the equilibrium market structures, the prices, and the shares in each one of these 20000 draws for each of the 8,163 markets. Next, for each market structure in each market we construct the 95% confidence interval of prices predicted by the model for a particular market and a particular parameter draw.[39] Finally, we verify whether the observed prices

parameters because we saved them during the minimization process. Notice that the confidence sets are not convex, so we cannot take the parameters individually from each of their respective confidence intervals. See Ciliberto and Tamer (2009) for another example of this type of approach.

[39] In practice, to construct the confidence interval for prices and shares we sort the prices and shares from the smallest to the largest value, and choose, for both prices and shares, the 2.5 and 97.5 percentile of the distribution.

Table 5: Aggregate Entry Probabilities

| | AA | DL | LCC | UA | US | WN |
|---|---|---|---|---|---|---|
| Data | 0.3899 | 0.7269 | 0.1755 | 0.5130 | 0.4876 | 0.4566 |
| Model Prediction | [0.411, 0.413] | [0.788, 0.790] | [0.183, 0.187] | [0.542, 0.544] | [0.510, 0.513] | [0.455, 0.456] |

Note: Entry probabilities across all markets in the sample described in the text. Intervals for the model are constructed using the sub-sampling routine described in the text.

and shares fall in the confidence intervals we constructed. If they do, then we count this as a market where the model successfully fits the data. We repeat this exercise for all parameters, and for all markets, and then compute the percentage of times that the model fits the data.

We find that we fit the prices 36.35 percent of the time, and our model fits the shares 41.85 percent of the times. The model fits the exact market structure 19.11 percent of the time (meaning all six carriers have the correct participation in the market). In Table 5 we display the empirical entry probabilities for each airline along with the confidence intervals for entry probabilities predicted by the model. In general, the model replicates the entry patterns fairly closely, 75.16 percent of the time correctly predicting the presence of any particular airline.

In Column 3 of Table 4 we estimate the coefficient of price to be included in [-1.650 -1.633] with a 95 percent probability, which is to be compared to the estimate from the model with exogenous market structure in Column 2 of Table 4. The estimate allowing for endogenous market structure is statistically and economically much closer to zero, which implies lower elasticities and higher markups. This is an important finding, which is consistent with the Monte Carlo exercise presented in Section C of the Appendix. These results imply that not accounting for endogenous market structure gives biased estimates of price elasticity.

We estimate $\lambda$ in Column 2 of Table 4 to be in the interval [0.600, 0.662], while in the Column 3 it is included in [0.226, 0.238]. Thus, we find that the within group correlation in unobservable demand is also estimated with a bias when we do not control for the endogenous market structure.

Overall, these sets of results lead us to over-estimate the elasticity of demand and under-estimate the market power of airline firms when we maintain that market structure is exogenous. To see this, we compare the implied mean elasticities in the bottom panel of Table 4. The mean elasticity for the exogenous market structure case is [-9.429, -7.020], while the we estimate the mean elasticity to be [-3.985, -3.953] when we allow for endogenous market structure. This leads to a difference in estimated markups [22.219, 33.006] in the exogenous case compared with [50.825, 51.136] in the endogenous market structure case.

Next, we show the results for the estimates of the fixed cost inequalities. Clearly, these are not comparable to the results from the previous model where market structure is assumed to be exogenous. Column 3 of Table 4 shows the constant in the fixed cost inequality condition to be included in [-1.353, -1.291], and greater values of the variables *Nonstop Origin* and *Nonstop Destination* lead to lower fixed costs, as one would expect if there were economies of density.

Finally, we investigate the estimation results for the variance-covariance matrix. The variances are precisely estimated in both columns, with the demand variance being included in [1.898,2.006] in Column 1 and in [1.510,1.570] in Column 2. The variance of the fixed cost unobservables is estimated in [2.152,2.240] in Column 1 and [2.010,2.086] in Column 2. Recall that the variance of the marginal cost unobservables is normalized to its value from the GMM estimation.

The correlation between the demand unobservables and fixed cost unobservables is estimated to be included in [0.764,0.795] in Column 1 and in [0.721,0.758] in Column 2. The correlation between the demand and marginal cost unobservables is also positive, as it is included in [0.621,0.709] in Column 1 and in [0.382,0.396] in Column 2.[40] This is one way that self-selection manifests itself in the model, in the sense that firms that face higher fixed costs are also the firms that are more likely to offer higher quality products.

These correlations imply that the unobservables that would, ceteris paribus, increase the demand for a given good, are positively correlated with those that would increase the fixed and marginal cost of producing that good. This makes intuitive sense if we think of the unobservables as measuring quality, for example, and thus higher quality increases demand,

[40]These intervals are very tight, and much of the precision is due to our use of the additional moments described in Section 3.

but it also increases the fixed and marginal costs, in the same spirit as Bresnahan (1987).

The results for the correlation between the marginal and fixed costs unobservables are different in Columns 1 and 2. They are positive and only marginally statistically different from zero in Column 1, while they are negative in Column 2. Since Column 2 presents the more flexible model, we will use it for our interpretation of the relationship between the marginal and fixed cost unobservables. The negative relationship implies that there is a potential trade-off between fixed and marginal costs unobservables. Continuing our interpretation of the unobservables as unobserved quality, the negative correlation would imply that the higher the fixed costs associated with producing a high quality good, the lower the corresponding marginal costs.

# 6 The Economics of Mergers When Market Structure is Endogenous

We present results from counterfactual exercises where we allow a merger between two firms, American Airlines and US Airways. A crucial concern of a merger from the point of view of a competition authority is the change in prices after the merger. It is typically thought that mergers imply greater concentration in a market, which, in turn, implies an increase in prices. However, in reality changes in the potential set of entrants along with changes in costs and demand after a merger may lead firms to optimally enter or exit markets. For example, cost synergies for the merged firm may cause entry into a new market to be profitable. Or, after the merger of the two firms, there might be room in the market for another entrant. Or, if demand is greater for the new merged firm, it may be able to steal market share from a rival such that the rival can not profitably operate.

Our methodology is ideally suited to evaluate both the price effects and the market structure effects of mergers. Importantly, as we discuss below, changes in market structure imply changes in prices, and vice versa, so incorporating optimal entry decisions into a merger analysis is crucial for understanding the total effect of mergers on market outcomes. Section 9 of the Horizontal Merger Guidelines (08/19/2010) of the Department of Justice states that entry alleviates concerns about the adverse competitive effects of mergers. In contrast, the canonical model of competition among differentiated products takes as exogenous the set of competing products (eg BLP and Nevo, 2001), and thus the post-merger and pre-merger market structures are the same, except that the products are now owned by a single firm.[41]

## 6.1 The Price and Market Structure Effects of the AA-US Merger

To simulate the effects of the AA-US Airways merger for a particular market, we use the following procedure. If US Airways (US) was a potential entrant we delete them.[42] If American is a potential entrant before the merger, they continue to be a potential entrant after the merger. If American (AA) was not a potential entrant and US Air was a potential entrant before the merger, we assume that after the merger American is now a potential entrant. If neither firm was a potential entrant before the merger this continues after the merger.

We consider three different assumptions about what it means for AA and US to merge. The three assumptions underscore the key observation that post-merger efficiencies could come from both observed and unobserved features of the carriers. Thus, the different assumptions that we discuss next have to do with potential efficiencies from the merger, and have two aims: to check the robustness of the results of the counterfactual exercise, and, to help with the interpretation of those empirical results.

First, we consider a case where the surviving firm, AA, takes on the best observed and unobserved characteristics of both pre-merger carriers, and we call this the "Best Case Scenario."[43] More specifically, we combine the characteristics of both firms and assign the "best"

[41]Mazzeo et. al. (2014) make a similar argument. They quantify the welfare effects of merger with endogenous enty/exit in a computational exercise using a stylized model that is similar to our model. In contrast, we provide a methodology to estimate an industry model and perform a merger analysis using those estimates. Also, we allow for multiple equilibiria in both estimation and the merger analysis, whereas Mazzeo et. al. (2014) assume a unique outcome from a selection rule based on ex ante firm profitability.

[42]In this merger, American is the surviving firm.

[43]This is the "best case" scenario that the firms would be able to present in court to make the strongest case that the merger is pro-competitive. Our reasoning for choosing to look at the "best case" scenario from the merging parties' viewpoint is that a merger should definitively not be allowed if there are no gains even under such "best case" scenario, whether in the form of lower prices or new entry, after the merger. However, this case may cause the exit of some firms or prices to rise in some markets, so this might not be best case

characteristic between AA and US to the new merged firm. For example, in the consumer utility function, our estimate of *Origin Presence* is positive, so, after the merger, we assign the maximum of *Origin Presence* between AA and US to the post-merger AA. For marginal costs, we assign the highest level of *Origin Presence* between AA and US to the post-merger AA. And for fixed costs, we assign the highest level of *Nonstop Origin* and *Nonstop Dest* between AA and US to the post-merger AA. We implement the same procedure for for the unobserved shocks. We use the same simulation draws from estimation for the merger scenario, and we assign the "best" simulation draw (for utility the highest and for costs the lowest) between AA and US to the post-merger AA.

Second, we consider the scenario where the surviving firm takes on the mean values of the observed and unobserved characteristics from the two pre-merger firms, and call this the "Average Case Scenario." Lastly, we consider the situation where the surviving firm inherits the best observed characteristics of the two pre-merger firms, but takes a new draw of the unobserved characteristics, and call this the "Random Case Scenario."

In Table 6, we present aggregate statistics to provide an industry wide analysis of how an hypothetical merger would impact market structure and prices.[44] The rows represent the pre-merger predictions of the model and the three scenarios we consider after the merger. The first column is 95% confidence interval for the median fare (share weighted across markets). The second column is the median consumer welfare across markets, and the third column is the median market level (summed over all firms) profits.[45] In Table 7, we display 95% confidence interval for entry probabilities for each of the airlines.

Under the "Best Case Scenario," the median fare would decrease slightly, while consumer welfare and profit would roughly double. In the other two cases, where the new AA realizes

from the point of view of the regulator."

[44]In all cases we report 95% confidence intervals constructed using the same procedure we use to construct intervals for inference on the parameters in the model, the sub-sampling procedure in Chernozhukov, Hong, and Tamer (2007). We run the counterfactual scenarios for 200 parameter vectors that are contained in the original confidence region. For example, to attain the confidence interval for average prices for a single firm across all markets, we would compute the statistic for each parameter vector and then take 2.5 and 97.5 percentiles of these estimates, across the 200 parameter vectors, as our confidence region.

[45]To compute changes in welfare we consider the log-sum logit compensating variation formula, see Train (2009).

only modest efficiencies (the merged firm takes the mean attributes of the pre-merger AA and US), the median fare rises slightly, while consumer welfare and total profit drop by roughly 20 percent. We will explore the mechanisms for these changes below, but the novelty of our model is the ability to endogenize product market structure changes due to a merger.

In Table 7 we can see that after the merger, AA's likelihood of entry increases substantially in the best case scenario. This happens at the expense of the other airlines, who see slight decreases in entry probabilities, even though they face one fewer potential entrant, overall. In the other two cases, AA sees a modest increase in the number of markets served, and the other airlines see a very slight increase in entry probabilities. In the remaining discussion in this section, we go deeper into the mechanisms that explain these aggregate changes by considering changes in particular types of markets.

Table 6: Aggregate Effects of Merger, per market ($)

| | Prices | Consumer Welfare | Profit |
|---|---|---|---|
| Pre-merger | [175.88, 177.80] | [55,835, 58,420] | [63,933, 66,997] |
| Post-merger | | | |
| *Best Case* | [167.78, 169.54] | [110,547, 116,031] | [130,660, 137,159] |
| *Average Case* | [177.46, 179.41] | [41,467, 43,312] | [47,507, 49,745] |
| *Random Case* | [177.51, 179.42] | [44,378, 46,401] | [51,193, 53,556] |

Note: All figures are median USD per market. Confidence intervals are constructed using the sub-sampling routine described in the text.

Table 7: Entry Probabilities, Post-merger

| | AA | DL | LCC | UA | US | WN |
|---|---|---|---|---|---|---|
| Pre-merger | [0.411, 0.413] | [0.788, 0.790] | [0.183, 0.187] | [0.542, 0.544] | [0.510, 0.513] | [0.455, 0.456] |
| Post-merger | | | | | | |
| *Best Case* | [0.860, 0.862] | [0.770, 0.772] | [0.176, 0.179] | [0.525, 0.527] | – | [0.446, 0.447] |
| *Average Case* | [0.564, 0.567] | [0.795, .798] | [0.187, 0.191] | [0.550, 0.553] | – | [0.459, 0.460] |
| *Random Case* | [0.531, 0.534] | [0.794, 0.796] | [0.187, 0.190] | [0.549, 0.551] | – | [0.458, 0.459] |

Note: Entry probabilities across all markets in the sample described in the text. Confidence intervals are constructed using the sub-sampling routine described in the text.

We begin our detailed analysis looking at two sets of markets that are at the polar opposites in terms of post-merger effects: markets that were not served by any airline before the merger; and markets that were served by American and USAir as a duopoly before the merger. These are natural starting points because we want to ask whether new markets could be profitably served as a consequence of the merge of American and USAir, which is clearly a strong reason for the antitrust authorities to allow for a merger to proceed. We also want to examine the markets that are most likely to see higher prices and bigger welfare losses post-merger.

In the following tables we report the likelihood of observing particular market structures and expected percentage change in prices conditional on a particular market structure transition. Table 8 is a simple "transition" matrix that relates the probability of observing a market structure post-merger (columns) conditional on observing a market structure pre-merger (rows).[46] The 2 x 2 matrix consists of the two pre-merger market structures, with no firm in the market, and with a duopoly of US and AA. The post-merger market structures are those markets with no firm in the market and with a monopoly of AA/US.[47]

Table 8 shows that under the *Best Case Scenario* the probability that the merged firm AA/US will enter a market that was not previously being served is between 64.2 and 64.7 percent, which is a substantial and positive effect of the merger taken into account by the standard analysis with exogenous market structure. We also find that there is a probability between 99.8 and 100 percent that the merged firm will continue serving a market that both independent firms were serving pre-merger, and the merged firm would charge a *lower* price (between -18.7 and -18.5 percent) because of the efficiency gains from the merger.

Under the *Average Case* and the *Random Case Scenario* the findings are remarkably different, which illustrates the importance of the assumptions we make on the observed and unobserved characteristics of the merged firm. More specifically, under the *Average Case* we find that the probability that the merged firm AA/US will enter a market that was not previously being served is between 8.7 and 8.8 percent, and under the *Random Case* it is between 34.2 and 34.6 percent. The prices would now *increase*, in sharp contrast with the predictions made under the *Best Case*. These price increases reflect upward pricing pressure

[46] Although our model is static, we use the terminology "transition" in order to convey predicted changes pre-merger to post-merger.

[47] The complete transition matrix would be of dimension 64 x 32, which we do not present for practical purposes.

from an increase in concentration.

Table 8: Market Structures in AA and US Monopoly and Duopoly Markets

| | Post-merger Entry | | Post-merger %Δ Price |
|---|---|---|---|
| Pre-merger | No Firms | AA Monopoly | AA Monopoly |
| *Best Case Scenario* | | | |
| No Firms | [0.353, 0.358] | [0.642, 0.647] | – |
| AA/US Duopoly | [0.000, 0.000] | [0.998, 1.000] | [-18.7, -18.5] |
| *Average Case Scenario* | | | |
| No Firms | [0.912, 0.913] | [0.087, 0.088] | – |
| AA/US Duopoly | [0.000, 0.000] | [0.824, 0.836] | [+4.3, +4.5] |
| *Random Case Scenario* | | | |
| No Firms | [0.654, 0.658] | [0.342, 0.346] | – |
| AA/US Duopoly | [0.183, 0.195] | [0.445, 0.456] | [+13.6, +14.1] |

Next, we can investigate how the entry of the other potential entrants would change the prices in those markets that were AA and US duopolies pre-merger. Table 9 shows the probability that one of the other four competitors will enter into the market where there was a duopoly of American and USAir pre-merger and the change in prices.

Under the *Best Case Scenario* (top panel of Table 9) we find very little evidence that other competitors would enter. Yet, due to efficiencies prices would not increase in consolidated markets. Under the *Average Case Scenario* and the *Random Case Scenario* we find that the prices would not change when DL or UA enters into a market that was previously an AA/US duopoly. Prices would rise substantially in the case of the low cost carriers and WN. We interpret these results as suggesting that the merged firm faces a stronger threat of entry from rival legacy carriers.

We now take a different direction of investigation. Instead of focusing on markets where there would be an ex-ante concern that prices increase after the merger, we explore in more depth the possible benefits of a merger, which could allow a new, possibly more efficient, firm to enter into markets that were monopolies pre-merger.

In Table 10 we consider the likelihood that after its merger with US, AA enters a market where it was *not present* pre-merger. In this table we only consider those markets that were

Table 9: Entry in former AA and US Duopoly Markets

| *Best Case Scenario* | Duopoly AA/US & DL | Duopoly AA/US & LCC | Duopoly AA/US & UA | Duopoly AA/US & WN |
|---|---|---|---|---|
| Prob mkt structure | [0.000, 0.001] | [0.000, 0.000] | [0.000, 0.001] | [0.000, 0.000] |
| Percent Change in price of AA | [-14.3, +0.7] | [–, –] | [-27.1, +1.3] | [–, –] |
| *Average Case Scenario* | | | | |
| Prob mkt structure | [0.065, 0.073] | [0.009, 0.015] | [0.051, 0.058] | [0.017, 0.021] |
| Percent Change in price of AA | [-0.5, +0.8] | [-5.7, +4.7] | [+3.6, +6.0] | [+7.9, +9.8] |
| *Random Case Scenario* | | | | |
| Prob mkt structure | [0.065, 0.068] | [0.005, 0.008] | [0.044, 0.045] | [0.010, 0.012] |
| Percent Change in price of AA | [+28.2, +29.9] | [+31.6, +62.1] | [+11.2, +15.3] | [+42.8, +51.5] |

monopolies before the merger. In the first column we display the likelihood that AA replaces the monopolist after the merger, and in the second column we display the likelihood that AA joins the monopolist and forms a duopoly after the merger. For example, AA would replace DL as a monopolist with a probability between 4.4% and 4.7%, for the "Best Case Scenario." It is much more likely that AA enters to form a duopoly, between 62% and 62.6%, and the DL prices would fall by roughly 4%.[48] AA is more likely to replace an LCC than other airlines, and in all cases of duopoly we should expect lower prices. Our findings under "Average Case Scenario" and the "Random Case Scenario" are similar, although in those cases the likelihood of entry is much less than in the "Best Case Scenario." These results highlight the potential benefits of the merger. They also highlight, again, that the merged firm faces a stronger threat of entry from rival legacy carriers, given the estimated higher entry probabilities in UA and DL monopoly markets that in WN and LCC ones.

The intuition for the new market entry by AA/US and the corresponding changes in prices is straightforward. Under our assumptions about the merger, the new firm will typically generate higher utility and/or have lower costs in any given market than each of AA and US did separately before the merger. Low costs will promote entry of AA and lower prices for rivals after entry (in our model prices are strategic complements) and higher utility will

[48] We can only construct price changes for firms that were in the market pre- and post-merger. So, for example, we do not have a change in price in markets where AA/US replaces DL. For markets where AA/US enters to form a duopoly with Delta, we will have the change in prices for DL, but not for AA/US.

promote entry by AA and upward price pressure, or even lead to exit by incumbents, as we see in those monopoly markets where AA/US replaces the incumbent.

Table 10: Post-merger Entry of AA in Former Monopolies

| | AA Replacement | AA Entry | |
|---|---|---|---|
| Pre-merger Firm | Entry Probability | Entry Probability | Price Change (%) |
| *Best Case Scenario* | | | |
| DL | [0.044, 0.047] | [0.620, 0.626] | [-4.2, -4.1] |
| LCC | [0.130, 0.145] | [0.488, 0.496] | [-4.4, -4.2] |
| UA | [0.076, 0.082] | [0.600, 0.606] | [-4.0, -3.9] |
| WN | [0.050, 0.056] | [0.518, 0.523] | [-3.5, -3.4] |
| *Average Case Scenario* | | | |
| DL | [0.002, 0.003] | [0.086, 0.089] | [-2.5, -2.5] |
| LCC | [0.004, 0.009] | [0.061, 0.067] | [-2.5, -2.4] |
| UA | [0.054, 0.058] | [0.085, 0.091] | [-2.5, -2.4] |
| WN | [0.003, 0.003] | [0.077, 0.081] | [-2.0, -2.0] |
| *Random Case Scenario* | | | |
| DL | [0.018, 0.019] | [0.349, 0.351] | [-3.7, -3.7] |
| LCC | [0.038, 0.052] | [0.246, 0.253] | [-4.0, -3.8] |
| UA | [0.029, 0.034] | [0.335, 0.342] | [-3.3, -3.2] |
| WN | [0.021, 0.023] | [0.285, 0.289] | [-2.9, -2.9] |

In Table 11, we focus on markets where AA is already present in the market and another incumbent duopolist *exits* after the merger. This is clearly different than what we have just investigated, where (the new) AA was simply adding itself into a market, and the consumers would clearly benefit, generally with lower prices and greater product variety. There are two reasons why a competitor would drop out of a market after a merger. First, after the merger AA might become more efficient in terms of costs, therefore lowering price and making it difficult for the rival to earn enough variable profit to cover fixed costs.[49] Second, AA might become more attractive to consumers after the merger and steal business from rivals. For ease of exposition we only consider markets where AA and other incumbents were in the market, and we do not report the results for the other merging firm, USAir.

The first row of Column 1 in Table 11 shows that, for the *Best Case Scenario*, there is a

[49]AA could either experience a decrease in marginal costs, or a decrease in fixed costs. For the fixed costs case, AA could have been a low marginal costs firm before the merger, but high fixed costs prevented entry. After the merger and decrease in fixed costs could lead to entry with the already low marginal costs.

probability between 4.4 and 4.5 percent that DL will leave the duopoly market with AA after American merges with USAir. In such cases, AA's price will be between 12.3% and 11.3% lower. Overall the greatest likelihood of exit is for the LCC airline. In most cases, AA's new price will be slightly lower than before the merger, suggesting that under our assumptions the efficiency effects dominate the business stealing effects. In contrast, when there are not sizable efficiencies, the likelihood of rival exit is small, up to 2.5% for LCC in the *Random Case Scenario*, but as low as 0. In those cases when the market becomes more concentrated, the model predicts that prices will rise.[50]

Table 11: Likelihood of Exit by Duopoly Competitors after AA-US Merger

| Pre-merger Firm | Probability of Exit | AA Price Change (%) |
|---|---|---|
| *Best Case Scenario* | | |
| DL | [ 0.044, 0.045] | [-12.3, -11.3] |
| LCC | [0.089, 0.119] | [-7.4, -4.4] |
| UA | [0.067, 0.072] | [-4.7, -3.9] |
| WN | [0.050, 0.056] | [-3.8, -1.9] |
| *Average Case Scenario* | | |
| DL | [0.001, 0.001] | [-3.7, +2.9] |
| LCC | [0.001, 0.011] | [+52.7, +100.1] |
| UA | [0.002, 0.003] | [+8.3, +22.7] |
| WN | [0.000, 0.001] | [-2.9, +26.7] |
| *Random Case Scenario* | | |
| DL | [0.008, 0.009] | [+5.9, +7.7] |
| LCC | [0.020, 0.025] | [-3.4, +7.6] |
| UA | [0.014, 0.014] | [+5.9, +0.0] |
| WN | [0.007, 0.008] | [+1.4, +0.7] |

## 6.2 The Economics of Mergers at a Concentrated Airport: Reagan National Airport

The Department of Justice reached a settlement with American and USAir to drop its antitrust challenge if American and USAir were to divest assets (landing slots and gates) at Reagan National (DCA), La Guardia (LGA), Boston Logan (BOS), Chicago O'Hare (ORD),

[50]Even in the *Average Case Scenario* and the *Random Case Scenario*, AA may experience some efficiencies. Although AA could also have higher costs after the merger, which is probably more likely in cases where AA was already an entrant (because they probably were more efficient than US in such markets).

Dallas Love Field (DAL), Los Angeles (LAX), and Miami International (MIA) airports. The basic tenet behind this settlement was that new competitors would be able to enter and compete with AA and US, should the new merged airline significantly raise prices.

Here, we conduct a counterfactual exercise on the effect of the merger in markets originating or ending at DCA. These markets were of the highest competitive concern for antitrust authorities because both merging parties had a very strong incumbent presence.[51]

Table 12 reports the results of a counterfactual exercise that looks at the exit of competitors and changes in price in markets with DCA as an endpoint that were served by both AA and US before the merger.[52]

Let us begin with the triopoly AA/US/DL. We find that there is a significant likelihood that the market becomes more concentrated. The AA/US/DL market turns into a AA/DL market with probability [0.770, 0.793] for the "Average Case Scenario", for example. We find that in all three cases, this would not result in a significant rise in price.

In none of the pre-merger markets where AA and US were both present, LCC or WN are likely to replace US. This finding confirms that DL and UA offer a service that is a closer substitute to the one provided by AA and US than WN and LCC do.

For market with four firms,, the most likely outcome across all cases is a consolidation to AA/DL/UA. For the *Best Case Scenario*, this is accompanied by lower prices. For the *Average Case Scenario* and the *Random Case Scenario*, we find evidence of higher prices in several markets.

Overall, our results suggest that the decisions made by the Department of Justice to facilitate the access to airport facilities to new entrants were justified under two of the three scenarios, and should help controlling the post-merger increase in prices.

[51] Although we do not model slot constraints, our model would provide crucial information on which airports would be the ones where anticompetitive concerns would be the most relevant and the results suggest DCA was indeed one where there should have been competitive concerns regarding AA/US.

[52] None of the DCA markets in our sample were a AA/US duopoly before the merger, so we look at other market structures that are present in the data.

Table 12: Post-merger entry and pricing Reagan National Airport

| *Best Case Scenario* | | | | | |
|---|---|---|---|---|---|
| | Post-merger Market Structure | | | | |
| Pre-merger Markets | AA/DL | AA/UA | AA/DL/LCC | AA/DL/UA | AA/DL/WN |
| *AA,US,DL Markets* | | | | | |
| Mkt Struct. Transitions | [0.978, 0.983] | [0.000, 0.000] | [0.000, 0.000] | [0.000, 0.000] | [0.000, 0.000] |
| %Δ Shares Weighted Price | [-13.1, -12.7] | [n.a.] | [n.a.] | [n.a.] | [n.a.] |
| *AA,US,DL,UA Markets* | | | | | |
| Mkt Struct. Transitions | [0.008, 0.012] | [0.015, 0.019] | [0.000, 0.000] | [0.970 0.976] | 0.000, 0.000] |
| %Δ Shares Weighted Price | [-21.8, -17.1] | [-26.6, -20.6] | [n.a.] | [-12.4, -11.7] | [n.a.] |
| *Average Case Scenario* | | | | | |
| *AA,US,DL Markets* | | | | | |
| Mkt Struct. Transitions | [0.770, 0.793] | [0.000, 0.000] | [0.007, 0.020] | [0.025, 0.062] | [0.006, 0.016] |
| %Δ Shares Weighted Price | [+0.1, +0.7] | [n.a.] | [-32.3, +30.6] | [-5.0, +2.0] | [-18.2, -8.0] |
| *AA,US,DL,UA Markets* | | | | | |
| Mkt Struct. Transitions | [0.000, 0.000] | [0.001 0.003] | [0.000, 0.000] | [0.913, 0.929] | [0.000, 0.000] |
| %Δ Shares Weighted Price | [n.a.] | [-33.4, -12.2] | [n.a.] | [+3.6, +3.8] | [n.a.] |
| *Random Case Scenario* | | | | | |
| *AA,US,DL Markets* | | | | | |
| Mkt Struct. Transitions | [0.725, 0.744] | [0.000, 0.000] | [0.000, 0.007] | [0.027, 0.048] | [0.012, 0.032] |
| %Δ Shares Weighted Price | [-1.0, +0.2] | [n.a.] | [-33.3 -32.8] | [-7.7 +1.5] | [-9.0, -0.7] |
| *AA,US,DL,UA Markets* | | | | | |
| Mkt Struct. Transitions | [0.000, 0.000] | [0.007 0.008] | [0.000, 0.000] | [0.749 0.765] | [0.000, 0.000] |
| %Δ Shares Weighted Price | [n.a.] | [+0.9, +9.7] | [n.a.] | [+6.3, +6.8] | [n.a.] |

Note: Counterfactual predictions for markets with DCA as one endpoint.

# 7 Conclusions

We provide an empirical framework for studying the quantitative effect of self-selection of firms into markets and its effect on market power in static models of competition. The counterfactual exercise consist of a merger simulation that allow for changes in market structures, and not just in prices. The main takeaways are: i) that self-selection occurs, and ii) controlling for it can can lead to different estimates of price elasticities and markups than those that we find when we assume that market structure is exogenous to the pricing decision; iii) this in turn leads to potentially important differences from exogenous entry models in the projected response to policy counterfactuals, such as merger simulations.

More generally, this paper contributes to the literature that studies the effects that mergers or other policy changes have on the prices and structure of markets, and consequently the welfare of consumers and firms. These questions are of primary interest for academics and researchers involved in antitrust and policy activities.

One extension of our model is to a context where firms can change the characteristics of the products they offer. To illustrate, consider Sovinsky Goeree (2008) who investigates the role of informative advertising in a market with limited consumer information. Sovinsky Goeree (2008) shows that the prices charged by producers of personal computers would be higher if firms did not advertise their products, because consumers would be unaware of all the potential choices available to them, thus granting greater market power to each firm. However, this presumes that the producers would continue to optimally produce the same varieties if consumers were less aware, while in fact one would expect them to change the varieties available if consumers had less information, for example by offering less differentiated products. It is possible to extend our framework to investigate questions like this where firms choose product characteristics.

Also, the proposed methodology can be applied in all economic contexts where agents interact strategically and make both discrete and continuous decisions. For example, it can be applied to estimate a model of household behavior where a husband and a wife must decide whether to work and how many hours.

We wish to conclude with a discussion of the limitations of our approach. There are several components/variables in the classical model (Bresnahan, 1987; or Berry, 1994) that are taken as exogenous. More specifically, the classical model takes as exogenous: the entry decision; the location decision in the space of the observed characteristics; and the location decision in the space of the unobserved characteristics. Our goal is to relax one of those – the decision to participate in the market, and continue to assume that the location in the space of the observed and unobserved characteristics is exogenous. We leave to future work the next step, which is to relax those assumptions as well. Some recent important work in that direction is in Li et al. (2017). Also, Petrin and Seo (2017) propose an interesting approach for the problem of endogenous product characteristics (conditional on entry) by using information from the firms' necessary optimality conditions for the choice of product characteristics.

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