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 while allowing for correlations between unobserved cost and demand shocks. We use our framework to account for selection in the pricing stage. We estimate the model using data from the US airline industry and find that not accounting for endogenous entry leads to biased estimation of demand elasticities. We simulate a merger between American and US Airways and find that product repositioning and post-merger outcomes depend on how we model the characteristics of the merged firm as a function of the pre-merger firms' characteristics.

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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 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, possibly by reducing an excessive number of products in the market. Importantly, allowing

[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.

for entry (or product variety) to change as a response to a merger is important. For example, when a firm (or product) exits due to consolidation from a merger, it is likely that other firm may now find it profitable to enter (or to offer new products in the market). 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). Our innovation on this front is to show how to estimate demand and supply equations in the presence of multiple equilibria in the entry stage by constructing moment inequities from conditional distributions of the residuals. 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. 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 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.[5] 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

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

[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 C for more details.

[5]The selection problem could lead to overestimation or underestimation of demand elasticities, and thus markups, depending on the covariance of demand, marginal cost, and fixed costs unobservables. We illustrate this dependence in the numerical exercise in Appendix E.

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

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 allowing for equilibrium changes to market structure after a merger, which in turn may affect equilibrium prices charged by firms.

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 four 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*. Then we simulate two sub-cases, one in which the merged firm takes the best observable characteristics between the two pre-merger firms and the average of AA's and US's pre-merger unobservables; and another where we draw a new unobservable for the new merged firm. Lastly, we consider a case where the surviving firm inherits the average observed and unobserved characteristics between the two pre-merged firms, or what we call the *Average Case* scenario.

We find that under all four scenarios there is substantial post-merger entry and exit among the surviving airlines, especially for the surviving merged airline, American Airlines. For the scenario in which we assume the most merger efficiencies, the average price across all markets increases slightly, but consumer welfare also substantially rises due to post-merger entry from the new merged airline. Of course, there is a lot of heterogeneity across the types of markets, so we look at the effects of the merger on markets that share particular pre-merger market structures. For example, we find that the the merged airline would enter previously unserved markets with a likelihood of around 48 percent in the *Best Case Scenario*, and prices would increase by roughly 14 percent in markets that were previously only served by an AA and US duopoly. In contrast, when we assume that the post-merger airline takes the average characteristics from AA and US (the *Average Case* scenario), we find that the the merged airline would enter previously unserved markets with a likelihood of around nine percent and prices would rise by roughly five percent in markets that were previously only served by a AA and US duopoly. Clearly, assumptions about merger efficiencies matter – not just for pricing pressure, but also for post-merger entry/exit. We systematically document the these types of effects across many pre-merger market structures.

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. We find that prices would increase, though in different degrees that depend on the scenario under consideration. We also find that 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 other important work related to estimating static models of competition while allowing for market structure to be endogenous. Reiss and Spiller (1989) estimate a monopoly model of airline competition and entry. 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. Ellickson and Misra (2012) use a two-step method to estimate a static discrete game of incomplete information and correct for an outcome equation, in their case, revenues. Berry (1999), Draganska, Mazzeo, and Seim (2009), Pakes et al. (2015) (PPHI), and Ho (2009) assume that firms self-select themselves into markets based on *observable* characteristics by imposing restrictions on information about the unobservables. 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.[7] Similar timing assumptions are made by other papers as well, such Sweeting

[7] 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

(2013), Lee (2013), Jeziorksi (2014b), Jeziorksi (2014a) in dynamic empirical games; and Fan (2013) and Fan and Yang (2020) in static games.[8] Another related paper is Fan (2013), who does allow for arbitrary correlation between unobservablesbut her setting is one where firms choose a continuous product characteristic. Another paper that is closely related to ours is Li et al. (2021), 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. (2021) 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 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

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.

[8]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.

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).[9]

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 Σ 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 unobservables is the source of selectivity bias.

One reason why we would expect firms to self-select into markets is because the fixed

[9] It is simple to allow β and γ to be different among players, but we maintain this homogeneity for exposition.

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 workers who command higher wages and are more likely to receive offers.

In the structural model of the airline industry we present in Section 3, the unobservables that determine outcomes also enter directly into the selection equation (see equation 7 in section 3). So, even if the unobservables are mutually independent, the model would still lead to selection effects. Firms with higher unobserved demand or lower unobserved costs will be more likely to enter. This departs from the standard Heckman selection setup and its generalization to two firms above because the structural errors terms that appear in the outcome equations (the ξ_1 and ξ_2 in (1) above) do not enter the first two equations in (1) (the entry equations).

Given that the above model defined in equation (1) is parametric, the only non-standard complications that arise are multiplicity of equilibria in the underlying game and 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 such as prices).

The data we observe are $(S_1y_1, V_1y_1, y_1, S_2y_2, V_2y_2, y_2, \mathbf{X}, \mathbf{Z})$ 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 $(S_1y_1, V_1y_1, y_1, S_2y_2, V_2y_2, y_2, \mathbf{X}, \mathbf{Z})$; 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 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[10] 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.[11]

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* (β, α_1) *from this unknown function (identification of* (β, α_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 ξ_1 that are less than t_1 when the unobservables (ν_1, ν_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.

[10] Here we use the CDF, but we could also use probabilities of the form $P(t_0 \leq S_1 - \alpha_1 V_1 - X_1\beta \leq t_1;\, y_1 = 1, y_2 = 0|X, Z)$ for all $t_0 \leq t_1$. Bounding histogram like probabilities in some cases may be easier to compute.

[11] In the case where we have no endogeneity for example (α'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 $P(\xi_1 \leq -X_1\beta; y_1 = 1, y_2 = 0|\mathbf{X}, \mathbf{Z})$.

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 ξ_1 that are less than t_1 when the unobservables (ν_1,ν_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. 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 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 (α_1, β, 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. δ'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:

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

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

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

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

where

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

Hence, the above can be written as

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

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. Therefore, we 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:[12]

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* Σ*. 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*

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

function below to zero:

$$Q(\theta) = 0 = \int W(\mathbf{X}, \mathbf{Z}) \|\mathbf{G}(\theta, S_1 y_1, S_2 y_2, V_1 y_1, V_2 y_2, y_1, y_2) | \mathbf{Z}, X]\|_+ dF_{\mathbf{X},\mathbf{Z}} \tag{5}$$

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.[13]

Clearly, the stylized model above provides intuition about the conceptual issues involved, but in the next section, we link this system to a model of behavior where the decision to enter (or to provide a product) is more explicitly linked to an economic condition of profits. This entails specification of costs, demand, and an equilibrium solution concept. This is the subject of the next Section, the main contribution of the paper.

3 A Model of Entry and Price Competition

3.1 The Structural Model

Above, we described our methodology using a linear outcome and selection equation for clarity and consistency with the literature on selection. In this section, we present a structural model of demand, pricing, and entry that we take to data from the airline industry. We consider the case of two potential entrants who decide, simultaneously, whether to serve a market and the price to charge in the market.

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

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

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

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 prices $\mathbf{p} = \left(p_1, p_2\right)$. 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,

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

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 $\mathcal{M}$, $\mathbf{W} = \left(W_1, W_2\right)$, $\mathbf{Z} = \left(Z_1, Z_2\right)$, $\mathbf{X} = \left(X_1, X_2\right)$. So, putting these together, we get the following system:

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

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 in market structure. There are no multiple equilibria in the pricing game: Nocke and Schutz (2018) show that there is a unique pricing equilibrium in the case of single-product nested logit, which is what we consider in our application (See Appendix 3 of their On-line Appendix).

Even though the conceptual approach is the same, the inference procedure for this system is computationally more demanding for this model than the one we studied in Section 2. 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

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

We assume demand is derived from the canonical differentiated product discrete choice model (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995). We include a product nest which allows for all of the inside products to share unobserved heterogeneity. Specifically, indirect utility for consumer i from choosing carrier 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, (β, α) are the taste parameters, and ξ_j are product characteristics unobserved to the econometrician.

Following Berry (1994), carrier j's market share is

$$s_j(\mathbf{X}, \mathbf{p}, \xi, \beta_r, \alpha, \lambda) = \frac{e^{(X_j'\beta + \alpha p_j + \xi_j)/(1-\lambda)}}{D} \frac{D^{(1-\lambda)}}{1 + D^{(1-\lambda)}}, \tag{11}$$

where the D represents the sum of exponentiated utilities for all products

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

Unlike in typical demand estimation, we need to compute shares for any given potential market structure. To do this, we introduce some notation. Let

$$E \equiv \{(y_1, .., y_j, .., y_K) : y_j = 1 \text{ or } y_j = 0, \forall 1 \le j \le K\}$$

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 ξ^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.

We can express demand for any given market structure in the following way,

$$\ln s_j\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \ln s_0\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) = X_j\beta + \alpha p_j + \lambda \ln s_{j/g} + \xi_j, \tag{12}$$

where $s_{j/g}$ is share of carrier j among all other carriers in the market, excluding the outside option.

Lastly, unlike typical demand estimation but similar to the entry literature, we parameterize the joint distribution of unobservables. Following Berry (1992) and CT, we specify the unobservables that enter into the fixed cost inequality condition, η_{jm}, as including firm-specific unobserved heterogeneity, $\tilde{\eta}_{jm}$, as well as market specific unobserved heterogeneity, η_m. η_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:

$$\left(\nu_1, \nu_2, \xi_1, \xi_2, \tilde{\eta}_{1m}, \tilde{\eta}_{2m}\right) \sim N\left(0, \Sigma\right) \tag{13}$$

where Σ is the variance-covariance matrix to be estimated. Notice that here we do not include η_m because we assume it is independent of other errors.[14]

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,

[14]When we perform simulation, we draw $\tilde{\eta}_{jm}$ and η_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. See Online Appendix B for details.

we use the following variance-covariance matrix

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

where I_{Km} is a $K_m \times K_m$ identity matrix. 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).

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.

$$\begin{cases} y_j = 1 \Leftrightarrow \pi_j \equiv \left(p_j - \exp\left(\varphi W_j + \eta_j\right)\right) M s_j\left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \exp\left(\gamma Z_j + \nu_j\right) \geq 0, \\ \\ \ln s_j\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \ln s_0\left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) = X_j'\beta + \alpha p_j + \lambda s_{j|g} + \xi_j \\ \\ \ln\left[p_j - b_j\left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right)\right] = \varphi W_j + \eta_j, \end{cases}, \tag{14}$$

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

We present the simulation algorithm here and provide many more details, including computational guidance, in Appendix B.

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 $\Theta^0 = (\alpha^0, \beta^0, \varphi^0, \gamma^0, \Sigma^0)$.

1. We estimate the probability distributions of the residuals. The steps here do not involve any simulations.

   (a) Use α^0, β^0, φ^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 (14) above.

   (b) 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.

2. Next, we construct the probability distributions for the lower and upper bound of the "simulated errors"selected by the model for a guess of the parameters, Θ^0.

   (a) Simulate random vectors of unobservables (ν_r, ξ_r, η_r) from a multivariate normal density with a given covariance matrix, Σ^0, 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 (14) for the *equilibrium* prices $\bar{\mathbf{p}}_r^e$ and shares $\bar{\mathbf{s}}_r^e$.[15]

   (c) Compute $2^{|K|} - 1$ *total* profits.

[15] 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. Given the parametric assumptions, there is a unique pure-strategy price equilibrium, conditional on the market structure. See Nocke and Schutz (2018) for uniqueness in the single product nested logit case considered in our empirical exercise.

(d) 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 $\left(\xi_r^{e^{**}}, \eta_r^{e^{**}}\right)$.[16] 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).[17]

(e) 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 $\Pr\left(\xi_r^e, \eta_r^e; \nu \in A_e^U | \mathbf{X}, \mathbf{W}, \mathbf{Z}\right)$.[18]

3. We construct the distance function (5) in Section (2). The approach we use for inference follows the implementation of Chernozhukov, Hong, and Tamer (2007) in CT, where we use subsampling based methods to construct confidence regions.

Conceptually, the above is a minimum distance procedure that compares the distribution function from the data (constructed in Step 1 above) to the upper and lower bounds on this distribution predicted by the model (the upper and lower bounds are constructed in Step 2. The upper and lower bounds in Step 2 are a result of multiple equilibria while the complication in Step 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

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

[17] See Appendix B (page 4) for details, including how we handle situations where no pure-stategy equilibria exist.

[18] 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.

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.[19]

We define a market as a unidirectional trip between two airports, irrespective of intermediate transfer points.[20] The dataset includes the markets between the top 100 US Metropolitan Statistical Areas ranked by their population. We include markets that are not served by any carrier. 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.

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

[20] We do not model the decision of nonstop versus connecting flights. This is very difficult problem given the hub-network structure of airline markets. See Aguirregabiria and Ho (2012) for a treatment of hub-spoke networks using a dynamic game framework and Li et al. (2021) for a recent treatemnt in a static framework.

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.[21]

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.

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.

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.

[21] 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., 2016).

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.

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 (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 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

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

mean value of *Distance* is 1110 miles (one-way), which is slightly lower than the mean values for active airline-markets, 1170 miles.

Fixed and Marginal Costs in the Airline Industry.[22] The total costs of serving an airline market consists of three components: airport, flight, and passenger costs.[23]

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, to capture economies of density (Brueckner and Spiller (1994)).

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

[23] Other costs are incurred at the aggregate, national, level, and we do not estimate them here (advertising expenditures, for example, are rarely market specific).

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. In our static model, the flight costs are variable in the number of passengers transported in a quarter. 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. We maintain that the flight and passenger costs enter the *economic* opportunity cost of flying a passenger.[24]

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*.

The economic marginal cost is not observable (Rosse, 1970; Bresnahan, 1989; Schmalensee, 1989). We parameterize it as a function of the non-stop distance, *Distance*, between two airports. We also allow the marginal cost to be different for LCC and Southwest through the use of dummy variables.

4.2 Identification

We begin by discussing the source of exogenous variation in our estimation and how the parameters of the model are identified. 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 ξ. We instrument for price using the exogenous variables for *all potential* rivals. These instruments are different than the "BLP instruments" widely used in the literature (Berry, Levinsohn, and Pakes, 1995). The aggregation typically used in the form

[24]This can be interpreted as 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).

of the BLP instruments has been shown to be problematic (see Gandhi and Houde, 2019). [25] Our approach is slightly different from the standard one and capture greater variation in competitive environments 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. In addition, the exogenous variables that affect fixed costs, which correlate with equilibrium prices through the entry conditions in our model, 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 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. 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

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

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 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.

Next, we describe how the correlations between the unobservables are identified.[26] 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 that 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 that 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

[26]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.

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.

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. To facilitate the comparison across model specifications and methodologies, in all columns of Table 4 we report 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.[27]

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 12.[28]

In order to limit the space over which to draw for the minimization procedure, we standardize all the exogenous variables.[29] All the results are as expected and resemble those in previous work, for example Berry and Jia (2010) and Ciliberto and Williams (2014).[30] Starting from the demand estimates, we find the price coefficient to be negative, and included in

[27]This is the approach that was used in CT. See the On-line Supplement to CT and Chernozhukov, Hong, and Tamer (2007) for details. Notice that there are no multiple equilibria in Columns 1 and 2. In Column 3 multiple equilibria are allowed to occur, but, in practice, we did not find that multiple equilibria were as common as in CT in our estimates.

[28]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.

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

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

[-2.396,-2.194] and λ, the nesting parameter, to be between 0 and 1.[31] The corresponding median elasticity is included in [-8.181,-8.106], and the confidence interval for the median markup is [28.089,28.220]. 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 it is increasing in distance.

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. 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 structure version.

We present the results of this estimation in Column 2 of Table 4. We observe that all of the cost estimates in Column 2 overlap those in Column 1. Most of the demand estimates in Column 2 overlap with those in Column 1, and the ones that do not overlap are very close. The estimate of the median elasticity of demand and of the markup are close to the ones in Column 1.

5.2 Results with Endogenous Market Structure

Column 3 of Table 4 displays the estimates from our model using the methodology developed in Section 2.

We estimate the coefficient of price to be included in [-1.557,-1.488] with a 95 percent probability, which is statistically smaller than the estimate from the model with exogenous market structure in Column 2 of Table 4.

We estimate λ for the exogenous entry case to be in the interval [0.294,0.366] (Column 2 of Table 4), while in the endogenous entry case we estimate λ to be included in [0.186, 0.206]. Thus, we find that the within group correlation in unobservable demand is also estimated

[31] We denote fares in $100s for readability of the estimates.

Table 4: *Parameter Estimates*

	GMM	Exogenous Entry	Endogenous Entry
Demand			
Price (100$)	[-2.385, -2.185]	[-2.315, -2.282]	[-1.557, -1.488]
λ	[0.320, 0.519]	[0.294, 0.366]	[0.186, 0.206]
Distance	[0.308, 0.364]	[0.394, 0.461]	[0.724, 0.793]
Origin Presence	[0.291, 0.339]	[0.102, 0.169]	[1.688, 1.752]
LCC	[-0.333, -0.143]	[-1.078, -0.486]	[0.080, 0.273]
WN	[0.216, 0.335]	[-0.077, 0.206]	[-0.029, 0.128]
Constant	[-2.299, -1.817]	[-2.961, -2.851]	[-4.683, -4.587]
Marginal Cost			
Distance	[0.118, 0.124]	[0.112, 0.130]	[0.083, 0.094]
Cons LCC	[-0.313, -0.287]	[-0.419, -0.288]	[-0.027, 0.054]
Cons WN	[-0.144, -0.127]	[-0.247, -0.080]	[-0.079, -0.017]
Constant	[5.343, 5.351]	[5.339, 5.348]	[5.132, 5.179]
Fixed Cost			
Nonstop Origin	–	–	[-0.387, -0.327]
Nonstop Dest.	–	–	[-1.538, -1.473]
Constant	–	–	[1.227, 1.315]
Variance-Covariance*			
Variance Demand	1.514	[2.354, 3.425]	[1.736, 1.876]
Variance Marg. Cost	0.059	[0.072, 0.132]	[0.330, 0.353]
Variance Fixed Cost	–	–	[14.640, 15.636]
Demand-MC Covariance	0.184	[0.278, 0.504]	[0.470, 0.512]
Demand-FC Covariance	–	–	[0.674, 0.829]
MC-FC Covariance	–	–	[-0.709, -0.659]
Market Power			
Median Elasticity	[-8.163,-8.091]	[-7.281, -7.063]	[-4.105, -4.007]
Median Markup	[28.146,28.274]	[30.366, 31.564]	[53.617, 56.051]

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. Column 1 presents the standard 95% confidence intervals. Columns 2 and 3 contain 95% confidence bounds constructed using the method in Chernozhukov, Hong, and Tamer (2007). Price coefficient is multiplied by 100.

with a bias when we do not account for the endogenous market structure. We also find that the coefficient of the market distance is larger, suggesting that self-selection is associated with market distance.

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 [-7.281,-7.063], while we estimate the mean elasticity is [-4.105,-4.007] when we allow for endogenous market structure. This leads to a difference in estimated markups: [30.366,31.564] in the exogenous case compared with [53.617,56.051] in the endogenous market structure case.

Next, we show the results for the estimates of the fixed cost parameters. Clearly, these are not comparable to the results from the previous model where market structure is assumed to be exogenous and fixed cost estimates are not recoverable. Column 3 of Table 4 shows the constant in the fixed cost inequality condition to be included in [1.227,1.315], 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.

We compute the confidence interval for mean fixed costs, not shown in the table, to be [$52,990;$59,275]. To put these numbers in perspective, we need to recall that these are *market* fixed costs, and they are not the fixed costs paid to serve one of the legs of that market. Compared to the number of (uni-directional) non-stop segments served by an airline, the number of (uni-directional) markets served by that airline is many times larger. That is, a single non-stop leg will be part of the service on many markets, and we cannot infer the cost of serving the single non-stop leg, which is bound to be much larger, from the fixed costs of serving the markets.[32]

Next, we investigate the estimation results for the variance-covariance matrix. The variance of demand error is included in [2.354,3.425] in Column 2 (exogenous market structure) and in [1.736, 1.876] in Column 3 (endogenous market structure). The variance of the marginal cost unobservables is estimated in [0.072,0.132] in Column 2 and [0.330, 0.353] in Column 3. The larger values are explained in part by the fact that in the exogenous case, the distribution represents a *selected distribution* whereas in the endogenous case our estimates represent the full unselected distribution of the errors.[33] The variance of the fixed costs is included in [14.460,15.636].

The covariance between the demand and marginal cost is positive in all three columns. The covariance of the demand and fixed cost unobservables is estimated to be included in [0.674, 0.829] and the covariance between fixed and marginal costs unobservables is [-0.709,-

[32] See Aguirregabiria and Ho (2012) for a rigorous discussion of this point.

[33] See Appendix E for further discussion and comparisons of selected and unselected distribution of errors.

0.659]. Carriers with unexpectedly (not predicted by observables in the model) high demand also have unexpectedly high fixed costs. Firms with unexpectedly high fixed costs have unexpectedly low marginal costs.

The variance covariance matrix implies that unobservables that lead to high demand correlate with higher fixed and marginal costs. This is intuitive if unobservables represent quality and the cost of quality – higher quality increases demand but it comes at some cost to the airline that we do not capture in the covariates. This is in contrast to an alternative story that is more akin to the selection on ability in labor markets where high demand firms are also low-cost producers.

Finally, we discuss 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. The particular way we think about model fit is necessitated by the fact that the model does not make unique predictions and that, if we were to compare aggregate statistics, we would be comparing samples with different market structures. We compare model predictions to the data simulation-by-simulation and market-by-market and then tally up the number of times the model predictions are consistent with the data. For the model prediction to be consistent with the data, the data (e.g. a price) must lie in the 95 percent confidence interval.[34]

Specifically, we draw 100 parameters from the identified set, and simulate the model 200 times, using a new set of simulated unobservables. For any given market structure in any given market, we construct the confidence interval for prices by taking the 2.5 and 97.5 percentile across parameter vectors. Then we compare the price for each airline for that market in the data to the confidence error for the predicted price. We do this again for product shares.[35]

The data lie within the confidence interval for prices 45.51 percent of the time and our

[34]We construct the confidence interval for the prediction for an individual market in the same way we compute confidence intervals elsewhere, by sampling parameter vectors in the identified set.

[35]Note that in the typical econometric procedures used to estimate logit and random coefficient demand systems, shares and prices fit the data perfectly by construction. Our econometric procedure differs in that we do not have a completely flexible product characteristic residual that is allowed to adjust to exactly fit the data.

Table 5: Aggregate Entry Probabilities

	AA	DL	LCC	UA	US	WN	No Entry
Data	0.390	0.727	0.175	0.513	0.488	0.457	0.087
Model Prediction	[0.391, 0.395]	[0.742, 0.745]	[0.185, 0.189]	[0.514, 0.518]	[0.485, 0.490]	[0.459, 0.464]	[0.044, 0.046]

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.

model fits the shares 39.77 percent of the times. The model replicates the entry patterns well. In Table 5 we display the empirical entry probabilities for each airline along with the confidence intervals for entry probabilities predicted by the model. Additionally, the model fits the exact market structure 31.26 percent of the time (meaning all six carriers have the correct participation in the market) and the model predicts a given airline's entry correctly 73.74 percent of the time.[36] In our sample, 8.7 percent of markets are not served by any carrier while our model predicts this outcome in between 4.4 percent and 4.6 percent of markets.

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.

[36]These four numbers are not included in Table 4 for sake of brevity.

Our methodology is ideally suited to evaluate both the endogenous price responses and the endogenous market structure responses as a consequence of a merger. 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.[37]

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 and consider American (AA) the surviving firm. 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 four different scenarios about what it means for AA and US to merge. The four scenarios underscore the key observation that post-merger efficiencies could come from both observed and unobserved features of the carriers. The different assumptions that we discuss next permit to check the robustness of the results of the counterfactual exercise, and, to help with the interpretation of those empirical results.

[37]Mazzeo, Seim, and Varela (2018) 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 equilibria in both estimation and the merger analysis, whereas Mazzeo, Seim, and Varela (2018) assume a unique outcome from a selection rule based on ex ante firm profitability.

First, we consider a case where the surviving firm, AA, takes on the best observed and unobserved characteristics of both pre-merger carriers and call this the "Best Case" scenario.[38] More specifically, we combine the characteristics of both firms and assign the "best" 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 the 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 the unobserved shocks. We use a new set of simulated unobservables (the same ones we used to determine the fit of our model), 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.

Our second scenario closely follows the "best case" scenario, but AA inherits only the best observable characteristics, and we assume the new firm inherits the average of AA's and US's pre-merger unobservables. The results are presented as a sub-case called "mean unobservables."

Our third scenario assumes that the new firm inherits the best observables and gets a new draw for the unobservables, which we term "new unobservables." We simulate these two sub-cases to help us quantify the relative importance to the merger simulations of the efficiency in observables versus unobservables.

Lastly, we consider a 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."

In Table 6, we present confidence intervals for *aggregate* statistics to provide an industry wide analysis of how an hypothetical merger would impact market structure, prices, and consumer and producer surplus. The rows in Table 6 represent the pre-merger predictions

[38] 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 scenario. However, this case may cause the exit of some firms or prices to rise in some markets, so this might not be, ex ante, the best case from the point of view of the regulator.

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

	Mean Fare	Consumer Surplus	Total AA+US Profit*
Pre-merger	[229.32, 239.50]	[8,969; 10,063]	[2,403; 2,711]
Post-merger			
Best Case	[232.06, 242.38]	[9,509; 10,733]	[3,303; 3,796]
... mean unobservables	[229.91, 240.09]	[8,367; 9,400]	[1,798; 2,034]
... new unobservables	[230.71, 240.95]	[8,663; 9,721]	[2,119; 2,390]
Average Case	[231.74, 242.03]	[7,501; 8,411]	[1,868; 2,104]

Note: Confidence intervals are constructed using the sub-sampling routine described in the text. Mean fares are in USD. Consumer surplus is the total compensating variation of the observed product offering in millions of USD. Total AA+US profit is the sum of profit across all markets in millions of USD.

of the model (first row) and the four scenarios we consider after the merger.[39] The first column is the 95% confidence interval for the average fare (share weighted across markets). The second column is the total consumer surplus across all markets in millions of dollars, the third column is the total profit for AA and US (summed over all markets) in millions of dollars.[40]

Under the "Best Case" scenario, the confidence interval for average prices is slightly greater than the baseline, although the two intervals overlap, [$229.32; $239.50] versus [$232.06; $242.38]. Consumer surplus would increase from [$8,969m; $10,063m] to [$9,509m; $10,733m], as would the the profit of the new merged firm compared with the sum of the pre-merger AA and US profit, [$2,403m; $2,711m] to [$3,303m; $3,796m]. This welfare increase is likely unreasonably large, but highlights the importance of merger efficiency assumptions, as our other assumptions on merger efficiency imply lower consumer surplus.

In the sub-cases where only the best observable characteristics are inherited by the merged firm, consumer welfare may fall, as does the merged firm's profit. In the case where the new firm inherits the average pre-merger characteristics, consumer welfare may fall by even more. These results foreshadow an observation that we will make later on again: unobservable characteristics of the firms play a crucial role in determining the welfare effects of a merger.

[39] Notice that, in contrast to standard approach that takes market structure as exogenous, the pre-merger simulations will not necessarily match the observed data on a market by market basis.

[40] To compute consumer surplus we consider the log-sum logit compensating variation formula, see Train (2009).

In Table 7 we report changes in predicted entry probabilities after the merger for all four cases. Specifically, we display 95% confidence interval for entry probabilities for each of the airlines for the baseline and all four merger scenarios. After the merger, AA's likelihood of entry increases substantially in the best case scenario, from entry in [0.391, 0.395] to [0.808, 0.812] of markets. The increase in entry is not surprising given that AA inherits all of USAir's potential markets. This happens at the expense of the other airlines, who see slight decreases in entry probabilities, even though they face one fewer potential entrant.

Under the other three scenarios, AA sees a more modest, but still substantial, increase in the number of markets served, and the other airlines realize very slight increases in aggregate 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 7: Entry Probabilities, Post-merger

	AA	DL	LCC	UA	US	WN
Pre-merger	[0.391, 0.395]	[0.742, 0.745]	[0.185, 0.189]	[0.514, 0.518]	[0.485, 0.490]	[0.459, 0.464]
Post-merger						
Best Case	[0.808, 0.812]	[0.739, 0.742]	[0.183, 0.187]	[0.511, 0.515]	–	[0.457, 0.462]
... mean unobservables	[0.637, 0.642]	[0.742, 0.745]	[0.185, 0.189]	[0.514, 0.518]	–	[0.459, 0.464]
... new unobservables	[0.585, 0.590]	[0.742, 0.745]	[0.186, 0.189]	[0.515, 0.519]	–	[0.459, 0.464]
Average Case	[0.538, 0.544]	[0.744, 0.747]	[0.187, 0.191]	[0.517, 0.521]	–	[0.461, 0.466]

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 analysis by 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 merger, which is clearly a strong reason for the antitrust authorities to allow for a merger to proceed. We also want to examine pre-merger duopolies, which are markets that are most likely to see high price increases and large 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).[41] The 2 x 2 table 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.[42]

Table 8 shows that under the *Best Case Scenario* the probability that the merged firm AA/US will enter a market as a monopolit that was not previously being served is between 47.9 and 48.3 percent, which is a large and positive effect of the merger that would be ignored by the standard economic analysis with exogenous market structure. We also find that there is a probability between 95.8 and 96.6 percent that a market with a AA-US duopoly would be served by the merged firm as a monopoly after the merger. In those two-to-one cases the merged firm would charge a higher price (between 13.6 and 14.7 percent).

Results under the *Best Case Scenario* are different from the *“new unobservables”* scenario in terms of the transition probabilities, but similar in terms prices. Thus, the prices are computed on fewer markets under the second scenario, which is consistent with the firms self-selecting into markets. Notice that the unobservables under the *Best Case Scenario* are necessarily good ones because firms decided to enter into those markets pre-merger with those unobservables. We interpret this finding as supporting our self-selection hypothesis.

The predictions from the other two scenarios are remarkably different from the *Best Case Scenario*, 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 9.2 and 9.4 percent, much lower than the *Best Case*. We also find it very likely that AA-US duopolies would turn into monopolies, and price would increase by 4.8 to 5.2 percent for those markets.

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

[42] The complete transition table would be of dimension 64 x 32 for each pre-merger market structure, which we do not present for practical purposes. Instead, we take slices of these tables.

Comparing the four scenarios, we conclude that the unobservable characteristics play a crucial role in determining the effect of the merger on the higher prices. This observation allows us to make an important point. In any merger simulation that uses empirical industrial organization techniques (e.g. our method or more traditional methods like BLP), synergies from a merger could come through variables modeled by the researcher, or variables unobserved to the researcher. This is an important distinction because it may be more viable for practitioners to successfully defend or prosecute a merger based on observable and measurable variables that can be clearly associated with the mechanisms of synergy. Clearly, it would help to have direct information on the synergies claimed by the parties and how they are merger-specific. We could use that knowledge to develop a fifth scenario that we could compare to the other four, which would allow to check on the credibility of the claimed synergies (under the maintained assumption that the model we are considering is correctly specified, of course).

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	[0.517 0.521]	[0.479 0.483]	–
AA/US Duopoly	[0.000 0.000]	[0.958 0.966]	[+13.6 +14.7]
...mean unobservables			
No Firms	[0.821 0.823]	[0.177 0.179]	–
AA/US Duopoly	[0.000, 0.000]	[0.947 0.959]	[+4.9, +5.2]
...new unobservables			
No Firms	[0.588 0.591]	[0.409 0.412]	–
AA/US Duopoly	[0.322 0.327]	[0.559 0.569]	[+16.5 +17.6]
Average Case Scenario			
No Firms	[0.906 0.908]	[0.092 0.094]	–
AA/US Duopoly	[0.000 0.000]	[0.904 0.916]	[+4.8, +5.2]

Note: Results from a counterfactual merger between AA and US. Post merger entry is the likelihood of observing a column market structure given a pre-merger row market structure. Post merger %Δ price is the percentage change in price for AA after the merger. Confidence intervals are constructed using the subsampling routine described in the text. The large price changes in the table are likely driven by extreme outliers in the simulation draws because they occur when the underlying probability of the event is very small.

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

Under all scenarios we find very little evidence that other competitors would enter. The most likely carriers to replace US are Delta and United, the two other major airlines. In those cases, we would expect prices to change by between -3.3 and 1.3 percent ("Average Case" Delta) or between 0.2 and 6.9 percent ("Average Case", United). There is up to a 3.6 percent chance one of these legacy carriers replaces US for the "Average Case" scenario. Overall, the large price effects should be taken with a good dose of caution because they are computed out of few observations.

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	[0.014 0.018]	[0.003 0.005]	[0.010 0.013]	[0.005 0.008]
Percent Change in price of AA	[+8.0 +24.8]	[+13.1 +39.9]	[+25.2 +38.2]	[+27.9 +43.5]
... mean unobservables				
Prob mkt structure	[0.015 0.023]	[0.004 0.007]	[0.009 0.013]	[0.006 0.010]
Percent Change in price of AA	[-1.0, +2.8]	[+4.6, +17.5]	[-5.1, +4.1]	[+-0.6, +11.7]
...new unobservables				
Prob mkt structure	[0.013 0.020]	[0.006 0.010]	[0.008 0.012]	[0.008 0.011]
Percent Change in price of AA	[+52.4 +73.4]	[+61.6 +90.1]	[+35.9 +90.4]	[+39.4 +78.1]
Average Case Scenario				
Prob mkt structure	[0.028 0.036]	[0.008 0.011]	[0.026 0.030]	[0.015 0.018]
Percent Change in price of AA	[-3.3 +1.3]	[+3.2 +13.4]	[-0.2 +5.0]	[+0.2 +6.9]

Note: Results from a counterfactual merger between AA and US. Post merger entry is the likelihood of observing a column market structure given a pre-merger row market structure. Post merger %Δ price is the percentage change in price for AA after the merger. Confidence intervals are constructed using the subsampling routine described in the text.

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* before the merger. In this table we only consider those markets that were 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 1.4% and 1.6%, for the "Best Case Scenario." It is much more likely that AA enters to form a duopoly, between 49.7% and 50.3%, and the DL prices would fall by roughly 2% in that case. AA is more likely to replace an LCC than other airlines, and in all cases of duopoly we should expect lower prices on the order of one to two percent.

Under the "Average Case Scenario" 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 competition in entry from the other major carriers but lower competition from low cost carriers.

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

In Table 11, we focus on markets where AA is already present in the market and another incumbent duopolist *exits* after the merger. 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.[43] Second, AA might become more attractive to consumers after the merger and steal business from rivals. For ease of exposition we only consider

[43] 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, a decrease in fixed costs could lead to entry with the already low marginal costs.

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	[0.014 0.016]	[0.497 0.503]	[-2.4 -2.2]
LCC	[0.091 0.106]	[0.399 0.415]	[-4.5 -4.2]
UA	[0.039 0.046]	[0.490 0.499]	[-3.4 -3.2]
WN	[0.025 0.029]	[0.432 0.438]	[-3.3 -3.1]
...mean unobservables			
DL	[0.005 0.005]	[0.201 0.204]	[-2.1 -1.9]
LCC	[0.027 0.034]	[0.163 0.171]	[-4.2 -3.9]
UA	[0.011 0.013]	[0.192 0.196]	[-3.1 -2.9]
WN	[0.008 0.010]	[0.176 0.182]	[-2.9 -2.7]
...new unobservables			
DL	[0.010 0.011]	[0.434 0.440]	[-1.9 -1.8]
LCC	[0.064 0.076]	[0.376 0.390]	[-4.0 -3.8]
UA	[0.025 0.028]	[0.441 0.449]	[-2.8 -2.7]
WN	[0.014 0.018]	[0.375 0.382]	[-2.8 -2.7]
Average Case Scenario			
DL	[0.001 0.001]	[0.081 0.083]	[-1.3 -1.2]
LCC	[0.009 0.014]	[0.082 0.089]	[-3.4 -3.1]
UA	[0.003 0.004]	[0.077 0.082]	[-2.3 -2.2]
WN	[0.002 0.003]	[0.085 0.087]	[-2.1 -1.9]

Note: Results from a counterfactual merger between AA and US. Post merger entry is the likelihood of observing a column market structure given a pre-merger row market structure. Post merger $\%\Delta$ price is the percentage change in price for the incumbent monopolist after AA joins as a duopolist after the merger. Confidence intervals are constructed using the subsampling routine described in the text.

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 probability between 0.9 and 1.0 percent that DL will leave the duopoly market with AA after the merger. In such cases, AA's price will be between 5.1% and 11.2% higher. Overall the greatest likelihood of exit, by far and across all scenarios, is for the LCC airline.

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	[0.009 0.010]	[+5.1 +11.2]
LCC	[0.048 0.077]	[-7.4 +1.6]
UA	[0.014 0.020]	[+6.4 +11.7]
WN	[0.015 0.020]	[+2.5 +11.2]
...mean unobservables		
DL	[0.005 0.008]	[-11.5 -4.3]
LCC	[0.032 0.048]	[-16.6 -3.1]
UA	[0.011 0.015]	[-12.2 -5.8]
WN	[0.008 0.012]	[-9.6 +2.4]
...new unobservables		
DL	[0.006 0.007]	[-12.2 -2.9]
LCC	[0.023 0.031]	[-43.0 -30.9]
UA	[0.012 0.014]	[-17.8 -10.9]
WN	[0.005 0.008]	[-25.8 -13.2]
Average Case Scenario		
DL	[0.002 0.003]	[-12.3 -1.4]
LCC	[0.013 0.023]	[-33.6 -8.5]
UA	[0.003 0.006]	[-19.0 -7.9]
WN	[0.002 0.006]	[-32.4 -16.0]

Note: Results from a counterfactual merger between AA and US. Post merger entry is the likelihood of observing a column market structure given a pre-merger row market structure. Row market structures are a duopoly between AA and the listed airline. Post merger %Δ price is the percentage change in price for AA after the merger and subsequent rival exit. Confidence intervals are constructed using the subsampling routine described in the text.

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), 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.

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.[44]

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.[45]

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 [0.959, 1.000] for the "Best Case" scenario and [0.922, 0.954] for the "Average Case" scenario, for example. We find that this would result in a rise in prices in both scenarios, but with a higher price rise in the "Best Case Scenario."

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. This also justifies the DOJs concern that airport slots go to Southwest or Jet Blue instead of incumbent majors.

For market with four firms, the most likely outcome across all cases is a consolidation to

[44]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. Two recent papers have looked specifically at slot divestitures, Ali (2020) and Park (2020).

[45]None of the DCA markets in our sample were a AA/US duopoly before the merger, so we look at other market structures that involve both airlines.

AA/DL/UA. This is accompanied by higher prices by about 3% to 5%, depending on the scenario. Similar results are found for the *Average Case Scenario*.

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, and should help control the post-merger increase in prices and promote low-cost carrier coverage at DCA.

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

	Post-merger Market Structure				
Pre-merger Markets	AA/DL	AA/UA	AA/DL/LCC	AA/DL/UA	AA/DL/WN
Best Case Scenario					
AA,US,DL Markets					
Mkt Struct. Transitions	[0.959 1.000]	[0.000 0.000]	[0.000 0.023]	[0.000 0.005]	[0.000 0.025]
%Δ Shares Weighted Price	[+6.5 +7.4]	[n.a.]	[-18.1 +34.2]	[+2.8 +2.8]	[-23.2 +3.8]
AA,US,DL,UA Markets					
Mkt Struct. Transitions	[0.001 0.003]	[0.000, 0.000]	[0.000, 0.000]	[0.987 0.999]	[0.000, 0.000]
%Δ Shares Weighted Price	[+18.5 +20.4]	[n.a]	[n.a.]	[+4.9 +5.4]	[n.a.]
Average Case Scenario					
AA,US,DL Markets					
Mkt Struct. Transitions	[0.922 0.954]	[0.000, 0.000]	[0.020 0.038]	[0.012 0.024]	[0.009 0.025]
%Δ Shares Weighted Price	[+3.1 +4.1]	[n.a.]	[-8.2 +4.3]	[-4.1 +5.9]	[-26.2 +2.8]
AA,US,DL,UA Markets					
Mkt Struct. Transitions	[0.000, 0.000]	[0.000, 0.000]	[0.000, 0.000]	[0.954 0.986]	[0.000, 0.000]
%Δ Shares Weighted Price	[n.a.]	[n.a.]	[n.a.]	[+3.4 +3.6]	[n.a.]

Note: Counterfactual predictions for markets with DCA as one endpoint. Pre-merger market structure of AA/DL/UA and AA/US/DL/UA. Post merger market structure listed in the column. Confidence intervals are constructed using the subsampling routine described in the text.

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 consists of a merger simulation that allows for changes in market structures, and not just in prices. The main takeaways are: i) allowing for the selection of firms into markets based on unobservables 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; ii) this in turn leads to potentially important differences from exogenous entry models in the predicted 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 also show that our results depend, as one would expect, on the assumptions that we make on the efficiency gains from a merger. First, quantifying the efficiency gains from a merger is a difficult empirical exercise that is at the center of all merger investigations by the federal agencies, and which is often based on confidential *accounting* cost data. Second, even if current and past *accounting* cost data are available, normally it takes time for the efficiencies to be fully realized. We believe that our approach, which is based on being upfront and clear about the efficiency gains, provides a promising path for future research in antitrust merger research. More generally, 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. We hope our approach provides a promising approach for future research in antitrust merger research.

To conclude, we summarize some 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. (2021). 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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