Market Structure and Competition in Airline Markets [*]

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Abstract

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

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1 Introduction

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

Generally, firms self-select into markets that better 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 themselves 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, and estimated 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 of the firms. Existing instrumental variables based methods to account for endogeneity of prices do not resolve this selection problem in general. Potentially biased estimates of the demand and cost functions can then lead to the mis-measurement demand elasticities, and consequently market power. This is problematic because correctly measuring market power and welfare is of crucial importance 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

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[1] See (Bresnahan, 1987; Berry, 1994; Berry, Levinsohn, and Pakes, 1995).

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

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. As in this single agent selection model, when estimating demand and supply equations, our econometric model accounts for this selection.

Our model consists of the following equations: i) entry conditions that require that in equilibrium a firm that serves a market must be making non-negative profits; 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 on unobservable to the econometrician random variables (structural errors) that are firm specific and also market/product specific unobservables that are also observed by the firms and unobserved by the econometrician. In equilibrium firms make entry and pricing decisions such that all three sets of equations 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 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 prod-

uct markets (see Berry, 1994; Berry, Levinsohn, and Pakes, 1995, henceforth BLP). We simultaneously estimate the parameters of the entry model (the observed fixed costs and the variances of the unobservable components of the fixed costs) and the parameters of the demand and supply relationships.

To estimate the model we use cross-sectional data from the US airline industry.[2] 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.[3] Each firm makes decides whether or not to enter and chooses the (median) price in that market. The other endogenous variable is the number of passengers transported by each firm. The identification of the three equations is off the variation of 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), Berry and Jia (2010), Ciliberto and Tamer (2009), and Ciliberto and Williams (2014). More specifically, we consider market distance and measures of the airline network, both nonstop and connecting of airlines out of the origin and destination airports.

We begin our empirical analysis by running a standard GMM estimation (see Berry, 1994) on the demand and pricing first order conditions for multiple specifications, allowing for differing levels of heterogeneity in the model. Next, we estimate the model with endogenous entry using our methodology and compare the results with the GMM results. We find that using our methodology the price coefficient in the demand function is estimated to be closer to zero than the case of GMM, and markups are on the order of 60% larger than the GMM results imply. The parameters in the fixed cost equation are precisely estimated and they are decreasing in measures of network size at the origin and destination airport. We examine the fit of our models along three dimensions: i) the predicted market structures; ii) the predicted

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[2]We also illustrate our methodology by conducting a Monte Carlo exercise, see the Online Supplement.
[3]An airline is considered a potential entrant if it is serving at least one market out of both of the endpoint airports.

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prices; iii) the predicted market shares.[4] Additionally, we estimate significant correlations between unobserved fixed costs, unobserved marginal costs, and unobserved demand shocks.

Finally, we use our estimated model to simulate the merger of two airlines in our data: American and US Airways.[5] Typical merger analysis involves predicting changes in market power and prices *given* a particular market structure using diversion ratios based on pre-merger market shares, or predictions from static models of product differentiation (see Nevo, 2000). Our methodology allows us to simulate a merger allowing for equilibrium changes to market structure after a merger, which in turn may affect equilibrium prices charged by firms. Market structure reactions to a merger are an important concern for policy makers, such as the DOJ, as they often require entry accommodation by merging firms after the approval of a merger. For example, in the two most recent large airline merger (United and American), the DOJ required the merging firms to cede gate access at certain airports to competitors. Our methodology can help policy makers understand how equilibrium entry would change after a merger, which would in turn help target tools like the divestiture of airport gates.

In our merger simulation we analyze a "best case" scenario where we assign the best characteristics from the two pre-merger firms to the new merged firm (both in demand and costs).[6] First, we predict that the new merged firm would enter the unserved markets with a probability of at least 20%. This highlights an important reason to consider endogenous entry responses after a merger, as entry into new markets is a potentially large source of additional consumer welfare. Second, we find, as we would expect, that there is a general tension between higher prices from greater concentration and lower prices from increased efficiency and increased entry of the merged firm. Concentrated markets where the merged firm is an incumbent are at greatest risk for price increases, but there are many cases where

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[4]Unlike the canonical model of demand for differentiated products (see Berry (1994) and BLP) our methodology does not by construction perfectly predict prices and shares by inverting a product level demand.

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

[6]Our reasoning for choosing to look at the "best case" scenario is that a merger should not be allowed if there are no gains even under the "best case" scenario, whether in the form of lower prices or new entry, after the merger.

prices decrease after the merger. Third, we find that the merged firm faces the greatest competition, in terms of new entry, from rival legacy carriers after the merger. This is because major carriers are more similar in characteristics to the merged firm than low cost carriers, and so are more likely to enter markets where the merged firm is an incumbent after the merger.

There is important work that has estimated static models of competition while allowing for market structure to be endogenous. Reiss and Spiller (1989) estimate an oligopoly model of airline competition but restrict the entry condition to a single entry decision. In contrast, we allow for multiple firms to choose whether or not to serve a market. Cohen and Mazzeo (2007) assume that firms are symmetric within types, as they do not include firm specific observable and unobservable variables. In contrast, we allow for very general forms of heterogeneity across firms. Berry (1999), Draganska, Mazzeo, and Seim (2009), Pakes et al. (2015) (PPHI), and Ho (2008) assume that firms self-select themselves into markets that better match their observable characteristics. In contrast, we focus on the case where firms self-select themselves into markets that better match their observable and *unobservable* characteristics. There are two recent papers that are closely related to ours. Eizenberg (2014) estimates a model of entry and competition in the personal computer industry. Estimation relies on a timing assumption (motivated by PPHI) requiring that firms do not know their own product quality or marginal costs before entry, which limits the amount of selection captured by the model. Roberts and Sweeting (2014) estimate a model of entry and competition for the airline industry, but only consider sequential move equilibria. In addition, Roberts and Sweeting (2014) do not allow for correlation in the unobservables, which is the 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 agent model. Section 3 analyzes a full model of entry and pricing.

Consider the following system of equations,

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

where $y_j = 1$ if firm j decides to enter a market, and $y_j = 0$ otherwise, where $j \in \{1, 2\}$. Let $K \equiv \{1, 2\}$ be 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 whereby that $(\nu_1, \nu_2, \xi_1, \xi_2)$ is independent of $(\mathbf{Z}, \mathbf{X})$ while the variables (V_1, V_2) are endogenous (such as prices or product characteristics).[7]

As can be seen, the above model is a simple extension of the classic selection model to cover cases with two decision makers. The key important distinction is the presence of simultaneity in the 'participation stage' where decisions are interconnected.

We will first make a parametric assumption on the joint distribution of the errors. In

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

principle, it is possible to study the identified features of the model without parametric assumptions on the unobservables, but that will lead to a model that is hard to estimate empirically. 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 one source of the selectivity bias that is important.[8]

One reason why we would expect firms to self-select into markets is because the fixed costs of entry are related to the demand and the variable costs. One would expect products of higher quality to be, at the same prices, in higher demand than products of lower quality and also to be more costly to produce. For example, a luxury car requires a larger up-front investment in technology and design than an economy car, and a unit of a luxury car costs more to produce than a unit of an economy car. This would introduce unobserved correlation in the unobservables of the demand, marginal and fixed costs. The unobservables might be correlated if a firm can lower its marginal costs by making investments that increase its fixed costs but are still profitable. In that case, we would observe a correlation between the unobservables in the marginal and fixed cost functions.

Given that the above model is parametric, the only non standard complications that arise are ones related to multiplicity and also endogeneity. 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). Throughout, we maintain the assumption that players are playing pure strategy Nash equilibria. Extending this to mixed strategy does not pose conceptual problems.

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

The data we observe are $(S_1y_1, V_1y_1, y_1, S_2y_2, V_2y_2, y_2, \mathbf{X}, \mathbf{Z})$ and 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 $(S_1y_1, V_1y_1, y_1, S_2y_2, V_2y_2, y_2, \mathbf{X}, \mathbf{Z})$ and 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

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

for all t_1. The particular form of the above probability is related to the residuals evaluated at t_1 and where we condition on all *exogenous variables* in the model.[9]

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). 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 $(\xi_1 \le t_1; \ (\nu_1, \nu_2) \in A^U_{(1,0)})$ 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. Next, let $\left(\xi_1 \le t_1; \ (\nu_1, \nu_2) \in A^M_{(1,0)}, d_{(1,0)} = 1\right)$ be the set of ξ_1 that are less than t_1 when the unobservables (ν_1, ν_2) belong to the set $A^M_{(1,0)}$.

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

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. For example by the law of total probability we have (suppressing the conditioning on $(\mathbf{X}, \mathbf{Z})$):

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

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

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

The middle part
$$
P(S_1 - \alpha_1 V_1 - X_1\beta \le t_1; y_1 = 1; y_2 = 0)
$$

can be consistently estimated from the data given a value for (α_1, β, t_1). The LHS and RHS on the other hand contain the following two probabilities

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

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 Ciliberto and Tamer 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 *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).*

Similarly, 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:

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

The statistical moment inequality conditions implied by the model at the true parameters are:

$$m^1_{(1,0)}(t_1, \mathbf{Z}; \Sigma) \leq E\left(1\left[S_1 - \alpha_1 V_1 - X_1\beta \leq t_1; y_1 = 1; y_2 = 0\right]\right) \leq m^2_{(1,0)}(t_1, \mathbf{Z}; \Sigma)$$

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

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

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

where

$$
\begin{aligned}
m^1_{(1,0)}(t_1, \mathbf{Z}; \Sigma) &= P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^U_{(1,0)}\right) \\
m^2_{(1,0)}(t_1, \mathbf{Z}; \Sigma) &= m^1_{(1,0)}(t_1, \mathbf{Z}; \Sigma) + P\left(\xi_1 \leq t_1; (\nu_1, \nu_2) \in A^M_{(1,0)}\right) \\
m^1_{(0,1)}(t_2, \mathbf{Z}; \Sigma) &= P\left(\xi_2 \leq t_2; (\nu_2, \nu_2) \in A^U_{(0,1)}\right) \\
m^2_{(0,1)}(t_2, \mathbf{Z}; \Sigma) &= m^1_{(0,1)}(t_2, \mathbf{Z}; \Sigma) + P\left(\xi_2 \leq t_2; (\nu_1, \nu_2) \in A^M_{(0,1)}\right) \\
m_{(1,1)}(t_1, t_2, \mathbf{Z}; \Sigma) &= P(\xi_1 \leq t_1, \xi_2 \leq t_2, \nu_1 \geq -\delta_2 - \gamma Z_1, \nu_2 \geq -\delta_1 - \gamma Z_2) \\
m_{(0,0)}(\mathbf{Z}, \Sigma) &= P(\nu_1 \leq -\gamma Z_1, \nu_2 \leq -\gamma Z_2)
\end{aligned}
$$

Hence, the above can be written as

$$
E[\mathbf{G}(\theta, S_1 y_1, S_2 y_2, V_1 y_1, V_2 y_2, y_1, y_2; t_1, t_2)|\mathbf{Z}, X] \leq 0 \tag{4}
$$

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

We use standard moment inequality methods to conduct inference on the identified parameter. In particular:[10]

Theorem 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 data set on $(y_1, y_2, S_1 y_1, V_1 y_1, S_2 y_2, V_2 y_2, \mathbf{X}, \mathbf{Z})$ the true parameter vector $\theta = (\delta_1, \delta_2, \alpha_1, \alpha_2, \beta, \gamma, \Sigma)$ minimizes the nonnegative objective function below to zero:*

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

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

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.

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[10]See the Online Supplement for more details. See CT for an analogous result and the proof therein.
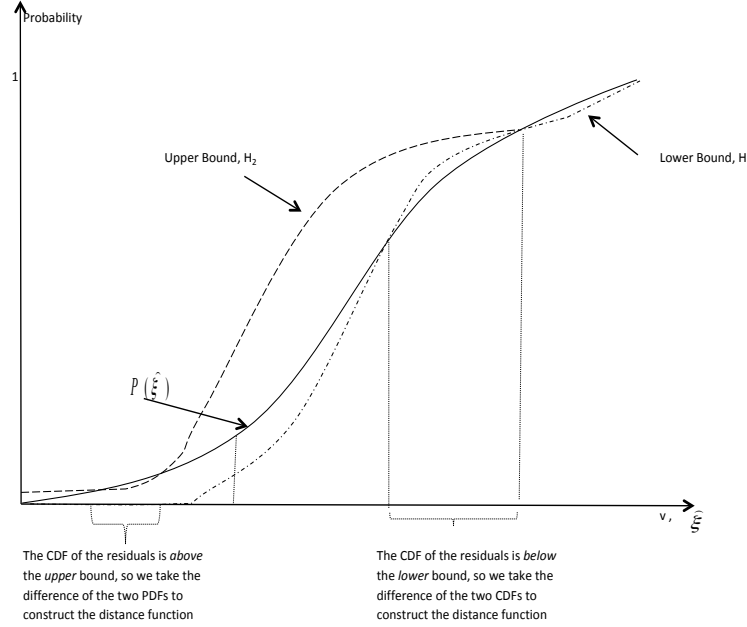
A Graphical Illustration of the Proposed Methodology. Figure 1 illustrates how the methodology works. Between the origin and the point A, the CDF of the data predicted residuals lies above the upper bound of the CDF of the errors predicted by the model, which violates the model under the null, hence the difference (squared) between the two is included in the computation of the distance function. Between the points A and B, and the points C and D, the CDF of the data predicted residuals lies between the lower and upper bounds of the CDF predicted by the model, and so the difference is not included in the computation of the distance function. Between the point B and C, the CDF of the data predicted residuals lies below the lower bound of the errors predicted by the model, again violating the model under the null and so this difference (squared) between the two is included in the computation of the distance function.

Clearly, the stylized model above provides intuition about the technical issues involved

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but we next link this model to a clearer model of behavior where the decision to enter (or to provide a product) is more explicitly linked to a usual economic condition of profits. This entails specification of costs, demand, and a solution concept.

3   A Model of Entry and Price Competition

3.1   The Structural Model

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

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

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

where

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

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

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

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

These 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:

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

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

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

$$(7)$$

The first two equations 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 equations are satisfied. The firm level unobservables that enter into the fixed costs are denoted by ν_j, $j = 1, 2$. The unobservables that enter into the variable costs are denoted by η_j, $j = 1, 2$ while the unobservables that enter into the demand equations are denoted by ξ_j, $j = 1, 2$. This system of equations (7) might have multiple equilibria.

It is interesting to compare this system to the ones we studied in Section 2 above and notice the added nonlinearities that are present. Even though the conceptual approach is the same, the inference procedure for this system is more computationally demanding. The model in (7) is more complex than the model (1) because one needs to *solve for the equilibrium of the full model*, which has six (rather than just four) endogenous variables. On

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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 equations 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 these two literatures together, while allowing the unobservables of the six equations 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 interactions of firms in 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   Parametrizing 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:

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

Also, and similarly to 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 will study how the results change as we allow for more heterogeneity among firms, and thus we will have specifications where $\varphi_j = \varphi$ and $\gamma_j = \gamma$ for all j and then we will relax these restrictions.

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

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discussed at length in Berry (1994).

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

The utility of consumer i from consuming j is

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

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.

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

The proportion of consumers who choose to fly is then

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

where

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

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

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

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

Product j's market share is

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

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. And 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.

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

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

where $D = \sum_{j \in J} exp(X_j'\beta + \alpha p_j + \xi_j)$ and $J = \{1, 2\}$ indicates the products in the market.[11]

Under the maintained distributional assumptions on ϵ, we can write the following relationship:

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

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

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

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

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

---

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

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

Finally, the unobservables have a joint normal distribution,

$$(\nu_1, \nu_2, \xi_1, \xi_2, \eta_1, \eta_2) \sim N(0, \Sigma), \tag{15}$$

where Σ is the variance-covariance matrix to be estimated. As discussed above, the off-diagonal terms pick up the correlation between the unobservables is part of the source of the selection bias in the model.

In this model, the variances of all the unobservables, in particular of the fixed costs that enter in the entry equations, are identified. This is different from previous work in the entry literature, where the variance of at least one firm has to be normalized to 1. Here, the scale of the observable component of the fixed costs is tied down by the estimates of the variable profits, which are derived from the demand and supply equations. This is because we observe revenues, which pins down the scale of entry costs. Again, the moment inequality based approach does not rely on parameters being point identified.

3.3 Simulation Algorithm

To estimate the parameters of the model we need to predict market structure 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.

$$\begin{cases} y_j = 1 \Leftrightarrow \pi_j \equiv (p_j - \exp(\varphi W_j + \eta_j)) \, M s_j \left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \exp(\gamma Z_j + \nu_j) \geq 0, \\[2mm] \ln s_j \left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) - \ln s_0 \left(\beta, \alpha, \mathbf{X}^e, \mathbf{p}^e, \xi^e\right) = X_j'\beta + \alpha p_j + \xi_j \\[2mm] \qquad\qquad \ln \left[p_j - b_j \left(\mathbf{X}^e, \mathbf{p}^e, \xi^e\right)\right] = \varphi W_j + \eta_j, \end{cases} \quad , \quad (16)$$

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

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

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

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

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

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

   (b) If the market structure in market m is equal to $\hat{e}$, 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 (16) above.

   (c) Repeat (b) above for all markets, and then construct $\Pr(\hat{\xi}^{\hat{e}}, \hat{\eta}^{\hat{e}} \mid \mathbf{X}, \mathbf{W}, \mathbf{Z})$, which are joint probability distributions of $\hat{\xi}^{\hat{e}}, \hat{\eta}^{\hat{e}}$ conditional on the values taken by the control variables.[12]

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

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

   (a) We simulate random vectors of unobservables (ν_r, ξ_r, η_r) from a multivariate normal density with a given covariance matrix, using the pseudo-random draws described above.

---

[12]Here, we use conditional CDFs evaluated at a grid. But, in principle, any parameter that obeys first order stochastic dominance can be used such as means and quantiles.

(b) For each potential market structure e of the $2^{|K|} - 1$ possible ones (excluding the one where no firm enters), we solve the subsystem of the N^e demand equations and N^e first order conditions in (16) for the *equilibrium* prices $\bar{\mathbf{p}}_r^e$ and shares $\bar{\mathbf{s}}_r^e$.[13]

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

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

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

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

3. We construct the distance function (5) as in Section (2).

Comments on procedure above: The above is a modified minimum distance procedure. In the absence of endogeneity and multiple equilibria, the above procedure compares the distribution function of the data to the CDF predicted by the model at a given parameter value. For example, in a linear model $y = x'\beta + \epsilon$ with $\epsilon \sim N(0, 1)$, a similar procedure compares the distribution of residuals $P(y - x'\beta | x)$ to the standard normal CDF. Endogeneity requires us to compare the distribution of residuals, and multiple equilibria leads to upper and lower probabilities, and hence the modified version of the well known minimum distance

---

[13]For example, if we look at a monopoly of firm j ($|e| = 1$) then the demand $Q_j\left(p_{jr}, X_{jr}, \xi_{jr}; \beta\right)$ is readily computed, and the monopoly price, p_{jr}, as well.

procedure. Many simplifications can be done to the above to ease the computational bur-
den. For example, though the inequalities hold conditionally on every value of the regressor
vector, they also hold at any level of aggregation of the regressors. So, this leads to fewer
inequalities, but simpler computations.

3.4 Estimation: Practical Matters

The estimation consists of minimizing a feasible version of the distance function given by
Equation 5, which is derived from the inequality moments that are constructed as explained
in Section 2. Also, the approach we use for inference is similar to the one used in CT, where
we use subsampling based methods to construct confidence regions. Below, we make some
observations regarding estimation.

There are two main practical differences between the empirical analysis that follows and
the theoretical model in Section 2.[14] First, the number of firms, and thus moments, is larger.
We will have up to six potential entrants, while in Section 2 there were only two. Second,
the number and identity of potential entrants will vary by market, which means that the set
of moments varies by market as well. In addition, since the inequalities hold for all values of
the exogenous variables and for all cutoffs t, we only use five cutoffs for each unobservable
(dimension of integration).

We use the following variance-covariance matrix, where we do not estimate σ_ν^2 and restrict
it to be equal to the value found in an initial GMM estiamtion that does not account for
endogenous entry:

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

Thus, this specification restricts the correlations to be the same for each firm which is
made for computational simplicity. We also assume that the correlation is only among the
unobservables of a firm (within-firm correlation), and not between the unobservables of the
K_m firms (between-firm correlation).

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[14]We discuss other, less crucial, differences at length in Section B of the Online Supplement.

Other Moment Inequalities. We have found that two additional sets of inequality moments improved the precision of our estimates of the variance-covariance matrix, and our ability to predict the market structures that we observe in the data[15].

First, we use the moment inequality conditions from CT. The moments from CT "match" the predicted and observed market structure. In practice, we add the value of the distance function given by Equation 11 in CT, constructed for this specific framework, to the value of the distance function given by Equation 5.

Second, we supplement these by constructing inequality moments that are aimed at matching the second moments of the residuals and of the simulated errors. So, going back to equation (3) above, if we replace ξ with its square, we can construct moment inequality bounds on its expected value.

4   Data and Industry Description

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

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[15]In principle, matching the CDFs would be sufficient, but since we choose a few cutoffs for the CDFs, we found that empirically including these additional moment conditions help.

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.[16]

We define a market as a unidirectional trip between two airports, irrespective of intermediate transfer points. The dataset includes the markets between the top 100 US Metropolitan Statistical Areas ranked by their population. We include markets that are *temporarily* not served by any carrier, which are the markets where the number of observed entrants is equal to zero. There are $6,322$ 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, AirTran, 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 $20,642$ market-carrier observations for which we observe prices and shares. There are 172 markets that are not served by any firm.

We denote the number of potential entrants in market m as K_m where $|K_m| \leq 6$. An airline is considered a potential entrant if it is serving at least one market out of both of the endpoint airports.[17]

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 48 percent of the markets, although it is a potential entrant in 90 percent of markets. Southwest, on the other hand, is a potential entrant in 38 percent of markets, and enters in 35 percent of the time. So this already shows some interesting heterogeneity in the entry patterns across

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[16] See Section C of the Online Supplement for a detailed discussion on the data cleaning and construction.

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

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 1 percent having just one potential entrant.

Table 1: *Entry Moments*

	Actual Entry	Potential Entry
AA	0.48	0.90
DL	0.83	0.99
LCC	0.26	0.78
UA	0.66	0.99
US	0.64	0.95
WN	0.35	0.38

Table 2: *Distribution of Potential Entrants*

	1	2	3	4	5	6
Fraction	0.08	1.11	5.16	18.11	42.87	32.68

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

Table 3 presents the summary statistics for the variables used in our empirical analysis. For each variable we indicate in the last Column whether the variable is used in the entry, demand, and marginal cost equation.

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 median ticket fare, p_{jm}, and the total number of passengers transported in the quarter, Q_{jm}. The average value of the median ticket fare is 243.21 dollars and the average number of passengers transported is 548.10.

Next we introduce the exogenous explanatory variables, explaining the rationale of our choice and in which equation they enter.

Table 3: *Summary Statistics*

	Mean	Std. Dev.	Min	Max	N	Equation
Price ($)	243.21	54.20	139.5	385.5	20,470	Entry, Utility, MC
Passengers	548.10	907.40	20	6770	20,470	Entry, Utility, MC
All Markets						
Origin Presence (%)	0.44	0.27	0	1	37,932	MC
Nonstop Origin	6.42	12.37	0	127	37,932	Entry, MC
Nonstop Destin.	6.57	12.71	0	127	37,932	Entry
Distance (000)	1.11	0.63	0.15	2.72	37,932	Utility, MC
Markets Served						
Origin Presence (%)	0.58	0.19	0.00	1	20.470	MC
Nonstop Origin	8.50	14.75	1	127	20.470	Entry, MC
Nonstop Destin.	8.53	14.70	1	127	20.470	Entry
Distance (000)	1.21	0.62	0.15	2.72	20,472	Utility, MC

Demand. Demand is here assumed to be a function of the number of non-stop routes that an airline serves out of the origin airport, *Nonstop Origin*. We maintain that this variable is a proxy of frequent flyer programs: the larger the share of nonstop 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).

Fixed and Marginal Costs in the Airline Industry.[18] The total costs of serving an

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

airline market consists of three components: airport, flight, and passenger costs.[19]

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*, and the number of non-stop routes that an airline serves out of the destination airport, *Nonstop Destination*. The inclusion of these variables is motivated by Brueckner and Spiller (1994) work on economies of density, whereby the larger the network out of an airport, the lower is the market specific fixed cost faced by a firm because the same gate and the same gate personnel can enplane and deplane many flights.

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

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

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

The economic marginal cost is not observable (Rosse, 1970; Bresnahan, 1989; Schmalensee, 1989). We parameterize it as a function of *Origin Presence*, which is defined as the *ratio* of markets served by an airline out of an airport over the total number of markets served out

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

of that airport by at least one carrier. The idea is that the the larger the whole network, not just the nonstop routes, the higher is the opportunity cost for the airline because the airline has more alternative trips for which to use a particular seat. That is, the variable *Origin Presence* affects the economic marginal cost, since it captures the alternative uses of a seat on a plane out of the origin airport. Given our interpretation of flight costs, we also allow the marginal cost to be a function of the non-stop distance, *Distance*, between two airports.

4.2   Identification

Identification of the Entry Equation. The fixed cost parameters in the entry equations 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 was also required to identify the parameters in Ciliberto and Tamer (2009). The variables that are used in this paper are *Nonstop Origin* and *Nonstop Destination*. A crucial source of identification is also the variation in the identity and number of potential entrants across markets. Intuitively, when there is only one potential entrant we are back to a single discrete choice model and the parameters of the exogenous variables are point identified.

Identification of the Demand Equation. Several variables are omitted in the demand estimation and enter in ξ_1 and ξ_2. 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. Because these variables are strategic choices of the airlines, their omission could bias the estimation of the price coefficient. The parameters of the demand functions are identified because, in addition to the variable *Nonstop Origin*, there are variables that affect prices through the marginal cost or through changes to the demand of the other goods as in Bresnahan (1987) and Berry, Levinsohn, and Pakes (1995). In our context, these are the *Nonstop Origin* of the competitors. In addition, we maintain that after controlling for *Nonstop Origin*, the variables *Origin Presence* and, especially, *Nonstop Destination* enter the fixed cost and marginal cost equations, but are

excluded from the demand equation.[20]

Identification of the Covariance Matrix. Next we describe how the correlations in fixed cost, marginal costs, and demand errors are identified. In general, these correlations are identified by the particular way in which outcomes (entry, demand, price) differ from predictions of the model. Conditional on the errors (and data and other parameters), our model predicts equilibrium entry probabilities, prices, and shares. If we observe a firm enter that the model predicts should not, and that firm has greater demand than the model predicts it should, then this suggests that the fixed costs and demand errors have a positive correlation. Conditional on entry, if we observe lower prices for a firm than our model predicts and also greater demand, then this implies that the marginal cost and demand errors are negatively correlated.

4.3 Self-Selection in Airline Markets: Preliminary Evidence

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. We compare these statistics later on in the paper.[21]

The mean value of *Origin Presence* is *0.44* across all markets, but it is up to *0.58* in markets that are actually served. This implies that firms are more likely to enter in markets where they have a stronger airport presence, and face a stronger demand *ceteris paribus*.

The mean value of *Nonstop Origin* is 6.42 in all markets, and 8.50 in markets that were actively served. This evidence suggests that firms self-select into markets out of airports from where they serve a larger number nonstop markets. This is consistent with the notion that fixed cost decline with economies of density. The magnitudes are analogous for *Nonstop Destination*.

The mean value of *Distance* is 1.11, which implies that most market are long-distance. We

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[20]We have also looked at specifications where we included the variable *Origin Presence* in the demand estimation. We found that *Origin Presence* was neither economically nor statistically strongly significant when *Nonstop Origin* was also included.

[21]Exogenous variables are discretized. See Section C of the Online Supplement.

do not find that the market distance has a different distribution in market that are served and the full sample.

To investigate further the issue of self-selection, we construct the distribution of prices against the number of firms in a market, and by the identity of the carriers.

Figure 2: *Yield by Number of Firms and Carrier Identity*

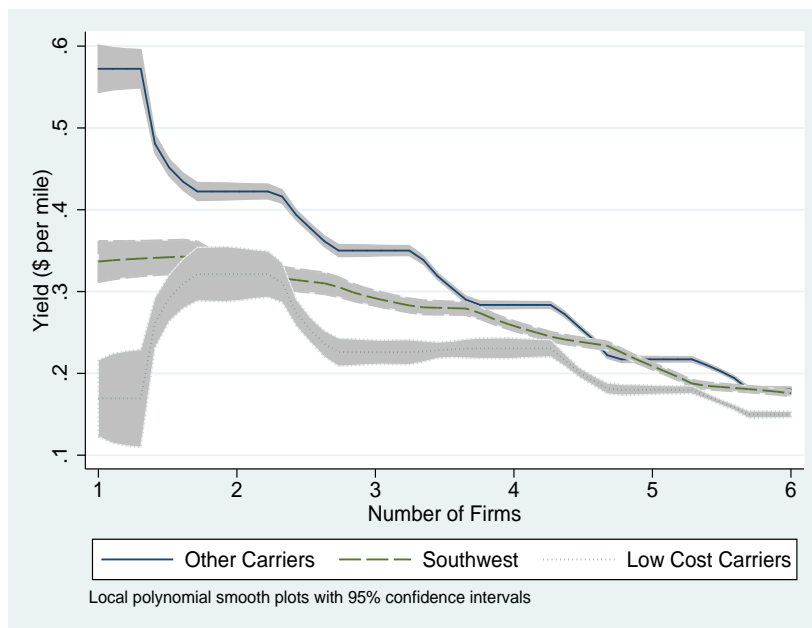Local polynomial smooth plots with 95% confidence intervals

Figure 2 shows yield (ticket fare divided by market distance) against the number of firms in a market, which is the simplest measure of market structure.[22] We draw local polynomial smooth plots with 95% confidence intervals for Southwest, LCCs, and the legacy carriers. In all three cases, the yield is declining in the number of firms, which is what we would expect: the larger the number of firms in a market, the lower the price each of the firms charges. This negative relationship between the price and the number of firms was shown to hold in five retail and professional homogeneous product industries by Bresnahan and Reiss (1991). This regularity holds in industries with differentiated products as well. The interesting feature in Figure 2 is that the distributions of yields for the three type of firms do not overlap in monopoly and duopoly markets.

Figure 3 shows that simple univariate distribution of yield by carrier identity when there

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[22]The market distance is in its original continuous values in Figures 2 and 3.

Figure 3: *Distribution of Yield by Carrier Identity*
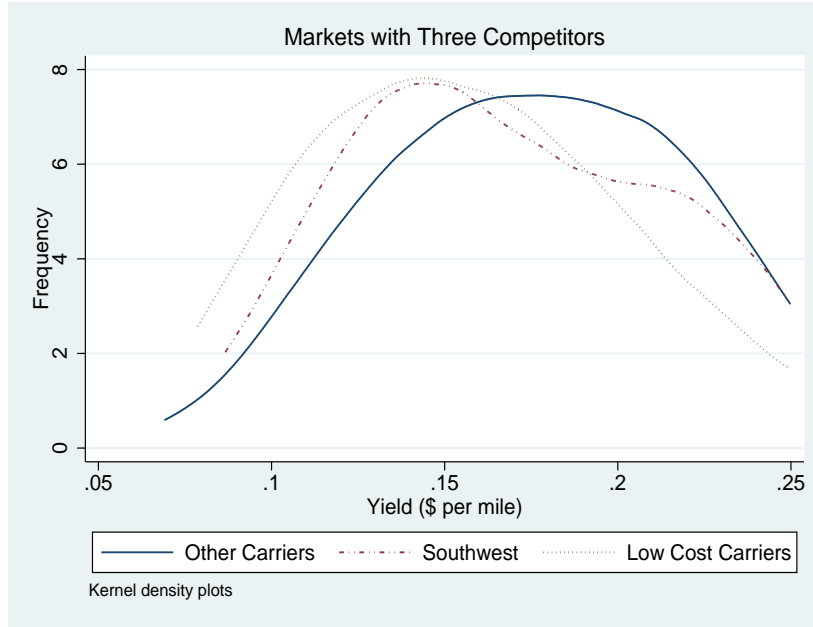
are three competitors in a market.[23] The distribution for the LCC is different from the one of the legacy carriers and of Southwest. In particular, the yield distribution for LCCs has a median of 15.9 cents per mile while the yield distribution for the legacy carriers (American, Delta, USAir, United) has a median of 22.3 cents per mile. The full distribution of the yield by type of carrier is presented in Table 4.

Table 4: *Distribution of Yield (Percentiles)*

	Min	10	25	50	75	90	Max
Legacy	0.059	0.120	0.153	0.223	0.342	0.515	2.205
Southwest	0.066	0.111	0.133	0.190	0.289	0.443	1.706
LCC	0.055	0.101	0.122	0.159	0.220	0.590	1.333

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[23]For sake of clarity, the Figure only show the distribution for the yield less than or equal to 75 cents per mile. The full distribution is available under request.

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. We present two specifications that differ by the degrees of heterogeneity in the marginal and cost functions. Then, we present the results when we use the methodology that accounts for firms' entry decisions, and we again allow for different degrees of heterogeneity in the specification our model.

5.1 Results with Exogenous Market Structure

Column 1 of Table 5 shows the results from GMM estimation of a model where the inverted demand is given by a nested logit regression, as in Equation 14, and where we set $\varphi_j = \varphi$ and $\gamma_j = \gamma$ in Equations 8 and 9.[24]

All the results are as expected and resemble those in previous work, for example Berry and Jia (2010) and Ciliberto and Williams (2014).[25]. Starting from the demand estimates, we find the price coefficient to be negative and σ, the nesting parameter, to be between 0 and 1. The mean elasticity equals -6.480, the mean marginal cost is equal to 209.77 and the mean markup is equal to 33.44. A larger presence at the origin airport is associated with more demand as in (Berry, 1990), and longer route distance is associated with stronger demand as well. The marginal cost estimates show that the marginal cost is increasing in distance, and increasing in the number of nonstop service flights out of an airport.

Column 2 of Table 5 shows the results from GMM estimation of a model where more flexible heterogeneity is allowed in the marginal cost equation. In particular, in Equations 8 we allow for the constant in φ_j to be different for LCCs and Southwest. The results on the demand side are largely unchanged. In particular, consumers value Southwest more the the major carriers all else equal, and consumers value LCCs less than the major airlines all else equal. The results on the marginal cost side are not surprising, but still quite interesting.

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[24]We instrument for price and σ using the value of the exogenous data for every firm, regardless of whether they are in the market. So for example, there are six instruments for every element in X, W, and Z.

[25]We also have estimated the GMM model only with the demand moments, and the results were very similar to those in Column 1 of Table 5

The legacy carriers have a mean marginal cost of 209.98, while LCCs and Southwest have considerably lower marginal costs. The mean of the marginal cost of LCC is 170.79, which is more than 15 percent smaller than the legacy mean marginal cost. The mean of the marginal cost of Southwest is 193.82, which is about 10 percent smaller than the legacy mean marginal cost. All the markups are approximately the same, with a mean equal to approximately 38.

Table 5: *Parameter Estimates with Exogenous Market Structure*

	Logit	Cost Heterogeneity
Demand		
Constant	-2.263 (0.230)	-2.863 (0.225)
Distance	0.348 (0.016)	0.319 (0.015)
Nonstop Origin	0.168 (0.009)	0.180 (0.008)
LCC	-1.033 (0.055)	-0.980 (0.053)
WN	0.343 (0.039)	0.416 (0.038)
Price	-0.027 (0.001)	-0.025 (0.001)
σ	0.151 (0.081)	0.080 (0.017)
Marginal Cost		
Constant	5.287 (0.002)	5.338 (0.003)
Distance	0.060 (0.002)	0.064 (0.002)
Origin Presence	0.027 (0.002)	-0.041 (0.003)
Cons LCC	–	-0.127 (0.007)
Cons WN	–	-0.282 (0.008)
Market Power		
	Mean	Mean
Elasticity	-6.480	-5.567
Marginal Cost (ALL)	209.770	–
Markup	33.441	–
Marginal Cost Legacy	–	209.982
Markup Legacy	–	38.167
Marginal Cost LCC	–	170.791
Markup LCC	–	37.770
Marginal Cost WN	–	193.822
Markup WN	–	38.524

5.2 Results with Endogenous Market Structure

In order to present the results when we control for self-selection of firms into markets, we report superset confidence regions that cover the true parameters with a pre-specified probability. In Table 6, we report the cube that contains the confidence region that is defined as the set that contains the parameters that cannot be rejected as the truth with at least 95% probability.[26]

Column 1 of Table 6 shows the results when we use the methodology developed in Section 2 and the inverted demand is given by a nested logit as in Equation 14. We set $\varphi_j = \varphi$ and $\gamma_j = \gamma$. We allow for correlation among the unobservables. In Column 2 of Table 6 we introduce cost heterogeneity among carriers by allowing the constant in the marginal cost and fixed cost equations to be different for LCCs and Southwest.

To begin with, to get a sense of the model fit, we do the following. We run 200 simulations over 100 parameters. The 100 parameters are randomly drawn from the confidence intervals presented in Column 3 of Table 6. For each parameter, we take the 200 simulations and compute the predicted equilibrium market structure, prices, and shares for each simulation. Next, for each market structure in each market we sort the prices and shares from the smallest to the largest value, and choose, for both prices and shares, the 2.5 and 97.5 percentile of the distribution. Next, we compare the observed prices and shares for the same market and market structure and see if they fall within the 2.5 and 97.5 confidence interval. If they do, then we count this as a market where the model successfully fits the data. We repeat this exercise for all parameters, and for all markets, and then compute the percentage of times that the model fits the data. We find that we fit the prices 33 percent of the times, and the shares 74 percent of the times. We find that we predict the market structure observed in the data 16 percent of the times.

In Column 1 of Table 6 we estimate the coefficient of price to be included in [-0.016, -0.015] with a 95 percent probability, which is to be compared to the estimate of -0.027

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[26]This is the approach that was used in CT. See the online appendix to CT and Chernozhukov, Hong, and Tamer (2007) for details.

(s.e. of 0.001) that we found in Column 1 of Table 5. The estimate in Table 6 is almost twice as large in absolute value than the one in Table 5, and the difference is even more striking when we compare the price estimates in the Columns 2 of the two tables. This is an important finding, which is consistent with the Monte Carlo exercise presented in Section C of the Online Supplement. These results imply that not accounting for endogenous market structure gives biased estimates of price elasticity.

Table 6: *Parameter Estimates with Endogenous Market Structure*

	Baseline	With Cost Heterogeneity
Utility		
Constant	[-4.333, -4.299]	[-5.499, -5.467]
Distance	[0.246, 0.256]	[0.184, 0.191]
Nonstop Origin	[0.157, 0.163]	[0.125, 0.130]
LCC	[-0.481, -0.401]	[-0.345, -0.333]
WN	[0.016, 0.144]	[0.222, 0.230]
Price	[-0.016, -0.015]	[-0.012, -0.011]
σ	[0.489, 0.508]	[0.481, 0.499]
Marginal Cost		
Constant	[5.143, 5.368]	[5.173, 5.221]
Distance	[-0.051, 0.013]	[0.030, 0.031]
Origin Presence	[-0.180, -0.173]	[-0.242, -0.233]
LCC	–	[-0.132, -0.127]
WN	–	[-0.088, -0.085]
Fixed Cost		
Constant	[7.726, 8.466]	[7.768, 8.066]
Nonstop Origin	[-0.079, -0.015]	[-0.142, -0.137]
Nonstop Dest.	[-0.456, -0.439]	[-0.333, -0.321]
LCC	–	[-0.003, -0.003]
WN	–	[-1.642, -1.583]
Variance-Covariance		
Demand Variance	[1.898, 2.006]	[1.510, 1.570]
FC Variance	[2.152, 2.240]	[2.010, 2.086]
Demand-FC Correlation	[0.764, 0.795]	[0.721, 0.758]
Demand-MC Correlation	[0.621, 0.709]	[0.382, 0.396]
MC-FC Correlation	[0.030, 0.159]	[-0.299, -0.288]

We estimate σ in Column 1 of Table 5 equal to 0.151 (s.e. 0.081), while here in the Column 1 of Table 6 it is included in [0.489,0.508]; and it is equal to 0.080 (0.017) in Column 2 of Table 5 and is included in [0.481,0.499] in Column 2 of Table 6. Thus, we find that the within correlation is also estimated with a bias when we do not control for the endogenous market structure. It is much larger in Table 6 than in Table 5.

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, observe that in Column 2 of Table 5 the (inferred) mean elasticity is -5.567, which is consistent with previous estimates (e.g. Ciliberto and Williams, 2014). The markup for legacy carriers is 38.167, the one for LCCs 37.770, and then one for Southwest 38.524 (0.848). In comparison, using our methodology the mean elasticity is included in [-2.43,-2.40], and the markup for the legacy carriers is included in [52.44, 53.32], which is, approximately, sixty percent larger (displayed in Table 7). Similarly, the markup for the LCCs and WN are included, respectively, in [47.29,48.1] and [49.85,50.73].

The marginal cost estimates are also different between the exogenous entry and endogenous entry specifications. In Table 5, we find the (mean) marginal cost equal to 209.982 for the legacy carriers, 170.791 for the LCCS, and 193.822 for WN. Because the markups are larger in Table 7, the marginal costs will have to be smaller, which is exactly what we find, as we estimate the mean of the marginal costs of the legacy carriers to be included in [194.75,196.90], the one of LCCs in [158.15,160.13], and the one of WN in [174.25,176.68].

Next, we show the results for the estimates of the fixed cost equations. Clearly, these are not comparable to the results from the previous model where market structure is assumed to be exogenous.

Column 1 of Table 6 shows the constant in the fixed cost equation to be included in [7.726,8.466], and the variables *Nonstop Origin* and *Nonstop Destination* to be negative, as one would expect if there were economies of density. The results are similar in Column 2, where the constant is included in [7.768,8.066], the coefficient of *Nonstop Origin* in [-0.142,-0.137], and the one of *Nonstop Destination* in [-0.333,-0.321]. In Column 2 we allow for the LCCs to have a different constant, but do not find evidence of that, as the estimate is included in [-0.003,-0.003]. The constant of WN is much smaller, as it is included in [-1.642,-1.583].

Finally, we investigate the estimation results for the variance-covariance matrix. The variances are precisely estimated in both Columns, with the demand variance being included in [1.898,2.006] in Column 1 and in [1.510,1.570] in Column 2. The variance of the fixed

Table 7: *Market Power Estimates with Endogenous Market Structure*

	Confidence Interval
Own Elasticity of Demand	[-2.43,-2.40]
Marginal Cost Legacy	[194.75,196.90]
Markup Legacy	[51.25,53.40]
Marginal Cost LCC	[158.15,160.13]
Markup LCC	[48.43,50.41]
Marginal Cost WN	[174.25,176.68]
Markup WN	[55.67,58.09]

cost unobservables is estimated in [2.152,2.240] in Column 1 and [2.010,2.086] in Column 2. Recall that the variance of the marginal cost unobservables is normalized to its value from the GMM estimation.

The correlation between the unobservables of the demand and fixed cost unobservables is estimated to be included in [0.764,0.795] in Column 1 and in [0.721,0.758] in Column 2. The correlation between the demand and marginal cost unobservables is also positive, as it is included in [0.621,0.709] in Column 1 and in [0.382,0.396] in Column 2.[27] This is one way that self-selection manifests itself in the model, in the sense that firms that face higher fixed costs are also the firms that are more likely to offer higher quality products.

These correlations imply that the unobservables that would, ceteris paribus, increase the demand for a given good, are positively correlated with those that would increase the fixed and marginal cost of producing that good. This makes intuitive sense if we think of the unobservables as measuring quality, for example, and thus higher quality increases demand, but it also increases the fixed and marginal costs, in the same spirit as Bresnahan (1987).

The results for the correlation between the marginal and fixed costs unobservables are different in Columns 1 and 2. They are positive and only marginally statistically different from zero in Column 1, while they are negative in Column 2. Since Column 2 presents the more flexible model, we will use it for our interpretation of the relationship between the marginal and fixed cost unobservables. The negative relationship implies that there

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[27]These intervals are very tight, and much of the precision is due to our use of the additional moments described in Section 3.4.

is a potential trade off between fixed and marginal costs unobservables. Continuing our interpretation of the unobservables as unobserved quality, the negative correlation would imply that the higher the fixed costs associated with producing a high quality good, the lower the corresponding marginal costs.

6 The Economics of Mergers When Market Structure is Endogenous

We present results from counterfactual exercises where we allow a merger between two firms, American Airlines and US Air. 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 would imply an increase in prices. Because of this concern with rising prices, the use of canonical models of product differentiation seems well suited to asses the impact of a merger. However, mergers may also lead to cost efficiencies, which would put downward pressure on prices. Also, a firm may gain some technology that improves its demand, allowing it to enter a market that was previously unprofitable. Because of these other consequences of a merger it is reasonable to think that firms would make different optimal entry/exit decisions in response to a merger. For example, if two firms become one in a particular market after their merger, there might be room in the market for another entrant. Or if the merged firm inherits a better utility characteristics in a particular market after the merger, it may be in a position to either enter a new market, or price out a rival in an existing market.

Our methodology is ideally suited to evaluate both the price effects of mergers like these traditional studies, as well as the *market structure effects* of mergers. Importantly, as we discuss below, changes in market structure imply changes in prices, and viceversa, so incorporating optimal entry decisions into a merger analysis is crucial for understanding the total effect of mergers on market outcomes. In contrast, the canonical model of competition among differentiated products takes as exogenous the set of products competing (eg BLP

and Nevo, 2001).[28]

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

To begin with, for a particular market, if US Airways (US) was a potential entrant, we delete them.[29] 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 a potential entrant. If neither firm was a potential entrant before the merger, American continues to not be a potential entrant after the merger.

Next, in the merger counterfactual that we perform, we consider the "best case" scenario from the point of view of the merging firms. We look at the "best case" scenario with the purpose of seeing if there would be any benefits under that most favorable scenario from the viewpoint of the merging parties. If there were no (or limited) benefits under the merger in our scenario, then it would be a strong case to argue against the merger.

Thus, to combine the characteristics of both firms, we assign the "best" characteristic between AA and US to the new merged firm. For example, in the consumer utility function, our estimate of "non-stop origin" is positive, so after the merger, we assign the maximum of "non-stop origin" between AA and US to the post-merger AA. For marginal costs, we assign the highest level of "origin presence" between AA and US to the post-merger AA. And for fixed costs, we assign the highest level of "non-stop dest." and "non-stop origin" between AA and US to the post-merger AA. We do the same exact procedure for the unobserved shocks. We use the same simulation draws from estimation for the merger scenario, and we assign the "best" simulation draw (for utility the highest and for costs the lowest) between AA and US to the post-merger AA.

In the following tables we report the likelihood of observing particular market structures

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

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

(sometimes conditional on the pre-merger market structure) and expected prices conditional on a particular market structure transition. In all cases we report 95% confidence intervals constructed using the procedure we used to construct intervals for inference on the parameters in the model, the sub-sampling procedure in Chernozhukov, Hong, and Tamer (2007). Given that we have already completed the sub-sampling for the parameter estimates, there is no extra sampling that needs to be done to construct confidence intervals for our counterfactual results. We run the counterfactual scenarios for 100 parameter vectors that are contained in the original confidence region. For example, to attain the confidence interval for average prices for a single firm across all markets, we would compute the statistic for each parameter vector and then take 2.5 and 97.5 percentiles of these estimates, across the 100 parameter vectors, as our confidence region.

We begin our analysis looking at two sets of markets: 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. This is a natural starting point because we want to ask whether, as the consequence of the merger of American and USAir, new markets could be profitably served, which is clearly a strong reason for the antitrust authorities to allow for a merger to proceed. We also want to ask whether, as the consequence of the merger, markets that were previously served only by the merging parties experience higher ticket prices.

Table 8 is a simple "transition" matrix that relates the probability of observing a market structure post-merge (Columns) conditional on observing a market structure pre-merge (Rows).[30] The complete transition matrix would be of dimension 64 x 32, which we do not present for practical purposes. Here we only present a 2 x 2 matrix, where the two pre-merger market structures are those markets with no firm in the market and with a duopoly of US and AA; and the post-merger market structures are those markets with no firm in the market and with a monopoly of AA/US.

Table 8 shows that conditional on observing a market with no firms pre-merge, the probability of observing the market not being served post-merge is between 36 and 90 percent. If

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

the market was an American and USAir duopoly pre-merger, there is a probability between 20 and 82 percent that the market will now be served by the merged firm. The probability that the merged firm AA/US will enter a market that was not previously being served is between 10 and 19 percent, which is a substantial and positive effect of the merger.

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

	Post-merger	
Pre-merger	No Firms	AA Monopoly
No Firms	[0.36,0.90]	[0.10,0.19]
AA/US Duopoly	[0.00,0.01]	[0.20,0.82]

We find (result not in the tables) that in markets where American and USAir were in a duopoly and now act as a monopolist the prices are unchanged (the confidence interval is equal to [0.00,0.01]). This might be a result driven by the fact that we are averaging across many different markets, and there might be some where the increase in prices was substantial. Also, it might be the case that the cost efficiencies were so substantial that any increase in price was offset by the cost gains. We explore both of these explanations below.

An argument that is made to allow for the merger of two firms looks at the markets where the merging parties are the only firms in the market, and then studies whether there is a potential entrant who would enter if the merging parties were to raise their prices as a consequence of their merger. Table 9 considers the probability that one of the other four competitors will enter into the market where there was a duopoly of American and USAir pre-merger. We find that Delta will enter with a probability included between 8 and 25 percent, which clearly suggest that there is a substantial possibility that Delta enters, with the consequence of limiting the market power of the new merged airline. We also find evidence that United, and, to a lesser extent, LCC and WN will enter after the merger in a market that would otherwise be a monopoly of AA/US.

We can now investigate how the entry of the other potential entrants would change the prices in those markets that were AA and US duopolies pre-merger. We find that the prices would drop when DL enters into the market, by a percentage included in [-0.12,-

Table 9: Entry of Competitors in AA and US Duopoly Markets

Prob mkt structure	Duopoly AA/US & DL	Duopoly AA/US & LCC	Duopoly AA/US & UA	Duopoly AA/US & WN
Duopoly AA & US	[0.08,0.25]	[0.01,0.02]	[0.05,0.11]	[0.00,0.01]

0.01], and when United enters, by a percentage included in [-0.06,0.00]. There would not be a statistically significant change in the prices when LCC enters, while there would be an *increase* in the prices when WN enters. We interpret these results as suggesting 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.

Table 10: Prices of Competitors in AA and US Duopoly Markets

Change in the price of AA	Duopoly AA/US & DL	Duopoly AA/US & LCC	Duopoly AA/US & UA	Duopoly AA/US & WN
Duopoly AA & US	[-0.12,-0.01]	[-0.01,0.03]	[-0.06,0.00]	[0.00,0.04]

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 new markets.

In Table 11 we consider the likelihood of entry of AA after its merger with US in markets where American was *not present* pre-merger, but is present post-merger. In this table we only consider a selected set of scenarios, which we chose as they appear most frequently in the data. In Columns 1 and 2 we consider the cases when the pre-merger market structure is a monopoly and AA enters to replace the pre-merger monopolist (Column 1), or adds itself to form a duopoly (Column 2). In Column 3 we present the case when AA enters to add itself to a duopoly, thus generating a triopoly market. In Columns 4 and 5 display the cases when the market structure changes, respectively, from a triopoly to quadropoly, and from a quadropoly to a quintopoly.

The first row of Column 1 shows that, conditional on observing a monopoly of Delta before the merger, we will predict that American/USAir would replace Delta with a probability between 2 and 9 percent. Conditional on observing a monopoly of a LCC before

the merger, we observe American replacing the LCC with a probability between 7 and 19 percent. Overall, there is clear evidence that AA/US will replace some of the other carriers as monopolist.

The first row of Column 2 shows that, conditional on Delta being a monopoly pre-merger, American is likely to enter, post-merger, with a probability between 19 and 25 percent. This is larger, in a way that is statistically significant, than what we had found in Column 1. Similarly, we find the probabilities that AA enters to form a duopoly with United and Southwest to be larger than AA replacing them as a monopolist. This provides evidence that markets may actually become less concentrated after a merger because of the optimal entry decision of the merged firms.

Table 11: Post-merger Entry of AA in New Markets

Monopoly	(1)	(2)	Duopoly	(3)	3-opoly	(4)	4-opoly	(5)
Pre-merger Firms	AA Replacement	AA Entry	Pre-merger Firms	AA Entry	Pre-merger Firms	AA Entry	Pre-merger Firms	AA Entry
DL	[0.02,0.09]	[0.19,0.25]	DL,LCC	[0.09,0.27]	DL,LCC,UA	[0.21,0.35]	DL,LCC,UA,WN	[0.27,0.44]
LCC	[0.07,0.19]	[0.02,0.14]	DL,UA	[0.24,0.32]	DL,LCC,WN	[0.10,0.33]		
UA	[0.04,0.12]	[0.10,0.21]	DL,WN	[0.16,0.27]	DL,UA,WN	[0.29,0.37]		
WN	[0.01,0.04]	[0.10,0.19]	LCC,UA	[0.05,0.22]	LCC,UA,WN	[0.07,0.29]		
			LCC,WN	[0.04,0.23]				
			UA,WN	[0.11,0.26]				

The first row of Column 3 shows that, conditional on observing a duopoly of DL and UA, American is likely to enter and form a triopoly with a probability between 24 and 32 percent. Columns 4 and 5 present results that show that the probability that American enters post-merger is generally increasing in the number of firms that are in the market pre-merger, though there is some considerable heterogeneity depending on the identity of the firms that were in the market pre-merger.

We can now proceed to see how prices would change after the entry of AA in a market. Clearly, we can only construct price changes for firms that were in the market pre- and post-merger. So, for example, we do not have a change in price in markets where AA/US replaces DL. For markets where AA/US enters to form a duopoly with Delta, we will have

the change in prices for DL, but not for AA/US. In Table 12, we present the price changes under different scenarios. The scenarios presented in Columns 1, 2, 3, and 4 of Table 12 correspond, respectively, the the ones in Columns 2, 3, 4, and 5 of Table 11.

The first row of Column 1 in Table 12 shows that the price of the median ticket on a flight with DL drops between by between 8 and 12 percent when American enters to form a duopoly. The results are quite similar when we look at the effect of AA/US's entry on the prices of the other competitors. The first row of Column 2 in Table 12 shows that the effect on the prices of the entry of American are smaller when the original market structure was a duopoly, and this is true for any of the duopolies we consider. The results in Columns 3 and 4 show that the entry of American has an increasingly smaller effect on the prices of the incumbent oligopolists as their number increases.

Table 12: Post-Merger Price Changes After the Entry of AA in New Markets

Monopoly		Duopoly		3-opoly		4-opoly	
Pre-merger Firms	%ΔPrice	Pre-merger Firms	%ΔPrice	Pre-merger Firms	%ΔPrice	Pre-merger Firms	%ΔPrice
DL	[-0.12,-0.08]	DL	[-0.05,-0.03]	DL	[-0.03, -0.01]	DL	[-0.02, -0.01]
		LCC	[-0.01,-0.01]	LCC	[-0.01,-0.00]	LCC	[-0.00,-0.00]
				UA	[-0.015 -0.010]	UA	[-0.01,-0.01]
						WN	[-0.01,-0.00]
LCC	[-0.10,-0.09]	DL	[-0.04,-0.02]	DL	[-0.028,-0.014]		
		UA	[-0.02,-0.02]	LCC	[-0.008,-0.004]		
				WN	[-0.012,-0.008]		
UA	[-0.12,-0.09]	DL	[-0.05,-0.03]	DL	[-0.021,-0.013]		
		WN	[-0.02,-0.01]	UA	[-0.016,-0.010]		
				WN	[-0.008,-0.006]		
WN	[-0.11,-0.08]	LCC	[-0.02,-0.01]	LCC	[-0.011,-0.005]		
		UA	[-0.04,-0.03]	UA	[-0.025,-0.015]		
				WN	[-0.009,0.001]		
		LCC	[-0.04,-0.02]				
		WN	[-0.05,-0.02]				
		UA	[-0.04,-0.03]				
		WN	[-0.02,-0.02]				

The intuition for why AA/US enters new markets and the corresponding change in prices is straightforward. Under our assumptions about the merger, the new firm will typically have higher utility and/or 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 see in those monopoly markets where AA/US replaces the incumbent.

Table 13 focuses on markets where AA is already present in the market and another incumbent *exits* after the merger. This is clearly different than what we have just investigated, where (the new) AA was simply adding itself into a market, and the consumers would clearly benefit, generally with lower prices and greater product variety. There are two reasons why a competitor would drop out of a market after a merger. First, after the merger AA might become more efficient in terms of costs, lowers the prices, and and now a rival cannot make enough variable profit to cover fixed costs.[31] Second, AA might become more attractive to consumers after the merger and steal business from rivals. For ease of exposition we only considers 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 13 shows that there is a probability between 3 and 5 percent that DL will leave the duopoly market with AA after American merges with USAir. The second row shows that the probability that a LCC exits the (duopoly) market is much larger, between 9 and 16 percent. United and Southwest exit the market with a probability, respectively, included in [0.06,0.08] and [0.02,0.05]. These are all economically and statistically significant probabilities, and provide another piece of evidence that the AA/US merger has complex effects, ranging well beyond the typical analysis that is circumscribed to markets where the merging parties are pre-merger duopolies.

Next, in Table 14 we consider what happens to prices after markets become more concentrated after the merger. We observe that, with the exception of Delta, all the price changes in the first Column of Table 14 are *positive.* For example, after the exit of a LCC in a AA-LCC duopoly, American (now a monopolist) would increase its price by a percentage

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[31] 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 an decrease in fixed costs could lead to entry with the already low marginal costs.

Table 13: Likelihood of Exit by Competitors after AA-US Merger

Duopoly with AA		3-opoly with AA	
Pre-merger Firm	Exit	Pre-merger Firms	Exit
DL	[0.03,0.05]	DL	[0.05,0.15]
		LCC	[0.01,0.01]
LCC	[0.09,0.16]	DL	[0.04,0.14]
		UA	[0.01,0.05]
UA	[0.06,0.08]	DL	[0.02,0.03]
		WN	[0.02,0.05]
WN	[0.02,0.05]	LCC	[0.02,0.03]
		UA	[0.05,0.12]
		LCC	[0.00,0.02]
		WN	[0.07,0.11]
		UA	[0.01,0.03]
		WN	[0.03,0.05]

included between 1 and 7 percent (Row 2, Column 1). This result makes sense to the extent that now American is a monopoly, while pre-merger it was a duopoly. However, it may surprising that American can increase its prices and the LCC decides to exit. One would think that the profit of the LCC would increase as American increases its prices, and that would make the LCC less likely to exit the market. The key to understand this apparent paradox is that, under the best scenario, American is not only incurring lower costs, but it is also facing a stronger demand for its product, which comes at the cost of its competitors in the market.

The results are different, mostly in the magnitudes in Table 14, when a competitor exits the market after the merger of AA and US, and the pre-merger market structure was a triopoly. Column 2 of Table 13 shows that the probability of exit of a competitor after the merger of AA and US is still significant, for example the probability that Southwest exits a triopoly market of AA, LCC, and WN is between 7 and 11 percent. The second and third Columns in Table 14 show, respectively, how the prices of American and the remaining competitor changed after the triopoly became a duopoly. We now observe that American systematically lowers its prices after the merger, for example by a percentage between 4 and 7 percent in markets where the triopoly was made of AA, DL, UA and UA exits. The

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Table 14: Price Changes From Exit of Competitor After Merger

Duopoly		3-opoly			
Pre-merger Firm	AA %ΔPrice	Pre-merger Firm	%ΔPrice	Pre-merger Firm	%ΔPrice
DL	[-0.02,0.04]	AA	[-0.07,-0.05]	DL	[-0.03,-0.00]
		AA	[-0.01,0.06]	LCC	[-0.02,0.01]
LCC	[0.01,0.07]	AA	[-0.07,-0.04]	DL	[-0.03,0.03]
		AA	[-0.02,-0.00]	UA	[-0.03,0.02]
UA	[0.01,0.08]	AA	[-0.05,-0.02]	DL	[-0.01,0.01]
		AA	[-0.04,-0.01]	WN	[-0.02,0.03]
WN	[0.01,0.07]	AA	[0.01,0.06]	LCC	[-0.02,0.02]
		AA	[-0.02,0.00]	UA	[-0.03,0.03]
		AA	[-0.03,0.11]	LCC	[-0.01,-0.01]
		AA	[-0.04,0.01]	WN	[-0.02,0.05]
		AA	[-0.03,-0.00]	UA	[-0.01,0.02]
		AA	[-0.00,0.02]	WN	[-0.02,0.03]

remaining competitor also has to lower the prices, but not by as much.

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 rise prices.

Here, we conduct a counter-factual 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.

Table 15 reports the results of a counterfactual exercise that looks at the entry of new competitors and at the price changes in markets with DCA as an endpoint that were AA and US duopoly before the merger. The first row shows that there is a probability included between 16.1 and 71 percent that there will be a AA monopoly post-merger. There is a

probability between 13.6 and 22.7 percent that Delta will enter into the market after AA and US merge. United is also likely to enter into these markets, with a probability included between 5.9 and 18.8 percent. The probability that a LCC or WN enters into the market is negligible.

The second row reports the price changes predicted under the new market structure. Most crucially, we observe that the prices *increase* by a percentage included between 1.9 and 8.9 percent when AA is the post-merger monopolist. This is the first, strong, piece of evidence that the AA and US merger would provide localized market power in important geographical markets, even under the "best" case scenario for the merging parties. When a competitor enters, the prices changes are not statistically different from zero, suggesting that new entry does limit the market power gained through a merger.

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

Table 15: Post-merger entry and pricing in pre-merger AA & US Duopoly markets, Reagan National Airport

Prob mkt structure	Monopoly AA/US	Duopoly AA/US & DL	Duopoly AA/US & LCC	Duopoly AA/US & UA	Duopoly AA/US & WN
Mkt Struct. Transitions	[0.161, 0.710]	[0.136, 0.227]	[0.000, 0.047]	[0.059, 0.188]	[0.000, 0.000]
% Change in Prices	[0.019, 0.089]	[-0.095, 0.018]	[-0.073, 0.126]	[-0.114, 0.068]	[n.a.]

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 exercises consist of merger simulation that allow for changes in market structures, and not just in prices. The main takeaways are: i) that self-selection occurs and controlling for it 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 responses 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 industrial organization economists, both 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 Goeree (2008) who investigates the role of informative advertising in a market with limited consumer information. 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.

In general, our approach shows that the standard merger analysis may lead to misleading policy recommendations that would not be justified when entry decisions are allowed to change. Understanding endogenous product characteristics choice, and allowing this to interact with optimal entry and pricing decisions, is a promising direction for future research, as this may also be important for policy consideration.

References

Berry, Steven and Panle Jia. 2010. "Tracing the Woes: An Empirical Analysis of the Airline Industry." *American Economic Journal: Microeconomics* 2 (3):1–43.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile prices in market equilibrium." *Econometrica: Journal of the Econometric Society* :841–890.

Berry, Steven T. 1990. "Airport presence as product differentiation." *The American Economic Review* :394–399.

———. 1992. "Estimation of a Model of Entry in the Airline Industry." *Econometrica: Journal of the Econometric Society* :889–917.

———. 1994. "Estimating discrete-choice models of product differentiation." *The RAND Journal of Economics* :242–262.

———. 1999. "Free entry and social inefficiency in radio broadcasting." *The RAND Journal of Economics* 30 (3):397–420.

Bresnahan, Timothy F. 1987. "Competition and collusion in the American automobile industry: The 1955 price war." *The Journal of Industrial Economics* :457–482.

———. 1989. "Empirical studies of industries with market power." *Handbook of industrial organization* 2:1011–1057.

Bresnahan, Timothy F and Peter C Reiss. 1990. "Entry in monopoly market." *The Review of Economic Studies* 57 (4):531–553.

———. 1991. "Entry and competition in concentrated markets." *Journal of Political Economy* :977–1009.

Brueckner, Jan K and Pablo T Spiller. 1994. "Economies of traffic density in the deregulated airline industry." *Journal of Law and Economics* :379–415.

Chernozhukov, Victor, Han Hong, and Elie Tamer. 2007. "Estimation and confidence regions for parameter sets in econometric models1." *Econometrica* 75 (5):1243–1284.

Ciliberto, Federico, Amalia Miller, Helena Skyt Nielsen, and Marianne Simonsen. 2010. "Playing the fertility game at work." *Unpublished manuscript* .

Ciliberto, Federico and Elie Tamer. 2009. "Market structure and multiple equilibria in airline markets." *Econometrica* 77 (6):1791–1828.

Ciliberto, Federico and Jonathan W Williams. 2014. "Does Multimarket Contact Facilitate Tacit Collusion? Inference on Conduct Parameters in the Airline Industry." *Inference on Conduct Parameters in the Airline Industry (February 12, 2014)* .

Cohen, Andrew M and Michael J Mazzeo. 2007. "Market structure and competition among retail depository institutions." *The Review of Economics and Statistics* 89 (1):60–74.

Draganska, Michaela, Michael Mazzeo, and Katja Seim. 2009. "Beyond plain vanilla: Modeling joint product assortment and pricing decisions." *QME* 7 (2):105–146.

Eizenberg, Alon. 2014. "Upstream Innovation and Product Variety in the US Home PC Market*." *The Review of Economic Studies* :rdu004.

Elzinga, Kenneth G and David E Mills. 2009. "Predatory Pricing in the Airline Industry: Spirit Airlines v. Northwest Airlines (2005)." *The Antitrust Revolution, 5th Edition, edited by J. Kwoka and L. White, Forthcoming* .

Goeree, Michelle Sovinsky. 2008. "Limited information and advertising in the US personal computer industry." *Econometrica* 76 (5):1017–1074.

Goolsbee, Austan and Chad Syverson. 2008. "How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines." *The Quarterly Journal of Economics* 123 (4):1611–1633.

Gronau, Reuben. 1974. "Wage Comparisons–A Selectivity Bias." *The Journal of Political Economy* :1119–1143.

Heckman, James J. 1976. "The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models." In *Annals of Economic and Social Measurement, Volume 5, number 4*. NBER, 475–492.

———. 1979. "Sample selection bias as a specification error." *Econometrica: Journal of the econometric society* :153–161.

Ho, Katherine. 2008. "Insurer-Provider Networks in the Medical Care Market." *American Economic* .

Mazzeo, Michael J. 2002. "Product choice and oligopoly market structure." *RAND Journal of Economics* :221–242.

Nevo, Aviv. 2000. "Mergers with differentiated products: The case of the ready-to-eat cereal industry." *The RAND Journal of Economics* :395–421.

Pakes, Ariel, J Porter, Joy Ishii, and Kate Ho. 2015. "Moment Inequalities and Their Application." *Econometrica* 83:315–334.

Panzar, John C. 1979. "Equilibrium and welfare in unregulated airline markets." *The American Economic Review* :92–95.

Reiss, Peter C and Pablo T Spiller. 1989. "Competition and entry in small airline markets." *Journal of Law and Economics* :S179–S202.

Roberts, Jimmy and Andrew Sweeting. 2014. "The Potential Entry Defense in Airline Mergers." *working paper, Duke University* .

Rosse, James N. 1970. "Estimating cost function parameters without using cost data: Illustrated methodology." *Econometrica: Journal of the Econometric Society* :256–275.

Schmalensee, Richard. 1989. "Inter-industry studies of structure and performance." *Handbook of industrial organization 2* 2.

Seim, Katja. 2006. "An empirical model of firm entry with endogenous product-type choices." *RAND Journal of Economics* :619–640.

Tamer, Elie. 2003. "Incomplete simultaneous discrete response model with multiple equilibria." *The Review of Economic Studies* 70 (1):147–165.