Market Structure and Competition in Airline Markets

Federico Ciliberto[y] Charles Murry[z] Elie Tamer[x]
University of Virginia Penn State University Harvard University

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Abstract

We provide an econometric framework for estimating a game of simultaneous entry and pricing decisions in kT1_1an pricing/eBDC the/M T-(create)Tj /T1_1 1 Tf (e)Tj /T1_1 19 Tf (1)Tj /T1_5 1 Tf unobser /C2_0 8 Tf 5.64 0

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 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 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 M4Ttiotincl 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 di erentiation (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 a ect 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 rms firm

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a an that \best

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,

$$\begin{aligned} y_1 &= 1[\ _2 y_2 + \ \ Z_1 + \ \ _1 \geq 0]; \\ y_2 &= 1[\ _1 y_1 + \ \ Z_2 + \ \ _2 \geq 0]; \\ S_1 &= X_1 \ \ + \ \ _1 V_1 + \ \ _1; \\ S_2 &= X_2 \ \ + \ \ _2 V_2 + \ \ _2 \end{aligned} \tag{1}$$

where $y_j = 1$ if firm j decides to enter a market, and $y_j = 0$ otherwise, where j 2 $f1;2g$. Let $K \equiv f1;2g$ 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 $Z \equiv (Z_1; Z_2)$ and $X \equiv (X_1; X_2)$ are exogenous whereby that $(\ _1;\ _2;\ _1;\ _2)$ is independent of $(Z; X)$ 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

[7] It is simple to allow and or joint of foT1_10 1 Tf 2.00 Tdr, (or)Tj /T1_1-451 Tf DC 2f ( )Tex1_0 1 Tsi Tf Td [(i

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,

($_1$; $_2$; $_1$; $_2$) N (0Tf ( ) 54.828 Tm (1) Tj/T1_2 1 Tf11.9552 2

The data we observe are $(S_1 y_1; V_1 y_1; y_1; S_2 y_2; V_2 y_2; y_2; X; Z)$ 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

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 $(X; Z)$):

$$
\begin{aligned}
P(\ _1 \leq t_1; y_1 = 1; y_2 = 0) \quad &= \quad P \quad _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{U}_{(1;0)} \\
&+ \quad P(d_{1;0} = 1\ j\ \ _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{M}_{(1;0)})\ P \quad _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{M}_{(1;0)}
\end{aligned} \tag{3}
$$

The probability $P(d_{1;0} = 1\ j\ \ _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{M}_{(1;0)})$ 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:

$$
\begin{aligned}
P \quad _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{U}_{(1;0)} \quad \leq P(S_1 + \ _1V_1 - X_1 \quad \leq t_1; y_1 = 1; y_2 = 0) \leq \\
P \quad _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{U}_{(1;0)} \quad + P \quad _1 \leq t_1; (\ _1;\ _2)\ 2\ A^{M}_{(1;0)}
\end{aligned}
$$

The middle part

$$
P(S_1 - \ _1V_1 - X_1 \quad \leq t_1; y_1 = 1; y_2 = 0)
$$

can be consistently estimated from the data given a value for $(\ _1;\ ; t_1)$. The LHS and RHS on the other

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 $(S_2 - {}_2V_2 - X_2 \quad \le t_2;\ y_1 = 0; y_2 = 1)$ can similarly be calculated. In addition, in the two player entry game (i.e. 's are negative) above with pure strategies, the events $(1;1)$ and $(0;0)$ are uniquely determined, and so

$$P(S_1 - {}_1V_1 - X_1 \quad \le t_1;\ S_2 - {}_2V_2 - X_2 \quad \le t_2; y_1 = 1; y_2 = 1)$$

is equal to (moment equality)

$$P({}_1 \le t_1;\ {}_2 \le t_2;\ {}_1 \ge - {}_2 - \ Z_1;\ {}_2 \ge - {}_1 - \ Z_2)$$

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

$$P(y_1 = 0; y_2 = 0) = P({}_1 \le - \ Z_1;\ {}_2 \le - \ Z_2)$$

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

$$m^1_{(1;0)}(t_1; Z; \Sigma) \le E \ 1 \ S_1 - {}_1V_1 - X_1 \quad \le t_1; y_1 = 1; y_2 = 0 \quad \le m^2_{(1;0)}(t_1; Z; \Sigma)$$

$$m^1_{(0;1)}(t_2; Z; \Sigma) \le E \ 1 \ S_2 - {}_2V_2 - X_2 \quad \le t_2; y_1 = 0; y_2 = 1 \quad \le m^1_{(0;1)}(t_2; Z; \Sigma)$$

$$E \ 1 \ S_1 - {}_1V_1 - X_1 \quad \le t_1; S_2 - {}_2V_2 - X_2 \quad \le t_2; y_1 = 1; y_2 = 1 \quad = m_{(1;1)}(t_1; t_2; Z; \Sigma)$$

$$E \ 1 \ y_1 = 0; y_2 = 0 \quad = m_{(0;0)}(y)$$

where

$$
\begin{aligned}
m^1_{(1;0)}(t_1; Z; \Sigma) &= P \quad _1 \leq t_1; (\, _1; \, _2) \in A^U_{(1;0)} \\
m^2_{(1;0)}(t_1; Z; \Sigma) &= m^1_{(1;0)}(t_1; Z; \Sigma) + P \quad _1 \leq t_1; (\, _1; \, _2) \in A^M_{(1;0)} \\
m^1_{(0;1)}(t_2; Z; \Sigma) &= P \quad _2 \leq t_2; (\, _2; \, _2) \in A^U_{(0;1)} \\
m^2_{(0;1)}(t_2; Z; \Sigma) &= m^1_{(0;1)}(t_2; Z; \Sigma) + P \quad _2 \leq t_2; (\, _1; \, _2) \in A^M_{(0;1)} \\
m_{(1;1)}(t_1; t_2; Z; \Sigma) &= P(\, _1 \leq t_1; \, _2 \leq t_2; \, _1 \geq - \, _2 - \, Z_1; \, _2 \geq - \, _1 - \, Z_2) \\
m_{(0;0)}(Z; \Sigma) &= P(\, _1 \leq - \, Z_1; \, _2 \leq - \, Z_2)
\end{aligned}
$$

Hence, the above can be written as

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

where $G(:) \in R^k$.

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* $(X; Z) \perp (\, _1; \, _2; \, _2; \, _2)$ *where the latter is normally distributed with mean zero and covariance matrix* Σ*: Then given a large data set on* $(y_1; y_2; S_1y_1; V_1y_1; S_2y_2; V_2y_2; X; Z)$ *the true parameter vector* $\;\; = (\, _1; \, _2; \, _1; \, _2; \; ; \; ; \Sigma)$ *minimizes the nonnegative objective function below to zero:*

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

for a strictly positive weight function $(X; Z)$:

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.

[10] See the Online Supplement for more details. See CT for an analogous result and the proof therein.

Figure 1: *Estimation Methodology*

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 di erence (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 di erence 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 di erence (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 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 (used)

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:

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

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

$$\begin{cases} y_1 = 1 \;,\; {}_1 = (p_1 - c(W_1;\; {}_1))\, M \cdot \tilde{s}_1(p; X; y;\;) - F(Z_1;\; {}_1) \geq 0; & \text{Entry Conditions} \\ y_2 = 1 \;,\; {}_2 = (p_2 - c(W_2;\; {}_2))\, M \cdot \tilde{s}_2(p; X; y;\;) - F(Z_2;\; {}_2) \geq 0; & \\ & \\ S_1 = \tilde{s}_1(p; X; y;\;); & \text{Demand} \\ S_2 = \tilde{s}_2(p; X; y;\;); & \\ & \\ (p_1 - c(W_1;\; {}_1))\, @\tilde{s}_1(p; X; y;\;) = @p_1 + \tilde{s}_1(p; X; y;\;) = 0; & \text{Equilibrium Pricing} \\ (p_2 - c(W_2;\; {}_2))\, @\tilde{s}_2(p; X; y;\;) = @p_2 + \tilde{s}_2(p; X; y;\;) = 0; & \end{cases} \tag{7}$$

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, and fourth equations ehLo1_1 1 Tf ( )Tj /T1_0 1 Tf 3.7 /T1_1 1 Tf ( )Tj /T1289e89e3d7x0 Td [(e 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; Berry1_1 1 Tf ( )Tj /T1_0 1 Tf 10 trf ( )Tj 8 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

$$u_{ij} = X_j^{0} + p_j + {}_j + {}_{ig} + (1 -) {}_{ij}; \qquad (10)$$

$$u_{i0\,2\,0}$$

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

Finally, the unobservables have a joint normal distribution,

$$({}_1;\ {}_2;\ {}_1;\ {}_2;\ {}_1;\ {}_2) \quad N(0;\Sigma)\,; \tag{15}$$

where Σ is the variance-covariance matrix to be estimated. As discussed above, the o -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 di erent 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 construct

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 $r = 1, \ldots, ns$ 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 $\Theta^0 = ({}^0; {}^0; '^0; {}^0; \Sigma^0)$.

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 $e \in E$.

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

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

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

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 $({}_r; {}_r; {}_r)$ 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 $\overline{p}_r^e$ and shares $\overline{s}_r^e$.[13]

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

(d) We use the candidate parameter ^{0} and the simulated error $_{r}$ 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, $_r^e$ and $_r^e$. In addition, we collect $_r^e$ and include them in A_e^U , which was defined collect in in collect procedure. Many simplifications can be done to the above to ease the computational burden. 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 di erences 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 cuto s t, we only use five cuto s for each unobservable (dimension of integration).

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

$$\Sigma_m = \begin{bmatrix} {}^2 \cdot I_{Km} & \cdot I_{Km} & \cdot I_{Km} \\ \cdot I_{Km} & {}^2 \cdot I_{Km} & \cdot I_{Km} \\ \cdot I_{Km} & \cdot I_{Km} & {}^2 \cdot I_{Km} \end{bmatrix} :$$

Thus, this specification restricts the correlations to be the same for each firm which is made for computational

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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, To is airlines. Table 2 shows the distribution in the number of potential entrants, and we observe that

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 1a1WTeEfr( )T 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 *ight'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 o of an alternative trip that uses the same seat on the same plane, possibly as part of a flight connecting two di erent 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 functions (Rosse, 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* a ects 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. 53p betf ( )

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) di er 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

[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 di erent 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*

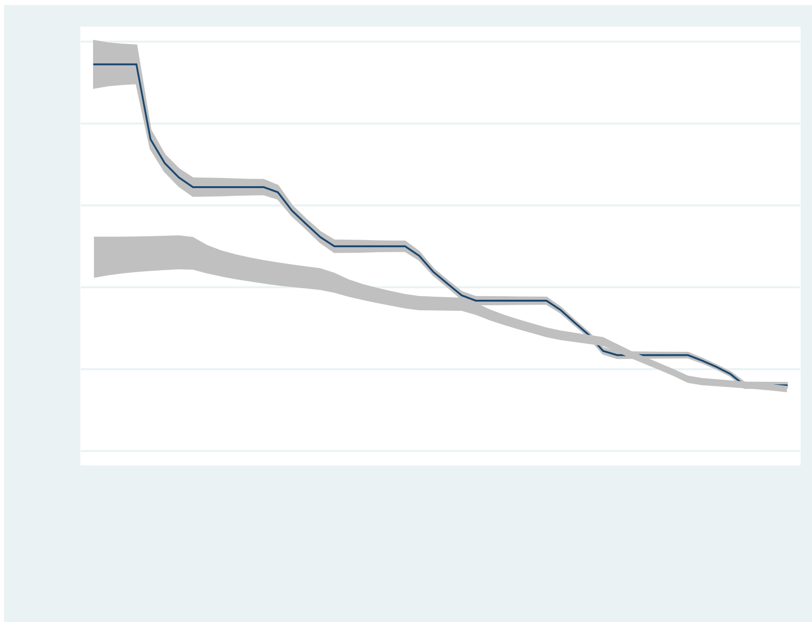

Figure 2 shows yield (ticket fare divided by market distance) against the number of firms in a market, which is the simplest measure of market structure.[22] We draw local polynomial smooth plots with 95% confidence intervals for Southwest, LCCs, and the legacy carriers. In all three cases, the yield 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 di erentiated 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 Bresnahan /T1_0 1 Tf4.514 0 Td (and)Tj /T1_1 1 Tf ( )Tj 84f ( )Tj /T1_0 1 Tf .752 0 Td (of)Tj /T1_1 1 Tf

Figure 3: *Distribution of Yield by Carrier Identity*

are three competitors in a market.[23] The distribution for the LCC is di erent 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

[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 di er 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 di erent 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 ’$_j$ = ’ and $_j$ = 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 coe cient to be negative and , 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 ’$_j$ to be di erent 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.

[24] We instrument for price and using the value of the exogenous data for every firm, regardless of whether they are in the market. regardless

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)
	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	{
Market	81 1 Tf5(Cost)Tj /T1_1 1 Tf( )Tj /T1_0 1 Tf2.491 0 Td(ALL)-1.20(BD)(81 1 Tf5(C	

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 $'_j = '$ and $_j =$. 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 di erent 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 (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 di erence 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]
	[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 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

Table

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
out in
a new market, or price out a rival in an existing market.

and Nevo, 2001).[28]

6.1 The Price and Market Structure E ects 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

(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 tic[illegible] 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 e ect of the merger.

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

	Post-merger

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 o er 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 di erent direction of investigation. Instead of focusing on markets 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 di erent 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 e cient in terms of costs, lowers the prices, and and now a rival cannot make enough variable profit tbe

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 e ect 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 di erent 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 simulations.

More generally, this paper contributes to the literature that studies the e ects that mergers or other policy changes have on the prices and structure of markets, and consequently the welfare of consumers and

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