Market Structure and Multiple Equilibria in Airline Markets*

Federico Ciliberto[†]
University of Virginia

Elie Tamer[‡]
Northwestern University

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Abstract

We provide a practical method to estimate the payoff functions of players in complete information, static, discrete games. With respect to the empirical literature on entry games originated by Bresnahan and Reiss (1990) and Berry (1992), the main novelty of our framework is to allow for general forms of heterogeneity across players without making equilibrium selection assumptions. We allow the effects that the entry of each individual airline has on the profits of its competitors, its "competitive effects", to be different across airlines. The identified features of the model are sets of parameters (partial identification) such that the choice probabilities predicted by the econometric model are consistent with the empirical choice probabilities estimated from the data.

We apply this methodology to investigate the empirical importance of different types of firm heterogeneity as determinants of market structure in the U.S. airline industry. We find that the competitive effects of large airlines (American, Delta, United) are different from those of low cost carriers and Southwest. We also find that the competitive effect of an airline is increasing in its airport presence, which is an important measure of observable heterogeneity in the airline industry. Then, we develop a policy experiment to estimate the effect of repealing the Wright Amendment on competition in markets out of the Dallas airports. We find that repealing the Wright Amendment would increase the number of markets served out of Dallas Love by 20 percent, and that most of them would be served by Southwest.

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[†]Department of Economics, University of Virginia, ciliberto@virginia.edu.

[‡]Department of Economics, Northwestern University, tamer@northwestern.edu. Research support from The National Science Foundation and The A. P. Sloan Foundation is gratefully acknowledged.

1 Introduction

We provide a practical method to estimate the payoff functions of players in complete information, static, discrete games. With respect to the empirical literature on entry games originated by Bresnahan and Reiss (1990) and Berry (1992), the main novelty of our framework is to allow for general forms of heterogeneity across players without making equilibrium selection assumptions. These assumptions are typically made on the form of firm heterogeneity to ensure that, for a given value of the exogenous variables, the economic model predicts a unique *number* of entrants. In the ensuing econometric models, multiple equilibria in the identity of the firms exist, but the number of entrants is unique across equilibria. This uniqueness leads to standard estimation of the parameter using maximum likelihood or method of moments. On the other hand, models with general forms of player heterogeneity have multiple equilibria in the number of entrants, and so the insights of BR and Berry do not generalize easily.

We present an econometric framework that allows for multiple equilibria and where different selection mechanisms can be used in different markets. This framework directs the inferential strategy on a "class of models," each of which corresponds to a different selection mechanism. We use the simple condition that firms serve a market only if, in equilibrium, they make non negative profits, to derive a set of restrictions on regressions.[1] In games with multiple equilibria this simple condition leads to *upper* and *lower* bounds on choice probabilities.[2] The economic model implies a *set* of choice probabilities, which lies between these lower and upper bounds. Heuristically, our estimator then is based on minimizing the distance between this set and the choice probabilities that can be consistently estimated from the data. Our econometric methodology restricts the parameter estimates to a set and thus partially identifies the parameters.[3] Each parameter in this set corresponds to a particular

[1]The idea of deriving results on a class of models goes back to Sutton (2000). Taking a class of models approach to game theoretic settings, one "abandon(s) the aim of identifying some unique equilibrium outcome. Instead, we admit some class of candidate models (each of which may have one or more equilibria) and ask whether anything can be said about the set of outcomes that can be supported as an equilibrium of any candidate model". The necessary and weak condition on behavior is similar to the "viability condition" discussed by Sutton (see also Sutton (1991)).

[2]Tamer (2003) also used this insight to show that, for a simple 2×2 game with multiple equilibria, the model provides inequality restrictions on regression. Sufficient conditions are then given to guarantee that these inequality restrictions point identify the parameter of interest. These conditions are not easy to generalize to larger games. However, the paper noted that in general, inequality restrictions constrain the parameter vector to lie in a set, the identified set, and an estimator was suggested (page 153).

[3]See footnote 2 above.

selection mechanism that is consistent with the model and the data. We use recently developed inferential methods in Chernozhukov, Hong, and Tamer (2002) (CHT) to construct confidence regions that cover the identified set with a prespecified probability.[4]

We apply our methods to data from the airline industry, where each observation is a market (a trip between two airports).[5] The idea behind cross-section studies is that in each market firms are in a long-run equilibrium. The objective of our econometric analysis is to infer long-run relations between the exogenous variables in the data and the market structure that we observe at some point in time, without trying to explain how firms reached the observed equilibrium. For example, we model the entry decision of American Airlines as having a different effect on the profit of its competitors than the entry of Delta or of low cost carriers has. More importantly, we perform a policy exercise using our estimated model to study how the Wright Amendment, a law restricting competition in markets out of Dallas Love airport, affects the state of these market with respect to competition, or their structure. This law has been partially repealed in 2006, so we can compare the predictions of our model with what actually happened.

We estimate two versions of a static complete information entry game. These versions differ in the way that the entry of a firm, its "competitive effect," affect the profits of its competitors. In the simpler version, which follows the previous literature, these competitive effects are captured by *firm-specific indicator variables* in the profit functions of other airlines. These indicator variables measure the firms' "fixed competitive effects." In the more complex version, a firm's competitive effect is a variable function of the firm's measure of observable heterogeneity. The measure of observable heterogeneity that affects competitors' profits is an airline's airport presence, which is a function of number of markets served by a firm out of an airport. The theoretical underpinnings for these "variable competitive effects" are in Hendricks, Piccione, and Tan (1997), who show that, as long as an airline has a large airport presence, its dominant strategy is not to exit from a spoke market, even if that means to suffer losses in that market. Thus, the theoretical prediction is that the larger an airline's airport presence, the larger its "variable competitive effects" should be.

There are four sets of results. First, we find that the fixed competitive effects are much smaller when we allow for variable competitive effects, suggesting that a firm's competitive

[4]CHT that focus on constructing confidence regions for the argmin of a function (in this paper, the minimum distance objective function). These methods cover the identified set with a prespecified probability. Other econometric methods that can be used are Romano and Shaikh (2006), Bugni (2007), Molinari (2003) and Andrews and Soares (2007).

[5]Berry (1992) used the same data source, but from earlier years.

effect is a function of its airport presence (Table 3). Second, the competitive effects are particularly large when a low cost carrier or Southwest are analysed (Table 5). In particular, the entry of a low cost carrier or Southwest is associated with a marked lower probability of observing large carriers in the same market, and viceversa. On the other hand, the entry of a large carrier has a relatively smaller effect on the profits of another large carrier. Third, we develop a policy experiment to estimate the effect of repealing the Wright Amendment on competition in markets out of the Dallas airports (Table 6). We find that repealing the Wright Amendment would increase the number of markets served out of Dallas Love by 20 percent, and most of them would be served by Southwest. Finally, when we estimate the variance-covariance matrix, we find positive correlation in the errors (Table 4). The competitive effects are smaller than when the unobservables are assumed to be independent across firms, but are still economically and statistically significant. We infer that we need to allow for positive correlation in the firm-specific unobservables to get the appropriate measure of the competitive effects .

This paper contributes to a growing literature on inference in discrete games. In the complete information setting, complementary approaches include Bjorn and Vuong (1985) and Bajari, Hong, and Ryan (2005), where equilibrium selection assumptions are imposed. Another approach makes informational assumptions. For example, Seim (2002), Sweeting (2004), and Aradillas-Lopez (2005) consider the case where the entry game is with incomplete information, so that neither the firms nor the econometrician observe the profits of all competitors. Recently, Pakes, Porter, Ho, and Ishii (2005) provide a novel economic framework that leads to a set of econometric models with inequality restrictions on regressions. They also provide a method for obtaining confidence regions. Andrews, Berry, and Jia (2003) have recently proposed methods to construct confidence regions for models with inequality restrictions that apply to entry models. Finally, further insights about identification in these settings is given in Berry and Tamer (2006).

The remainder of the paper is organized as follows. Section 2 presents the empirical model of market structure and the main idea of the econometric methodology. Section 3 formalizes the inferential approach, providing conditions for the identification and estimation of the parameter sets. Then, Section 4 discusses market structure in the US airline markets. Section 5 presents the estimation results. Section 6 reports the results of our policy experiment. Section 7 concludes and provides limitations and future work.

2 An Empirical Model of Market Structure

We follow Berry (1992) in modelling market structure. In particular, let the profit function for firm i in market m be $\pi_{im}(\theta; \mathbf{y}_{-im})$ where $\mathbf{y}_{-im}$ is a vector that represents other potential entrants in market m, θ is a finite parameter of interest determining the shape of π_{im}. This function can depend on both market specific and firm specific variables.[6]

A market m is defined by X_m where $X_m = (S_m, Z_m, W_m)$. S_m is a vector of market characteristics, which are common among the firms in market m and K is the number of potential entrants. $Z_m = (Z_{1m}, \ldots, Z_{Km})$ is a vector of firm characteristics that enter into the profits of all the firms in the market, for example some product attributes that consumers value. $W_m = (W_{1m}, \ldots, W_{Km})$ are firm characteristics that enter only into firm i's profit, such as the cost variables.

The profit function is

$$\pi_{im} = S_m'\alpha_i + Z_{im}'\beta_i + W_{im}'\gamma_i + \sum_{i \neq j} \delta_j^i y_{im} + \sum_{j \neq i} Z_{jm}'\phi_j^i y_{jm} + \epsilon_{im} \tag{1}$$

where ϵ_{im} is the part of profits that is unobserved to the econometrician.[7] We assume throughout that ϵ_{im} is observed by all players in market m. Thus, this is a game of complete information. It is interesting to note the similarity between this setup and the one recently considered by Pakes, Porter, Ho, and Ishii (2005). There, the authors consider two sets of unobservables. In addition to an unobservable that is similar to ϵ above, they allow for another expectational unobservable that can arise as a result of players' incomplete knowledge of the exact profit function.

An important feature of this profit function is the presence of $\{\delta_j^i, \phi_j^i\}$, which summarize the effect other airlines have on i's profits. In particular, notice that this function can depend directly on the identity of the firms (y_j's, $j \neq i$). Also, the effect on the profit of firm i of having j in its market is allowed to be different than having k in its market ($\delta_j^i \neq \delta_k^i$). For example, the parameters δ_j^i's can measure a particularly aggressive behavior of one airline

[6] The fully structural form expression of the profit function should be written in terms of prices, quantities, and costs. However, because of lack of data on prices, quantities, and costs, most of the previous empirical literature on entry games had to specify the profit function in a reduced form. There exist data on airline prices and quantities, but these variables would be endogenous in this model. We would have to find adequate instruments and extend our methodology to include additional regression equations, one for the demand and one for the supply side. This is clearly beyond the scope of our paper. As stated in the introduction, the main contribution of this paper is to take the models used by previous empirical literature on entry games and allow for general forms of heterogeneity across players without making equilibrium selection assumptions.

[7] The linearity imposed on the profit function is not essential. We only require that the profit function be known up to a finite dimensional parameter.

(e.g. American) against another airline (e.g. Southwest).[8] These competitive effects could also measure the extent of product differentiation across airlines (Mazzeo (2002)). Finally, the δ_j^i's and ϕ_j could measure cost externalities among airlines at airports.[9]

3 Identification

We examine the conceptual framework that we use to identify the model. For simplicity, we start with a bivariate game where we show how to analyze the identified features of this game without making equilibrium selection assumptions. We then show that the same insights carry over to richer games.

3.1 Simple Bresnahan and Reiss 2×2 game

Consider the following version of the model above with two players:

$$\begin{cases} y_{1m} & = 1[\alpha_1 X_{1m} + \delta_2 y_{2m} + \epsilon_{1m} \geq 0] \\ y_{2m} & = 1[\alpha_2 X_{2m} + \delta_1 y_{1m} + \epsilon_{2m} \geq 0] \end{cases} \tag{2}$$

Here, a firm is in market m if in a pure strategy Nash equilibrium it makes non-negative profit. Following BR, Berry (1992), and Mazzeo (2002), we do not consider mixed strategy equilibria[10].

The econometric structure in (2) is a binary simultaneous equation system. With large enough support for ϵ's, this game has multiple equilibria. The presence of multiple equilibria complicates inference due to the coherency issue (see Heckman (1978) and Tamer (2003)). The likelihood function predicted by the model will sum to more than one. A way to complete the model is by specifying a rule that "picks" a particular equilibrium in the region of multiplicity. Another way to solve the coherency issue is to find some feature that is common to all equilibria, and transform the model into one that predicts this feature uniquely. Bresnahan and Reiss (1991a) and Berry (1992) follow this second approach.

When $\delta_1, \delta_2 < 0$ (monopoly profits are larger than duopoly profits), the map between the support of the unobservables (the ϵ) and the set of pure strategy equilibria of the game is

[8] See the discussion in Bresnahan (1989)'s Section 2.2.3, "Supply Equations in "conjectural variations" language," for an interpretation of the δ_j^i's as measures of the expectations that each firm has on the behavior of its competitors.

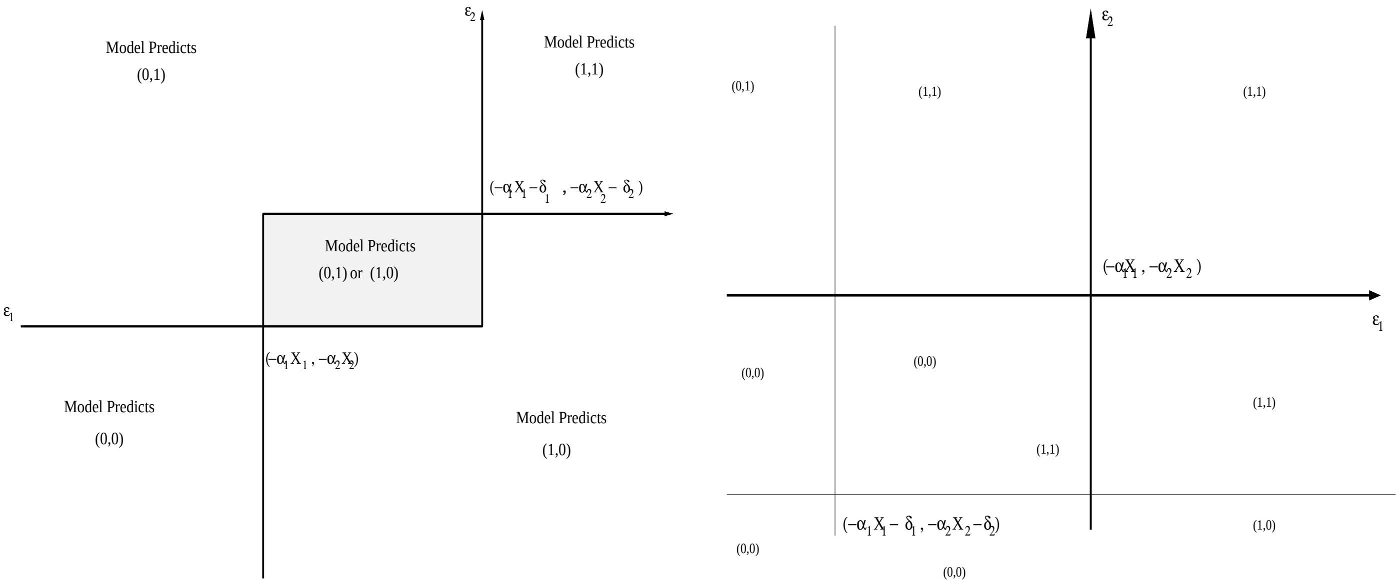
[9] See Borzekowski and Cohen (2004) for an example of a game of technology adoption with multiple equilibria.

[10] It is simple, conceptually, to accommodate mixed strategies in our framework. We discuss this below. See also Berry and Tamer (2006).

illustrated in Figure 1. Notice that multiple equilibria in the identity, but not number of firms, happen when $-\alpha_i X_i \leq \epsilon_i \leq -\alpha_i X_i - \delta_{3-i}$ for $i = 1, 2$ (we suppress dependence on m for simplicity). The shaded center region of the figure contains payoff pairs where either firm could enter as a monopolist in the simultaneous-move entry game.

small

Figure 1: Regions for multiple equilibria :



Bresnahan and Reiss (1990) and Berry (1992) ensure the uniqueness of equilibrium in the number of firms by assuming that the firms' unobservable determinants of profits are independent of the identity of the firms that are in the market. This assumes that firms' heterogeneity enters in one another's profit equations in the same way. If we drop these assumptions, different equilibria can exist with different numbers of players.[11]

BR's approach requires that one knows the sign of δ's. Multiple equilibria exist when externalities are present. The relevance of positive externalities can be represented in the simple 2×2 discrete game illustrated in Figure 2. In this case, where $\delta_i > 0$ for $i = 1, 2$, and for $-\delta_{3-i} - \alpha_i X_i \leq \epsilon_i \leq -\alpha_i X_i$ both players enter or no player enters. Here, a player benefits from the other player entering the market. We can again use BR's approach and estimate the probability of the outcome $(1, 0)$, of the outcome $(0, 1)$, and of the outcome

[11]Heuristically, in 3-player games where one is a large firm and the other two are small firms, there can be multiple equilibria where one equilibrium includes the large firm as a monopolist, while the other has the smaller two firms enter as duopolists (as we will discuss in the empirical section). This happens when one allows differential effect on profits from the entry of a large firm vs a small one ($\delta^{large} \neq \delta^{small}$).

"either $(1,1)$ or $(0,0)$."

3.1.1 Main Idea

We illustrate the main idea starting with the case where the δ's are negative. The choice probabilities predicted by the model are

$$\begin{aligned}
\Pr(1,1|X) &= \Pr\left(\epsilon_1 \geq -\alpha_1 X_1 - \delta_2;\ \epsilon_2 \geq -\alpha_2 X_2 - \delta_1\right) \\
\Pr(0,0|X) &= \Pr\left(\epsilon_1 \leq -\alpha_1 X_1;\ \epsilon_1 \leq -\alpha_2 X_2\right) \\
\Pr(1,0|X) &= \Pr\left((\epsilon_1,\epsilon_2) \in R_1(X,\theta)\right) + \int \Pr\left((1,0)|\epsilon_1,\epsilon_2,X\right)1\left[(\epsilon_1,\epsilon_2)\in R_2(\theta,X)\right]dF_{\epsilon_1,\epsilon_2}
\end{aligned} \tag{3}$$

where

$$\begin{aligned}
R_1(\theta,X) &= \left\{(\epsilon_1,\epsilon_2):\ \ (\epsilon_1 \geq -\alpha_1 X_1; \epsilon_2 \leq -\alpha_2 X_2) \cup (\epsilon_1 \geq -\alpha_1 X_1 - \delta_2; -\alpha_2 X_2 \leq \epsilon_2 \leq -\alpha_2 X_2 - \delta_1)\right\} \\
R_2(\theta,X) &= \left\{(\epsilon_1,\epsilon_2):\ \ (-\alpha_1 X_1 \leq \epsilon_1 \leq -\alpha_1 X_1 - \delta_1; -\alpha_2 X_2 \leq \epsilon_2 \leq -\alpha_2 X_2 - \delta_2\right\}
\end{aligned}$$

$X = (X_1, X_2)$ and θ is a finite dimensional parameter of interest that contains the α's, the δ's and parameters of the joint distribution of the ϵ's.

The first two equalities in (3) are simple. For example, the model predicts $(1,1)$ *uniquely* if and only if the ϵ's belong to the upper right hand side quadrant. The third equality provides the predicted probability for the $(1,0)$ event. This probability consists of the case when $(1,0)$ is the unique equilibrium of the game, i.e., when $(\epsilon_1,\epsilon_2) \in R_1$, and also when $(1,0)$ is a *potentially observable outcome* of the game and it is the outcome that "was selected." The selection mechanism is the function $\Pr((1,0)|\epsilon_1,\epsilon_2,X)$ which is allowed to depend on the unobservables in an arbitrary way, is unknown to the econometrician and can differ in different markets. This term is an infinite dimensional nuisance parameter.[12]

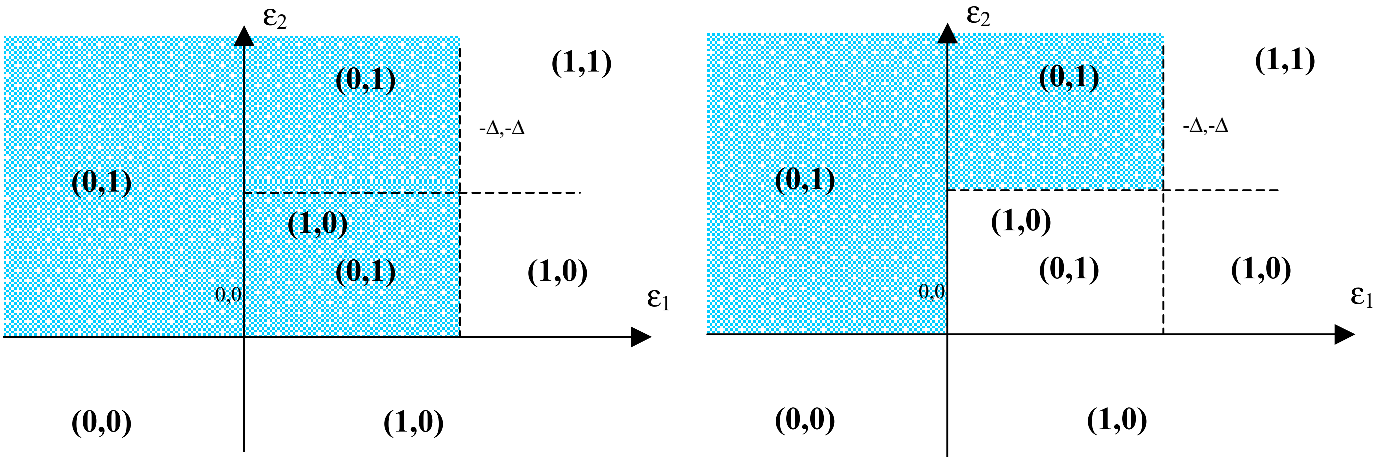
Heuristically, the identified features of the above model is the set of parameters for which there exists a proper selection function such that the choice probabilities predicted by the model are equal to the empirical choice probabilities obtained from the data (or consistently estimated). We exploit the fact that this (selection) function is a proper probability and hence lies in $[0,1]$. Hence, an *implication* of the above model is the following:

$$\Pr\left((\epsilon_1,\epsilon_2)\in R_1\right) \leq \Pr((0,1)) \leq \Pr\left((\epsilon_1,\epsilon_2)\in R_1\right) + \Pr\left((\epsilon_1,\epsilon_2)\in R_2\right) \tag{4}$$

[12] If we were to allow for mixed strategy equilibria, then each choice probability in (3) will need to be adjusted to account for each outcome being on the support of the mixed strategy equilibrium. More on this below.

The model predicts the first two equations in (3) above and the inequality restriction on the choice probability of the $(1,0)$ in (4). The upper and lower bound probabilities for the $(1,0)$ event are illustrated in Figure 3 below. Sufficient point identification conditions based

Figure 2: Upper and Lower probability Bounds on the $\Pr(0,1)$:



The shaded area in the graph on the right hand side represents the region for (ϵ_1, ϵ_2) that would predict the outcome $(0,1)$ uniquely. The shaded region in the graph on the left hand side represents the region where $(0,1)$ would be predicted if we *always* select (0,1) to be the equilibrium in the region of multiplicity. The probability of the epsilons falling in the respective regions provide an upper and a lower bound on the probability of observing (0,1).

on the predicted choice probabilities of the $(0,0)$ and $(1,1)$ outcomes were given in Tamer (2003). In the next section, we extend this inferential approach to more general games.

3.2 Identification: General Setup

Here, we consider general games with many players and basically extend the insights from the previous section on bivariate games. We consider models where the number of markets is large, as opposed to requiring that the number of players within each market is large. We also require that the joint distribution of $\boldsymbol{\epsilon}$ be known up to a finite parameter vector which is part of the parameter vector θ. As in the setup above, our approach to identification is to "compare" the (conditional) distribution of the observables (the data) to the one predicted by the model at a given parameter value.

To estimate the conditional choice probability vector $P(\mathbf{y}|\mathbf{X})$, a nonparametric conditional expectation estimator can be used. We then derive the predicted choice probabilities in any given market m and find parameters that minimize their distance (to be formally defined below). We first provide an assumption that is used throughout.

Assumption 1 *We have a random iid sample of observations* $(\mathbf{y}_m, \mathbf{X}_m), m = 1 \dots n$. *Let* $n \to \infty$. *The unobserved random vector* ϵ *is continuously distributed on* R^K *independently of* $X = (X_1, \dots X_K)$ *with a joint distribution function* F *that is known up to a finite dimensional parameter that is part of* θ.

The predicted choice probability for y' given X:

$$\begin{aligned} \Pr(y'|X) &= \int \Pr(y'|\epsilon, X) dF \\ &= \int_{R_1(\theta,X)} \Pr(y'|\epsilon, X) dF + \int_{R_2(\theta,X)} \Pr(y'|\epsilon, X) dF \\ &= \underbrace{\int_{R_1(\theta,X)} dF}_{\text{Unique Outcome Region}} + \underbrace{\int_{R_2(\theta,X)} \Pr(y'|\epsilon, X) dF}_{\text{Multiple Outcome Region}} \end{aligned}$$

where $y' = (y'_1, \dots, y'_K)$ is some outcome, for example American, Southwest, and Delta serving the market. The third equality splits the likelihood of observing y' into two regions, $R_1(\theta, X)$ and $R_2(\theta, X)$. The first region of the unobservables, $R_1(\theta, X)$, is one where y' is the unique observable outcome of the entry game. The second region, R_2, is where the game admits *multiple potentially observable outcomes* one of which is y'. The region R_2 can be complicated. For example, in a subregion of R_2, y' and y'' are the equilibria, while in another subregion of R_2, y' and y''' are the equilibria.

Mixed strategy equilibria can also exist in region R_2 and if y' is on the support of the mixing distribution, then y' is a potentially observable outcome. Hence, allowing for mixed strategies does not present additional problems, but in our empirical application, for computational simplicity, we do not allow for mixing (for more on inference with mixed strategies, see Berry and Tamer (2006)).

The probability function $\Pr(y'|\epsilon, X)$ is the selection function for outcome y' in regions of multiplicity. This function is unspecified. Bjorn and Vuong (1985) assume that this function is a constant. More recently, Bajari, Hong, and Ryan (2005) use a more flexible parametrization.

To obtain the sharp identified set, one way to proceed is to use semiparametric likelihood where the parameter space contains the space of unknown probability functions that include the selection functions. Although this is an attractive avenue to proceed theoretically, it is difficult to implement practically since one would need to optimize over a set of infinite dimensional nuisance functions. A practical way to proceed is to exploit the fact that the selection functions are probabilities and hence bounded between 0 and 1, and so an implication of the above model is

$$\int_{R_1(\theta,X)} dF \leq \Pr(y'|X) \leq \int_{R_1(\theta,X)} dF + \int_{R_2(\theta,X)} dF \tag{5}$$

In vectorized format, these inequalities correspond to the following upper and lower bounds on conditional choice probabilities

$$\mathbf{H}_1(\boldsymbol{\theta},\mathbf{X}) \equiv \begin{bmatrix} H_1^1(\boldsymbol{\theta},X) \\ \vdots \\ H_1^{2^K}(\boldsymbol{\theta},X) \end{bmatrix} \leq \begin{bmatrix} \Pr(\mathbf{y}_1|X) \\ \vdots \\ \Pr(\mathbf{y}_{2^K}|X) \end{bmatrix} \leq \begin{bmatrix} H_2^1(\boldsymbol{\theta},X) \\ \vdots \\ H_2^{2^K}(\boldsymbol{\theta},X) \end{bmatrix} \equiv \mathbf{H_2}(\boldsymbol{\theta},\mathbf{X}) \tag{6}$$

where $\Pr(\mathbf{y}|X)$ (the vector of the form $(\Pr(0,0), \Pr(0,1), \ldots)$ is a 2^k vector of conditional choice probabilities. The inequalities are interpreted element by element.

The $\mathbf{H}$'s are functions of θ and the distribution function F_Ω where Ω is part of the vector θ. For example, these functions were derived analytically in (4) for the 2×2 game . The lower bound function $\mathbf{H}_1$ represents the probability that the model predicts a particular market structure as the unique equilibrium.[13] $\mathbf{H_2}$ contains in addition the probability mass of the region where there are multiple equilibria.

The identified feature is the *set* of parameter values that obey these restrictions for all $\mathbf{X}$ almost everywhere and represents the set of economic models that is consistent with the empirical evidence. More formally,

Definition 1 *Let Θ_I be such that*

$$\Theta_I = \{\theta \in \Theta \quad \textit{s.t. inequalities } (6) \textit{ are satisfied at } \theta \quad \forall\ \mathbf{X} \quad \textit{a.s.}\} \tag{7}$$

We say that Θ_I is the identified set.

In general, the set Θ_I is not a singleton and it is hard to characterize this set, i.e., find out whether it is finite, convex, etc. Next, following Tamer (2003) we provide sufficient conditions that guarantee point identification.

[13]Notice that there are cross equation restrictions that one can exploit in the "cube" defined in 5 above, like the fact that the selection probabilities sum to one.

3.3 Exclusion Restriction

The system of equation we consider is similar to a simultaneous equation system except that here the dependent variable takes finitely many values. As in the classical simultaneous equation system, exclusion restrictions can be used to reach identification. In particular, exogenous variables that enter one firm's profit function and not the other's play a key role. We explain using model (2) above.

Theorem 2 *We have a random iid sample of observations* $(y_{1i}, y_{i2}, x_{1i}, x_{2i}), i = 1 \dots n$. *Let* $n \to \infty$. *The unobserved random vector* (ϵ_1, ϵ_2) *is continuously distributed on* R^2 *independently of* (x_1, x_2) *with a (unknown) joint distribution function* $F(.,.)$. *Suppose* x_1 (x_2) *is such that* $x_1^1|x_1^{-1}, x_2$ $(x_2^1|x_2^{-1}, x_1)$ *is continuously distributed with support on* R, $\alpha_1^1 = \alpha_2^1 = 1$ *and* $x_i = (x_i^1, x_i^{-1})$ *for* $i = 1, 2$, *and similarly for* $(\alpha_1^1, \alpha_1^{-1})$. *Then,* $(\alpha_1^{-1}, \alpha_1^{-1}, \delta_1, \delta_2)$ *and* F *are identified.*

proof: First, consider the choice probabilities for $(0, 0)$:

$$\begin{aligned} P(0,0|x_1,x_2) = P(0,0|x_1^1, x_1^{-1}; x_2^1, x_2^{-1}) &= P(\epsilon_1 \geq x_1\alpha_1; \epsilon_2 \geq x_2\alpha_2) \\ \overset{as\, x_1^1 \to -\infty}{=} & P(\epsilon_2 \geq x_2\alpha_2) \end{aligned} \tag{8}$$

Hence, we see that the choice probabilities for $(0, 0)$ as we drive x_1^1 to $-infty$ isolates the distribution function for ϵ_2 and the parameter α_2. Hence, conditioning on those x_1^1's, (where player 1 is out of the market with probability one regardless of what 2 does), this $(0, 0)$ choice probability point identifies both the marginal distribution of ϵ_2 and α_2.
Similarly, by driving x_2^1 to $-\infty$, we can identify both the marginal distribution of ϵ_1 and α_1. The same lines as above can be used to also identify (δ_1, δ_2) along with the *joint* distribution of (ϵ_1, ϵ_2). $\square$

Independent variation in one regressor while driving another to take extreme values on its support (identification at infinity) identifies the parameters of Model (2). In more realistic games with many players, variation in excluded exogenous variables (like the airport presence or cost variables we use in the empirical application) help shrink the set Θ_I.

3.4 Estimation

The estimation problem is based on the following:

$$\mathbf{H}_1(\boldsymbol{\theta}, \mathbf{X}) \leq \Pr(\mathbf{y}|\mathbf{X}) \leq \mathbf{H_2}(\boldsymbol{\theta}, \mathbf{X}) \tag{9}$$

This is a statistical structure that is based on a set of moment inequalities. Our inferential procedures uses the following objective function:

$$Q(\boldsymbol{\theta}) = \int \left[\| \left(P(\mathbf{X}) - H_1(\mathbf{X}, \boldsymbol{\theta})\right)_- \| + \left\|\left(P(\mathbf{X}) - H_2(\mathbf{X}, \boldsymbol{\theta})\right)_+\right\|\right] dF_x$$

where $(A)_- = [a_1 1[a_1 \leq 0], \ldots, a_{2^k} 1[a_{2^K} \leq 0]]$ and similarly for $(A)_+$ for a 2^k vector A and where $\|.\|$ is the Euclidian norm. It is easy to see that $Q(\boldsymbol{\theta}) \geq \mathbf{0}$ for all $\theta \in \Theta$ and that $Q(\boldsymbol{\theta}) = \mathbf{0}$ if and only if $\theta \in \Theta_I$, the identified set in definition 1 above.

The object of interest is either the set Θ_I or the (possibly partially identified) θ_I. We mainly focus on inference on Θ_I since we view Θ_I as the set of parameters where each is consistent with an economic model based on particular selection mechanism that could have generated the observed data. For example, one such model selects in the region of multiplicity the airline with the largest market presence at either end of the market, while another model always selects the the airline with the largest profits in that market. The first model will yield a $\theta \in \Theta_I$ that is, possibly, different than one obtained using the second selection mechanism and both of these parameters are in Θ_I. Statistically, the main difference in whether one considers Θ_I or θ_I as the parameter of interest is that confidence regions for the former are weakly larger that for the latter. Evidently, in the case of point identification the regions coincide asymptotically.

Inference in partially identified models is a current area of research in econometrics and in this paper we follow the framework of Manski and Tamer (2001) and Chernozhukov, Hong, and Tamer (2004)[14]. To consistently estimate the set Θ_I, we first take a sample analog of $Q(.)$. To do that, we first replace $\Pr(\mathbf{y}|\mathbf{X})$ by a consistent estimator $P_n(\mathbf{X})$. Then, define the set $\widehat{\Theta}_I$ as

$$\widehat{\Theta}_I = \{\theta \in \Theta \mid nQ_n(\theta) \leq \nu_n\} \tag{10}$$

where $\nu_n \to \infty$ and $\frac{\nu_n}{n} \to 0$ (take for example $\nu_n = ln(n)$) and

$$Q_n(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^{n} \left[\left\|(P_n(X_i) - H_1(X_i, \theta))_-\right\| + \left\|(P_n(X_i) - H_2(X_i, \theta))_+\right\|\right] \tag{11}$$

[14]Other *set inference* methods that one can use to obtain confidence regions for sets include: Andrews, Berry, and Jia (2004) Beresteanu and Molinari (2005), Romano and Shaikh (2006), Pakes, Porter Ishii and Ho (2006) and Bugni (2007).

where $d(.;.)$ is a distance function that is continuously differentiable with respect to both arguments. The theorem below shows that the set estimator defined above is a Hausdorff-consistent estimator of the set Θ_I.

Theorem 3 *Let assumption 1 hold. Suppose that for the function Q_n defined in (11): i) $sup_\theta |Q_n(\theta) - Q(\theta)| = O_p(1/\sqrt{n})$ and ii) $Q_n(\theta_I) = O_p(1/n)$ for all $\theta_I \in \Theta_I$. Then, we have that w.p. approaching to one:*

$$\widehat{\Theta}_I \subseteq_{w.p.1} \Theta_I \quad \textit{and} \quad \Theta_I \subseteq_{w.p.1} \widehat{\Theta}_I$$

proof: First, we show that $\widehat{\Theta}_I \subseteq_{wp1} \Theta_I$. This event is equivalent to the event that $Q(\theta_n) = o_p(1)$ for all $\theta_n \in \widehat{\Theta}_I$. We have:

$$\begin{aligned} Q(\theta_n) &\leq |Q_n(\theta_n) - Q(\theta_n)| + Q_n(\theta_n) \\ &= O_P(1/\sqrt{n}) + O(\nu_n/n) = o_p(1) \end{aligned}$$

On the other hand, we now show that $\Theta_I \subseteq_{w.p.1} \widehat{\Theta}_I$. This event, again, is equivalent to the event that $Q_n(\theta_I) \leq \nu_n/n$ with probability one for all $\theta_I \in \Theta_I$. We have from the hypothesis of the theorem:

$$Q_n(\theta_I) = O_p(1/n)$$

The above can be made less than ν_n/n with probability approaching to one. □

To conduct inference in the above moment inequalities model we use the methodology of CHT where the above is a canonical example of a *moment inequality* model. We construct a set C_n such that $\lim_{n\to\infty} P(\widehat{\Theta}_I \subseteq C_n) = 1 - \alpha$ for a prespecified $\alpha \in (0, 1)$. In fact, the C_n we construct not only will have the coverage property above but will also be consistent in the sense of the theorem above. Our confidence regions will be also of the form of level sets, $C_n(c)$, i.e., $C_n(c) = \{\theta \in \Theta : nQ_n(\theta) \leq c\}$ (for example any level set $C_n(\nu_n)$ for any $\nu_n \to \infty$ and $\nu_n/n \to 0$ will be a consistent set). To build a set that obeys the coverage property also, we start with an initial estimate of Θ_I. This set can be for example $C_n(c_0) = C_n(0)$. Then, we will subsample the statistic $sup_{\theta \in C_n(c_0)} nQ_n(\theta)$ and obtain the estimate of its $(1 - \alpha)$ quantile, c_1. We will then redo the above step replacing c_0 with c_1. Then, we report $C_n \equiv C_n(c_2)$ as our confidence region. If the object of is a unique but unidentified parameter (as opposed to a set), it is possible to provide a modification of our confidence regions whereby these cover the parameter with at least the prespecified probability. Confidence regions for parameters are based on the principle of collecting all the parameters that cannot be rejected. These confidence regions are usually strictly smaller than ones that cover the set. In the Appendix, we provide the conditions needed for the estimated confidence sets to have desirable asymptotic coverage properties. These conditions are based on results obtained in CHT.

3.5 Simulation

In general games, it is not possible to derive the functions $\mathbf{H_1}$ and $\mathbf{H_2}$ analytically. We provide here a brief description of the simulation procedure that can be used to obtain an estimate of these functions for a given $\mathbf{X}$ and a given value for the parameter vector θ. The Appendix studies the large sample properties of the estimator based on the simulated objective function.

We first draw R simulations of market and firm unobservables for each market m. These draws remain fixed during the optimization stage. We transform the random draw into one with a given covariance matrix. Then, we obtain the "payoffs" for every player i as a function of other players' strategies, observables and parameters. This involves computing 2^k-vector of profits for each simulation draw and for every value of θ. If $\boldsymbol{\pi}(\mathbf{y}^j, \mathbf{X}, \theta) \geq \mathbf{0}$ for some $j \in \{1, ..., 2^K\}$, then $\mathbf{y_j}$ is an equilibrium of that game. If this equilibrium is unique, then we add 1 to the lower bound probability for outcome $\mathbf{y_j}$ and add 1 for the upper bound probability. If the equilibrium is not unique, then we add a 1 only to the upper bound of each of the multiple equilibria's upper bound probabilities. For example, the upper bound on the outcome probability $\Pr(1, 1, ..., 1|\mathbf{X})$ is

$$\widehat{H}_2^{2^K}(\mathbf{X}, \theta) = \frac{1}{R}\sum_{j=1}^{R} 1\left[\pi_1(\mathbf{X}_1, \theta; \mathbf{y}_{-1}^{2^K}, \epsilon_1^j) \geq 0, \ldots, \pi_{2^K}(\mathbf{X}_{2^K}, \theta; \mathbf{y}_{-2^K}^{2^K}, \epsilon_{2^K}^j) \geq 0\right]$$

where $\mathbf{1}[*]$ is equal to one if the logical condition $*$ is true and where R is the number of simulation where we assume here that R increases to infinity with sample size (more on the rate of increase is in the appendix[15]).

The methods developed by McFadden (1989) and Pakes and Pollard (1989) can be easily used to show that $\widehat{\mathbf{H}}_i(\mathbf{X}, \theta)$ converges almost surely uniformly in θ and $\mathbf{X}$ to $\mathbf{H}_i(\mathbf{X}, \theta)$ as the number of simulations increases for $i = 1, 2$. More detailed arguments for consistency of the simulated estimator are given in the appendix.

[15]Since the objective function is nonlinear in the moment condition that contains the simulated quantities, it is important to drive the number of simulations to infinity since otherwise, there will be a simulation error that does not vanish and can lead to inconsistencies

4 Market Structure in the U.S. Airline Industry

Our work contributes to the literature started by Reiss and Spiller (1989) and continued by Berry (1992). Reiss and Spiller (1989) provided evidence that unobservable firm heterogeneity in different markets is important in determining the effect of market power on airline fares. Berry (1992) shows that firm observable heterogeneity, such as airport presence, plays an important role in determining airline profitability, providing support to the studies that show a strong positive relationship between airport presence and airline fares.[16] Berry also finds that profits decline rapidly in the number of entering firms, consistently with Bresnahan and Reiss (1991b).

In this paper, we investigate the role of heterogeneity in the effects that each firm's entry has on the profits of its competitors, and we call this their "competitive effect". Then, we use our model to perform a policy exercise on how market structures will change in markets out of and into Dallas after the repeal of the Wright Amendment.

4.1 Data Description

To construct the data we follow Berry (1992) and Borenstein (1989). Our data comes from the second quarter of 2002's Airline Origin and Destination Survey (DB1B). We discuss the data construction in detail in the Appendix. Here, we provide information on the main features of the dataset.

Market Definition We define a market as the trip between two airports, irrespective of intermediate transfer points and of the direction of the flight. The dataset includes a sample of markets between the top 50 MSAs, ranked by the population size. In this sample we also include markets that are *temporarily* not served by any carrier, which are the markets where the number of observed entrants is equal to zero. The selection of these markets is discussed in the Appendix. Our dataset includes 3,332 markets.

Carrier Definition We focus our analysis on the strategic interaction between American, Delta, United, and Southwest because one of the objectives of this paper is to develop the policy experiment to estimate the impact of repealing the Wright Amendment. To this end, we need to pay particular attention to the nature of competition in markets out of Dallas.

Competition out of Dallas has been under the close scrutiny of the Department of Justice. In May 1999, the Department of Justice filed an antitrust lawsuit against American Airlines

[16] See Borenstein (1989) and Evans and Kessides (1993).

charging that the major carrier tried to monopolize service to and from its Dallas-Fort Worth hub (DFW).[17] So, using data from 2002, a year after American won the case against the DOJ, we investigate whether American shows a different strategic behavior than other large firms. Among the other large firms, Delta and United are of particular interest because they interact intensely with American at its two main hubs, Dallas (Delta) and Chicago O'Hare (United).

In addition to considering American, Delta, United, and Southwest individually, we build two additional categorical variables that indicate the types of the remaining firms.[18]

The categorical variable `Medium Airlines`, MA_m, is equal to 1 if either America West, Continental, Northwest, or USAir is present in market m. Lumping these four national carriers in one type makes sense if we believe that they do not behave in strategically different ways from each other in the markets we study. To facilitate this assumption, we drop markets where one of the two endpoints is a hub of the four carriers included in the type `Medium Airlines`.[19]

The categorical variable `Low Cost Carrier Small`, LCC_m, is equal to 1 if at least one of the small low cost carriers is present in market m. Small low cost carrier include 13 smaller airlines.

4.2 Variable Definitions and Descriptive Statistics

We now introduce the variables used in our empirical analysis. Table 1 presents the summary statistics for these variables.

[17] In particular, in April 27, 2001, the District Court of Kansas dismissed the DOJ's case, granting summary judgement to American Airlines. The Doe's complaint focused on American's responses to Vanguard Airlines, Sun Jet, and Western Pacific. In each case, fares dropped dramatically and passenger traffic rose when the LCCs began operations at DFW. According to the Department, American then used a combination of more flights and lower fares until the low cost carriers were driven out of the route or drastically curtailed their operations. American then typically reduced service and raised fares back to monopoly levels once the low cost carriers were forced out of DFW routes. The complaint can be downloaded at *www.usdoj.gov/atr/public/press_releases/*1999/2439*.htm*. In the lawsuit, the DOJ claimed that American responded aggressively against new entry of low cost carriers in markets out of Dallas/Fort Worth, a charge that was later dismissed. The Memorandum and Order is available at *http://www.usdoj.gov/atr/cases/f*8100/8134*.htm*.

[18] In a previous draft of this paper, which is available from the authors' websites, we showed that we could also construct vectors of outcomes where an element of the vector is the *number* of how many among Continental, Northwest, America West and USAir are in the market. This is analogous to a generalized multi-variate version of Berry [1992] and, especially, of Mazzeo (2002). We chose to let MA_m and LCC_m be categorical variables since most of the time they take either a 0 or 1 value.

[19] See the Appendix for a list of these hubs.

Airport Presence Using Berry's (1992) insight, we construct measures of carrier heterogeneity using the carrier's airport presence at the market's endpoints. First, we compute a carrier's ratio of markets served by an airline out of an airport over the total number of markets served out of an airport by at least one carrier.[20] Then, we define the carrier's airport presence as the average of the carrier's airport presence at the two endpoints. We maintain that the number of markets that one airline (e.g. Delta) serves out of one airport (e.g. Atlanta) is taken as given by the carrier when it decides whether to serve another market.[21]

There might be an interacting effect between one carrier (e.g. Delta) serving a particular market and its airport presence on another carrier's (e.g American) profit of serving that market. To address this possibility, we run specifications where the competitive effect of a firm varies with its airport presence. As mentioned in the introduction, the theoretical underpinnings for these variable competitive effects are in Hendricks, Piccione, and Tan (1997).

Cost In specifications where the airport presence of one carrier is excluded from the profit equations of its competitors, airport presence of its competitors is the excluded variable that identifies the competitive effects of the firms. This exclusion restriction was first used by Berry (1992). Airport presence is a market-carrier specific variable that shifts the individual profit functions without changing the competitors' profit functions. For example, the market presence of American is excluded from the profit function of Delta.

In specifications where we include a *competitor's* market presence in the profit equations, we need new exclusion restrictions. Cost variables only enter into the profit equation of one firm but not of its competitors. A firm-market specific measure of cost is not available. Thus, we use the geographical distance between a market's endpoints and the closest hub of a carrier as a proxy of the cost that a carrier has to face to serve that market.[22] Notice that this is a good measure of the opportunity cost of serving a market even when a carrier serves that market on a nonstop basis because it measures the cost of the best alternative

[20] See the discussion in the Appendix for more on this.

[21] The entry decision in each market is here interpreted as a "marginal" decision which takes the network structure of the airline as given. This marginal approach to the study of the airline markets is also used in the literature that studies the relationship between market concentration and pricing. For example, Borenstein (1989) and Evans and Kessides (1993) do not include prices in other markets out of Atlanta (e.g. ATL-ORD) to explain fares in the market ATL-AUS. The reason for this "marginal" approach is that modeling the design of a network is too complicated.

[22] Data on the distances between airports are from the dataset *Aviation Support Tables : Master Coordinate*, available from the National Transportation Library.

to non-stop service, which is a connecting flight through the closest hub.

The Wright Amendment The Wright Amendment was passed in 1979 to stimulate the growth of the airport Dallas/Fort Worth. To achieve this objective, the Congress restricted airline service out of Dallas Love, the other major airport in the Dallas area. In particular, the Wright Amendment permitted air carrier service between Love Field and only airports in Texas, Louisiana, Arkansas, Oklahoma, New Mexico, Alabama, Kansas, and Mississippi, provided the air carrier does not permit through service or ticketing and does not offer for sale transportation outside these states.[23] In October 2006, a bill was enacted that determined the full repeal of the Wright Amendment in 2014. Between 2006 and 2014, nonstop flights outside the Wright zone would still be banned; connecting flights outside the Wright zone would be allowed immediately; and only domestic flights would be allowed out of Dallas Love.

We construct a binary variable, *Wright*, equal to 1 if entry into the market is regulated by the Wright Amendment, and 0 otherwise. *Wright* is equal to 1 for the markets between DAL or DFW and any airport except the ones located in Texas, Louisiana, Arkansas, Oklahoma, New Mexico, Alabama, Kansas, and Mississippi.

We also construct another categorical variable, called *Dallas Market*, which is equal to 1 if the market is between any of the two Dallas airports and any other airport in the dataset. This variable controls for the presence of a Dallas fixed effect. More details on the Wright Amendment are given in the appendix.

Control Variables We use six control variables. Three of these are demographic variables. The average of the city populations at the market endpoints measures the market size. The averages of the per capita incomes and of the rates of income growth of the cities at the market endpoints measure the strength of the economies at the market endpoints. The other three are geographical variables. The non-stop distance between the endpoints is the measure of market distance. The distance from each airport to the closest alternative airport controls for the possibility that passengers can fly from different airports to the same destination.[24] Finally, we construct the distance from the market endpoints to the geographical center of

[23]The Shelby Amendment, passed in 1997, dropped the original restriction on flights between Dallas Love and airports in Alabama, Kansas, and Mississippi. In 2005, an amendment was passed that exempted Missouri from the Wright restrictions.

[24]For example, Chicago Midway is the closest alternative airport to Chicago O'Hare. Notice that for each market we have two of these distances, since we have two endpoints. Our variable is equal to the *minimum* of these two distances.

the United States. This variable is intended to control for the fact that, just for purely geographical reasons, cities in the middle of the US have a larger set of close cities than cities on the coasts or cities at the borders with Mexico and Canada.[25]

Table 1: **Summary Statistics**

	Markets Served All Markets
	Mean (s.d.)
Airport Presence (Carrier Specific) (pct)	0.266 (0.218)
Cost, Distance from Hub (Carrier Specific) (1e2)	0.341 (0.265)
Wright Amendment (0/1)	0.067 (0.250)
Dallas Airport (0/1)	0.072 (0.259)
Market Size (Population) (1e7)	0.297 (0.256)
Per Capita Income (1e5)	0.323 (0.037)
Income Growth Rate	5.191 (0.565)
Market Distance (1e3)	1.055 (0.613)
Closest Airport (1e2)	0.353 (0.212)
Distance from Center (1e3)	1.563 (0.592)
N	3,332

Market Size Does Not Explain Market Structure To motivate the analysis that follows, we have classified markets by market size of the connected cities. The relevant issue is whether market size alone determines market structure (Bresnahan and Reiss (1990)). Table 2 contains quartiles of market size vs the number of firms serving the market. This table provides some evidence that the variation in the number of firms across markets cannot be explained by market size alone.

[25] Notice that for each market we have two of these distances, since we have two endpoints. Our variable is equal to the *sum* of these two distances.

Table 2: **Distribution of the Number of Carriers by Market Size**

Number of Firms	Large	Medium Large	Medium Small	Small	Total
0	8.59	15.25	8.40	14.89	11.76
1	29.05	35.17	33.49	52.70	37.61
2	22.81	23.17	22.93	22.21	22.78
3	15.49	14.89	16.93	7.20	13.63
4	12.00	6.24	11.52	2.40	8.04
5	10.68	4.56	4.92	0.48	5.16
6	1.44	0.72	1.80	0.12	1.02
N	833	833	833	833	3,332

Cross tabulation of the number of firms serving a market by the Market Size, which is here measured by the average of the populations at the market endpoints.

5 Empirical Results

This section presents the results for various specifications of Model 1. Throughout the rest of the paper, we simplify the analysis by introducing the following restrictions: $\beta_i = \beta$, $\alpha_i = \alpha$, and $\phi_j^i = \phi_j$, $\forall i, j$. These restrictions are not necessary, but reduce the number of parameters to be estimated, and the computational burden. We also modify the error structure. First, we include firm-specific unobserved heterogeneity, u_{im}. In one specification (Column 2 of Table 4), we estimate the covariance matrix of the unobserved variables. Then, we add market specific unobserved heterogeneity, u_m. Finally, we add airport specific unobserved heterogeneity, u_m^o and u_m^d. u_m^o is an error that is common across all markets whose origin is o and u_m^d is an error that is common across all markets whose origin is d.[26] u_{im}, u_m, u_m^o, and u_m^d are independent normally distributed, except than when explicitly mentioned. Recall that ϵ_{im} is the sum of all four errors. To use our inference methods, we first need to compute the conditional choice probabilities. We estimate these using a multinomial logit model.[27].

[26] Recall that our markets are defined irrespective of the direction of the flight. Thus, the use of the terms origin and destination is only made to mean either one of the market endpoints.

[27] Ideally, one would want to use a nonparametric estimator of the conditional choice probabilities. This was done in a previous version of the paper. the problem with this is the fact that the bins for the data can contain a small number of observations because of the large number of market structures (2^k) crossed with the richer set of covariates that we use in this version. So, for computational simplicity, and to avoid the problem of too few observations in a given bin, we use a multinomial logit model. In the previous version where we did use the nonparametric estimator, we also used a multinomial logit estimator and the results were not significantly different.

We estimate two versions of the following model:

Main Empirical Model

$$\pi_{im} = S'_m\alpha + Z'_{im}\beta + W'_{im}\gamma_i + \sum_{j\neq i}\delta^i_j y_{im} + \sum_{j\neq i} Z'_{jm}\phi_j y_{jm} + u_{im} + u_m + u^o_m + u^d_m \qquad (12)$$

The first version, called "Fixed Competitive Effects," does not include cost variables and the competitor's airport presence in the profit equations ($\gamma_i = 0$, $\phi_j = 0$, $\forall i, j.$). The second version, called "Variable Competitive Effects," includes cost variables and the competitor's airport presence. Within these two versions of the model, we present specifications that differ by the restrictions on δ^i_j and by whether or not we estimate the variance-covariance matrix of the firm-specific errors.

5.1 Fixed Competitive Effects

Table 3 presents estimates from three specifications of model (12) when $\gamma_i = 0$, $\phi_j = 0$, $\forall i, j$. Here, the airport presence variables are market and carrier specific and act as exclusion restrictions and thus help in the identification. Furthermore, in Table 3, we require independence among the ϵ_{im}'s so any correlation among the profits is due to correlation among the observables. We relax this assumption later.[28]

We report the cube that contains the confidence region that is defined as the set that covers the underlying identified set with 95% probability.[29]

Column 1 of Table 3 presents the estimation results for a variant of the model estimated by Berry (1992). This model imposes that $\delta^i_j = \delta$, $\forall i, j$ in Model 12, in addition to the two restrictions discussed above. This implies that the effect of firms on each other is the same. In Column 1 of Table 3, the reported confidence interval is the "usual" 95% confidence interval since the coefficients are point identified. The main limitation of this model is that the effects of firms on each other are identical, which ensures that in each market there is a unique equilibrium in the number of firms. The results from this model are presented in

[28] In previous versions of the paper we addressed the concern that many large cities have more than one airport. For example, it is possible to fly from San Francisco to Washington on nine different routes. In a previous version of the paper,we allowed the firms' unobservables to be correlated across markets between the same two cities. In the estimation, whenever a market was included in the subsample that we drew to construct the parameter bounds, we also included any other market between the same two cities. This is similar to adjusting the moment conditions to allow for spatial correlation. In our context, it was easy to adjust for it since we knew which of the observations were correlated, i.e., ones that had airports in close proximity.

[29] Not every parameter in the cube belongs to the confidence region. This region can contain holes but here we report the smallest "cube" that contains the confidence region.

column 1.

Column 2 allows for firms to have different competitive effects on their competitors and for multiple equilibria in the number of firms. For example, the effect of American's presence on Southwest and Delta's entry decision is given by δ_{AA}, while the effect of Southwest's presence on the decision of the other airlines is given by δ_{WN}. Notice that the dummies introduce a measure of heterogeneity, as they capture how each firm affects the entry decision of the other five firms.

Column 3 of Table 3 presents the results from a model that allows the competitive effects to be the same for each airline, for example we allow Delta's effect (Delta's effect is coded as the effect of a type "LAR" firm) on American (whose effect is also coded as the effect of a type "LAR" firm) to be different than Delta's effect on Southwest. Here, the competitive effects of American, Delta, United, and the type MA are coded as the effect of a type "LAR" firm. Therefore, δ^{LAR}_{LAR} measures the competitive effect of the entry of a large carrier, for example American, on another large carrier, for example Delta. δ^{WN}_{LAR} measures the competitive effect of Southwest on one of the four "LAR" firms. The other parameters are defined similarly.

Berry Specification The estimates are in Column 1 of Table 3. The parameter *Average Competitive Effect* captures the effect of the number of firms on the probability of observing another firm entering a market. We estimate the effect of an additional firm to be $[-10.322, -8.818]$. This effect is negative, as we would expect. The larger the number of firms, the less likely it is that an additional firm enters into the market. As the number of markets that an airline serves at an airport increases, the probability that the firm enters into the market increases as well. This is seen from the positive effect of *Airport Presence*, which is $[2.666, 3.098]$. A higher *Per Capita Income* increases the probability of entry ($[9.619, 12.168]$), as do the distance between the two market endpoints ($[0.008, 0.290]$), the distance from the center of the US ($[0.227, 0.630]$), and the distance from the closest alternative airport ($[0.734, 1.733]$). We cannot find evidence of a clear effect of market size (*Population*) and of the change in income growth rate. The *Wright Amendment* has a negative impact on entry, as its coefficient is estimated to be in $[-7.468, -1.581]$. The Dallas fixed effect is also negative, indicating that there are fewer firms in markets out of the two Dallas airports than in other similar markets.

Next, we present values of the distance function at the parameter values where this function is minimized. This function can be interpreted as a measure of "fit" among different specifications that use the same exogenous variables.

Table 3: **Empirical Results 1**

	Berry (1992)	Heterogeneous Interaction	Firm-to-Firm Specific Interaction
Average Competitive Effect	[-10.322,-8.818]		
AA		[-10.079, -9.288]	
DL		[-9.923, -9.482]	
UA		[-10.979, -9.722]	
MA		[-10.544, -9.933]	
LCC		[-12.294, -11.411]	
WN		[-10.741, -9.984]	
LAR on LAR LAR: AA, DL, UA, MA			[-8.624, -8.443]
LAR on LCC			[-11.907, -11.396]
LAR on WN			[-9.649, -9.285]
LCC on LAR			[-8.319, -7.946]
WN on LAR			[-7.481, -7.071]
LCC on WN			[-8.889, -8.663]
WN on LCC			[-10.022, -9.331]
Airport Presence	[2.666, 3.098]	[3.759, 4.408]	[5.838, 6.097]
Wright	[-7.468, -1.581]	[-3.323, -2.515]	[-1.718, -0.869]
Dallas	[-7.111, -1.544]	[-6.765, -5.976]	[-7.732, -7.031]
Population	[-0.594, 0.318]	[-0.118, 0.228]	[-0.427, -0.219]
Per Capita Income	[9.619, 12.168]	[10.618, 10.900]	[10.417, 10.986]
Income Growth Rate	[-0.006, 0.256]	[0.095, 0.115]	[0.075, 0.103]
Market Distance	[0.008, 0.290]	[0.098, 0.229]	[-0.136, -0.023]
Close Airport	[0.734, 1.733]	[1.381, 1.609]	[0.442, 1.073]
Distance from US Geographical Center	[0.227, 0.630]	[0.525, 0.606]	[0.364, 0.490]
Constant	[1.209, 2.405]	[1.771, 1.876]	[0.793, 0.878]
Function Value	600.846	564.124	556.2837
Multiple in Identity (pct)	72.02	92.42	90.72
Multiple in Number (pct)	0	15.43	19.95
Predicted Market Structure (%)	29.59	29.97	29.86

These set estimates are appropriately constructed level sets of the sample objective function that cover the identified set (which might not be convex) with 95% (See Chernozhukov, Hong, and Tamer (2002) and the Appendix for more details on constructing these confidence regions).

Berry's (1992) methodology ensures that the equilibrium is unique in the number of firms, though there might be multiple equilibria in the identity of firms. To examine the existence of multiple equilibria in the identity of firms, we simulate results for every market in the following way. We draw 100 times from the distribution of the errors and calculate the number of pure strategy equilibria observed at the point where the objective function is minimized.[30] We find that in 72.02% of the markets there exist multiple equilibria in the identity of firms.

Finally, we report the percentage of outcomes that are correctly predicted by our model. Clearly, in each market we only observe one outcome in the data. The model, however, predicts several equilibria in that market. If one of them is the one observed in the data, then we conclude that our model did predict the outcome correctly. We find that our model predicts 29.59% of the outcomes in the data. This is a measure of "fit" that can be used to compare models.

Heterogeneous Competitive Effects The estimates are in Column 2 of Table 3. All the δ's are estimated to be negative, which is in line with the intuition that profits decline when other firms enter a market. The row denoted AA reports the estimates for the effect of American on the decision of the other airlines to enter into the market. We estimate the effect of American on the other airlines, the confidence regions for δ_{AA}, to be $[-10.079, -9.288]$. Notice that its magnitude is in line with the homogeneous competitive effect estimated in column 1. In particular, the confidence regions for these coefficients overlap. The same can be said about the competitive effect of the other large carriers, Southwest included. Instead, the entry decision of Low Cost Carriers (LCC) has a slightly stronger effects on other airlines. The estimate of this effect is included in $[-12.294, -11.411]$.

The coefficient estimates for the control variables are qualitatively similar in Columns 1 and 2. There is a marked difference, however, in the effects of *Wright* and of *Dallas*, which are more precisely estimated; and the Income Growth Rate is now estimated to have a positive effect on entry.

The presence of multiple equilibria implies that the differences in the competitive effects are large enough to lead to multiple equilibria in the number of firms in 15.43 percent of the markets.

With regard to the fit, the percentage of predicted equilibria is 29.97 percent of the markets

[30] We have experimented with evaluating these findings with other parameter values and found the predictions to be stable.

in the sample, not different from the 29.59 percent computed in Column 1. However, the minimum objective function drops from 600.846 in the "Berry specification" to 564.124 in the "Heterogenous Interaction" model.

Firm-to-Firm Specific Competitive Effects The estimates are in Column 3 of Table 3. We find that the competitive effect of large firms on other large firms ("LAR on LAR", or δ_{LAR}^{LAR}) is $[-8.624, -8.443]$, which is smaller than the competitive effect of large firms on low cost firms ("LAR on LCC"). The competitive effects are not symmetric, in the sense that δ_{LAR}^{LCC} is larger than δ_{LCC}^{LAR}. Finally, the competitive effects of Southwest and large firms on each other are symmetric. Overall, these results suggest that the competitive effects are firm-to-firm specific. In later specifications we do not allow for the competitive effects to vary in this very general way to reduce the number of parameters to be estimated. However, we find that allowing for variable competitive effects and for a flexible variance-covariance structure leads to results that are equally rich in terms of firm-to-firm effects.

5.2 Variable Competitive Effects

In this Section, we study models where the competitive effect of a firm on the other carriers' profits of serving that market varies with its airport presence. Following our discussion in Section 4.2, the exclusion restrictions involve variables that measure the geographical distance between a market's endpoints and the closest hub of a carrier, which we maintain it is correlated with the opportunity cost of providing a market on a non stop basis.

Table 4 presents the results for three specifications of this model. Column 1 of Table 4 reports the estimation results for the model (12) when the errors are assumed to be iid.
In Column 2 we estimate the model (12) but we relax the iid assumption on the firm-specific errors, ϵ_{im}, which includes the other unobservables. We estimate the model with heterogeneous variances and covariances. The variances we estimate are σ_{DL}^2, σ_{UA}^2, σ_{MA}^2, σ_{LCC}^2, σ_{WN}^2. We normalize the variance of AA to one. The covariances we estimate are $\sigma_{LAR,LAR}$, $\sigma_{LAR,WN}$, $\sigma_{LAR,LCC}$, $\sigma_{WN,LCC}$. The covariance $\sigma_{LAR,LAR}$ measures the covariance of the firm specific unobservables of American, Delta, United, and the MA type. Similarly, $\sigma_{LAR,WN}$ measures the covariance of the firm specific unobservables of American, Delta, United, and the MA with the unobservables of Southwest. This correlation structure of the unobservable errors allows the unobservable profits of the firms to be correlated. For example, in markets where large firms face high fuel costs, small firms also face high fuel costs. Another possibility is that there are unobservable characteristics of a market that we

are unable to observe and that affect large firms and Southwest differently, so that when American enters, Southwest does not, and vice versa.

Column 3 estimates the model without the variables measuring airport presence. We estimate the model of entry using only cost information. Thus, we estimate the Model (12) under the assumptions $\beta = 0$, $\phi_j = 0$, $\forall j$. Notice that this specification has fixed, not variable, competitive effects. We present this specification to address the concern that airport presence could be endogenous if airlines choose their network, instead of choosing just whether to enter into a particular market for a given, exogenous, network. This concern is particularly reasonable when we perform our policy simulation.

Variable Competitive Effects with Independent Unobservables Column 1 of Table 4 provides the results for the full Model (12) when the unobservables are assumed to be iid. We compare these results to those presented in Column 2 of Table 3. To facilitate the comparison, it is worth mentioning that in Table 3, the competitive effect of one firm, for example American, on the others is captured by a constant term, δ_{AA}. In Table 4, the same competitive effect is captured by a linear function of the American's airport presence, $\delta_{AA} + \phi_{AA} Z_{AA,m}$. Thus, the estimate of δ_{AA} should be smaller in Table 4 than in Table3, the larger is the estimate of ϕ_{AA}.

We find that the fixed competitive effect, measured in the first six rows (AA to WN) of Table 4 is smaller, in absolute value, than in Table 3. The only exception is the competitive effect of low cost carriers ($\delta_{LCC} = [-10.504, -9.516]$), which is the same in the two tables. The variable competitive effect, measured by the rows InteractAA to InteractWN, is negative, implying that the stronger the market presence of an airline, the less likely is the entry of its competitors in markets where the airline is present. Notice that the only carrier whose airport presence does not affect in a statistically meaningful way the profits of its competitors is the LCC type. The cost variable has a negative sign: after controlling for anything else, a higher cost is associated to lower profits and lower probability of entry. Finally, multiple equilibria in the number of firms are endemic, as we find that there are in 92.36 percent of the markets. The model predicts 31.13 percent of the market structures correctly.

Variable Competitive Effects with Correlated Unobservables Column 2 of Table 4 presents the results for this specification. We first discuss the economic magnitude (that is, the marginal effects) of the parameters estimated in this Column. Then, we conclude by discussing the results for the variances and the covariances.

Table 4: **Variable Competitive Effects**

	Independent Unobs	Variance-Covariance	Only Costs
AA	[-5.308, -4.050]	[-1.118,-0.757]	[-2.866, -2.851]
DL	[-3.028, -1.728]	[-1.177,-0.986]	[-4.346, -4.337]
UA	[-5.332, -4.149]	[-1.177,-0.986]	[-2.782, -2.763]
MA	[-7.348, -6.419]	[-2.114,-1.897]	[-3.272, -3.258]
LCC	[-10.504, -9.516]	[-2.806,-2.354]	[-2.733, -2.675]
WN	[-1.099, 2.126]	[-1.697,-1.304]	[-4.758, -4.748]
InteractAA	[-7.238, -4.748]	[-2.115,-1.551]	
InteractDL	[-9.231, -7.898]	[-1.601,-1.317]	
InteractUA	[-10.670, -7.710]	[-2.575,-1.580]	
InteractMA	[-11.537, -6.628]	[-2.341,-1.638]	
InteractLCC	[-13.839, 21.120]	[-6.532,-4.364]	
InteractWN	[-19.538, -14.254]	[-2.131,-1.426]	
Airport Presence	[4.199, 4.583]	[1.542,1.641]	
Cost	[-0.834, -0.067]	[-0.115,0.124]	[-0.320, -0.313]
CostWN			[-2.332, -2.267]
Wright	[-9.787,-6.434]	[-0.942,-0.741]	[-3.262, -3.251]
Dallas	[-2.100, 1.291]	[-1.064,-0.874]	[-0.412, -0.403]
Population	[-1.089, 0.038]	[0.126,0.295]	[1.151, 1.164]
Per Capita Income	[6.014, 11.426]	[0.260,0.456]	[4.121, 4.131]
Income Growth Rate	[-0.213, 0.227]	[-0.011,0.003]	[0.672, 0.673]
Market Distance	[-0.682, -0.313]	[-0.082,-0.050]	[-0.006, -0.002]
Close Airport	[0.380, 0.826]	[0.118,0.214]	[-1.053, -1.045]
Distance from US Geographical Center	[0.798, 1.191]	[0.255,0.275]	[0.317, 0.321]
Constant	[2.028, 2.712]	[0.674,0.710]	[-2.688, -2.683]
Variance DL		[1.247,1.605]	
Variance UA		[0.838,1.594]	
Variance MA		[1.225,1.859]	
Variance LCC		[1.481,2.258]	
Variance WN		[1.053,1.566]	
Covariance LAR,LAR		[0.968,0.995]	
Covariance LAR,LCC		[0.937,0.963]	
Covariance LAR,WN		[0.962,0.976]	
Covariance WN,LCC		[0.895,0.995]	
Function Value	659.780	647.30	124.2
Multiple in Identity %	92.36	91.09	89.71
Multiple in Number %	38	17.61	22.28
Predicted Market Structure %	31.13	31.81	31.08

Notice that the results are quite similar in Columns 1 and 2, except for the competitive effects and two control variables, the Wright Amendment dummy and Per Capita Income. The parameters measuring the competitive effects, δ_j and ϕ_j, are smaller than in Column 1, but still statistically significant. The coefficients of the Wright Amendment and Per Capita Income are smaller, indicating that in Column 1 they were picking up some variation in the data that is now measured by the covariances.

Table 5 presents the marginal effects of the variables. The results are organized in three panels. The top and middle panel show the marginal effects associated with a change of 1% at the mean value of each corresponding variable. The bottom panel shows the effect that the entry of a carrier, for example American, has on the probability that we observe one of its competitors in the market.

Before presenting our results we clarify up front an important point. Normally, the marginal effects are a measure of how changes in the variables of the model affect the probability of observing the discrete event that is being studied. Here, there are *six* discrete events that our model must predict, as many as the carriers that can enter into a market, and there are *eight* market structures in which we can observe any given carrier. For example, we can observe American as a monopoly, as a duopoly with Delta, United, and so on. If there were no multiple equilibria, this would not create any difficulty: We could simply sum over the probability of all the market structures where American is in the market, and that would give us the total probability of observing American in the market. However, we do have multiple equilibria, and we only observe lower and upper bounds on the probabilities of each market structure. Summing over the upper bounds of the probabilities of the market structures where American is in the market is not the appropriate solution, because the maximum probability of observing one market structure, for example an American monopoly, necessarily excludes that we see another market structure, for example a duopoly with American and Delta, with its maximum probability.

There is one important exception to the point just made. The probability of observing the market structure with no firms is uniquely identified because the outcome where no firm enters is uniquely determined in the data. This is because the competitive effects are negative. Thus, in our discussion we will pay particular attention to this outcome, where no firm enters into a market.

In the top and middle panel we report the *largest change* in the average upper bounds of the probabilities of observing a given carrier in any possible market structure. We compute these average upper bounds by taking the means of the upper bounds for one market structure across markets at the observed values of the exogenous variables. To compute the change in the upper bounds, we first take the observed values of the exogenous variables and add, one at a time, a 1% change of its mean value. Then, we recompute the upper bounds of each market structure in each market and take the average of these upper bounds across markets after dividing the change by the 1% change in the mean value. Finally, we take the differences of all the upper bounds for all 64 market structures and we report the largest change among them.

In the top panel, a 1% increase in the variable Per Capita Income is associated with a maximum effect of 6.88 percent in the probability of observing American Airlines. The interpretation of the effect of an increase in Per Capita Income on the probability of observing other carriers is similar. We find a drop of 2.32 percent in the percentage of markets not served by any airline ("No Firms"). The interpretation of the results for the other exogenous market specific variables in the top panel is analogous. Overall, we find that all effects are reasonably large, with the exception of those for Market Distance and Income Growth Rate (not reported).

The middle panel reports the effect of a one percent increase in the variables measuring heterogeneity on the probability of observing an airline, or no airlines ("No Firms"), in the market. Generally, the effects are much larger in this middle panel than in the top panel, suggesting that observable heterogeneity is a key determinant of entry. For example, a 1% increase in American's airport presence increases the probability of observing American by as much as 37.76 percent.

The numbers in the bottom panel of Table 5 are derived in a slightly different fashion from the ones in the top and middle panel. For example, the upper bound is 30.39% for the market structure where Delta is a monopolist. The upper bound for a duopoly with American and Delta is 32.31%. Then, the effect of Delta entering into the market alone on the probability of observing American and Delta can be positive and as high as 1.92%. However, Delta can also be present in a market with American and other firms. We take the maximum of the changes in the upper bounds of outcomes where Delta is in, and report it in the table.

We find that American's entry can decrease the probability of observing Delta in the market by as much as 7.69 percent. The effect of American's entry varies a lot by the identity of the opponent, as we observe that it is as low as -5.07% on United and as high as

-28.29% on Low Cost Carriers. Overall, there is a large deal of heterogeneity in the effect that firms have on each other.

Table 5: **Marginal Effects**

	AA	DL	UA	MA	LCC	WN	No Firms
Per Capita Income	6.88	7.99	6.79	6.23	7.99	6.04	-2.32
Distance from Center	5.66	6.24	5.80	5.45	6.24	5.45	-1.82
Population	4.76	6.07	4.35	4.25	6.07	3.54	-1.62
Market Distance	0.97	1.22	0.65	1.14	0.63	0.68	0.48
Close Airport	4.26	5.79	4.26	3.74	5.79	3.66	-1.45
Airport Presence AA	37.76	34.01	25.73	37.76	29.49	29.03	-4.67
Airport Presence DL	19.43	24.34	14.00	24.17	24.34	17.37	-3.54
Airport Presence UA	30.84	34.93	34.93	30.84	24.91	25.18	-0.40
Airport Presence MA	7.63	19.56	6.68	25.76	15.42	8.43	0
Airport Presence LCC	1.87	24.28	3.74	11.21	24.28	1.87	0
Airport Presence WN	24.27	27.81	20.12	28.66	22.56	28.66	-2.93
AA	...	-7.69	-5.07	-23.71	-28.29	-11.47	
DL	1.91	...	-2.65	-16.14	-21.23	-6.61	
UA	-8.03	-13.31	...	-28.13	-32.27	-16.18	
MA	-12.20	-12.31	-13.65	...	-28.93	-17.09	
LCC	-16.03	-16.66	-17.04	-28.19	...	-20.41	
WN	-9.62	-12.45	-11.36	-26.75	-30.81	...	

The numbers that we report are marginal effects. They are appropriately selected percentage changes in the original probability of a particular outcome. In the top and middle panel we report the *largest change* in the average upper bounds of the probabilities of observing a given carrier in any possible market structure. For example, the market structure where Delta is a monopoly has an upper bound of 30.39%. We find that this upper bound drops to 30.37% when the Per Capita Income increases by 1% of its mean (that is, by 0.0032). Then, the change in the upper bound is equal to -6.23%. We repeat this for all the market structures and we take the largest of these changes. In the bottom panel, we report the the maximum of the changes in the upper bounds of outcomes where a firm is in, when another firm enters into the market, and report it in the table.

With regard to the estimated variances, they are all quite close to 1, which is the value at which we normalized the variance of the unobservables of American. Only the variance for the unobservables of LCCs can be twice as large as the one of American. This might be a result of our aggregation process, where possibly very different low cost carriers are lumped in a single type. It might also be indicating that the profits made by low cost carriers are significantly smaller than the one made by the larger carriers.

With regard to the estimated correlations, they are all high. We interpret this as evidence that there are unobservable determinants of profits that are highly correlated across firms. These might be demand unobservables or common market shocks that the market and airport unobservables do not pick up. We leave the study of the nature of these unobservable variables that are correlated across firms to future research.

Only Costs Column 3 of Table 4 reports the results when we exclude airport presence and only include the costs as firm-specific determinants of profitability. These results should be compared with those in Column 2 of Table 3. In both of these Columns the competitive effects are negative but they are larger in Table 3. The differences in the magnitudes are explained by the differences in the estimates of the constant terms and of the variable Per Capita Income. Notice, however, that the fits, measured by the percentage of predicted market structures are very close. We will use the results for this specification to check the robustness of our findings in the Policy Experiment section.

6 Policy Experiment: The Repeal of the Wright Amendment

We develop a policy experiment to examine how our model predicts that the market structures change in markets out of Dallas Love after the repeal of the Wright Amendment. To this end, it is crucial to study the individual firms' strategic response to the repeal of the amendment.

In practice, we first take all the 113 markets out of Dallas-Love and simulate the predicted outcomes when the Wright Amendment is still in place. We then repeal the law (we set the variable Wright equal to zero) and recompute the new predicted outcomes. Following the same approach as when we computed the marginal effects, we report the *maximum* change in the average upper bounds of the probabilities of observing a given carrier in any possible market structure before and after the Wrigth Amendment is repealed. Our estimates provide a within model prediction of the effect of the repeal that should be interpreted in the short term.

We present the policy simulations when we use two different specifications. The specifications are a select choice of those in Table 4.

Column 1 of Table 6 reports the policy results when we use the specification in Column

Table 6: **Predicted Probabilities for Policy Analysis: Markets out of Dallas-Love**

Airline Specification	Variance-Covariance (Col 2 of Table 4)	Cost (Col 3 of Table 4)
No Firms	[-18.86,-20.13,-21.28]	-.282
AA	[3.78,5.24,5.44]	0.162
DL	[4.67,4.83,5.11]	0.179
UA	[6.60,7.63,10.57]	0.136
MA	[11.36,12.27,14.05]	0.170
LCC	[13.19,14.01,15.02]	0.184
WN	[14.36,15.73,16.75]	0.184

2 of Table 4. We report confidence intervals on the effect along with the minimized value of the objective function. The first result of interest is in the first row, which reports the probability of observing markets not served by any carrier. We find that the percentage of markets that would not be served would drop by 20.13 percent after the repeal of the Wright Amendment, suggesting that its repeal would increase the number of markets served out of Dallas Love. Of those new markets, as many as 16.75 percent could be served by Southwest. American and Delta, which have strong airport presences at Dallas/Fort Worth would serve a percentage of these markets that is, respectively, at most equal 5.44 and 5.11 percent.

These marked changes in market structures suggest that one reason why the Wright Amendment had not been repealed until 2006 was to protect American monopolies in markets out of Dallas/Fort Worth. Repealing the Wright Amendment would lead to a remarkable increase in service in new markets out of Dallas Love, and thus reduce the incentive for American to prevent entry of new competitors in markets out of Dallas/Fort Worth. As we said, these are dramatic increases, and raise some concern that our methodology might overestimate the effects of the repeal of the Wright Amendment. First, we tried to get some anecdotal information on how Southwest plans to react to the repeal of the Wright Amendment. We checked Southwest's webpage, and found out that since the partial repeal of the Wright Amendment in October 2006, Southwest has started offering one-stop, same plane or connecting service itineraries to and from Dallas Love Field to 43 cities beyond the Wright Amendment area. This pattern of entry in new markets confirms that the repeal of the Wright Amendment is bound to have dramatic effects on airline service out of the Dallas

Love airport.

As a second check, we compare our results with those that we would derive from a specification where the airport presence variables are not included. The policy change might be so major that firms change their network structure when the Wright Amendment is repealed. Column 3 of Table 6 reports the policy results (only the minimized function values) when we use the specification presented in Column 3 of Table 4. This last specification shows results that are close to the ones in Column 1 of Table 6.

7 Conclusions

This paper is a first step in the development of methods that study inference in entry models without making equilibrium selection assumptions. To that extent, these methods can be used to study the effect of multiple equilibria on parameters of interest. However, the methodology used in this paper has important limitations. The model imposes distributional assumptions on the joint distribution of the unobservables and on the shape of the variable profit function. Though it is conceptually possible to study the identification problem in our model without making strong parametric assumptions, it is not clear at this point that the ensuing results are practically attractive. We leave the important work of relaxing further the parametric assumptions to future research. The econometric analysis allows for flexible correlation among firm unobservables and for spatial correlation among market unobservables. In addition, it is possible to test whether a certain selection mechanism is consistent with the data and model by verifying whether estimates obtained under a given mechanism lie in our sets. To do that, one needs to deal with model misspecification, a topic that we leave for future research.

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8 Appendix

8.1 Simulation Procedure

We simulate the functions $\mathbf{H}_1(\mathbf{X}, \theta)$ and $\mathbf{H}_2(\mathbf{X}, \theta)$ for a given $\mathbf{X}$ and θ as follows.
Set $\widehat{\mathbf{H}}_1(\mathbf{X}, \theta) = \widehat{\mathbf{H}}_2(\mathbf{X}, \theta) = 0$. Moreover, for every market, generate and store R draws from the distribution F with identity variance covariance matrix. The number of simulation is assumed to go to infinity with sample size. More on this below. For each simulation $r = (1, \ldots, R)$:

- Step 1:
  Transform the given matrix of epsilon draws into a draw with covariance matrix specified in θ. This is stored in $\boldsymbol{\epsilon}^{\mathbf{r}}$.[31]

- Step 2:
  Using the profits functions from (1), calculate

  $$\boldsymbol{\pi}(\mathbf{y_j}, \mathbf{X}, \theta, \boldsymbol{\epsilon}^{\mathbf{r}}) = [\pi_1(\mathbf{y_{-1}}, \mathbf{X}, \theta, \epsilon_1^r), ..., \pi_K(\mathbf{y_{-K}}, \mathbf{X}, \theta, \epsilon_k^r)]$$

  for all $j = 1, ..., 2^K$.

- Step 3:
  This step finds the equilibria of the game:

  1. For all $j \in \{1, ..., 2^K\}$ such that $\boldsymbol{\pi}(\mathbf{y_j}, \mathbf{X}, \theta, \boldsymbol{\epsilon}^r) \geq 0$, set $\widehat{H}_2^j = \widehat{H}_2^j + 1$.
  2. If there is a $j \in \{1, ..., 2^K\}$ such that $\boldsymbol{\pi}(\mathbf{y}_j, \mathbf{X}, \theta, \boldsymbol{\epsilon}^r) \geq 0$ *uniquely*, i.e., there is no $j' \neq j$ such that $\boldsymbol{\pi}(\mathbf{y_{j'}}, \mathbf{X}, \theta, \boldsymbol{\epsilon}^r) \geq 0$, then $\widehat{H}_1^j = \widehat{H}_1^j + 1$.

This will provide us with the simulated versions

$$\frac{1}{R}\widehat{\mathbf{H}}_2(\mathbf{X}, \theta) \text{ and } \frac{1}{R}\widehat{\mathbf{H}}_1(\mathbf{X}, \boldsymbol{\theta})$$

8.2 Consistency, Practical Estimation and Confidence Regions

In this section, we describe consistency and set estimation.

First Stage Estimation of Choice Probabilities: Our minimum distance estimator calls for estimating the choice probability vector $\mathbf{P}(\mathbf{x}) = \mathbf{P}(\mathbf{y}|\mathbf{X} = \mathbf{x})$ used in (6) in a first step. We can use a nonparametric conditional expectation estimator to obtain this estimator, $\mathbf{P_n}(\mathbf{x})$. The CHT theory that is developed for obtaining confidence regions for sets rely

[31] There are many ways to do this, one of which is to obtain the Cholesky decomposition of the given covariance matrix and use it to transform independent draws into dependent draws.

on having a *finite number* of moment inequalities, hence we assume that the data has finitely many support points (discrete support), or that

$$X \in S_x = \{x_1, \ldots, x_J\} \tag{13}$$

Here, we bin the continuous observations (like Per Capita Income) into 10 decile groups. To estimate the choice probabilities, one can use a nonparametric frequency or cell based estimator. The slight negative of this estimator is that with a large number of support points crossed with market structures, one runs into having too few data points in some cells. This is a typical finite sample problem[32]. We use here a multinomial logit estimator to get, $P_n^{(y')}(x)$, and assume that these consistently estimate the conditional choice probabilities. It is easy to see that in this case

$$sup_x|P_n^{(y')}(x) - P^{(y')}(x)| = max_x\{P_n^{(y')}(x_1) - P^{(y')}(x_1), \ldots, P_n^{(y')}(x_J) - P^{(y')}(x_J)\} = o_p(1)$$

The objective function we use again is

$$\begin{aligned} Q(\boldsymbol{\theta}) &= \int \left[\| (P(x) - H_1(x, \theta))_- \| + \left\|(P(x) - H_2(x, \theta))_+\right\|\right] dF_x \\ &= \sum_{j=1}^{J} p_j \left[\| (P(x_j) - H_1(x_j, \theta))_- \| + \left\|(P(x_j) - H_2(x_j, \theta))_+\right\|\right] \end{aligned}$$

where $(A)_- = [a_1 1[a_1 \leq 0], \ldots, a_{2^k} 1[a_{2^k} \leq 0]]$ and similarly for $(A)_+$ for a 2^k vector A, $\|.\|$ is the Euclidian norm, and p_j is the probability conditional on $X = x_j$. It is easy to see that $Q(\boldsymbol{\theta}) \geq \mathbf{0}$ for all $\theta \in \Theta$ and that $Q(\boldsymbol{\theta}) = \mathbf{0}$ if and only if $\theta \in \Theta_I$, the identified set in definition 1 above. The sample analog of the above objective function is:

$$Q_n(\boldsymbol{\theta}) = \frac{1}{N} \sum_{i=1}^{n} \left[\left\|\left(P_n(x_i) - \widehat{H}_1(x_i, \theta)\right)_-\right\| + \left\|\left(P_n(x_i) - \widehat{H}_2(x_i, \theta)\right)_+\right\|\right] \tag{14}$$

where $||.||$ is the Euclidian distance and again $P_n(x)$ is the vector of 2^k choice probabilities estimated from the data (using a multinomial logit here). The confidence regions are appropriately constructed level sets of the objective function. To apply theorem 3 above, we need to check the uniformity results in the statement of the theorem.

Theorem 4 *Let assumption 1 hold. Let $n, R \to \infty$ (# of markets goes to infinity), and $n/R \to 0$. Let $x \in S_x = \{x_1, \ldots, x_d\}$. Suppose that $P_n(x_i) \to_{a.s.} P(x_i)$ for all $x \in S_x$. Let $\nu_n \to \infty$, $\frac{\nu_n}{n} \to 0$. Suppose also that $\sqrt{n}(P_n(x_i) - P(x_i)) \to_d N(0, \sigma_i^2)$ for all $i = 1, \ldots, d$. Then:*

$$sup_{\theta \in \Theta}|Q_n'(\theta) - Q(\theta)| = o_p(1)$$

[32]This is usually handled by using a "stochastic" window, similar to a kernel, that joins multiple cells into one. This window shrinks as sample size increases. Hence, these methods in finite samples, depend on choosing smoothing parameters and hence are cumbersome to use. In a previous version of the paper, we used these nonparametric methods, but the current version contains a richer set of regressors which makes the use of these methods cumbersome.

proof: First, for simplicity let us assume that x takes one value, i.e., $d = 1$. Then we have,

$$Q_n(\theta) = (P_n - \hat{H}_1(\theta))_-^2 + (P_n - \hat{H}_2(\theta))_+^2$$

The calculations below are derived from the observation that

$$|a_+^2 - b_+^2| \leq (a_+ + b_+)|(a - b)|$$
$$|a_-^2 - b_-^2| \leq |a_- + b_-||a - b|$$

$$\begin{aligned}
|Q_n(\theta) - Q(\theta)| &= |(P_n - \hat{H}_1(\theta))_-^2 + (P_n - \hat{H}_2(\theta))_+^2 - (P - H_1(\theta))_-^2 - (P - H_2(\theta))_+^2| \\
&\leq \Big((P_n - \hat{H}_2(\theta))_+ + (P - H_2(\theta))_+\Big)\left(|P_n - P| + |\hat{H}_2(\theta) - H_2(\theta)|\right) \\
&\quad + \Big|(P_n - \hat{H}_1(\theta))_- + (P - H_1(\theta))_-\Big|\left(|P_n - P| + |\hat{H}_1(\theta) - H_1(\theta)|\right) \\
&\leq K_1|\hat{H}_1(\theta) - H_1(\theta)| + K_2|\hat{H}_2(\theta) - H_2(\theta)| + o_p(1)
\end{aligned}$$

Hence,

$$sup_\theta|Q_n(\theta) - Q(\theta)| =_{(i)} o_p(1)$$

where (i) follows from the class of indicator functions being Glivenko-Cantelli. Q.E.D.

A key statistic for building confidence regions is

$$\mathcal{C}_n = \sup_{\theta \in \Theta_I} nQ_n(\theta)$$

This is because our confidence regions are level sets, $\mathcal{C}_n(c)$ of the objective function $Q_n(.)$ as follows:

$$\mathcal{C}_n(c) = \{\theta \in \Theta : nQ_n(\theta) \leq c\} \tag{15}$$

Hence, a set $\hat{\Theta}_I = \mathcal{C}_n(c)$ covers Θ_I at level α:

$$P(\Theta_I \subseteq \hat{\Theta}_I) = P\left(\sup_{\theta \in \Theta_I} nQ_n(\theta) \leq c\right) = P(\mathcal{C}_n \leq c)$$

if c is chosen as the level-α quantile of $\mathcal{C}_n$. As usual we use large n asymptotics to approximate this cutoff level. To do that we need to derive this asymptotic distribution of $\mathcal{C}_n$. First, define the boundary of the set as

$$\partial\Theta_I = \{\theta_i \in \Theta_I : H_1(x_j; \theta_I) = P(x_j) \; or \; H_2(x_j; \theta_I) = P(x_j), \quad \text{for some } j \leq J\}$$

and let $n_j = \frac{1}{n}\sum_i 1[x_i = x_j]$. Define, $\hat{W}_j := \sqrt{n}(P_n(x_j) - P(x_j))$ for $j = 1, \ldots, J$. Assume also that a central limit theorem and a law of large number apply such that

$$\begin{aligned}
&\left(\hat{W}_1, \ldots, \hat{W}_J\right) \to_d (W_1, \ldots, W_J) \sim \mathcal{N}(0, \Omega) \quad \text{and} \\
&n_j/n \to_p p_j \quad \text{for each } j \leq J
\end{aligned} \tag{16}$$

To deal with the presence of the simulated quantities, we assume that the number of simulations, R, goes to infinity at a rate $R = O(n^{2+\alpha})$ where $\alpha > 0$. This will guarantee that the simulations will not have an effect on the asymptotic distribution and hence can be ignored. Given the above, assumption 1 and assuming also that the parameter space is a compact subset of a finite dimensional Euclidian space, one can show using similar steps as for example page 16 of CHT (2002 Working Paper version) that

$$\mathcal{C}_n \to_d \mathcal{C} \tag{17}$$

where

$$\mathcal{C} = \sup_{\theta \in \partial\Theta_I} \sum_{j=1}^{J} (W_j)_+^2 1\left[P_j = H_1(x_j)\right] + (W_j)_-^2 1\left[P_j = H_2(x_j)\right] \tag{18}$$

It is hard to simulate the α-quantile of the above statistic since it is not pivotal. We follow CHT and subsample the distribution of $\mathcal{C}_n$ above to obtain an asymptotic approximation to its α quantile. We use a modified procedure to account for misspecification of the model (where the minimum of the function Q in the population might not be equal or even close to zero). We instead report the following:

$$\widehat{\Theta}_I = \left\{\theta \in \Theta : n\left(Q_n(\theta) - \min_{\mathbf{t}} Q_n(t)\right) \leq c\right\} \tag{19}$$

First, we construct all subsets B_n of size $b << n$. We take b to be equal to $n/4$.[33] We start with an initial value $c_{(0)}$ for the cutoff (see below for a way to choose this $c_{(0)}$). We then compute

$$\widehat{\mathcal{C}}_{i,b,n,c_0} = \sup_{t \in C_n(c_{(0)})} b(Q_b(t) - q_b) = \sup_{t \in C_n(c_{(0)})} b\big(Q_b(t) - \min_t Q_b(t)\big) \tag{20}$$

for each i-th subset, $i \leq B_n$ where $C_n(c_{(0)}) = \{\theta \in \Theta : n\left(Q_n(\theta) - \min_t Q_n(\mathbf{t})\right) \leq c_0\}$. This involves minimizing the objective function at each subsample. Here, we use Nelder Mead with a starting value equal to the argmin obtained using the full dataset.

Initial Choice of $\mathbf{c}_{(0)}$:
The initial choice of the cutoff that we use here is always 25% above the minimum sample objective function value. Starting with this initial choice, we iterate the objective function twice and use that final cutoff level as the quantile that defines our confidence region. We find that iterating further does not change the cutoff by much. We then compute the α-quantile of the numbers $\widehat{\mathcal{C}}_{i,b,n,c_{(2)}}$ which provides appropriate coverage properties (asymptotically). Hence, our confidence regions reported in the tables are $C_n(c_{(2)})$. One can also use $c_{(0)} = 0$ as the starting cutoff. This was shown in CHT, for this class of models, to deliver a set with the appropriate confidence property.

Summary of Procedure to Obtain Confidence Regions:
1- We minimize the objective function $Q_n(.)$ using a genetic algorithm that we describe

[33] There is not general theory of picking a subsample size. See Politis, Romano, and Wolf (1999) for more on this point. However, trying different $b's$ in this paper led to similar results.

below. In the process, we collect values for the objective function at many ($\approx 10,000$) randomly chosen parameters using this MCMC-like procedure.
2- For every subsample, we minimize the *subsampled* objective function (the one constructed with the subsample as opposed to the full dataset)over the initial estimate of the set we constructed in step (1) above. We then obtain the empirical α-quantile of the set $\{\widehat{\mathcal{C}}_{i,b,n,c_0} : i \leq B_n\}$. That gets us a new cutoff $\hat{c}_{(1)}$. Note that here, we need to evaluate q_b at each subsample which requires an optimization step. We do this using Nelder Mead starting at the overall minimum found in step 1 above.
3- We iterate steps 1 and 2 above two times to obtain $\hat{c}_{(2)}$.
4- We replace c with $\hat{c}_{(2)}$ in (19) to obtain the confidence region we report. It is then easy to prove (similar to Lemma 3.1 of CHT) the following lemma.

Lemma 5 *Suppose that (**??**) holds where $\mathcal{C}$ is as in (18). Then for any $\widehat{c} \rightarrow_p c(\alpha) := \inf\{c \geq 0 : P\{\mathcal{C} \leq c\} \geq \alpha\}$ for $\alpha \in (0,1)$, such that $\widehat{c} \geq 0$ with probability 1, we have that as $n \rightarrow \infty$, $P\{\Theta_I \subseteq C_n(\widehat{c})\} = P\{\mathcal{C}_n \leq \widehat{c}\} = P\{\mathcal{C} \leq c(\alpha)\} + o(1) = \alpha + o(1)$ if $c(\alpha) > 0$, and $P\{\Theta_I \subseteq C_n(\widehat{c})\} = P\{\mathcal{C}_n \leq \widehat{c}\} \geq P\{\mathcal{C} = 0\} + o(1) \geq \alpha + o(1)$ if $c(\alpha) = 0$.*

It is also worth noting that the confidence region in this model, $\widehat{\Theta}_I$ is a consistent estimator of Θ_I.

Computational Issues:
The optimization was done using some version of simulated annealing and Nelder Mead. For each specification, we started our search from at least 5 starting values and used both the simulated annealing and its adaptive version.[34] This is helpful since genetic algorithms, although slow, scan the surface of the function and thus allow us to obtain the level sets needed to construct our set estimates. From the overall minimum, we run annealing for a while longer (usually a day or two for every specification) to evaluate the functions at many different parameter values close to the minimum we found. This will give us a snapshot of the surface of the function.

One issue when solving for equilibria of a given game, is that sometimes the game only admits equilibria in mixed strategies. We ignore this problem when looking for the minimum. But, as a robustness check, we then compute at the optimal parameter value, the percentage of markets with only mixed strategy equilibria. This turned out to be at most 2% over all the specification we ran.

To construct the confidence intervals we subsample the data sets with subsample sizes equal to 10% of the data. The results did not change much when using subsamples of smaller sizes. We also simulate from the error term in every subsample which guarantees that the simulation error is taken care of. Moreover, note that subtracting the minimum of the function as in (20) above is essential to guarantee that the confidence regions are nonempty. This is important since, we assume throughout that the model is well specified and that the set Θ_I is non-empty.

[34]For the simulated annealing, we used Bill Goffe's algorithm (Goffe, Ferrier, and Rogers (1994)). For the adaptive version we used L. Ingber's methods available at www.ingber.com

8.3 Data Construction

We use three datasets from the Origin and Destination Survey (DB1B), which is a 10 percent sample of airline tickets from reporting carriers. The observations are from the first quarter of 1993 to the third quarter of 2004. These data are collected by the U.S. Department of Transportation.[35]

The first dataset is the DB1B Coupon Origin and Destination Dataset, which provides coupon-specific information for each domestic itinerary of the Origin and Destination Survey, such as the operating carrier, origin and destination airports, number of passengers, fare class, coupon type, trip break indicator, and distance. We merge this dataset by operating carrier with the T-100 Domestic Segment Dataset. The T-100 Domestic Segment Dataset contains domestic market data by air carriers, origin and destination airports for passengers enplaned. The T-100 is not a sample: It reports all flights occurred in the United States in a given month of the year.

¿From the merged dataset we drop those tickets involving flights that are not provided on a regular basis or for which there is no record in the T-100 segment. We drop all tickets that involve a flight that is not provided at least once a week.

Then, we merge by ticket id numbers the reduced DB1B Coupon Origin and Destination Dataset with the DB1B Market and Ticket Origin and Destination Datasets. The DB1B Market Origin and Destination Dataset contains directional market characteristics of each domestic itinerary of the Origin and Destination Survey, such as the reporting carrier, origin and destination airport, prorated market fare, number of market coupons, market miles flown, and carrier change indicators. The DB1B Ticket contains summary characteristics of each domestic itinerary on the Origin and Destination Survey, including the reporting carrier, itinerary fare, number of passengers, originating airport, roundtrip indicator, and miles flown. The unit of observation in this dataset is a ticket.

One important issue is how to treat regional airlines that operate through code-sharing with national airlines. We assume that the decision to serve a spoke is made by the regional carrier, which then signs code-share agreements with the national airlines. As long as the regional airline is independently owned and issues tickets, we treat it separately from the national airline.

We define a market as the trip between two airports, irrespective of intermediate transfer points. Because of data limitations, Berry (1992) defined a market as the market for air passenger travel between two cities, which rules out that demand is different for airports in the same city or metro area. Following Borenstein (1989), we assume that flights to different airports in the same metropolitan area are in separate markets.

We drop: 1) Tickets with more than 6 coupons; 2) Tickets involving US-nonreporting carrier flying within North America (small airlines serving big airlines) and foreign carrier flying between two US points; 3) Tickets that are part of international travel; 4) Tickets involving non-contiguous domestic travel (Hawaii, Alaska, and Territories); 5) Tickets whose fare credibility is questioned by the DOT; 6) Tickets that are neither one-way nor round-trip travel; 7) Tickets including travel on more than one airline on a directional trip (known as interline tickets); 8) Tickets with fares less than 20 dollars; 9) Tickets in the top one percentile

[35]These data are publicly available at `http://transtats.bts.gov/homepage.asp`.

of the year-quarter fare distribution. Finally, Berry (1992) defines a firm as serving a market if it transported at least 90 passengers in one quarter. This corresponds to a once a week flight by a medium size jet. Since we already control for firms that fly less than once a week and since markets can be served by small regional jets, we change the threshold to 20 passengers. We then aggregate the ticket data by ticketing carrier and thus the unit of observation is market-carrier-year-quarter specific.

In this paper we are only interested in knowing whether a carrier served a market. Therefore the aggregation is straightforward: For each carrier, we construct a categorical variable that is equal to 1 if the carrier serves the market, and 0 otherwise. After constructing the categorical variables, the relevant unit of observation is market-year-quarter specific.

To select the markets, we merge this dataset with demographic information on population from the U.S. Census Bureau for all the Metropolitan Statistical Areas of the United States. We then construct a ranking of airports by the MSA's market size.

As mentioned in the text, we include markets that are *temporarily* not served by any carrier. To identify markets that are almost never served by any carrier from markets that are only temporarily not served by any carrier we proceed as follows. We consider the full 1993-2006 dataset of market-carrier-year-quarter observations. For each market, we compute the number of quarters that a market has been served by at least one carrier. Then, we drop from the dataset those markets that have not been served in at least 30 percent of the 47 quarters in the full dataset. We keep markets out and to Dallas Love airport which are at least 500 miles distant from the Dallas airport. This last condition is to investigate the effect of the Wright Amendment on carriers' entry decision.

We drop markets where one of the two endpoints is one of these hubs: Minneapolis, Detroit, Memphis, Cleveland, Newark, Houston International, Charlotte, Philadelphia, Pittsburgh, Phoenix, Las Vegas.

8.4 Medium Airlines and Low Cost Carrier Types

We lump some of the carriers in our dataset in two types. There are two reasons why do this. First, many low cost carriers are present in only a few markets, and lumping them allows us to use a meaningful grouping capturing the impact of a small low cost carrier presence in the market. Second, the number of possible market structures that can be an equilibrium grows exponentially with the number of firms. For any K firms, there are 2^K possible market structures. In the most general specification of the model, one in which the payoffs for each firm depends on whether 18 other firms enter a market, one needs to compute the choice probabilities for a vector of size 2^{18}. This is clearly prohibitive.

8.5 Carrier Airport Presence in more detail

The construction of the variable Carrier Airport Presence is straightforward. For example, when we consider Delta, we proceed as follows. If Delta serves 60 markets out of Atlanta and there are 84 markets that are served out of Atlanta, then for each market that we consider out of Atlanta (e.g. Atlanta-Chicago O'Hare), Delta serves $59/83 \simeq 71$ percent of the other markets out of Atlanta. We repeat the same computation for the other endpoint, and then take the average.

The construction of the variable requires some additional steps when we consider types of firms. When we consider the Medium Airlines (MA), we first compute the airport presence for USAir, Continental, and America West, and then we take the maximum of the three. When we consider the Low Cost Carriers (LCC), we first compute the airport presence of each of the low cost carriers, and then again we take their maximum.

8.6 Details on the Wright Amendment

The Wright Amendment restricted flight to states neighboring Texas by only allowing only flights with only a small commuter plane with up to a total capacity of 56 passengers. To understand how the amendment affected competition in markets out of Dallas Love, it is essential to know that one characteristic that distinguishes Southwest Airlines from other national carriers is Southwest's reliance on only one aircraft type, the Boeing 737. Southwest flies a single type of aircraft to simplify operations in terms of maintenance (older planes can be used for replacement parts), staffing, and training. Boeing 737s have a capacity of no less than 100 passengers.

The two main arguments in support of the Wright Amendment were that the amendment only applied to Love Field, not to Southwest; and that Southwest could fly nationwide from Dallas/Fort Worth, which is done by other low-cost carriers.[36]

Southwest, however, claimed that providing service at Dallas/Fort Worth would split their operation unnecessarily between the two airports, breaking their network and driving their costs up.

Southwest lobbied for the repeal of the Wright Amendment, claiming that it was "protectionist, anti-competitive, and anti-consumer".[37] Finally, in October 2006, a bill was enacted that determined the full repeal of the Wright Amendment in 2014.

[36]See www.keepdfwstrong.com, for example.

[37]From the statement regarding repeal of the Wright Amendment from Southwest Airlines' CEO Gary Kelly, available from Southwest's website. See *http://www.southwest.com/travel_center/wright_timeline.html*.