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MARKET STRUCTURE AND MULTIPLE EQUILIBRIA IN AIRLINE MARKETS

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MARKET STRUCTURE AND MULTIPLE EQUILIBRIA IN AIRLINE MARKETS

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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 differ 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 firm heterogeneity as a determinant of market structure in the U.S. airline industry. We find evidence of heterogeneity across airlines in their profit functions. The competitive effects of large airlines (American, Delta, United) are different from those of low cost carriers and Southwest. Also, 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.

KEYWORDS: Entry models, inference in discrete games, multiple equilibria, partial identification, airline industry, firm heterogeneity.

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) (BR) 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

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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 for 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 they make nonnegative profits in equilibrium to derive a set of restrictions on regressions.[2] In games with multiple equilibria, this simple condition leads to *upper* and *lower* bounds on choice probabilities.[3] 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 (see footnote 3). Each parameter in this set corresponds to a particular selection mechanism that is consistent with the model and the data. We use recently developed inferential methods in Chernozhukov, Hong, and Tamer (2007) (CHT) to construct confidence regions that cover the identified parameter 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 relationships 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

[2]The idea of deriving results for 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)).

[3]Tamer (2003) also used this insight to show that, for a simple 2×2 game with multiple equilibria, the model provides inequality restrictions on the 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 the identified set, and an estimator was suggested (Tamer (2003, p. 153)).

[4]CHT focused on constructing confidence regions for the arg min of a function (in this paper, the minimum distance objective function) and also confidence regions for the true but potentially partially identified parameter. Other econometric methods that can be used are Romano and Shaikh (2008), Bugni (2007), Beresteanu and Molinari (2008), Andrews and Soares (2009), and Canay (2007).

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

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. In addition, 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 markets with respect to competition or market structure. This law was 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 in which the entry of a firm, its "competitive effect," affects 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 the number of markets served by a firm out of an airport. The theoretical underpinnings for these "variable competitive effects" are given in Hendricks, Piccione, and Tan (1997), who showed 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 it suffers 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.

We find evidence of heterogeneity across airlines in their profit functions. 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 (negative) competitive effect of an airline is increasing in its airport presence, which is an important measure of observable heterogeneity in the airline industry. Moreover, we also find evidence of heterogeneity in the effects of control variables on the profits of airline firms, which affects the probability of observing different airlines as the control variables change. 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. As part of our analysis, we also estimate the variance–covariance matrix, and find evidence of correlation in the unobservables as well as evidence of different variances and distributions of the firm unobservable heterogeneity.

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) considered the case where the entry game has incomplete information, so that neither the firms nor the econometrician observe the profits of all competitors. Andrews, Berry, and Jia (2003) proposed methods applicable to entry models to construct confidence regions for models with inequality restrictions. More recently, Pakes, Porter, Ho, and Ishii (2005) provided 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. Finally, further insights about identification in these settings is given in Berry and Tamer (2006).

This article also adds to the literature on inference in partially identified models. This literature has a history in econometrics, starting with the Frisch bounds on parameters in linear models with measurement error (Frisch (1934)) and the work of Marschak and Andrews (1944) (which contains one of the earliest examples of a structural model with partially identified parameters). More recently, Manski and collaborators further developed this literature with new results and made it part of the econometrics toolkit starting with Manski (1990). See also Manski (2007) and the references therein, Manski and Tamer (2002), and Imbens and Manski (2004). In the industrial organization literature, Haile and Tamer (2003) used partial identification methods to construct bounds on valuation distributions in second price auctions. In the statistics literature, the Frechet bounds on joint distributions given knowledge of marginals are well known (see also Heckman, Lalonde, and Smith (1999)), and these were used starting with the important result of Peterson (1976) in competing risks. In the labor literature, the bounds approach to inference has been prominent in the treatment–response and selection literature where several papers discuss and use exclusion restrictions to tighten the bounds and gain more information. See Manski (1994) for a discussion of the selection problem using partial identification and exclusion restrictions, and Blundell, Gosling, Ichimura, and Meghir (2007) and Honoré and Lleras-Muney (2006) for important empirical papers that use and expand this methodology. See also bounds based on revealed preference in Blundell, Browning, and Crawford (2003), and bounds on various treatment effects derived in Heckman and Vytlacil (1999).

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 U.S. 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 modeling 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 and 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; $Z_m = (Z_{1m}, \dots, Z_{Km})$ is a matrix of firm characteristics that enter into the profits of all the firms in the market, for example, some product attributes that consumers value; K is the total number of potential entrants in market m; $W_m = (W_{1m}, \dots, W_{Km})$ are firm characteristics where W_{im} enters only into firm i's profit in market m, such as the cost variables.

The profit function for firm i in market m is

$$\pi_{im} = S'_m\alpha_i + Z'_{im}\beta_i + W'_{im}\gamma_i + \sum_{j\neq i}\delta^i_j y_{jm} + \sum_{j\neq i} Z'_{jm}\phi^i_j y_{jm} + \varepsilon_{im}, \tag{1}$$

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.

An important feature of the profit function in this paper is the presence of $\{\delta^i_j, \phi^i_j\}$, 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 firm j in its market is allowed to be different from that of having firm k in its market ($\delta^i_j \neq \delta^i_k$). For example, the parameters δ^i_j can measure a particularly aggressive behavior of one airline (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, δ^i_j and ϕ_j could measure cost externalities among airlines at airports.[9]

[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 side 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.

[8]See the discussion in Bresnahan (1989, Section 2.2.3) for an interpretation of the δ^i_j'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.

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 version of the model above with two players:

$$\begin{aligned} (2) \qquad & y_{1m} = 1[\alpha_1' X_{1m} + \delta_2 y_{2m} + \varepsilon_{1m} \geq 0], \\ & y_{2m} = 1[\alpha_2' X_{2m} + \delta_1 y_{1m} + \varepsilon_{2m} \geq 0], \end{aligned}$$

where (X_{1m}, X_{2m}) is a vector of observed exogenous regressors that contain market-specific variables. Here, a firm is in market m if, in a pure strategy Nash equilibrium, it makes a nonnegative 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 1. A way to complete the model is to specify 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. This is the solution adopted by Bresnahan and Reiss (1991a) and Berry (1992), which we illustrate next.

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 as illustrated in the left-hand panel (LHP) of Figure 1. Notice that multiple equilibria in the identity, but not in the number of firms, happen when $-\alpha_i' X_i \leq \varepsilon_i \leq -\alpha_i' X_i - \delta_{3-i}$ 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.

To ensure the uniqueness of equilibrium in the number of firms, Bresnahan and Reiss (1990) assumed that the sign of the δ's is known. Consider, however, the simple 2×2 discrete game illustrated in the right hand panel (RHP) of Figure 1. In this case, where $\delta_i > 0$ for $i = 1, 2$, and for $-\delta_{3-i} - \alpha_i' X_i \leq \varepsilon_i \leq -\alpha_i' X_i$, both players enter or no player enters.[11] Here, a player benefits from

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

[11] This could be the case when positive externalities are present.

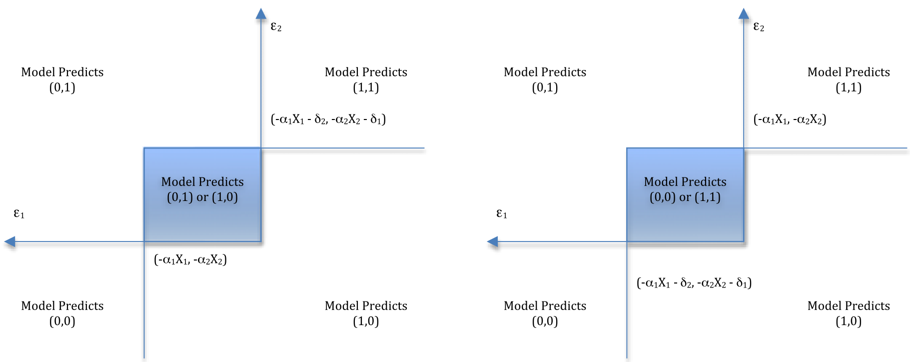

FIGURE 1.—Regions for multiple equilibria: LHP, $\delta_1, \delta_2 < 0$; RHP, $\delta_1, \delta_2 > 0$.

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 "either $(1, 1)$ or $(0, 0)$," but it is clear that we need to know the sign of the δ's. Our methodology does not require knowledge of the signs of the δ's.

Finally, with more than two firms, one must assume away any heterogeneity in the effect of observable determinants of profits, including the presence of a competitor, on the firms' payoff functions. If one drops these assumptions, different equilibria can exist with different numbers of players, even if the signs of the δ's are known. Heuristically, in three-player games where one player is a large firm and the other two players 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 versus a small one ($\delta^{\text{large}} \neq \delta^{\text{small}}$). In contrast, our methodology allows for general forms of heterogeneity in the effect of the observable determinants of profits.

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

$$
\begin{aligned}
(3)\qquad & \Pr(1,1|X) = \Pr(\varepsilon_1 \geq -\alpha_1' X_1 - \delta_2;\ \varepsilon_2 \geq -\alpha_2' X_2 - \delta_1), \\
& \Pr(0,0|X) = \Pr(\varepsilon_1 \leq -\alpha_1' X_1;\ \varepsilon_1 \leq -\alpha_2' X_2), \\
& \Pr(1,0|X) = \Pr((\varepsilon_1, \varepsilon_2) \in R_1(X, \theta)) \\
& \qquad\qquad + \int \Pr((1,0)|\varepsilon_1, \varepsilon_2, X) 1[(\varepsilon_1, \varepsilon_2) \in R_2(\theta, X)]\, dF_{\varepsilon_1, \varepsilon_2},
\end{aligned}
$$

where

$$R_1(\theta, X) = \big\{(\varepsilon_1, \varepsilon_2): (\varepsilon_1 \geq -\alpha_1' X_1; \varepsilon_2 \leq -\alpha_2' X_2) \\ \cup (\varepsilon_1 \geq -\alpha_1' X_1 - \delta_2; -\alpha_2' X_2 \leq \varepsilon_2 \leq -\alpha_2' X_2 - \delta_1)\big\},$$

$$R_2(\theta, X) = \big\{(\varepsilon_1, \varepsilon_2): (-\alpha_1' X_1 \leq \varepsilon_1 \leq -\alpha_1' X_1 - \delta_2; \\ -\alpha_2' X_2 \leq \varepsilon_2 \leq -\alpha_2' X_2 - \delta_1)\big\},$$

$X = (X_1, X_2)$, 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 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, that is, when $(\varepsilon_1, \varepsilon_2) \in R_1$, 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 $\Pr((1, 0)|\varepsilon_1, \varepsilon_2, X)$, which is allowed to depend on the unobservables in an arbitrary way. It is unknown to the econometrician and can differ across markets. This term is an infinite dimensional nuisance parameter.[12]

Heuristically, the identified feature 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

$$\Pr((\varepsilon_1, \varepsilon_2) \in R_1) \leq \Pr((1, 0)) \leq \Pr((\varepsilon_1, \varepsilon_2) \in R_1) + \Pr((\varepsilon_1, \varepsilon_2) \in R_2). \tag{4}$$

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 2.

Sufficient point-identification conditions based 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 mod-

[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.

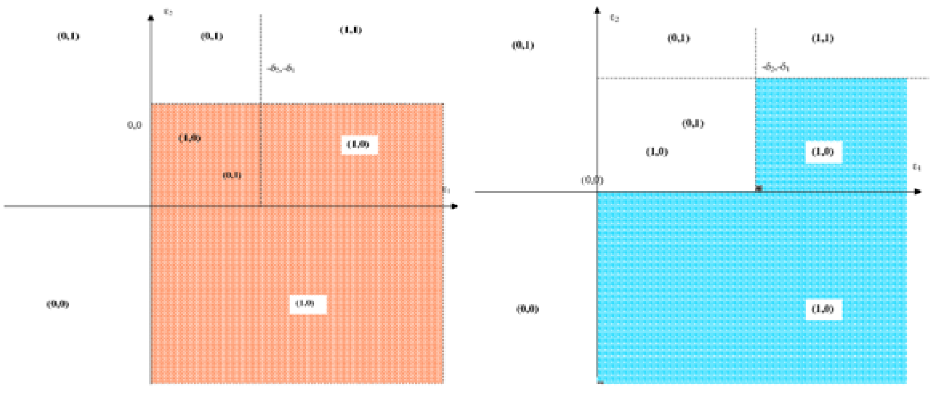

FIGURE 2.—Upper and lower probability bounds on the $\Pr(1,0)$. The shaded area in the graph on the right hand side represents the region for $(\varepsilon_1, \varepsilon_2)$ that would predict the outcome (1, 0) uniquely. The shaded region in the graph on the left hand side represents the region where (1, 0) would be predicted if we *always* select (1, 0) to be the equilibrium in the region of multiplicity. The probability of the epsilons falling in the respective regions provides an upper and a lower bound on the probability of observing (1, 0).

els 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 ε 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 distribution predicted by the model for 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 sample of observations* $(\mathbf{y}_m, \mathbf{X}_m)$, $m = 1, \dots, n$.[13] *Let* $n \to \infty$. *Assume that the 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.

[13]We do not need independent and identically distributed (i.i.d.) random sampling here. All that is needed is for the law of large numbers to hold. Moreover, an i.i.d. assumption can be made conditional on fixed effects.

The predicted choice probability for y' given X is

$$\begin{aligned}\Pr(y'|X) &= \int \Pr(y'|\varepsilon, X)\,dF \\ &= \int_{R_1(\theta,X)} \Pr(y'|\varepsilon, X)\,dF + \int_{R_2(\theta,X)} \Pr(y'|\varepsilon, X)\,dF \\ &= \underbrace{\int_{R_1(\theta,X)} dF}_{\text{unique outcome region}} + \underbrace{\int_{R_2(\theta,X)} \Pr(y'|\varepsilon, X)\,dF}_{\text{multiple outcome region}},\end{aligned}$$

where $y' = (y'_1, \dots, y'_K)$ is some outcome which is a sequence of 0's or/and 1's, 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 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 in pure strategies, while in another subregion of R_2, y' and y'' can be the multiple pure strategy equilibria.

Mixed strategy equilibria can also exist in region R_2 (sometimes uniquely), 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 for computational simplicity we do not allow for mixing in our empirical application.[14]

The probability function $\Pr(y'|\varepsilon, X)$ is the selection function for outcome y' in regions of multiplicity. This function is not specified, and one objective of the methodology in this paper is to examine the question of what can be learned when researchers remain agnostic about this selection function. One can condition this function further on the various equilibria as functions of both ε and X, in which case the statistical model becomes one of a mixture. See Berry and Tamer (2006) for more on this. Generally, without assumptions on equilibrium selection, the model partially identifies the finite dimensional parameter of interest. Bjorn and Vuong (1985) assumed that this function is a constant. More recently, Bajari, Hong, and Ryan (2005) used 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 down which to proceed theoretically, since this will provide

[14]An important consequence of this is the fact that in some cases, when one estimates the model, there might only be mixed strategy equilibria. In the application below, this *never* happened. For more on inference with mixed strategies, see Berry and Tamer (2006).

information on the selection functions, it is difficult to implement practically.[15] A practical way to proceed that can be used in many games 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 upper and lower bounds on conditional choice probabilities:

$$\begin{aligned}\mathbf{H}_1(\boldsymbol{\theta}, \mathbf{X}) &\equiv \begin{bmatrix} H_1^1(\boldsymbol{\theta}, X) \\ \vdots \\ H_1^{2K}(\boldsymbol{\theta}, X) \end{bmatrix} \leq \begin{bmatrix} \Pr(\mathbf{y}_1|X) \\ \vdots \\ \Pr(\mathbf{y}_{2^K}|X) \end{bmatrix} \leq \begin{bmatrix} H_2^1(\boldsymbol{\theta}, X) \\ \vdots \\ H_2^{2K}(\boldsymbol{\theta}, X) \end{bmatrix} \\ &\equiv \mathbf{H}_2(\boldsymbol{\theta}, \mathbf{X}),\end{aligned} \tag{6}$$

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 of the distribution function F. 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.[16] $\mathbf{H}_2$ contains, in addition, the probability mass of the region where there are multiple equilibria.

This is a conditional moment *inequality* model, and 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, we can state the definition:

DEFINITION 1: Let Θ_I be such that

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

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, that is, to find out whether it is finite, convex, etcetera. Next, following Tamer (2003), we provide sufficient conditions that guarantee point-identification.

[15]Another approach to sharp inference in this setup is the recent interesting work of Beresteanu, Molinari, and Molchanov (2008).

[16]Notice that there are cross-equation restrictions that can be exploited in the "cube" defined in (5), like the fact that the selection probabilities sum to 1.

3.3. *Exclusion Restriction*

The system of equation that 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 point-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: *In model* (2), *let Assumption* 1 *hold with* $K = 2$. *Suppose* X_1 (X_2) (*suppressing the dependence on* m) *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* $\mathcal{R}$ *and that* $(\alpha_1^1, \alpha_2^1) \neq (0, 0)$, *where* $X_i = (x_i^1, X_i^{-1})$ *and* $\alpha_i = (\alpha_i^1, \alpha_i^{-1})$ *for* $i = 1, 2$. *Finally, normalize* $\alpha_i^1 = 1$ *for* $i = 1, 2$. *Then* $(\alpha_1^{-1}, \alpha_2^{-1}, \delta_1, \delta_2)$ *is identified.*[17]

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

$$
\begin{aligned}
(8) \qquad P(0, 0|X_1, X_2) &= P(0, 0|x_1^1, X_1^{-1}; x_2^1, X_2^{-1}) \\
&= P(\varepsilon_1 \geq \alpha_1' X_1; \varepsilon_2 \geq \alpha_2' X_2) \\
&\overset{\text{as } x_1^1 \to -\infty}{=} P(\varepsilon_2 \geq \alpha_2' X_2).
\end{aligned}
$$

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 vector α_2. Hence, conditioning on those x_1^1's, (where player 1 is out of the market with probability 1 regardless of what player 2 does), this $(0, 0)$ choice probability point-identifies the marginal distribution of ε_2 and α_2.

Similarly, by driving x_2^1 to $-\infty$, we can identify 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 $(\varepsilon_1, \varepsilon_2)$. In the above discussion, we implicitly assumed that the signs of $\alpha_i^1 = 1$ for $i = 1, 2$ are positive. This is without loss of generality, since large positive values of x_i^1 conditional on other x's will yield that firm 1 always enters in case α_i^1 is positive; when α_1^1 is negative, firm 1 does not enter. Now, we can use the choice probabilities for $(1, 1)$ to identify (δ_1, δ_2). *Q.E.D.*

Independent variation in one regressor while driving another to take extreme values on its support (identification at infinity) identifies the parameters of model (2). Identification at infinity arguments have been used extensively

[17] The identification in this theorem relies on driving values of one regressor to $\pm\infty$ while keeping the others finite. What this effectively does is render the game into a single decision problem, since the player with the large value for one of the regressors will always be in the market or out, regardless of what the other player does.

in econometrics. See, for example, Heckman (1990) and Andrews and Schafgans (1998). 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. The support conditions above are sufficient for point identification, and are not essential since our inference methods are robust to non-point-identification. However, the exogeneity of the regressors and the exclusion restrictions are important restrictions that are discussed in Section 4.2.

3.4. *Estimation*

The estimation problem is based on the conditional moment *inequality* model

$$\mathbf{H}_1(\boldsymbol{\theta}, \mathbf{X}) \leq \Pr(\mathbf{y}|\mathbf{X}) \leq \mathbf{H}_2(\boldsymbol{\theta}, \mathbf{X}). \tag{9}$$

Our inferential procedures uses the objective function

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

where $(A)_- = [a_1 1[a_1 \leq 0], \dots, a_{2^k} 1[a_{2^K} \leq 0]]$ and similarly for $(A)_+$ for a 2^k vector A, and where $\|\cdot\|$ 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.

The object of interest is either the set Θ_I or the (possibly partially identified) true parameter $\theta_I \in \Theta_I$. We discuss inference on both θ_I and Θ_I, but we present confidence regions for θ_I, which is the true but potentially non-point-identified parameter that generated the data.[18]

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 than 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 (2002), Imbens and Manski (2004), and Chernozhukov, Hong, and Tamer (2007).[19] We discuss first the building of consistent estimators for the

[18]Earlier versions of the paper contained estimators for sets C_n such that $\lim_{n\to\infty} P(\Theta_I \subseteq C_n) = \alpha$. The current results provide confidence regions for points instead, as the co-editor suggested. The earlier results for the sets, which were not very different, can be obtained from the authors upon request.

[19]Other *set inference* methods that one can use to obtain confidence regions for sets include Andrews, Berry, and Jia (2003), Beresteanu and Molinari (2008), Romano and Shaikh (2008) Pakes, Porter, Ho, and Ishii (2005), Bugni (2007), and Canay (2007).

identified set, which contains parameters that cannot be rejected as the truth. To estimate Θ_I, we first take a sample analog of $Q(\cdot)$. To do that, we first replace $\Pr(\mathbf{y}|\mathbf{X})$ with a consistent estimator $P_n(\mathbf{X})$. Then we 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 $\nu_n/n \to 0$ (take for example $\nu_n = \ln(n)$) and

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

where $\|\cdot\|$ is the Euclidian norm. Theorem 3 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 with probability (w.p.) approaching 1,*

$$\widehat{\Theta}_I \subseteq_{w.p.1} \Theta_I \quad and \quad \Theta_I \subseteq_{w.p.1} \widehat{\Theta}_I \quad as \quad n \to \infty.$$

PROOF: Following the proof of Theorem 3.1 in CHT, first we show that $\widehat{\Theta}_I \subseteq_{\text{w.p.1}} \Theta_I$. This event is equivalent to the event that $Q(\theta_n) = o_p(1)$ for all $\theta_n \in \widehat{\Theta}_I$. We have

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

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

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

This can be made less than ν_n/n with probability approaching 1. *Q.E.D.*

To conduct inference in the above moment inequalities model, we use the methodology of CHT where the above equality is a canonical example of a *moment inequality* model. We construct a set C_n such that $\lim_{n\to\infty} P(\theta_I \in C_n) \geq \alpha$ for a prespecified $\alpha \in (0, 1)$ for any $\theta_I \in \Theta_I$. In fact, the set C_n that we construct will not only have the desired coverage property, but will also be consistent in the sense of Theorem 3. This confidence region is based on the principle of collecting all of the parameters that cannot be rejected. The confidence regions we report are constructed as follows. Let

$$C_n(c) = \left\{\theta \in \Theta : n\left(Q_n(\theta) - \min_t Q_n(t)\right) \leq c\right\}. \tag{12}$$

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 $n(Q_n(\theta_0) - \min_t Q_n(t))$ for $\theta_0 \in C_n(c_0)$ and obtain the estimate of its α-quantile, $c_1(\theta_0)$. That is, $c_1(\theta_0)$ is the α-quantile of $\{b_n(Q_{b_n,j}(\theta_0) - \min_t Q_{b_n,j}(t)), j = 1, \dots, B_n\}$. We repeat this for all $\theta_0 \in C_n(c_0)$. We take the first updated cutoff c_1 to be $c_1 = \sup_{\theta_0 \in C_n(c_0)} c_1(\theta_0)$. This will give us the confidence set $C_n(c_1)$. We then redo the above step, replacing c_0 with c_1, which will get us c_2. As the confidence region we can report $C_n \equiv C_n(c_2)$ or the generally "smaller"

$$\widehat{\Theta}_I = \Big\{\theta \in \Theta : n\Big(Q_n(\theta) - \min_t Q_n(t)\Big) \le \min(c_2, c_n(\theta))\Big\},$$

where $c_n(\theta)$ is the estimated α-quantile of $n(Q_n(\theta) - \min_t Q_n(t))$. In our data set, we find that there is not much difference between the two, so we report $C_n(c_2)$. See CHT for more on this and for other ways to build asymptotically equivalent confidence regions. Also, more on subsampling size and other steps can be found in the online Supplemental Material (Ciliberto and Tamer (2009)).

3.5. *Simulation*

In general games, it is not possible to derive the functions $\mathbf{H}_1$ and $\mathbf{H}_2$ analytically. Here, we provide 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. 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 a 2^k vector of profits for each simulation draw and for every value of θ. If $\pi(\mathbf{y}^j, \mathbf{X}, \theta) \ge \mathbf{0}$ for some $j \in \{1, \dots, 2^K\}$, 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 $\Pr(1, 1, \dots, 1|\mathbf{X})$ is

$$\widehat{H}_2^{2^K}(\mathbf{X}, \theta) = \frac{1}{R}\sum_{j=1}^{R} 1\big[\pi_1\big(\mathbf{X}_1, \theta; \mathbf{y}_{-1}^{2^K}, \varepsilon_1^j\big) \ge 0, \dots,$$
$$\pi_{2^K}\big(\mathbf{X}_{2^K}, \theta; \mathbf{y}_{-2^K}^{2^K}, \varepsilon_{2^K}^j\big) \ge 0\big],$$

where $\mathbf{1}[*]$ is equal to 1 if the logical condition $*$ is true and where R is the number of simulations, here we assume that R increases to infinity with sample size.[20]

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 $i = 1, 2$.

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) showed 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.[21] Berry also found that profits decline rapidly in the number of entering firms, consistent with the findings of 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: we call this their *competitive effect*. Then we use our model to perform a policy exercise on how market structures will change, at least in the short run and within our model, in markets out of and into Dallas after the repeal of the Wright Amendment. We start with a data description.

4.1. *Data Description*

To construct the data, we follow Berry (1992) and Borenstein (1989). Our main data come from the second quarter of the 2001 Airline Origin and Destination Survey (DB1B). We discuss the data construction in detail in the Supplemental Material. Here, we provide information on the main features of the data set.

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 data set includes a sample of markets between the top 100 metropolitan statistical areas (MSAs), ranked by population size.[22] In this sample we also include markets that are

[20]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; otherwise, there will be a simulation error that does not vanish and can lead to inconsistencies.

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

[22]The list of the MSAs is available from the authors.

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 Supplemental Material. Our data set includes 2742 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 close scrutiny by the Department of Justice. In May 1999, the Department of Justice (DOJ) filed an antitrust lawsuit against American Airlines, charging that the major carrier tried to monopolize service to and from its Dallas/Fort Worth (DFW) hub.[23] So, using data from 2001—the year when 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.[24]

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 into 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*.[25]

[23] In particular, in April 27, 2001, the District Court of Kansas dismissed the DOJ's case, granting summary judgment to American Airlines. The DOJ'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 low cost carriers (LCCs) began operations at DFW. According to the DOJ, 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. 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.

[24] 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 multivariate 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.

[25] See the Supplemental Material for a list of these hubs.

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.

4.2. *Variable Definitions*

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

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.[26] 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.[27]

Cost

Firm- and market-specific measures of cost are not available. We first compute the sum of the geographical distances between a market's endpoints and the closest hub of a carrier as a proxy for the cost that a carrier has to face to serve that market.[28] Then we compute the difference between this distance and the nonstop distance between two airports, and we divide this difference by the nonstop distance. This measure can be interpreted as the percentage of the nonstop distance that the airline must travel in excess of the nonstop distance if the airline uses a connecting instead of a nonstop flight. This is a good measure of the opportunity fixed 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 to nonstop service, which is a connecting flight through the closest hub. It is associated with the fixed cost of providing airline service because it is a function of the total capacity of a plane, but does not depend on the number of passengers transported on a particular flight. We call this variable *cost*.

[26]See the discussion in the Supplemental Material for more on this.

[27]The entry decision in each market is 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) did 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.

[28]Data on the distances between airports, which are also used to construct the variable close airport are from the data set *Aviation Support Tables: Master Coordinate*, available from the National Transportation Library. See the Supplemental Material for the list of hubs.

TABLE I

SUMMARY STATISTICS

%	AA	DL	UA	MA	LCC	WN
Airline (%)	0.426 (0.494)	0.551 (0.497)	0.275 (0.447)	0.548 (0.498)	0.162 (0.369)	0.247 (0.431)
Airport presence (%)	0.422 (0.167)	0.540 (0.180)	0.265 (0.153)	0.376 (0.135)	0.098 (0.077)	0.242 (0.176)
Cost (%)	0.736 (1.609)	0.420 (1.322)	0.784 (1.476)	0.229 (0.615)	0.043 (0.174)	0.302 (0.860)
Market level variables						
Wright amendment (0/1)			0.029 (0.169)			
Dallas airport (0/1)			0.070 (0.255)			
Market size (population)			2,258,760 (1,846,149)			
Per capita income ($)			32,402.29 (3911.667)			
Income growth rate ($\% * 100$)			5.195 (0.566)			
Market distance (miles)			1084.532 (624.289)			
Closest airport (miles)			34.623 (20.502)			
U.S. center distance (miles)			1570.614 (593.798)			
Number of markets			2742			

The Wright Amendment

The Wright Amendment was passed in 1979 to stimulate the growth of the Dallas/Fort Worth airport. To achieve this objective, 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 airports only in Texas, Louisiana, Arkansas, Oklahoma, New Mexico, Alabama, Kansas, and Mississippi, provided that the air carrier did not permit through service or ticketing and did not offer for sale transportation outside of these states.[29] 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 equal to 0 otherwise. *Wright* is equal to 1 for the markets between Dallas Love 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 either of the two Dallas airports and any other airport in the data set. This variable controls for the presence of a Dallas fixed effect. More details on the Wright Amendment are given in the Supplemental Material.

Control Variables

We use six control variables. Three of these are demographic variables.[30] The geometric mean of the city populations at the market endpoints measures the *market size*. The average per capita incomes (*per capita income*) and the average rates of income growth (*income growth rate*) of the cities at the market endpoints measure the strength of the economies at the market endpoints. The other three variables are geographic. The nonstop 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 (*close airport*).[31] Finally, we use

[29]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.

[30]Data are from the Regional Economic Accounts of the Bureau of Economic Analysis, download in February 2005.

[31]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. 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

the sum of the distances from the market endpoints to the geographical center of the United States (*U.S. center distance*). This variable is intended to control for the fact that, just for purely geographical reasons, cities in the middle of the United State have a larger set of close cities than cities on the coasts or cities at the borders with Mexico and Canada.[32]

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 II provides some evidence that the variation in the number of firms across markets cannot be explained by market size alone.

Identification in Practice

We assume that the unobservables are not correlated with our exogenous variables. This is part of the content of Assumption 1. Notice that this assumption would be clearly violated if we were to use variables that the firm can

TABLE II

DISTRIBUTION OF THE NUMBER OF CARRIERS BY MARKET SIZE[a]

Number of Firms	Large	Medium	Small	Total
0	7.07	7.31	7.73	7.29
1	41.51	22.86	20.91	30.63
2	29.03	24.30	22.14	25.93
3	12.23	19.67	16.34	15.72
4	8.07	15.14	14.59	11.93
5	1.66	9.58	16.17	7.48
6	0.42	1.13	2.11	1.02
Number	1202	971	569	2742

[a]Cross-tabulation of the percentage of firms serving a market by the market size, which is here measured by the geometric mean of the populations at the market endpoints.

from San Francisco to Washington on nine different routes. In a previous version of the paper, we allowed the firms' unobservables to be spatially 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, that is, ones that had airports in close proximity.

[32]The location of the mean center of population is from the Geography Division at the U.S. Bureau of the Census. Based on the 1990 census results, it was located in Crawford County, Missouri.

choose, such as prices or quantities. However, we are considering a reduced form profit function, where all of the control variables (e.g., population, distance) are maintained to be exogenous.[33]

The main difficulty of estimating model (1) is given by the presence of the competitors' entry decisions, since we consider a simultaneous move entry game. Theorem 2 in Section 3.3 shows that an exclusion restriction helps to point identify θ_I. Here, an exclusion restriction consists of a variable that enters firm i's profit but not firm j's. If this variable has wide support (e.g., a large degree of variation), then this reduces the size of the identified set.

Berry (1992) assumed that the variable *airport presence* of one carrier is excluded from the profit equations of its competitors. Then airport presence is a market–carrier-specific variable that shifts the individual profit functions without changing the competitors' profit functions. We refer to this model as the *fixed competitive effect* specification (that is, $\phi^i_j = 0\ \forall i, j$). For example, the airport presence of American is excluded from the profit function of Delta. In the version *fixed competitive effects* we have two exclusion restrictions. Both the *airport presence* (used by Berry) and the *cost* of the competitors are excluded from the profit function.

The second version of model (1) that we estimate is called variable competitive effects. This version includes the market presence of one airline in the profit function of all airlines. As mentioned in the Introduction, the theoretical underpinnings for these variable competitive effects are in Hendricks, Piccione, and Tan (1997). In this version, *variable competitive effects*, only the *cost* variable shifts the individual profit functions without changing the competitors' profit functions, while *airport presence* is included in the profit functions of all firms.

Generally, the economic rationale for excluding the competitors' *cost* but including their *airport presence* in a firm's profit function is the following. The *airport presence* variable is a measure of product differentiation. Thus, the *airport presence* of each firm is likely to enter the demand side of the profit function of all firms.[34] In contrast, a variable that affects the fixed cost of one firm directly enters the (reduced form) profit function of only that firm.[35]

We maintain that this variable does not enter the profit function of the competitors directly.

[33]The presence of market-, airport-, and airline-specific random effects controls for unobserved heterogeneity in the data.

[34]Berry (1990) used *airport presence* as a measure of product differentation in a discrete choice model of demand for airline travel.

[35]Notice that variables affecting the variable costs would not work as instruments because they would enter into the reduced form profit functions. The excluded variables must be determinants of the fixed cost.

Reporting of Estimates

In our results, we report superset confidence regions that cover the truth, θ_I, with a prespecified probability. This parameter might be partially identified, and hence our confidence intervals are robust to non-point-identification. Since generically these models are not point identified, and since the true parameter, along with all parameters in the identified set, minimize a nonlinear objective function, it is not possible to provide estimates of the bounds on the true parameter.[36] So our reported confidence regions have the coverage property and can also be used as consistent estimators for the bounds of the partially identified parameter θ_I. So in each table, we report the cube that contains the confidence region that is defined as the set that contains the parameters that cannot be rejected as the truth with at least 95% probability.[37]

5. EMPIRICAL RESULTS

Before discussing our results, we specify in detail the error structure of our empirical model and discuss the first stage estimation.

First, we include firm-specific unobserved heterogeneity, u_{im}.[38] Then we add market-specific unobserved heterogeneity, u_m. Finally, we add airport-specific unobserved heterogeneity u_m^o and u_m^d, where 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.[39] u_{im}, u_m, u_m^o, and u_m^d are independent and normally distributed, except where explicitly mentioned. Recall that ε_{im} is the sum of all four errors.

With regard to the first stage estimation of the empirical probabilities, we first discretize the variables and then use a nonparametric frequency estimator. We discuss the way we discretize the variables in the Supplemental Material. The nonparametric frequency estimator consists of counting the fraction of markets with a given realization of the exogenous variables where we observe a given market structure.[40]

[36]The reason is that it is not possible to solve for the upper and lower endpoints of the bounds, especially in a structural model where the objective function is almost always mechanically minimized at a unique point.

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

[38]In one specification (third column of Table IV in Section 5.2), we estimate the covariance matrix of the unobserved variables (reported in Table VI).

[39]Recall that our markets are defined irrespective of the direction of the flight. Thus, the use of the terms "origin" and "destination" means either one of the market endpoints.

[40]An alternative to discretization and nonparametric estimation is to add a distributional assumption in the first stage. In previous versions of the paper, we estimated the empirical probabilities using a multinomial logit. This discretization is necessary since inference procedures with a nonparametric first step with continuous regressors have not been developed.

5.1. *Fixed Competitive Effects*

This section provides the estimation results for model (1) when we restrict $\phi_j^i = \phi_j = 0\ \forall i, j$. Essentially, this is the same specification as the one used by Bresnahan and Reiss (1990) and Berry (1992), and therefore it provides the ideal framework with which to compare our methodology. This first version is also useful for investigating the case where the competitive effect of one airline is allowed to vary by the identity of its competitors. For example we allow Delta's effect on American to be different than Delta's effect on Southwest. In this case, the number of parameters to be estimated gets large very quickly. Thus, this specification allows for a more flexible degree of heterogeneity that is computationally very difficult to have without restricting $\phi_j^i = 0\ \forall i, j$.

Berry Specification

The second column of Table III presents the estimation results for a variant of the model estimated by Berry (1992). Here we assume $\beta_i = \beta$, $\alpha_i = \alpha$, and $\delta_j^i = \delta\ \forall i, j$. Most importantly, this implies that the effects of firms on each other, measured by δ, are identical.

In the second column of Table III, 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 parameter *competitive fixed 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 $[-14.151, -10.581]$. The entry of a firm lowers the probability that we see its competitors in 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 $[3.052, 5.087]$. As expected, the higher is the value of the variable *cost*, the lower is the probability that the firm serves that market ($[-0.714, 0.024]$). A higher *income growth rate* increases the probability of entry ($[0.370, 1.003]$), as do *market size* ($[0.972, 2.247]$), *U.S. center distance* ($[1.452, 3.330]$), *market distance* ($[4.356, 7.046]$), *per capita income* ($[0.568, 2.623]$), and *close airport* ($[4.022, 9.831]$). The *Wright Amendment* has a negative impact on entry, as its coefficient is estimated to be $[-20.526, -8.612]$.

Next, we present values of the distance function at the parameter values where this function is minimized. In the first column, the distance function takes the value 1756.2. This function can be interpreted as a measure of "fit" among different specifications that use the same exogenous variables.

Berry's (1992) (symmetry) assumptions ensure 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,

TABLE III

EMPIRICAL RESULTS[a]

	Berry (1992)	Heterogeneous Interaction	Heterogeneous Control	Firm-to-Firm Interaction
Competitive fixed effect	[−14.151, −10.581]			
AA		[−10.914, −8.822]	[−9.510, −8.460]	
DL		[−10.037, −8.631]	[−9.138, −8.279]	
UA		[−10.101, −4.938]	[−9.951, −5.285]	
MA		[−11.489, −9.414]	[−9.539, −8.713]	
LCC		[−19.623, −14.578]	[−19.385, −13.833]	
WN		[−12.912, −10.969]	[−10.751, −9.29]	
LAR on LAR				
LAR: AA, DL, UA, MA				[−9.086, −8.389]
LAR on LCC				[−20.929, −14.321]
LAR on WN				[−10.294, −9.025]
LCC on LAR				[−22.842, −9.547]
WN on LAR				[−9.093, −7.887]
LCC on WN				[−13.738, −7.848]
WN on LCC				[−15.950, −11.608]
Airport presence	[3.052, 5.087]	[11.262, 14.296]	[10.925, 12.541]	[9.215, 10.436]
Cost	[−0.714, 0.024]	[−1.197, −0.333]	[−1.036, −0.373]	[−1.060, −0.508]
Wright	[−20.526, −8.612]	[−14.738, −12.556]	[−12.211, −10.503]	[−12.092, −10.602]
Dallas	[−6.890, −1.087]	[−1.186, 0.421]	[−1.014, 0.324]	[−0.975, 0.224]
Market size	[0.972, 2.247]	[0.532, 1.245]	[0.372, 0.960]	[0.044, 0.310]
WN			[0.358, 0.958]	
LCC			[0.215, 1.509]	

(*Continues*)

TABLE III—*Continued*

	Berry (1992)	Heterogeneous Interaction	Heterogeneous Control	Firm-to-Firm Interaction
Market distance	[4.356, 7.046]	[0.106, 1.002]	[0.062, 0.627]	[−0.057, 0.486]
WN			[−2.441, −1.121]	
LCC			[−0.714, 1.858]	
Close airport	[4.022, 9.831]	[−0.769, 2.070]	[−0.289, 1.363]	[−1.399,−0.196]
WN			[1.751, 3.897]	
LCC			[0.392, 5.351]	
U.S. center distance	[1.452, 3.330]	[−0.932, −0.062]	[−0.275, 0.356]	[−0.606, 0.242]
WN			[−0.357, 0.860]	
LCC			[−1.022, 0.673]	
Per capita income	[0.568, 2.623]	[−0.080, 1.010]	[0.286, 0.829]	[0.272, 1.073]
Income growth rate	[0.370, 1.003]	[0.078, 0.360]	[0.086, 0.331]	[0.094, 0.342]
Constant	[−13.840, −7.796]	[−1.362, 2.431]	[−1.067, −0.191]	[0.381, 2.712]
MA			[−0.016, 0.852]	
LCC			[−2.967, −0.352]	
WN			[−0.448, 1.073]	
Function value	1756.2	1644.1	1627	1658.3
Multiple in identity	0.837	0.951	0.943	0.969
Multiple in number	0	0.523	0.532	0.536
Correctly predicted	0.328	0.326	0.325	0.308

[a] These set estimates contain the set of parameters that cannot be rejected at the 95% confidencet level. See Chernozhukov, Hong, and Tamer (2007) and the Supplemental Material for more details on constructing these confidence regions.

we simulate results and find that in 83.7% 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 outcome observed in the data, then we conclude that our model predicted the outcome correctly. We find that our model predicts 32.8% of the outcomes in the data. This is also a measure of fit that can be used to compare models.

Heterogeneous Competitive Fixed Effects

The third column allows for firms to have different competitive effects on their competitors. We relax the assumption $\delta_j^i = \delta \ \forall i, j$. Here we only assume $\delta_j^i = \delta_j \ \forall i, j$. For example, the effect of American's presence on Southwest's and Delta's entry decisions is given by δ_{AA}, while the effect of Southwest's presence on the decision of the other airlines is given by δ_{WN}.

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. There is quite a bit of heterogeneity in the effects that firms have on each other. 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 to be $[-10.914, -8.822]$. Instead, the entry decision of low cost carriers (LCC) has a slightly stronger effect on other airlines. The estimate of this effect is $[-19.623, -14.578]$.

The coefficient estimates for the control variables are quite different in the second and third columns. This suggests that assuming symmetry introduces some bias in the estimates of the exogenous variables. For example, in the second column we estimate the effect of market distance to be $[4.356, 7.046]$, while in the third column the effect is $[0.106, 1.002]$. The estimates for the constant are also different: $[-13.840, -7.796]$ in the second column and $[-1.362, 2.431]$ in the third column.

The differences in the competitive effects are large enough to lead to multiple equilibria in the *number* of firms in 52.3% percent of the markets. Thus, even the simplest form of heterogeneity introduces the problem of multiple equilibria in a fundamental way. Next, we show that multiple equilibria can also be present when we allow for other types of heterogeneity in the empirical model.

Control Variables With Heterogeneous Fixed Effects

The fourth column allows the control variables to have different effects on the profits of firms. In practice we drop the assumption $\alpha_i = \alpha \ \forall i$. This is interesting because relaxing this assumption leads to multiple equilibria, even if the competitive effects are the same across firms.

We estimate *market size* to have a similar positive effect on the probability that all firms enter into a market (the estimated sets overlap). On the contrary, we find that *market distance* increases the probability of entry of large national carriers, but it has a negative effect on the entry decision of Southwest. This is consistent with anecdotal evidence that Southwest serves shorter markets than the larger national carriers.

Firm-to-Firm Specific Competitive Effects

We now allow Delta's effect (Delta's effect is coded as the effect of a (LAR) large type 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 (WN). Here, the competitive effects of American (AA), Delta (DL), United (UA), and the type MA are coded as the effect of a type LAR firm. Therefore, $\delta_{\mathrm{LAR}}^{\mathrm{LAR}}$ measures the competitive effect of the entry of a large carrier, for example, American, on another large carrier, for example, Delta. $\delta_{\mathrm{LAR}}^{\mathrm{WN}}$ measures the competitive effect of Southwest on one of the four LAR firms. The other parameters are defined similarly. We find that the competitive effect of large firms on other large firms (LAR on LAR or $\delta_{\mathrm{LAR}}^{\mathrm{LAR}}$) is $[-9.086, -8.389]$, 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 $\delta_{\mathrm{LAR}}^{\mathrm{LCC}}$ is larger than $\delta_{\mathrm{LCC}}^{\mathrm{LAR}}$. 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 from serving that market varies with its airport presence. Here, the main focus is on the estimation of ϕ_j.[41]

Variable Competitive Effects With Independent Unobservables

The second column of Table IV reports the estimation results when the errors are assumed to be i.i.d. Most importantly, the coefficients ϕ_j, which measure the variable competitive effects, are all negative, as we would expect. This implies that the larger is the airport presence of an airline, the less likely is the entry of its competitors in markets where the airline is present.

[41]We restrict $\phi_j^i = \phi_j$ for computational reasons.

TABLE IV

VARIABLE COMPETITIVE EFFECTS

	Independent Unobs	Variance–Covariance	Only Costs
Fixed effect			
AA	[−9.433, −8.485]	[−8.817, −8.212]	[−11.351, −9.686]
DL	[−10.216, −9.255]	[−9.056, −8.643]	[−12.472, −11.085]
UA	[−6.349, −3.723]	[−4.580, −3.813]	[−10.671, −8.386]
MA	[−9.998, −8.770]	[−7.476, −6.922]	[−11.906, −10.423]
LCC	[−28.911, −20.255]	[−14.952, −14.232]	[−11.466, −8.917]
WN	[−9.351, −7.876]	[−6.570, −5.970]	[−12.484, −10.614]
Variable effect			
AA	[−5.792, −4.545]	[−4.675, −3.854]	
DL	[−3.812, −2.757]	[−3.628, −3.030]	
UA	[−10.726, −5.645]	[−8.219, −7.932]	
MA	[−6.861, −4.898]	[−7.639, −6.557]	
LCC	[−9.214, 13.344]		
WN	[−10.319, −8.256]	[−11.345, −10.566]	
Airport presence	[14.578, 16.145]	[10.665, 11.260]	
Cost	[−1.249, −0.501]	[−0.387, −0.119]	
AA			[−0.791, 0.024]
DL			[−1.236, 0.069]
UA			[−1.396, −0.117]
MA			[−1.712, 0.072]
LCC			[−17.786, 1.045]
WN			[−0.802, 0.169]
Wright	[−17.800, −16.346]	[−16.781, −15.357]	[−14.284, −10.479]
Dallas	[0.368, 1.323]	[0.839, 1.132]	[−5.517, −2.095]
Market size	[0.230, 0.535]	[0.953, 1.159]	[1.946, 2.435]
WN	[0.260, 0.612]	[0.823, 1.068]	
LCC	[−0.432, 0.507]		
Market distance	[0.009, 0.645]	[0.316, 0.724]	[−0.039, 1.406]
WN	[−3.091, −1.819]	[−2.036, −1.395]	
LCC	[−1.363, 1.926]		
Close airport	[−0.373, 0.422]	[0.400, 1.433]	[3.224, 6.717]
WN	[1.164, 3.387]	[2.078, 2.450]	
LCC	[1.059, 3.108]	[1.875, 2.243]	
U.S. center distance	[−9.271, 0.506]	[0.015, 0.696]	[2.346, 3.339]
WN	[0.276, 1.008]	[0.668, 1.097]	
LCC	[−0.930, 0.367]		
Per capita income	[0.929, 1.287]	[0.824, 1.052]	[1.416, 2.307]
Income growth rate	[0.136, 0.331]	[0.151, 0.316]	[1.435, 2.092]
Constant	[−0.522, 0.163]	[−0.827, −0.523]	[−12.404, −10.116]
MA_m	[0.664, 1.448]	[0.279, 0.747]	
LCC	[−1.528, −0.180]	[−0.233, 0.454]	
WN	[1.405, 2.215]	[1.401, 1.659]	
Function value	1616	1575	1679
Multiple in identity	0.9538	0.9223	0.9606
Multiple in number	0.6527	0.3473	0.0728
Correctly predicted	0.3461	0.3375	0.3011

We compare these results to those presented in the fourth column of Table III. To facilitate the comparison it is worth mentioning that in Table III, the competitive effect of one firm (for example, American) on the others is captured by a constant term, for example, δ_{AA}. In Table IV, the same competitive effect is captured by a linear function of American's airport presence, $\delta_{\mathrm{AA}} + \phi_{\mathrm{AA}} Z_{\mathrm{AA},m}$. Our findings suggests that both the fixed and variable effects are negative. For example, we find δ_{AA} equal to $[-9.433, -8.485]$ and ϕ_{AA} equal to $[-5.792, -4.545]$. Thus, a firm's entry lowers the probability of observing other firms in the market. Moreover, the larger is the *airport presence* of the firm, the smaller is the probability of a competitor's entry. This is consistent with the idea that entry is less likely when the market is being served by another firm that is particularly attractive, because of the positive effect on the demand of *airport presence*.

Variable Competitive Effects With Correlated Unobservables

In the third column, we relax the i.i.d. assumption on the unobservables and estimate the variance–covariance matrix.[42] Notice that the results are quite similar in the second and third columns. For this reason, here we provide a discussion on the economic magnitude (that is, the marginal effects) of the parameters estimated in the third column.

Table V presents the marginal effects of the variables. The results are organized in three panels. The top and middle panels show the marginal effects associated with a unit discrete change.[43] 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 or 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

[42]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.

[43]Recall that we have discretized our data.

TABLE V
MARGINAL EFFECTS[a]

	AA	DL	UA	MA	LCC	WN	No Firms
Market size							
Positive	*0.1188*	*0.1136*	*0.0571*	*0.1188*	*0.0849*	*0.1118*	−0.0033
Negative	−0.0494	−0.0720	−0.0001	−0.0442	*−0.1483*	−0.0300	−0.0033
Market distance							
Positive	0.0177	0.0165	0.0106	0.0177	0.0099	0.0000	0.0006
Negative	*−0.0354*	*−0.0377*	*−0.0110*	*−0.0360*	*−0.0128*	*−0.0377*	0.0006
Close airport							
Positive	*0.1178*	*0.1122*	*0.0312*	*0.1048*	0.0662	*0.1178*	−0.0033
Negative	−0.0375	−0.0518	−0.0004	−0.0318	*-0.0911*	−0.0175	−0.0033
Change income							
Positive	*0.0283*	*0.0265*	*0.0149*	*0.0283*	0.0171	*0.0277*	−0.0007
Negative	−0.0140	−0.0193	−0.0001	−0.0120	*−0.0339*	−0.0086	−0.0007
Per capita income							
Positive	*0.0576*	*0.0546*	*0.0291*	*0.0576*	0.0364	*0.0573*	−0.0015
Negative	−0.0270	−0.0377	−0.0002	−0.0237	*−0.0699*	−0.0160	−0.0015
U.S. center distance							
Positive	*0.0177*	*0.0181*	*0.0052*	*0.0171*	0.0038	*0.0181*	−0.0004
Negative	−0.0044	−0.0055	−0.0001	−0.0033	*−0.0076*	−0.0011	−0.0004
Airport presence	0.0673	0.0498	0.1888	0.0734	0.0599	0.1040	
Cost	−0.0102	−0.0068	−0.0117	−0.0120	−0.0054	−0.0125	
AA	···	−0.3606	−0.2556	−0.4108	−0.0704	−0.2143	
DL	−0.3336	···	−0.2658	−0.3908	−0.0335	−0.2126	
UA	−0.2486	−0.2630	···	−0.2696	−0.0675	−0.2015	
MA	−0.3877	−0.3941	−0.2717	···	−0.0989	−0.2766	
LCC	−0.0998	−0.1579	−0.0721	−0.1415	···	−0.0411	
WN	−0.2256	−0.2356	−0.2030	−0.2868	−0.0242	···	

[a]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 panels we report the *largest change* in the average upper bounds of the probabilities of observing a given carrier in any possible market structure.

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 seeing 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 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 panels, we report the *largest positive and negative change* in the average upper bounds of the probabilities of observing a given carrier in any possible market structure. We report both the positive and negative changes because an increase in market size, for example, increases the profits of all firms. Thus, all firms *individually* are more likely to enter. However, here we are looking at the simultaneous decision of all firms. Consequently, we may see that some market structures become more likely to be observed at the expense of other market structures. The *dominant* effect for one particular firm might end up being negative. We identify the dominant effects in italics.

In practice, we increase *one variable at a time* and we compute the average by an economically meaningful amount and we compute the average upper bounds by taking the means of the upper bounds for one market structure across markets. Then we compute the average upper bounds by taking the means of the upper bounds for one market structure across markets at the observed values. Finally, we take the differences of all of the upper bounds for all 64 market structures, and report the largest positive and negative changes among them.

In the top panel, an increase in *market size* of 1 million people is associated with a maximum effect of an increase of 11.88% in the probability of observing American Airlines and a maximum decrease of −4.94% of not observing it. This means that there is one market structure where American is present that is 11.88% percent more likely to be observed and there is one other market structure where American is present that is 4.94% less likely to be observed. We interpret this combination of results as evidence that an increase in market size is associated with an overall increase in the likelihood of observing American in a market.

If the nonstop distance increases by 250 miles, then the overall likelihood of observing American in a market decreases by 3.54%. If the distance to the closest alternative airport increases by more than 50 miles, then the probability of observing American increases by 11.78%. If income grows 1% faster, then the probability of observing American serving the market increases by 2.83%. If the per capita income increases by 5,000 dollars, then the maximum probability of observing a market structure where American is serving the market increases by 5.76 percent. Finally, if the distance from the US geographical center increases of 250 miles, then the maximum probability of observing American increases by 1.77 percent. The interpretation of the results for the other firms is analogous.

The middle panel reports the effect of an 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. If American's airport presence increases by 15%, then the probability of observing American increases by 6.73%. Finally, an increase

TABLE VI
VARIANCE–COVARIANCE MATRIX

	AA	DL	UA	MA	LCC	WN
AA	1	[0.043, 0.761]	[−0.110, 0.442]	[0.103, 0.626]	[−0.217, 0.752]	[0.055, 0.355]
DL		[5.052, 6.895]	[−0.200, 0.190]	[0.629, 0.949]	[−0.128, 0.656]	[0.218, 0.834]
UA			[2.048, 3.340]	[−0.173, 0.309]	[−0.213, 0.652]	[0.192, 0.797]
MA				[2.396, 5.558]	[−0.094, 0.313]	[0.093, 0.862]
LCC					[2.026, 6.705]	[0.093, 0.764]
WN						[2.063, 2.331]

of 50% in the *cost* associated with serving a market lowers the probability of observing American by approximately 1%.[44]

The numbers in the bottom panel of Table V are derived in a slightly different fashion from those ones in the top and middle panels. They also require additional discussion. Let us say that we want to quantify the effect of American's entry on the probability of observing one of its competitors. If there were unique equilibria, then the answer would be straightforward. We could set the parameters that measure the competitive effects of American equal to zero and then recompute the new equilibria. Then we would just have to compute the change in the probabilities of observing the other firms in each market and take the averages across all markets. With multiple equilibria, the analysis of the marginal effects has to take into account that we estimate lower and upper bounds for the probability of observing any market structure in each market.

We find that Delta's entry can decrease the probability of observing American in the market by as much as 33.36%. The effect of Delta's entry varies a lot by the identity of the opponent, as we observe that it is just −3.35% for *low cost carriers*.

Next, we discuss the estimation results for the variance–covariance matrix. Recall that the unobservables are made up of four components. One of them is a firm-specific component. We estimate the covariances of these firm-specific components. In addition, we estimate the variance of the sum of the four components.

We find that the variances of all firms are larger than one. For example, the variance for Delta is [5.052, 6.895]. This suggests that the unobservable heterogeneity for these firms is larger than for American.

The estimated correlations are quite interesting. In general, it is hard to identify correlation coefficients among unobservables in multivariate discrete choice models, and here is no exception since the confidence regions are wide. A few points are worth making. For example, the unobservables of Southwest

[44]We do not report the negative effect, since for the variable airport presence, the increase in the maximum probability of observing a firm in one particular market structure is always larger in absolute value than the maximum decrease of observing that firm in another market structure.

and *low cost carriers* are positively correlated, suggesting that it is more likely that both of them would be in a market, ceteris paribus.

Only Costs

The fourth column of Table IV estimates the model without the variables that measure airport presence. In practice, we set $\beta_i = \beta = 0$, in addition to $\delta_j^i = \delta_j$ and $\phi_j^i = \phi_j = 0\ \forall i, j$. We present this specification so as to address the concern that airport presence could be endogenous if airlines choose their network, instead of choosing only whether to enter into a particular market for a given exogenous network. This concern is particularly reasonable when we perform our policy simulation. The results should be compared with those the third in column of Table III. With the exception of Southwest, the fixed competitive effects are all similar. This is reassuring because it suggests that the variation in the costs is enough to identify the competitive effects. This specification fits the data less than the specification in the third column of Table III.

6. POLICY EXPERIMENT: THE REPEAL OF THE WRIGHT AMENDMENT

We develop a policy experiment to examine how our model predicts 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 responses to the repeal of the amendment. In practice, we first take all 93 markets out of Dallas Love and simulate the predicted outcomes with the Wright Amendment 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 repeal of the Wright Amendment. Our estimates provide a within model prediction of the effect of the repeal that should be interpreted in the short term.

In Table VII, we present the policy simulations when we use three different specifications.

The second column of Table VII reports the policy results when we use the specification in the third column of Table IV. This is an interesting specification because it accounts for correlation in the unobservables. We report the results when we use the value of the parameters at which the objective function is minimized. This is the number in the middle. Then we report the lowest and largest numbers for the policy results that we derive when we use all the parameters in the estimated set.

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 63.84% 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 47.44%

TABLE VII

PREDICTED PROBABILITIES FOR POLICY ANALYSIS: MARKETS OUT OF DALLAS LOVE

Airline	Variance–Covariance	Independent Obs	Only Costs
No firms	[−0.6514, −0.6384, −0.6215]	[−0.7362, −0.6862, −0.6741]	[−0.6281, −0.6162, −0.5713]
AA	[0.4448, 0.4634, 0.4711]	[0.2067, 0.3013, 0.3280]	[0.3129, 0.3782, 0.4095]
DL	[[0.4768, 0.4988, 0.5056]	0.2733, 0.3774, 0.4033]	[0.3843, 0.4315, 0.4499]
UA	[0.1377, 0.1467, 0.1519]	[0.1061, 0.1218, 0.2095]	[0.2537, 0.3315, 0.3753]
MA	[0.4768, 0.4988, 0.5056]	[0.2733, 0.3774, 0.4033]	[0.3656, 0.4143, 0.4342]
LCC	[0.3590, 0.3848, 0.4156]	[0.8369, 0.8453, 0.8700]	[0.2839, 0.3771, 0.3933]
WN	[0.4480, 0.4744, 0.4847]	[0.2482, 0.2697, 0.3367]	[0.3726, 0.4228, 0.4431]

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, at most 46.34 and 49.88% respectively.

These marked changes in market structures suggest that one reason why the Wright Amendment was not 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 would 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 they do 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 web page 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 into 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 compared our results with those that we would derive using the coefficient estimates in the second column of Table IV. The main result, concerning the change in the number of markets that are not served, is almost identical. The other results, with the exception of that for the *low cost carriers*, are very similar.

Finally, we checked our predictions using 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. The fourth column of Table VII reports the policy results when we use the specification presented in the fourth column of Table IV. This last specification shows results that are almost identical to those in the third column of Table VII.

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 are used to study the effect of multiple equilibria on learning about 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 those results are practically attractive since they will involve a semiparametric model with possibly partially identified parameters.

Moreover, the empirical analysis of the paper looks at the airline industry and network from a long-run perspective where its network is taken as exogenous in the short run. To relax this assumption, one needs to use a more complicated model that accounts for the dynamics of entry and of adjustment to one airline's network in response to entry by a competitor. This is something we do not pursue here. Hence, the results, especially the policy experiments, need to be interpreted as the response in the short run and within our model. On the other hand, the econometric model 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 the 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 also for future research.

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