EMPIRICAL STUDIES OF
MICROECONOMIC AGENTS’ BEHAVIOR

A Dissertation in
Economics
by
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Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

August 2008
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Abstract

The economic decisions of rational agents can be analyzed by theoretical models and/or empirical models. This dissertation consists of two different applications of empirical models on two different economic conundrums, both based on theoretical hypotheses. The first chapter introduces the related literatures and background of each paper. In the second chapter, I analyze the concert ticket market by extending the theory present in the economic literature and estimating a parametric empirical model. In the third chapter we estimate the affiliation effect (Pinkse and Tan [26]) in a specific common value auction setting.

The second chapter investigates promoters’ and bands’ ticket price decisions and presents a theoretical model that demonstrates how their seemingly suboptimal decisions can be profit-maximizing. Here, I model the ticket price decision of a promoter and an artist based on two potential explanations: the effects of an artist’s future profit as well as merchandising profit on the pricing decision. When artists or promoters consider their future profit as well as their current profit, or they consider merchandising revenue as well as ticket revenue, they may charge a price lower than the price which maximizes only their static ticket profit. In order to test the credibility of these potential explanations, I
estimate a ticket supply equation with Pollstar Boxoffice historical data. The estimation results suggest that both the future profit of an artist and merchandising profit are credible explanations as to why promoters and bands set the ticket price lower than the static ticket profit maximizing price.

The third chapter estimates the affiliation effect defined in Pinkse and Tan [26] in which they showed that bids can be decreasing in the number of bidders in private value auctions provided that the bidders’ private values are affiliated. We use the Outer Continental Shelf auction data set to estimate three effects nonparametrically: the affiliation effect, the competition effect, and the winner’s curse effect. We find that the affiliation effect is in fact the smallest of the three.
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Acknowledgments

I am deeply grateful to Joris Pinkse, Edward Coulson, Mark Roberts, and Andrew Kleit for their insightful guidance and constant encouragement. I also thank Edward Green, Kalyan Chatterjee, and Neil Wallace for their meaningful commentary. Financial support for this research is provided by the College of Liberal Arts, the Pennsylvania State University. The second chapter has also benefited from conversations with Bernie Punt from the Bryce Jordan Center, University Park, PA, and Michael Friedman from BandMerch, LLC. Lastly, I would like to thank my family for their love and support and my friends who became my second family here at Penn State. Any remaining errors are mine.
Dedication

To my parents, Young Il Byun and Kwang Hae Chung, who are praying for me even at this very moment.


Chapter 1

Introduction

The economic decisions of rational agents can be analyzed by theoretical models and/or empirical models. This dissertation consists of two different applications of empirical models on two different economic conundrums, both based on theoretical hypotheses. This chapter introduces background information relevant for chapters two and three.

1.1 Monopolistic Behavior

Chapter two studies a ticket pricing decision. Behavior similar to the seemingly non-profit-maximizing decision making by Rock stars or promoters can be witnessed in many other settings, such as underpricing of video game consoles or initial public offerings (IPOs). This section explains some of the underlying theory.

Tirole [29] provides several models of relevant monopolistic behavior. The most important of these to my research is a model of a multi-product monopolistic firm which produces $n$ goods, and faces demand function $q_i(p)$ and cost function $C(q_1, \cdots, q_n)$, where $p = (p_1, \cdots, p_n)$ and $i = 1, \cdots, n$. The monopolist sets the price for each good.
where it maximizes the following profit function $\Pi_{\text{multi}}$,

$$\Pi_{\text{multi}} = \sum_{i=1}^{n} p_i q_i(p) - C(q_1(p), \cdots, q_n(p)).$$

The first order condition for the maximization problem is given in equation (1.1).

$$q_i + p_i \frac{\partial q_i}{\partial p_i} + \sum_{j \neq i} p_j \frac{\partial q_j}{\partial p_i} - \sum_{j} \frac{\partial C}{\partial q_j} \frac{\partial q_j}{\partial p_i} = 0, \quad i = 1, \cdots, n \tag{1.1}$$

If the third term of the first order condition (1.1) is non-zero, i.e. the demand for a good depends on the price of other goods as well as its own price, the profit maximizing price is different from the price maximizing a single product monopolist’s profit. Equation (1.1) can be rearranged as follows:

$$\frac{p_i - \partial C_i / \partial q_i}{p_i} = \frac{1}{e_{ii}} - \sum_{j \neq i} \frac{(p_j - \partial C_j / \partial q_j) q_j e_{ij}}{p_i q_i e_{ii}}, \tag{1.2}$$

where $e_{ij} = -\frac{\partial q_j / q_j}{\partial p_i / p_i}$. Note that the left hand side of equation (1.2) is the Lerner index, which is the ratio of profit to price, which in turn is the markup rate that the monopolist charges. The first term on the right hand side of equation (1.2) is the inverse price elasticity. If the firm were a single product monopolist, the Lerner index would equal the inverse price elasticity. In other words the second term on the right hand side of equation (1.2) would necessarily equal zero.

The second term on the right hand side of equation (1.2) includes $e_{ij} = -\frac{\partial q_j / q_j}{\partial p_i / p_i}$. This term is negative if the goods are substitutes and positive if they are complements. If
two of the goods produced by the multi-monopolist are substitutes, then $e_{ij}$ is negative. The markup will be higher than the markup if the firm were a single product monopolist. If the monopolist’s goods are complements, then $e_{ij}$ is positive and the markup will be lower than the markup if the firm were a single product monopolist.

Intuitively, decreasing the price for good $i$ will cause the demand for good $j$ to increase if the goods are complements. Therefore, the multi-product monopolist will charge a relatively lower price for each good. Inversely, decreasing the price of good $i$ will cause the demand of good $j$ to decrease if the goods are substitutes. Therefore, the multi-product monopolist will charge a relatively higher price for each good.

My paper deals with a multi-product monopolist who is selling complementary goods that have dependent demands: merchandising demand which is positively correlated with concert ticket demand, and future ticket demand which depends on current ticket demand.

1.2 Auction Theory

In the third chapter we estimate the affiliation effect defined in Pinkse and Tan [26] in a specific common value auction case. In their paper, they showed that bids can be decreasing in the number of bidders in private value auctions provided that the bidders’ private values are affiliated.

Before moving on to the discussion of auction paradigms, the concept of affiliation of random variables needs to be explained. The following definition is from Krishna [17]. Consider vectors $s$ and $s'$ in $\mathbb{R}^n$ where $s = (X_1, \cdots, X_n)$ and $s' = (X'_1, \cdots, X'_n)$ with
the density function $f(\cdot)$. Random variables $X_1, \cdots, X_n$ are affiliated if for all $s$ and $s'$,

$$f(s \lor s')f(s \land s') \geq f(s)f(s'),$$

where $s \lor s'$ is the component-wise maximum of $s$ and $s'$, and $s \land s'$ is the component-wise minimum of $s$ and $s'$. In this case, the p.d.f. $f$ is also called affiliated. In the context of auctions, if bidders’ private signals $X_1, \cdots, X_n$ are affiliated, then it means that if a subset $X_i$ values are high, other $X_j$ values are more likely to be high. See Krishna [17] and Milgrom and Weber [20] for more rigorous and detailed discussions.

Auctions can be categorized according to the characteristics of bidders’ valuation of the auction object. In a private value auction, each bidder is aware of her own valuation of the auction object when she bids for it, and this value is her private information. A bidder’s valuation does not affect other bidders’ valuations or vice versa in this setting. If bidders compete for an object that is only for their consumption not for resale or investment, the auction can be considered a private value auction. An art auction can be an example, if no bidders are involved in the auction for the purpose of investment or resale of the object.

In a pure common value auction, there exists a value of the auction object which is universal to all bidders. Bidders do not know the exact value ex ante, and they only have their own signals, which are correlated with the value. Oil drilling rights auctions are good examples of common value auction because at the time of the auction, bidders do not know the real value of the tract. However, bidders have access to various
geological test results are correlated with the actual value of the tract. See Krishna [17] and Klemperer [16] for more examples and discussions.

Milgrom and Weber [20] introduced affiliation in bidders’ values into the auction literature. They provide a general symmetric model which includes the independent private value and the common value models as extreme cases. A symmetric auction occurs when:

- The function mapping the bidders’ private signals and the common components to the value of the auctioned object is the same for all bidders and this function is symmetric in the other bidders’ signals; and
- The joint density function of the signals is symmetric in its arguments.

These symmetry assumptions are a different generalization of the symmetry assumption in an independent private value auction model, which is that bidders are symmetric if their private values are drawn from the same distribution.

There are $n$ bidders, and each bidder gets a signal, which is a private information. Let $X_i$ be the private signal of bidder $i$. There are some variables $Z_j$, which affect the bidders’ common valuation of the object ($j = 1, \cdots, m$). Bidder $i$’s valuation of the object is given by the function $u$:

$$V_i = u(X_1, \cdots, X_n; Z_1, \cdots, Z_m).$$

Note that in an independent private value auction, $m = 0$ and $V_i = X_i$, while in a pure common value auction, $m = 1$ and $V_i = Z_1$. Bidders are risk neutral, so they maximize their expected profits.
Milgrom and Weber [20] characterize Bayesian-Nash equilibrium bid functions in the first price auction case. Note that in a first price (sealed bid) auction, bidders submit their bids, then the bidder with the highest bid wins the object and pays what he bid. This is different from second price auction, where the bidder submitting the highest bid wins the object but pays the second highest bid.

Let $X = X_1$ be bidder 1’s private signal and $Y$ be the maximum of rivals’ signals, i.e. $Y = \max(X_2, \cdots, X_n)$. Suppose that the other bidders choose an increasing and differentiable bid function $B^*(\cdot)$. Define $r$ to be the bidder’ reserve price. Then for any $r \leq x \leq \bar{x}$ the expected payoff of bidder 1 is:

$$
\Pi(b; x) = E[(V_1 - b)I(B^*(Y) < b)|X = x]
= E[E[(V_1 - b)I(B^*(Y) < b)|X, Y]|X = x]
= E[(v(X, Y) - b)I(B^*(Y) < b)|X = x]
= \int_{r}^{B^* - 1(b)} (v_n(x, t) - b) f_Y(t|x) dt ,
$$

where

$$
v_n(x, y) = E[V_1|X = x, Y = y].
$$

The first order condition for bidder 1’s expected profit maximization problem is as follows:

$$
\frac{\partial \Pi}{\partial b}(b; x) = \frac{(v_n(x, B^* - 1(b) - b) f_Y(B^* - 1(b)|x)}{B^{*'}(B^* - 1(b))} - F_Y(B^* - 1(b)|x) = 0 ,
$$
such that

\[ B^*'(x) = (w_n(x) - B^*(x)) \frac{f_Y(x|x)}{F_Y(x|x)}, \]

(1.3)

where \( w_n(x) = v_n(x, x) \)

From the first order differential equation (1.3), the equilibrium bid function \( B^*(\cdot) \) is:

\[ B^*(x) = \int_x^r w_n(t)R_n(t)exp\left(-\int_t^x R_n(s)ds\right)dt, \]

where

\[ R_n(x) = \frac{f_Y(x|x)}{F_Y(x|x)}. \]

In chapter three, we will begin from the bid function \( B^*(x) \) to decompose the total effect of the number of bidders on bid level based on the equilibrium bid function above in a common value auction model.

### 1.3 Supply Function Estimation

This section discusses the use of two stage least squares (2SLS). In the second chapter, I estimate a ticket supply function with 2SLS in order to deal with an endogeneity problem which arises when any regressor in ordinary least squares (OLS) estimation is correlated with the regression error. When a regressor is endogenous, then OLS estimators are inconsistent. This problem occurs when there is measurement error in regressors, when there are omitted variables, or because of simultaneity.

Consider for example supply and demand functions. Observed price \( p_i \) and quantity \( q_i \) are equilibrium price and quantity determined by supply and demand functions,
\[ p_i = q_i \gamma_1 + z_i' \beta_1 + u_{i1}, \quad \text{(Supply function)} \]
\[ q_i = p_i \gamma_2 + z_i' \beta_2 + u_{i2}, \quad \text{(Demand function)} \]

In the demand and supply system, quantity \( q_i \) is generally correlated with error term \( u_{i1} \). In order to deal with this endogeneity problem due to simultaneity, I use 2SLS estimation methods.

Consider a linear model

\[ y_i = x_i' \beta + u_i, \quad i = 1, \ldots, n, \]

where \( x_i \) and \( \beta \) are \( K \times 1 \) vectors and \( \{(x_i, y_i, z_i)\} \) is an independently and identically distributed (i.i.d) sequence. Suppose that there exists an endogeneity problem, in other words \( E(u_i|x_i) \neq 0 \). With this instrumental variables estimation, one can obtain a consistent estimator of \( \beta \). Valid instruments \( z_i \) should satisfy the following conditions: \( z_i \) is orthogonal to the errors and \( \text{rank}(E(z_1 x_1')) = K \).

Let \( X \) be an \( n \times K \) matrix with \( x_i' \) as its \( i \)th row element, \( y \) be a \( n \times 1 \) vector with \( y_i \) as its \( i \)th element, and \( Z \) be \( n \times b \) instrumental variable matrix with \( z_i' \) as its \( i \)th row vector where \( b \geq K \). Then the 2SLS estimator can be written as,

\[ \hat{\beta}_{2SLS} = (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'y. \]

This can be interpreted in the following way. First, one conducts OLS estimation with \( x_i \) as regressands and \( z_i \) as regressors, then obtains the predictions \( \hat{x}_i \). Second, the
OLS regression of $y_i$ on $\hat{x}_i$ provides the instrumental variables estimator $\hat{\beta}_{2SLS}$.

\[
\hat{\beta}_{2SLS} = (\hat{X}' \hat{X})^{-1} \hat{X}' y ,
\]

where $\hat{X} = Z(Z'Z)^{-1}Z'X$. This two stage method of estimation is why the technique is called two stage least squares. \(^1\) This estimator has the following limiting distribution

\[
\sqrt{n}(\hat{\beta}_{2SLS} - \beta) \xrightarrow{d} N \left(0, \left(E(x_1z_1') \left(E(u_1^2 z_1 z_1') \right)^{-1}E(z_1 x_1') \right)^{-1} \right).
\]

If $Z_i$ contains valid instruments, then a Durbin-Wu-Hausman test can be used to test the exogeneity of regressors.

\[
DWH = (\hat{\beta}_{2SLS} - \hat{\beta}_{OLS})' \left(\hat{\sigma}^2((X'Z(Z'Z)^{-1}Z'X)^{-1} - (X'X)^{-1}) \right)^{-1} (\hat{\beta}_{2SLS} - \hat{\beta}_{OLS})
\]

(1.4)

Under the null of exogeneity, this DWH test statistic has an asymptotic chi-square distribution $\chi^2_K$.

**1.4 Nonparametric Estimation Methodology**

In order to estimate the three different effects of the number of bidders on bid level, we exploit nonparametric estimation methodology. Nonparametric methods are different from parametric ones in the sense that they do not impose assumptions of any specific functional form. These methods have been developed since the early 1950’s in Statistics and are sometimes referred as distribution free methods. Since nonparametric

\(^1\)See Wooldridge [32] and Pinkse [25].
methods do not depend on any functional specification, nonparametric estimation results are robust to functional misspecification. Also, preliminary analysis of data with nonparametric methods can give some guidance for the correct parametric specification. However, nonparametric estimation methods have many challenges such as their slow convergence rate, computational complexity, difficulty in establishing asymptotic properties, and the need for a large data set. There are many different nonparametric methods such as kernels, splines, series, nearest-neighbor, and local polynomials. See Härdle [11], and Pagan and Ullah [22] for more discussion. Here I describe kernel estimation methods since we will use these methods to estimate conditional means and their derivatives in the third chapter.\footnote{See Vuong [30] and Pinkse [24].}

1.4.1 Kernel Density Estimation

Let $X_1, \cdots, X_n$ be independently and identically distributed (i.i.d.) random variables in $\mathbb{R}$, where each $X_i$ is drawn from a distribution function $F(\cdot)$ with a twice continuously differentiable density function $f(\cdot)$. For any bounded, symmetric around zero, and integrable kernel function $k(\cdot)$ with $\int k(x)dx = 1$, and a bandwidth $h > 0$, a kernel density estimator of the density $f(x)$ at $x$ is defined as follows:

$$\hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left(\frac{x - X_i}{h}\right).$$

The bandwidth $h$ determines the degree of smoothness of the density estimate, and it should have the properties $h \to 0$ and $nh \to \infty$ as $n \to \infty$. By increasing the value of
the bandwidth, one decreases the variance but increases the bias of the estimates, and vice versa.

The kernel estimator has the following finite sample properties.

\[
E(\hat{f}(x)) = \frac{1}{h} E(k(\frac{x - X_i}{h})) \\
= \frac{1}{h} \int k(\frac{t - X_i}{h}) f(t) dt \\
= \int k(s)f(x + sh)ds .
\]

Therefore, the bias is:

\[
\text{bias}(\hat{f}(x)) = E(\hat{f}(x)) - f(x) = \int k(s)[\int f(x + sh) - f(x)]ds .
\]

Also, its variance can be written as:

\[
V(\hat{f}(x)) = \frac{1}{nh} \int k^2(s)f(x + sh)ds - \frac{1}{n} [\int k(s)f(x + sh)ds]^2 .
\]

Kernel density estimation provides a consistent and asymptotically unbiased estimator, however the kernel density estimator with a finite sample size is biased. The bias of the kernel density estimator is greater as it is closer to the boundaries. To deal with this problem, we use a boundary kernel \( k_b(\cdot) \) instead of a standard kernel:

\[
k_b(\frac{x - X_i}{h}) = \frac{k(\frac{x - X_i}{h})}{K(\frac{x - \bar{x}}{h}) - K(\frac{\bar{x} - x}{h})} , \tag{1.5}
\]

where \( X_i \in [\underline{x}, \bar{x}] \) and \( K(\cdot) \) is the cumulative kernel density function.
1.4.2 Kernel Regression Estimation

Again let $X_1, \cdots, X_n$ be i.i.d. random variables drawn from the distribution function $F(\cdot)$ with density function $f(\cdot)$, and $\{ (X_i, Y_i) \}$ be i.i.d. Consider a regression model:

$$Y_i = m(X_i) + U_i,$$

where $m(x) = E[Y_1 | X_1 = x]$. This function can also be estimated using the kernel estimation method, and the kernel regression estimator for $m(x)$ can be written as:

$$\hat{m}(x) = \frac{1}{nh} \sum_{i=1}^{n} k\left( \frac{x-X_i}{h} \right) \frac{Y_i}{f(x)}. \quad (1.6)$$

This can be interpreted as a weighted sum of the $Y_i$’s, which gives more weight towards $Y_i$ if $X_i$ is close to $x$.

Equation (1.6) can be viewed as an effort to fit a horizontal line at $x$ if it is rewritten as follows:

$$\hat{m}(x) = \arg \min_t \sum_{i=1}^{n} (Y_i - t)^2 k\left( \frac{x-X_i}{h} \right).$$

One can try to fit a polynomial locally, to use a local polynomial estimator for $m(x)$ defined as:

$$\hat{m}_a(x) = \hat{i}_{a0}(x), \cdots, \hat{i}_{aa}(x) = \arg \min_{t_1, \cdots, t_a} \sum_{i=1}^{n} \left( Y - t \sum_{j=0}^{a} t_j (x-X_i)^j \right)^2 k\left( \frac{x-X_i}{h} \right)$$

$$\hat{m}_a(x) = \hat{i}_{a0}(x).$$
The local polynomial smoothing method can be used as a solution to a boundary problem along with boundary kernels.

1.5 The Bootstrap

In chapter three to construct confidence bands for the estimates, we use bootstrap resampling. Bootstrap is a resampling method for test statistics or estimators. This method can be used when there are computational difficulties in obtaining the asymptotic distribution of an estimator or asymptotic approximations for test statistics, such as confidence intervals, standard errors, etcetera. In many finite sample cases the bootstrap provides approximations which are more accurate than first order asymptotic approximations, called an ‘asymptotic refinement’. See Horowitz [13] for extensive discussions on the bootstrap: sampling procedures, consistency conditions, asymptotic refinements, and evidence on the numerical performance of the bootstrap.
Chapter 2

Why Rock Stars Do Not Raise Their Ticket Prices

2.1 Introduction

Popular music concert tickets ordinarily resell at prices well above their face values. For example, $39.50 tickets for Nickelback, a popular rock band, concerts are traded at around $120 in the resale ticket market. This fact may imply that most promoters and bands are not optimizing their profits. This paper investigates the reason that ticket prices are chosen such that ticket resale is profitable. I model the ticket price decision of a promoter and an artist, where they may consider the artist’s future profit, their merchandising profit, or both, in addition to their static ticket profit. This model suggests that when artists and promoters consider their future profits or merchandising profits as well as their current ticket profits, they may charge a lower price than the price which maximizes only their static ticket profit. In order to test the credibility of these potential explanations, I estimate a supply side ticket price equation with Pollstar U.S. Boxoffice historical data between March 1981 and January 2007. The estimation results suggest

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1These are for open air seats of Nickelback’s concert on July 13, 2007, at Tweeter Center for the Performing Arts in Mansfield, MA.
that both the potential future profit of an artist and merchandising profit are credible explanations.

This paper extends the existing literature, which suggests several reasons for the existence of the ticket resale market. These include the possible existence of other sources of revenue, such as complementary concessions sales (Happel and Jennings [10] and Marburger [19]), and the interrelation between current and future ticket demand (Diamond [5] and Swofford [27]).

I first look at future profits of an artist as a potential explanation. If current ticket sales of an artist affect her popularity, then it will affect the artist's income in the future. Therefore, the artist who considers her future profits may price her concert ticket lower than the static ticket profit maximizing price. This explanation was considered by Swofford [27]. He points out the tradeoffs between current profit gain and the future sales loss that might come from raising prices. Diamond [5] also mentions a possible relationship between promoters' reputations and the success of future events.

The second explanation considers merchandising profits as another possible reason why promoters or bands do not raise their ticket prices. Some studies argue that ticket underpricing stems from the existence of complementary goods. (See Happel and Jennings [10] and Marburger [19].) Marburger [19] models ticket pricing for performance.

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2While all of these studies consider the supply side, there are other studies which focus on the nature of the ticket demand: the variance in the timing of realization of demand over consumers (Courty [3]), interdependence among consumers (Becker [1], DeSerpa [1994]), and consumers' views on fairness (Kahneman et al. [15]). However, since the limitation of data on ticket demand makes it challenging to explore these explanations empirically, I do not consider them here.

3Swofford also presents different cost functions for promoters versus scalpers, which allow the resale markets exist.
goods when the price setter gets a part of the profit from concessions, which can be purchased only if a consumer attends the event. Since the demand for concessions depends on attendance rate, the promoter may have an incentive to set their ticket price lower than market rate.\footnote{Marburger [19] finds that Major League Baseball (MLB) tickets are priced in the inelastic part of the demand and argues that this fact supports his model. However, an artist who considers her profits also may price in the inelastic part of the demand.}

Instead of considering each explanation separately, I combine them in a ticket price decision model, where I implicitly assume that ticket scalping does not affect promoters’ or bands’ decisions. I estimate a parsimonious ticket price equation, which allows me not only to test the credibility of these two explanations, but also to estimate the relative importance of these effects. Even though the literature provides insights into possible reasons for underpricing or the existence of ticket resale markets in the entertainment industry, few studies have tested the credibility of their hypotheses empirically.

The next section defines key players and describes some basic features of several contracts in the music concert market. Section 3 describes a simple model of a concert ticket price decision problem of a promoter and a band. In section 4, I estimate the ticket price equation to test the model. Section 5 provides conclusions and implications for future research.

### 2.2 Music Industry

A professional music artist has relationships with specialized agents: promoters and venues related to concert tours, record labels related to records and music videos,
and publishing companies related to copyrights. Promoters in particular play a prominent role in concert scheduling. They hire artists for shows, book venues, advertise the events, and collect the revenue from ticket sales. Venues provide the place for events on specific dates, and receive rental fees and part of the merchandising sales. Record labels deal with producing, manufacturing, and promoting records and music videos. Publishing companies collect publishing royalties on reproductions and distributed copies of songs and public performances on behalf of songwriters through performance rights organizations, such as BMI (Broadcast Music Incorporated).

The main sources of artists’ incomes are concert ticket sales, merchandising sales, and record sales. In addition, if songs are written by the artist, then the copyrights on the songs can also be a source of an artist’s income. In general, the sharing rule - the percentage of sales that the artist receives - for concert ticket profits and merchandising royalties are higher than artist royalties for record deals. Also, the contracts on record deals are generally long term, while the contracts on concerts are shorter than record deals. Therefore, concert ticket profits and merchandising profits may be more important for artists than record profits. Moreover, since downloading music on the Internet was introduced in the popular music market, record sales have decreased; consequently, the importance of concert profits will likely continue to increase. In this context, I will focus on concert profits and merchandising profits.

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5 Passman [23] provides an extensive review on the popular music industry.
6 Artist royalty varies with the popularity of an artist. According to Passman [23], the royalties are 9% - 14% of SRLP for new artists, 15% - 16% of SRLP for mid level artists, and 18% - 20% or more of SRLP for superstars.
7 According to RIAA.com, total album sales has dropped since 2000, except a small peak between 2003 and 2004. However, the relation between the diffusion of digital music and record sales is controversial (See Burkart and McCourt [2]).
The key players and their payoffs of the contracts on concert deals and merchandising contracts are as follows. First, concert deals are made by artists and promoters and they share ticket profits after the shows. They bargain over ticket price and the sharing rule for concert ticket profits. Contracts for payment methods may be different depending on the popularity of the artist. However, the promoter generally pays a ‘guarantee’ to the artist in advance, then pays the rest of the net revenue from the show according to their ‘split rate’ after the show. The split rate for artists is usually 85 - 90 % of the net profits of the concert (See Passman [23]). Next, at a concert venue, people can buy T-shirts, posters, or other products as souvenirs. Merchandisers, artists, and venues split the merchandising profits. Merchandisers produce merchandising goods with the license from the artists. They generally pay 25 - 40 % of gross sales as merchandising royalties to the artists, and give 35 - 40 % of gross sales to venues (See Passman [23] and Thall [28]). The contracts on concert deals between promoters and artists and the contracts for merchandising are usually separate contracts. In some cases the promoter who promotes an event can be the owner of the venue. Then the promoter will get a part of the merchandising profit as well as a part of the ticket sales profit.

2.3 Model

This section introduces the concert ticket price decision problem of a promoter and a band. First, I define the demands for tickets and T-shirts, the profit function

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8 Sometimes promoters contract with booking agents, instead of contracting directly with artists. Booking agents take charge of the artist’s live appearance for certain periods and are paid with 5 - 10 % of the artist’s revenue from concerts.

9 In my data set, 27% of the events are held at venues owned by the promoters.
for each player, and the ticket price decision by the two players. Then I show how the different types of promoters or bands affect their ticket prices.

2.3.1 Setup

There are two players: a band and a promoter, with two types of each player. The band can be young or old, and the promoter can be the owner of the venue or not the owner. Every band exists for two periods. A young band considers forthcoming future profit as well as current profit, while an old band considers only current profit. A promoter who does not own the venue (type $\tau = 0$) gets only a part of the ticket sales revenue for the event, while a promoter who owns the venue (type $\tau = 1$) receives the profit from a part of the merchandising revenue as well as a part of the ticket revenue.

There exist two goods: tickets and T-shirts. In period 1, the band’s popularity is given as $a_1$ and they provide a concert. After the concert, the popularity $a_2$ in period two is formed. If the band is young, they offer another concert in period 2.

The demand for concert tickets $q_t$ in period $t$ depends on the price. Ticket demand is decreasing in the ticket price, i.e. $\frac{\partial q_t}{\partial p_t} \leq 0$. At the concert venue, T-shirts with the band logo are sold at price $p_m$, which is set by the merchandiser and the band before the ticket prices are determined. The demand for T-shirts $q_{tm}$ depends on their price, but also on the demand for tickets. Since the T-shirts can be purchased only at the venue, the number of concert tickets sold can be considered equal to the number of potential T-shirt buyers. Consequently, merchandising demand is affected by the ticket price via

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10Here T-shirts represent all of the merchandising. Merchandising includes artists’ individual names, photographs, artwork identified with artists, etc. (Thall [28])
the ticket demand. I assume that both ticket demand and T-shirt demand are linear. In other words, for constant $a_t$, ticket demand $q_t$ and T-shirt demand $q_{tm}$ are:

$$q_t(p_t) = a_t - b p_t, \text{ and}$$
$$q_{tm}(p_t, p_m) = c q_t - d p_m = -bc p_t - dp_m + a t c, \ t = 1, 2,$$  \hspace{1cm} (2.1)

where $b, c > 0$ and $d \geq 0$.

Current demand affects future demand via the band’s popularity. The popularity of the band in the second period depends on the band’s popularity $a_1$ in the first period as well as ticket demand $q_1$ in the first period. I assume that there is always a positive relationship between popularity and concert attendance. In other words, if a person attends a concert of a band, the person tends to like the band and to return to the concert of the band in the future. Then

$$a_2(p_1) = a_1 + \alpha q_1(p_1), \text{ and}$$
$$q_2(p_1, p_2) = a_2(p_1) - b p_2, \text{ and}$$
$$q_{2m}(p_1, p_2) = c q_2(p_1, p_2) - d p_m.$$ \hspace{1cm} (2.2)

where $\alpha > 0$ and $b, c$, and $d$ are the same parameters as in (2.1).

I next define ticket profit, merchandising profit, and future profit, which together constitute each player’s profit. Let $\kappa$ be the fixed cost for concert production, and $\kappa_m$ be the marginal cost for T-shirt production.\footnote{In reality, the band and the venue get certain portions of the merchandising revenue, then the merchandiser, who produced the merchandise, gets the rest of the merchandising revenue.} Then the ticket profit $\Pi_t$ and the
merchandising profit $\Pi_{tm}$ are

$$
\Pi_t = p_t q_t(p_t) - \kappa, \quad \text{and}
$$

$$
\Pi_{tm} = p_m q_m(p_t) - \kappa_m q_m(p_t),
$$

where $p_m \geq \kappa_m$. Define $\Pi_f$ as the future profit of a young band. A young band gets a part of the current profits, but also will receive a part of the profits in the next period.

In the second period, the band can have a contract with a promoter who may or may not own the venue. The future profit of a young band is thus as follows:

$$
\Pi_f = \frac{\delta}{2} E \left[ \Pi_2(p_1, p_2) + \Pi_{2m}(p_1, p_2) \right],
$$

where $p_2 = \begin{cases} 
  p_2^{\tau=0}, & \text{with probability } \beta, \text{ and} \\
  p_2^{\tau=1}, & \text{with probability } (1 - \beta),
\end{cases}$

where $p_2^{\tau^*} = \arg \max_{p_2} \Pi_2(p_1, p_2) + \frac{1 + \tau^*}{2} \Pi_{2m}(p_1, p_2)$, and $0 < \delta \leq 1$ is a discount rate.

Since current ticket price $p_1$ affects the future popularity of the band, which shifts the future ticket demand and the future merchandising demand, the future profit $\Pi_f$ is a function of $p_1$ as well as future ticket price $p_2$.

Now I define each player’s profit, and describe their ticket price decision process.

First, I consider the profit of the promoter from the concert. Assume that the split ratio of the ticket sales profit as well as the merchandising profit is 1:1; and, for simplicity,
that the band and the promoter maximize joint profit. This eliminates the necessity to
model the players’ bargaining structure. Then the promoter’s profit $\Pi_p$ is:

$$
\Pi_p = \frac{1}{2} \Pi_1(p_1) + \tau \frac{1}{2} \Pi_{1m}(p_1),
$$

where $\tau = 0, 1$; where $\Pi_t$ is the profit from ticket sales; and $\Pi_{pm}$ is the merchandising
profit. A band may earn future profit which is affected by current ticket demand. Let
$\eta = 0$ for an old band and $\eta = 1$ for a young band. The band’s profit $\Pi_b$ is:

$$
\Pi_b = \frac{1}{2} \Pi_1(p_1) + \frac{1}{2} \Pi_{1m}(p_1) + \eta \Pi_f(p_1, p_2), \quad \text{where} \quad \eta = 0, 1.
$$

I assume that the promoter and the band set the ticket price for the concert where it
maximizes their joint profit (2.3):

$$
\Pi_1 + \frac{1 + \tau}{2} \Pi_{1m} + \eta \Pi_f. \quad (2.3)
$$

Since the joint profit varies over different types of players, the ticket price depends on
the types.

---

12I assume there is no capacity constraint. This is reasonable because they players have the
choice of multiple shows for each run.
2.3.2 Ticket Price

The band and the promoter maximize the joint profit (2.3), so the first order condition for the maximization problem is:  \(^1\)

\[
a_1 - 2bp_1 - \frac{1 + \tau}{2}bc(p_m - \kappa_m) + \eta \frac{\partial \Pi_f}{\partial p_1} = 0 \tag{2.4}
\]

During the first period, it is still unknown with which type of promoter a band will book. Therefore ticket price \(p_2\) in the second period takes one of two possible values, depending on the type of promoters: \(p_2^{\tau=0}\) and \(p_2^{\tau=1}\) with probability \(\beta\) and \((1 - \beta)\) respectively, where \(p_2^{\tau=0}\) is the optimal ticket price of the concert presented by a promoter who does not own the venue, and \(p_2^{\tau=1}\) is the optimal ticket price of the concert presented by the promoter who owns the venue. Then the future profit of a young band is:

\[
\Pi_f = \frac{\delta}{2} E\left[p_2q_2(p_2, p_1) - \kappa + (p_m - \kappa_m)q_{2m}(p_2, p_1)\right].
\]

The second period maximization problem in cases with different promoter types gives ticket prices \(p_2^{\tau=0}\) and \(p_2^{\tau=1}\), and the partial derivative of future profit with respect to

\(^1\)If the band and the promoter consider only their static ticket sales profits, then they will set their ticket price \(p_1\) such that maximizes \(\Pi_1\).
current ticket price can be written as follows: 14

\[
\frac{\partial \Pi_f}{\partial p_1} = -\frac{\alpha \delta}{4} \left[ a_1 + \alpha (a_1 - bp_1) + bc(p_m - \kappa_m) \right].
\]

Therefore, the optimal current ticket price \( p_1^* \) can be derived:

\[
p_1^* = \frac{1}{(8 - \alpha^2 \delta \eta)b} \left[ 4a_1 - 2(1 + \tau)bc(p_m - \kappa_m) - \alpha \delta \eta \left( a_1 + \alpha a_1 + bc(p_m - \kappa_m) \right) \right]. \quad (2.5)
\]

**Proposition 2.1 (Venue Ownership).** Suppose that the demand for tickets and the demand for T-shirts in each period are defined as (2.1) and (2.2). When a band gives a concert, the concert presented by a promoter who owns the venue for the event has a lower current ticket price than the one presented by a promoter who does not own the venue.

14 Let \( p_2^{\tau=0} \) be the optimal ticket price in the second period when the concert is presented by a promoter who does not own the venue, and \( p_2^{\tau=1} \) be the optimal ticket price in second period, when the concert is presented by the promoter who owns the venue. Then I have the maximization problems:

\[
\max p_2q_2(p_2, p_1) - \pi + \frac{1}{2}(p_m - \kappa_m)q_2m(p_2, p_1), \quad \text{and}
\]

\[
\max p_2q_2(p_2, p_1) - \pi + (p_m - \kappa_m)q_2m(p_2, p_1).
\]

Maximizing gives the following optimal ticket prices:

\[
p_2^{\tau=1} = \frac{a_1 + \alpha(a - bp_1) - bc(p_m - \kappa_m)}{2b} \quad \text{and}
\]

\[
p_2^{\tau=0} = \frac{a_1 + \alpha(a_1 - bp_1) - \frac{1}{2}bc(p_m - \kappa_m)}{2b}.
\]
Proof By equation (2.5) the difference between the optimal price in each case is

\[ p_1^{\tau=0} - p_1^{\tau=1} = \frac{2}{8 - \alpha^2 \delta \eta} c(p_m - \kappa_m). \tag{2.6} \]

Note that \((p_m - \kappa_m)\) is non-negative. Therefore, for an old band \((\eta = 0)\), equation (2.6) is positive. For a young band, since the ticket demand \(q_1\) at the optimal price is positive, \((8 - \alpha^2 \delta)\) is non-negative, consequently, \(p_1^{\tau=1}\) is lower than \(p_1^{\tau=0}\).\footnote{The ticket demand which a young band faces at their optimal ticket price is can be written as: \(q_1(p_1^{\eta=1}) = \frac{1}{8 - \alpha^2 \delta} \left[ 4a_1 + \alpha \delta a_1 + 2(1 + \tau)bc(p_m - \kappa_m) + \alpha \delta bc(p_m - \kappa_m) \right].\)} Therefore, for both a young band and an old band, the ticket price of the concert presented by a promoter who owns the venue is lower than the ticket price of the concert presented by a promoter who does not own the venue.

Proposition 2.2 (Band Age). Suppose that the demand for tickets and the demand for T-shirts in each period are defined as (2.1) and (2.2). Consider two types of bands: a young band with \(\eta = 1\) and an old band with \(\eta = 0\). The young band charges a lower ticket price than the old band.

Proof By equation (2.5) the difference between the optimal price for a young band and the optimal price for an old band can be written:

\[ p_1^{\eta=0} - p_1^{\eta=1} = \frac{1}{8(8 - \alpha^2 \delta)b} \left[ 8\alpha \delta a_1 + 4\alpha^2 \delta a_1 + 2\alpha \delta bc(p_m - \kappa_m)(\alpha(1 + \tau) + 4) \right]. \tag{2.7} \]
Since the ticket demand \( q_1(p_1^{\eta=1}) \) at the optimal price is positive, \((8 - \alpha^2\delta)\) is non-negative. Consequently, equation (2.7) is weakly positive. This fact implies that an old band charges a higher ticket price than a young band, under the linear ticket demand assumption.

\[\blacksquare\]

**Proposition 2.3.** Let \( p_1^o \) be the optimal ticket price when a promoter and a band consider only their static ticket profit. The ticket price set by a promoter and a band who consider their merchandising profit, their future profit, or both is lower than \( p_1^o \).

**Proof**

\[ p_1^o = \arg \max (a_1 - bp_1)p_1 - \pi \]

\[ p_1^o - p_1^{\eta=0} = \frac{1}{4}(1 + \tau)c(p_m - \kappa_m) \geq 0, \quad \tau = 0, 1 \]

By Proposition(2.3.2) the following inequality holds:

\[ p_1^o \geq p_1^{\eta=0} \geq p_1^{\eta=1}, \quad \tau = 0, 1. \]

Therefore, the static profit maximizing ticket price, \( p_1^o \), is higher than any ticket price set by a promoter and a band, when at least one of them considers her merchandising profit or her future profit.

\[\blacksquare\]
2.4 Data and Results

The model derived in section three predicts how the ownership of the venue or the age of a band may affect ticket price. In order to test whether those factors are important in the U.S. popular concert market, I will estimate the price equation with Pollstar Boxoffice historical data.\textsuperscript{16}

2.4.1 Data Description

The Pollstar Boxoffice historical data set contains information on venue location and capacity, gross sales, the number of attendees, ticket prices (face value), and promoters for 14,231 concerts held in the U.S. between August 1981 and April 2007.\textsuperscript{17} Artists’ information, such as debut years, musical styles, and the ages of the artists, are collected from Billboard.com, allmusic.com and the artists’ official web sites.\textsuperscript{18} Venue characteristics information, such as location and ownership, is collected from each venue’s web page and each promoter’s web page.

Table 2.1 presents summary statistics. The main variables used in this study are the number of tickets sold, ticket prices, the ages of artists, and venue capacities. All prices are real values calculated with U.S. city average Consumer Price Index (CPI) for all urban consumers with 2006 = 100.\textsuperscript{19} Here I use the age of artists when the event took place. The number of tickets sold is the total number of tickets sold for the events per show.

\textsuperscript{16} Pollstar is a company which provides concert tour schedules, music industry contact directories, and concert tour database.

\textsuperscript{17} The data set includes 72 artists, who offered comparatively many shows in different locations, among relatively prominent artists who have at least more than 1 golden album award.

\textsuperscript{18} For bands, the ages of the lead singers of the bands are used as the ages of artists.

\textsuperscript{19} CPI’s are collected from the Bureau of Labor Statistics. http://www.bls.gov/cpi/home.htm
by an artist at a venue for all dates of a given show.\footnote{About 54\% of the shows were sold out. See Figure 2.1.} Therefore, if an artist performs multiple shows at the same venue over consecutive days, the number of tickets sold may be greater than the capacity of the venue. Most of the events (61\%) were held at venues with seat capacity of between 5,000 and 30,000 (See Figure 2.2).\footnote{In this data set, 36\% of the events took place at the venue with capacity of less than 5,000 and 3\% of the events took place at the venue with capacity of greater than 30,000.}

---

\textbf{Fig. 2.1. Attendance Rate}  \hspace{2cm}  \textbf{Fig. 2.2. Capacity}

\begin{center}
\includegraphics[width=\textwidth]{attendance_rate.pdf}
\end{center}

\begin{center}
\includegraphics[width=\textwidth]{capacity.pdf}
\end{center}

In order to account for demand side information and real market situations, I use additional data. The U.S. Census Bureau provides population and per capita income for each state.\footnote{http://quickfacts.census.gov/qfd/index.html} The Recording Industry Association of America provides the numbers of awards, such as golden albums and platinum albums, for the artists, via RIAA.com.
Table 2.1. Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ticket price for the cheapest seats for each concert (2006 dollars)</td>
<td>31.90</td>
<td>14.50</td>
</tr>
<tr>
<td>Ticket price for the most expensive seats for each concert (2006 dollars)</td>
<td>49.00</td>
<td>90.60</td>
</tr>
<tr>
<td>Age of artist</td>
<td>37</td>
<td>11</td>
</tr>
<tr>
<td>Number of tickets sold (thousands)</td>
<td>11</td>
<td>17</td>
</tr>
<tr>
<td>Venue capacity (thousands)</td>
<td>12</td>
<td>17</td>
</tr>
<tr>
<td>Number of observations (thousands)</td>
<td></td>
<td>14</td>
</tr>
</tbody>
</table>

I also include information on anti-scalping laws for each state, which is provided by the National Conference of State Legislatures because ticket scalping can affect ticket prices.

2.4.2 Estimation Results

The key question is whether the future profits, the merchandising profits, or both, can be the explanation for the ticket underpricing practice in the popular music concert market. To answer this question, I estimate the following supply equation:

\[
\log(\text{ticket price}) = \alpha_1 + \alpha_2 \log(\text{attendance}) + \alpha_3 D_{\text{own}} + \alpha_4 (\text{age}) + \alpha_5 D_{\text{law}} + u.
\]

When I estimate the supply equation, I run into an endogeneity problem arising from simultaneity and omitted variables. Note that what I observe are the ticket prices and the number of attendees in equilibrium. Since these are determined simultaneously, attendance is correlated with error term \(u\), therefore the number of attendees is endogenous. I suspect that the ownership dummy is also endogenous because both ticket price and the ownership dummy may determined by such factors as attractiveness of location
and cost reference. Since these factors are not observable, these may be part of the error term $u$.

In order to deal with the endogeneity problem, I employ 2SLS estimation method allowing attendance and the ownership dummy to be endogenous with instrumental variables (IVs) which affect the endogenous variables but do not directly affect ticket price. The instrumental variables that I have chosen are population and income of the state where the event was held, how many years the artist has been playing since his/her debut, and the total number of multi-platinum album awards for each artist before the event takes place as a proxy of the popularity of an artist. These are good instruments because they are correlated with the endogenous variables, but uncorrelated with supply side error term.

Table 2.2 presents the estimation results of the price equations. Ticket prices are for the most expensive seats, the ticket price for the cheapest seats, and the average of both, after accounting for endogeneity.\footnote{Since there are six concerts which have a ticket price of zero, the number of observations used in the estimation for the cheapest ticket price is smaller than the number used in the estimation of the other ticket prices. The result for the first stage estimation is presented in Table 2.3.} The regressors are attendance, a venue ownership dummy, the age of each artist, and an anti-scalping law dummy. The number of tickets sold for each concert is used as the number of individuals attending the concert. The venue ownership dummy, $D_{own}$, is one if the venue is owned by the promoter, and zero otherwise. In order to analyze how the future profits of artists affect their ticket price decision, I use the age of an artist. In addition to the variables above, I include the anti-scalping law dummy as a regressor, since some studies on the entertainment
industry indicate that anti-scalping laws can affect ticket prices.\textsuperscript{24} The anti-scalping law dummy $D_{\text{law}}$ is one if the state where the event was held has an anti-scalping law, and zero otherwise.

\begin{table}[h]
\centering
\begin{tabular}{lcccccc}
& \multicolumn{2}{c}{log(max(price))} & \multicolumn{2}{c}{log(mid(price))} & \multicolumn{2}{c}{log(min(price))} \\
& OLS & 2SLS & OLS & 2SLS & OLS & 2SLS \\
log(attendance) & 0.16 & 0.53 & 0.15 & 0.47 & 0.12 & 0.38 \\
 & (51.48) & (25.82) & (53.07) & (25.76) & (43.9) & (21.95) \\
D(ownership) & 0.03 & -0.22 & -0.02 & -0.28 & -0.11 & -0.47 \\
 & (4.35) & (-1.67) & (-3.06) & (-2.36) & (-16.99) & (-4.23) \\
age of artist & 0.03 & 0.02 & 0.03 & 0.01 & 0.02 & 0.00 \\
 & (99.95) & (13.54) & (91.23) & (10.89) & (49.99) & (1.48) \\
D(anti-scalping law) & -0.01 & -0.07 & -0.02 & -0.06 & -0.03 & -0.06 \\
 & (-1.65) & (-4.58) & (-2.86) & (-4.96) & (-4.68) & (-4.69) \\
constant & 0.94 & -1.41 & 1.24 & -0.79 & 1.78 & 0.21 \\
 & (37.44) & (-9.15) & (56.04) & (-5.84) & (79.72) & (1.61) \\
DWH** & 365.77 & 358.69 & 270.59 & 270.59 & & \\
number of observations & 14231 & 14225 & & & & \\
\end{tabular}
\caption{2SLS Estimation of Price Equation with Instrumental Variables*}
\label{table:price_estimation}
\end{table}

* The values in parentheses are t-values.
**DWH is Durbin-Wu-Hausman Statistics (See 1.4)

The main interests of this paper are in the coefficient of the dummy for venue ownership, which indicates the effect of the merchandising profits on ticket prices, and the coefficient of the age of the artist, which suggests the effect of the future profits on ticket prices. The coefficient for the venue ownership dummy is negative and significant.

\textsuperscript{24}Williams [31] tests the effect of anti-scalping laws on ticket prices in the National Football League (NFL) and finds that the NFL charges higher prices on tickets with the absence of anti-scalping laws. Also, Depken, II [4] finds that NFL and National Baseball League (NBL) charge higher ticket prices with the presence of anti-scalping laws.
for the prices for the cheapest seats and the average prices; in other words, the ticket price for a concert presented by a promoter who owns the venue is lower than the ticket price for a concert presented by a promoter who does not own the venue. For example, the ticket price for the cheapest seats in a concert presented by a promoter who owns the venue is about 37% lower than it would be if the concert were held in a venue which is not owned by the promoter. This supports the explanation that promoters may price tickets under market clearing price in order to maximize their merchandising profits as well as ticket sales profits, because a promoter who does not own the venue does not consider merchandising profits.

For the prices for the most expensive seats and the average prices, the coefficients of the age of the artist are significant and positive. This fact implies that an older artist charges a higher ticket price than a younger artist. In the case of two artists who are identical in popularity, venue characteristics, etc., but are different ages, the older artist will charge 2% more for each year difference between their ages for the most expensive tickets. This supports the theory that artists may price tickets below static equilibrium price in order to maximize their future profits, which depend on current ticket demand, as well as their current static profits.

The estimation results also suggest that there are significant and negative effects of anti-scalping laws on ticket prices. For example, in the case of the most expensive seats, the ticket price for a concert held in a state with anti-scalping laws is about 7% lower than the ticket price for a concert in a state without anti-scalping law. This fact is consistent with Williams (1994)’s results that ticket scalping provides information about ticket demand.
2.5 Conclusion

This paper investigates the reason that promoters and bands choose their concert ticket price such that ticket resale is profitable. Even though there exists persistent excess demand in the primary ticket market, i.e., the face values of the tickets are lower than resale market prices, promoters and bands do not raise their ticket prices. In order to explain this puzzle, I modelled the ticket price decision of a promoter and a band who may consider other profit sources besides ticket sales profits. The model predicted that when the promoter and the band consider merchandising revenue as well as ticket revenue, or when the band considers their future profit as well as their current profit, they may charge a price lower than the price which maximizes their static ticket profit.

I tested the credibility of these potential explanations by estimating a ticket supply equation with Pollstar Boxoffice historical data. I found that the ticket price for a concert presented by a promoter who owns the venue is lower than the ticket price for a concert presented by a promoter who does not own the venue. This supports the theory that promoters price tickets below market clearing price in order to maximize their merchandising profits as well as ticket profits. My results imply that an older artist may charge a higher ticket price than a younger artist, provided that other conditions are the same. This supports the theory that artists may price tickets below static equilibrium price in order to maximize their future profit, which depends on current ticket demand, as well as their current static profits.

The estimation results suggest that the existence of ticket resale markets may affect the price decision in the primary market. A valuable extension of the model in
this paper would add the secondary market. This addition would necessitate introducing demand uncertainty into the primary market. My future research plans include developing this model as well as an estimation of the effects of the secondary market on the primary ticket sales market.
Table 2.3. First Stage Regression\(^*\)

<table>
<thead>
<tr>
<th></th>
<th>log(attendance)</th>
<th>D(ownership)</th>
</tr>
</thead>
<tbody>
<tr>
<td>the age of the artist</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(16.70)</td>
<td>(-1.03)</td>
</tr>
<tr>
<td>D(anti-scalping law)</td>
<td>0.10</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(4.72)</td>
<td>(2.94)</td>
</tr>
<tr>
<td>log(population)</td>
<td>0.06</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>(5.76)</td>
<td>(4.92)</td>
</tr>
<tr>
<td>log(per capita income)</td>
<td>0.39</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>(5.56)</td>
<td>(6.98)</td>
</tr>
<tr>
<td># of multi-platinum albums</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(26.52)</td>
<td>(-4.82)</td>
</tr>
<tr>
<td>(event year) - (debut year)</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(-0.62)</td>
<td>(-0.69)</td>
</tr>
<tr>
<td>constant</td>
<td>1.73</td>
<td>-2.38</td>
</tr>
<tr>
<td></td>
<td>(2.21)</td>
<td>(-7.00)</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.26</td>
<td>0.01</td>
</tr>
</tbody>
</table>

* The values in parentheses are t-values.
Chapter 3

The Size of the Affiliation Effect

3.1 Introduction

It was traditionally believed that in order to differentiate empirically between the private and common value paradigms in first price sealed bid auctions, it was sufficient to explore the variation in bids in terms of the number of bidders \( n \) (see e.g. Gilley and Karels [7]). The belief was that if bids are anywhere decreasing in \( n \), then the implication is that the common value paradigm applies because the winner’s curse only occurs in common value models. This belief is correct if the number of bidders is exogenous, there is no heterogeneity in the value distributions across auctions and bidders’ information/values are independent of each other (conditional on the common value). The need for exogeneity of \( n \) and the absence of auction–specific heterogeneity (that cannot be corrected by conditioning on covariates) were well–known. What was not known until recently, however, is that dependence across values/signals within a given auction also invalidates this practice. Pinkse and Tan [26] have shown that if signals in a private
value model are affiliated,\footnote{See 1.2.} then bids can be decreasing in the number of bidders due to an affiliation effect. Hence, even under favorable circumstances, a structural approach, such as Paarsch [21], Haile, Hong and Shum [9] or Hortacsu and Kastl [14], appears necessary. The purpose of this chapter is to estimate the size of the affiliation effect relative to that of other effects and in particular to see whether the affiliation effect can realistically offset the competition effect in practice. The discussion below assumes symmetry across bidders.

Pinkse and Tan [26] identify two separate effects to explain the variation in bids in private value models (without unobserved heterogeneity) due to exogenous variation in \( n \), namely the competition effect and the affiliation effect. In common value models, there is an additional effect, namely the winner’s curse effect. The competition effect arises because an increase in the number of bidders increases the degree of competition for the object, thereby causing a bidder to bid more at a given level of her private value (or signal). The winner of a (pure) common value auction has a signal that is higher than that of her rivals and hence the true unknown value of the object is likely less than her signal suggested. The greater is the number of rivals, the larger (in a probabilistic sense) is the discrepancy between the true value of the object and the winner’s signal, which causes bidders to bid less as \( n \) increases. Because in private value models bidders know the value of the object, the winner’s curse effect is absent in private value models.

Like the winner’s curse effect, the affiliation effect involves the use of the discrepancy between prior and posterior knowledge but, unlike the winner’s curse effect, the affiliation effect is strategic in nature. Pinkse and Tan [26] give the example of a modern
art auction in an affiliated private value model setting. Suppose that there are two states of the world. In one of these states, the distribution of tastes in the population from which bidders are drawn at random is such that most people dislike a given painting (state L). In the other state (state H) tastes are more evenly distributed. Assume that bidders do not know which state applies; they assign a prior probability to each state which depends on their private value. A bidder knows that if she wins the auction, then the posterior probability of state L exceeds her prior probability of state L. Further, the posterior probability of state L is increasing in $n$. And because her bid is decreasing in the probability of state L (she bids less if her perceived probability of being in state L is greater), she will bid less when $n$ is greater. So with the winner’s curse effect, the event of winning the auction provides information about the ex post (common) value of the object to the winner, whereas with the affiliation effect it provides information about the value distribution of the other bidders. Please note that for the affiliation effect to exist in the above example, there must be dependence across signals, which is generated by the state of the world variable. In an independent private value model, there is nothing to learn about the state of the world from the event of winning, so the affiliation effect is then zero.

If instead of analyzing the variation of bids as a function of $n$, one considers the variation of price (the winning bid) as a function of $n$, then an additional effect arises: the sampling effect; see Pinkse and Tan [26]. The reason for this effect is that the highest value/signal in auctions with $n + 1$ bidders exceeds that in auctions with $n$ bidders in $1/\binom{n+1}{1} = 1$ out of $n+1$ cases. Pinkse and Tan [26] have shown analytically that the affiliation effect
can exceed the competition effect, but have not been able to show that the affiliation
effect can (or cannot) exceed the sum of the competition and sampling effects.

Here we estimate the affiliation, competition and winner’s curse effects using the
Outer Continental Shelf (OCS) data set of drilling rights in the Gulf of Mexico. Details of this data set are provided in section 3.4. We use the OCS data set for several reasons. First, the data set is rich in the sense that the number of objects is large, all bids are observed and (this is rare) it contains data on ex post revenues. Further, all bidders are (mostly large) oil companies, so some of the usual concerns relating to inexperienced bidders and credit constraints are mitigated, albeit that the analysis here does have limitations, which are spelled out in section 3.5. The OCS data set is moreover well–known and has been used in a number of existing papers, including Hendricks, Pinkse and Porter [12] and Li, Perrigne and Vuong [18]. Finally, although the OCS data is analyzed using the tools of affiliated private value models in one paper (Li, Perrigne and Vuong [18]), the OCS mineral rights auctions are generally considered to be common value auctions.

We will proceed with the definition of the objects of estimation in section 3.2, discuss their estimation in section 3.3, and present our estimation results in section 3.6.

3.2 The Effects

Consider a first price pure common value auction with \( n \) symmetric bidders and a reserve price \( r \). Let \( X = X_1 \) denote the signal of bidder 1 (one) and \( Y = \max(X_2, \ldots, X_n) \) the maximum signal of bidders 2, \ldots, \( n \), and \( V \) the common value of
the object. Assume that, conditional on the common value, the signals are drawn independently, i.e. the signals are independent conditional on \( V \). Assume that the joint support of the signals is the \( n \)-fold Carthesian product of \([0, \bar{x}]\), where \( 0 \leq r < \bar{x} < \infty \).

Assume further that the conditional distribution of \( Y \) given \( X \) is continuous with distribution function \( F_n(y|x) = F_{Y|X;n}(y|x) \) and corresponding density function \( f_n(y|x) \).

Then by theorem 14 of Milgrom and Weber [20], the bid function for any \( r \leq x \leq \bar{x} \) is given by

\[
B_n(x) = \int_r^x w_n(t)R_n(t) \exp\left(-\int_t^x R_n(s)ds\right)dt, \tag{3.1}
\]

where \( w_n(x) = E(V|X = x, Y = x; n) \) and \( R_n(x) = f_n(x|x)/F_n(x|x) \). See the derivation of the equilibrium bid function in 1.2.

Given symmetry and given that signals are drawn independently conditional on \( V \), it follows that the joint distribution function \( F_{XY;n}(x,y) \) of \( X, Y \) is given by

\[
F_{XY;n}(x,y) = P(X \leq x, Y \leq y; n) = P(X_1 \leq x, \ldots, X_n \leq y)
= E\left(P(X_1 \leq x, \ldots, X_n \leq y|V)\right) = E\left(P(X_1 \leq x|V) \prod_{i=2}^n P(X_i \leq y|V)\right)
= E(H(x|V)H^{n-1}(y|V)) = \int H(x|v)H^{n-1}(y|v)dG(v),
\]

where \( G \) is the distribution function of \( V \). Hence

\[
F_n(y|x) = P(Y \leq y|X = x; n) = \frac{\partial F_{XY;n}(x,y)}{f_X(x)} = \frac{\int h(x|v)H^{n-1}(y|v)dG(v)}{\int h(x|v)dG(v)},
\]
where \( f_X(x) \) is the density function of \( X \). Thus,

\[
f_n(y|x) = (n - 1) \frac{\int h(x|v) h(y|v) H^{n-2}(y|v) dG(v)}{\int h(x|v) dG(v)},
\]

such that

\[
R_n(x) = \frac{f_n(x|x)}{F_n(x|x)} = (n - 1) \frac{\int H^{n-2}(x|v) h^2(x|v) dG(v)}{\int H^{n-1}(x|v) h(x|v) dG(v)}.
\]

The only missing component to determine the bid function in (3.1) is \( w_n(x) \). Since by Bayes’ theorem,

\[
E(V|X = x, Y = y) = \frac{\int vf_{XY|V}(x, y|v) dG(v)}{f_{XY|V}(x, y)} = \frac{\int vH^{n-2}(y|v) h(x|v) h(y|v) dG(v)}{\int H^{n-2}(y|v) h(x|v) h(y|v) dG(v)},
\]

it follows that

\[
w_n(x) = \frac{\int vH^{n-2}(x|v) h^2(x|v) dG(v)}{\int H^{n-2}(x|v) h(x|v) dG(v)}.
\]

Pinkse and Tan [26] showed that the change in bid \( B_n(x) \) for a given signal \( x \) due to a change in \( n \) can be decomposed into three additive terms provided that \( n \) is treated as a continuous variable. We follow Pinkse and Tan [26] here and write

\[
\frac{\partial B_n}{\partial n}(x) = \mathcal{E}_{CE;n}(x) + \mathcal{E}_{WC;n}(x) + \mathcal{E}_{AE;n}(x),
\]

(3.2)

where the right hand side terms are the competition, winner’s curse and affiliation effects, respectively. The affiliation effect due to a change from \( n \) to \( n + 1 \) bidders at \( x \) is then the integral over \( \mathcal{E}_{AE;n}(x) \) from \( n \) to \( n + 1 \) with \( x \) fixed, which in most instances will
be between $\mathcal{E}_{AE;n}$ and $\mathcal{E}_{AE;n+1}$ and fairly close to both. Here we concentrate on the
computation of each of the right hand side terms in (3.2).

The effects definitions below are those of Pinkse and Tan [26]. As mentioned
in the introduction, the winner’s curse effect measures the change in expected ex post
revenue (conditional on winning) due to a change in $n$ and is hence defined as

$$
\mathcal{E}_{WC} = \int_r^x \frac{\partial w_n(t)}{\partial n} R_n(t) \exp\left(-\int_t^x R_n(s) ds\right) dt.
$$

(3.3)

Both the competition effect and the affiliation effect are related to the way $R_n$ changes
with $n$. Indeed, by (3.2) and (3.3),

$$
\mathcal{E}_{CE} + \mathcal{E}_{AE} = \int_r^x w_n(t) \left(\frac{\partial R_n(t)}{\partial n} - R_n(t) \int_t^x \frac{\partial R_n(s)}{\partial n} ds\right) \exp\left(-\int_t^x R_n(s) ds\right) dt.
$$

(3.4)

The affiliation effect incorporates the change in $R_n$ due to changes in the (posterior)
distribution of $V$ conditional on winning whereas with the competition effect we use the
change in $R_n$ with the posterior distribution equal to the prior distribution. Let

$$
Q(y|x) = F_{Y|X;n=2}(y|x) = \frac{\int H(y|v) h(x|v) dG(v)}{\int h(x|v) dG(v)},
$$

(3.5)

and $q(y|x)$ the corresponding density function. $Q$ is the marginal distribution (function)
of a rival’s signals that a bidder infers from its signal $x$ alone. Define $R_{Qn} = (n - 1)q(x|x)/Q(x|x)$, which is the $R$–function in an independent private value model in
which private values (signals here) are drawn from $Q$. Then

$$\frac{\partial R_n}{\partial n}(x) = \frac{\partial R_Q}{\partial n}(x) + \left( \frac{\partial R_n}{\partial n}(x) - \frac{\partial R_Q}{\partial n}(x) \right),$$

(3.6)

which leads to

$$E_{CE} = \int_r^x w_n(t) \left( \frac{\partial R_Q}{\partial n}(t) - R_n(t) \int_t^x \frac{\partial R_Q}{\partial n}(s) \, ds \right) \exp \left( - \int_t^x R_n(s) \, ds \right) \, dt,$$

(3.7)

and

$$E_{AE} = \int_r^x w_n(t) \left( \left( \frac{\partial R_n}{\partial n}(t) - \frac{\partial R_Q}{\partial n}(t) \right) - R_n(t) \int_t^x \left( \frac{\partial R_n}{\partial n}(s) - \frac{\partial R_Q}{\partial n}(s) \right) \, ds \right)$$

$$\times \exp \left( - \int_t^x R_n(s) \, ds \right) \, dt.$$ (3.8)

We now turn to the question of how to estimate $E_{WC}, E_{CE}$ and $E_{AE}$ defined in equations (3.3), (3.7) and (3.8)

3.3 Estimation

3.3.1 Normalization

To estimate the three effects defined in section 3.2 it suffices to estimate $H(x|v)$ and $h(x|v)$ at all values of $x, v$. Although the OCS data set provides us the luxury of having data on ex post revenue $V$, we do not observe bidders' signals, only their bids. In fact, although in independent private value models the private values can be recovered using a method like that of Guerre, Perrigne and Vuong [8], the signal distributions in
common value models are not identified, not even in pure common value models, so there is no hope of recovering the actual signals.

To see that this is true, suppose that a new set of signals $X_1^*, \ldots, X_n^*$ is for some monotonic function $m$ defined by $X_i^* = m(X_i)$ for $i = 1, \ldots, n$. If $\eta_n, \eta_n^*$ are the old and new inverse bid functions, respectively, then the new profit function bidders maximize is

$$E[(V - b)I(Y^* \leq \eta_n^*(b))|X^* = x^*] = E[(V - b)I(Y \leq m^{-1}(\eta_n^*(b)))|X = m^{-1}(x^*)],$$

so $\eta_n(b) = m^{-1}(\eta_n^*(b))$ such that $B_n^*(x^*) = B_n(m^{-1}(x^*)) = B_n(x)$. So arbitrary monotonic transformations of all signals do not change the bids and hence the signal distributions are not identified.

It is however possible to apply a normalization such that the signal distributions are identified. We follow Hendricks, Pinkse and Porter [12] in using the normalization

$$E(V|X = x) = x. \quad (3.9)$$

To see how (3.9) helps, note that

$$\eta_n(b) = E(V|X = \eta_n(b); n) = E(V|B = b; n),$$

so the inverse bid distribution is then identified.
3.3.2 Nonparametric Estimation

Our nonparametric estimation strategy is simple. We estimate all conditional means and their derivatives by their nonparametric kernel estimation counterparts (see 1.4). $X_i$ is the $i$-th signal, $B_i$ is the corresponding bid, and likewise for other symbols.

Thus, $\hat{X}_i = \hat{\eta}_n(B_i)$, where

$$\hat{\eta}_n(b) = \frac{\sum_{i=1}^{N} V_i k((b - B_i)/a_1)}{\sum_{i=1}^{N} k((b - B_i)/a_1)}, \quad (3.10)$$

where $k$ is a kernel and $a$ a bandwidth. Using the estimated signals $\hat{X}_{ti}$ we then estimate $H$ and $h$ by

$$\hat{H}(x|v) = \begin{cases} \frac{\sum_{i=1}^{N} I(V_i < 0) K((x-X_i)/a_2)}{\sum_{i=1}^{N} I(v_i \leq 0)}, & \text{if } v \leq 0 \\ \frac{\sum_{i=1}^{N} I(V_i > 0) K((x-X_i)/a_2) k((v-V_i)/a_3)}{\sum_{i=1}^{N} I(V_i > 0) k((v-V_i)/a_3)}, & \text{if } v > 0 \end{cases}, \quad (3.11)$$

and

$$\hat{h}(x|v) = \begin{cases} \frac{\sum_{i=1}^{N} I(V_i \leq 0) k((x-X_i)/a_2)}{\sum_{i=1}^{N} I(V_i \leq 0)}, & \text{if } v \leq 0 \\ \frac{\sum_{i=1}^{N} I(V_i > 0) k((x-X_i)/a_2) k((v-V_i)/a_3)}{\sum_{i=1}^{N} I(V_i > 0) k((v-V_i)/a_3)}, & \text{if } v > 0 \end{cases}, \quad (3.12)$$

The functions $\hat{H}, \hat{h}$, together with a similar estimator $\hat{w}_n \ (\text{and } \partial \hat{w}_n / \partial n)$, are then used in lieu of $H, h, w_n$ in equations (3.3), (3.7) and (3.8).

As in some other nonparametric estimation problems, there is a boundary problem here which arises because of the implicit discontinuity in a density or regression function when either is nonzero at the boundary of the regressor support. Guerre, Perrigne and Vuong [8] resolve this by ignoring signals close to the boundary and Gabrielli and
Vuong [6] do likewise using local polynomials, both in a much simpler setting than the present one. We instead use boundary kernels, as introduced in equation (1.5).

### 3.3.3 Confidence Bands

For each function we construct confidence bands by means of the bootstrap (see e.g. Horowitz [13] and section 1.5). We do so because obtaining analytic critical values in the present context is difficult. Since the object that is bootstrapped is nonpivotal, i.e. it depends on unknown population quantities, no asymptotic refinements obtain, i.e. the accuracy of the confidence bands is no better than those obtained using first order asymptotic theory. The confidence bands are pointwise, not uniform, in that we took the 95% quantile of the bootstrap sample estimates at each individual point.

### 3.4 Data

As mentioned earlier, we use the OCS data set, available from the Center for the Study of Auctions, Procurements and Competition Policy website, to carry out our analysis. The OCS data set contains the results of all auctions of drilling rights in the Outer Continental Shelf, an area of sea off the coasts of Louisiana and Texas, from 1954 onwards. At each auction (drilling rights to) a large number of tracts were sold off simultaneously, each of the tracts going as an individual lot.\(^2\) Oil companies submit sealed bids and the tract is assigned to the highest bidder, except in cases in which the announced reserve price is not met (exceedingly rare) or in which the government decided to refuse the bid (occurred mostly if there were too few bids). The winner of each tract

\(^2\)There are a few cases in which tracts were subdivided into blocks or zones.
obtains the right to drill on the specified tract. If the winner does not commence drilling within five years, then the mineral rights revert to the government, otherwise she will have the right to all minerals until the resources of the tract are depleted.

The data set contains characteristics of the tract offered, including its size (almost invariably 5,000 acres) and location, all bids, bidder identities and even production data. Like Hendricks, Pinkse and Porter [12], we limit ourselves to tracts auctioned between 1954 and 1970, inclusive, to limit the effect of the first oil crisis and to avoid complications due to major technological advances from the late 1970’s onward. We further only consider wildcat tracts, i.e. tracts in whose vicinity no drilling has taken place prior to its sale, again to improve the ex ante degree of homogeneity across tracts.

The information available to bidders prior to the sale is hence limited to some preliminary seismic studies they may have conducted and is hence similar across bidders. There are twelve large firms participating and a large number of fringe firms, which win only a small fraction of the total number of tracts. Like Hendricks, Pinkse and Porter [12] we hence only use bids submitted by the big twelve firms.

Our remaining data set consists of a total of 3363 bids on 1168 tracts. Summary statistics can be found in tables 3.1–3.3. To control for some tract-specific heterogeneity we follow Hendricks, Pinkse and Porter [12] and analyze tracts with a high (seven or more) number of potential bidders separately from those with a low number of potential bidders. A bidder is classified as a potential bidder for a given tract if she bid on the tract in question or a neighboring tract at or before the time of the auction. The net revenue figures are computed by computing the discounted future revenue stream and
subtracting estimated drilling costs (if drilling took place) and royalty rates. All amounts are in 1982 dollars.

<table>
<thead>
<tr>
<th># of potential bidders</th>
<th># of bids</th>
<th># of tracts</th>
<th># of potential bidders</th>
<th># of bids</th>
<th># of tracts</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>41</td>
<td>41</td>
<td>7</td>
<td>416</td>
<td>136</td>
</tr>
<tr>
<td>2</td>
<td>92</td>
<td>69</td>
<td>8</td>
<td>435</td>
<td>148</td>
</tr>
<tr>
<td>3</td>
<td>176</td>
<td>107</td>
<td>9</td>
<td>712</td>
<td>175</td>
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<tr>
<td>4</td>
<td>118</td>
<td>66</td>
<td>10</td>
<td>562</td>
<td>144</td>
</tr>
<tr>
<td>5</td>
<td>219</td>
<td>89</td>
<td>11</td>
<td>311</td>
<td>81</td>
</tr>
<tr>
<td>6</td>
<td>234</td>
<td>97</td>
<td>12</td>
<td>47</td>
<td>15</td>
</tr>
<tr>
<td></td>
<td>880</td>
<td>469</td>
<td></td>
<td>2483</td>
<td>699</td>
</tr>
</tbody>
</table>

As one would expect, tracts with a high number of potential bidders are on average more valuable, have more bidders and higher bids than tracts with a low number of potential bidders. Bids and revenues are moreover highly dispersed. Indeed, Hendricks, Pinkse and Porter [12] found that even on a single tract log bids rather than bids are approximately symmetrically distributed. So bidders face substantial uncertainty about the value of a tract.

3.5 Limitations

We have made a number of assumptions to keep our analysis tractable, but which may not hold in practice. We have assumed bidders to be symmetric even though the oil companies in question differ in size, often participate in consortia and include
### Table 3.2. Summary Statistics for Tract Data

<table>
<thead>
<tr>
<th></th>
<th>low $\ell$ tract</th>
<th>mean</th>
<th>stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>net revenue</td>
<td>7.63</td>
<td>3.39</td>
<td></td>
</tr>
<tr>
<td>actual number of bidders</td>
<td>1.88</td>
<td>1.18</td>
<td></td>
</tr>
<tr>
<td>winning bids</td>
<td>2.89</td>
<td>4.64</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>high $\ell$ tract</th>
<th>mean</th>
<th>stdev</th>
</tr>
</thead>
<tbody>
<tr>
<td>net revenue</td>
<td>12.08</td>
<td>44.62</td>
<td></td>
</tr>
<tr>
<td>actual number of bidders</td>
<td>3.55</td>
<td>2.26</td>
<td></td>
</tr>
<tr>
<td>winning bids</td>
<td>9.04</td>
<td>14.30</td>
<td></td>
</tr>
</tbody>
</table>

*Net revenues are in $1,000,000 (1982).*

a large number of infrequently participating fringe firms. We have also assumed the number of bidders to be exogenous for a given number of potential bidders. Related to this, we ignore the presence of a reserve price in our estimations. Further, there may be unobserved heterogeneity across tracts. Finally, the assumption of a pure common values model excludes the presence of cost differences across firms and affiliation is an extreme assumption on the signal dependence structure.

But the theory for common value auctions with asymmetric bidders is not well-developed and is beyond the scope of our current analysis and affiliation is a standard assumption in the literature. We have no information on the nature of any possible unobserved heterogeneity, so any attempt at modelling it here would be ad hoc and arbitrary, would complicate the estimations and could well lead to less accurate estimates. The reserve price in the OCS auctions is set very low and ignoring it is unlikely to affect our conclusions qualitatively.
Table 3.3. Summary Statistics for Bid Data

<table>
<thead>
<tr>
<th></th>
<th>low ℓ tract</th>
<th>high ℓ tract</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>stdev</td>
</tr>
<tr>
<td>bids</td>
<td>2.02</td>
<td>3.14</td>
</tr>
</tbody>
</table>

*Bids are in $1,000,000 (1982).

The most serious limitation here is the assumption of an exogenous entry decision. Entry can be endogenous because tracts that have a higher value ex ante on average attract more bidders and have a higher value ex post. Conditioning on the number of potential bidders mitigates but does not remove this effect.

As stated in the introduction, the objective here is to determine whether the affiliation effect is of the same order of magnitude as the competition and winner’s curse effects. Endogeneity of $n$ can have a large effect on the winner’s curse effect estimates, especially when a larger number of bidders is associated with higher tract values, as is the case here.\(^3\) It is more difficult to see how it can substantively change the affiliation and competition effects since both effects only depend on the relationship between signals and ex post value, not on the relationship between ex post value and the number of bidders. For the purpose of this paper, it hence suffices to make an order–of–magnitude comparison between the competition and affiliation effects.

\(^3\)See the tables in Hendricks, Pinkse and Porter [12] for more detailed information.
3.6 Results

The estimation results are depicted in figures 3.1 through 3.12. They are organized by the number of potential bidders $\ell$, the number of actual bidders $n$ and the type of effect (competition/winner’s curse/affiliation). Each graph contains separate curves for the estimated curve and (one–sided) bootstrapped confidence bands, both 90% and 95%.

It is evident from the distance between the estimates and the corresponding confidence bands that our estimates are inaccurate. Although our data set is large, this is not surprising because bids and revenues (even conditional on each other) are highly variable and our estimation procedure consists of several steps, each one involving nonparametric estimation. A second observation is that in most instances the estimated effects are significantly different from zero, albeit not always by much.

The most interesting aspect of the comparison, however, is that the affiliation effect appears small compared to the winner’s curse and competition effects. As mentioned earlier, in the case of the winner’s curse effect this may be due to endogeneity of the number of bidders, which we do not address here. But at least in this application it appears unlikely that the affiliation effect would often offset the competition effect.
Fig. 3.1. Affiliation Effect for low $\ell$ tracts (n=3)

Fig. 3.2. Affiliation Effect for low $\ell$ tracts (n=5)

*blue solid line: 95% quantile, blue dotted line: 90% quantile.
Fig. 3.3. Competition Effect for low ℓ tracts (n=3)

*blue solid line: 95% quantile, blue dotted line: 90% quantile

Fig. 3.4. Competition Effect for low ℓ tracts (n=5)
Fig. 3.5. Winner’s Curse Effect for low $\ell$ tracts ($n=3$)

*blue solid line: 95% quantile, blue dotted line: 90% quantile

Fig. 3.6. Winner’s Curse Effect for low $\ell$ tracts ($n=5$)
Fig. 3.7. Affiliation Effect for high $\ell$ tracts ($n=4$)

Fig. 3.8. Affiliation Effect for high $\ell$ tracts ($n=6$)

*blue solid line: 95% quantile, blue dotted line: 90% quantile
Fig. 3.9. Competition Effect for high $\ell$ tracts ($n=4$)

*blue solid line: 95% quantile, blue dotted line: 90% quantile

Fig. 3.10. Competition Effect for high $\ell$ tracts ($n=6$)
Fig. 3.11. Winner’s Curse Effect for high $\ell$ tracts (n=4)

*blue solid line: 95% quantile, blue dotted line: 90% quantile

Fig. 3.12. Winner’s Curse Effect for high $\ell$ tracts (n=6)
Appendix A

The Confidence Bands

We follow the following bootstrap procedure to obtain the confidence bands for specific estimators in 3.6. First, we randomly draw $T$ tract numbers, where $T$ is the number of tracts in our original sample. Then, a random sample is constructed with the bids for the drawn tracts. We estimate the three effects with this sample and label them $\hat{E}_{WC}^1$, $\hat{E}_{CE}^1$, and $\hat{E}_{AE}^1$. Note that the number of observations $N$ can be different for each sample because the number of bids for each tract can be different from one another. We repeat this procedure $S = 1000$ times, and compute the three effects for each bootstrap iteration. Those estimates are ordered by their magnitudes at each $x$ point. We obtain 95% and 90% confidence intervals for $\hat{E}_{AE}$ and $\hat{E}_{WC}$ by finding 95 and 90 percentiles of $\{\hat{E}_{AE}^s, \hat{E}_{WC}^s : s = 1, \cdots, S\}$. The 95% and 90% confidence intervals for $\hat{E}_{CE}$ are constructed with 5% and 10% percentiles of $\{\hat{E}_{CE}^s : s = 1, \cdots, S\}$. 
References


Vita

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