EMPIRICAL ANALYSIS OF USED CONSTRUCTION EQUIPMENT AND AUCTION HOUSE REVENUES

By

SRINIVASA SASDHAR PONNALURU

A dissertation submitted in partial fulfillment of
the requirements for the degree of

DOCTOR OF PHILOSOPHY

WASHINGTON STATE UNIVERSITY
School of Economic Sciences

DECEMBER 2009

To the Faculty of Washington State University:

The members of the Committee appointed to examine the dissertation of SRINIVASA SASDHAR PONNALURU find it satisfactory and recommend that it be accepted.

Thomas L. Marsh, Ph.D., Chair

Ron C. Mittelhammer, Ph.D.

Jonathan K. Yoder, Ph.D.

ACKNOWLEDGMENT

I would like to extend my most sincere gratitude and respect to Dr. Thomas L. Marsh, my major advisor and chair of my doctoral committee, whose guidance, insightful discussions, and encouragement helped me at all times during the research and writing of this dissertation. His endless support, positive attitude and valuable advice made this dissertation possible. I consider it an honor to be one of his students.

I am also very grateful to Dr. Ron Mittelhammer. His insights and advice had great influence on the direction of my research and helped a great deal in improving the quality of this dissertation. I also extend my thanks to Dr. Jonathan K. Yoder for his constructive suggestions and professional contributions to my manuscripts and final dissertation. I would like to thank Dr. Gunnar Lucko for his valuable insights on the data. I also would like to thank Dr. Douglas Young and Dr. Tauhidur Rahman for their support and guidance.

I am very grateful and indebted to my Guru - His Holiness Sri Sri Sri Ganapathi Sachchidananda Swamiji and His Holiness Sri Datta Vijayananda Teertha Swamiji for providing me with spiritual and divine support throughout my entire life. I am also thankful to His Holiness Sri Sri Sri Ganapathi Sachchidananda Swamiji as his music for meditation and healing kept my mind sharp and focused on my goals even during challenging times.

I would like to thank all the teachers and professors who taught me throughout my entire education from preschool to PhD, without whose help, I would not have reached this level in my life. I am thankful to Han Quek and Wesley Andrews of Graduate and Professional Writing Center for providing me valuable suggestions and comments on my dissertation draft.

Finally, I would like to thank my family members – my parents, my brothers and sisters in law, and my wife Akula and my daughter Anagha for their love, inspiration and support throughout my life, without whom I would never have been able to reach this stage in life. I would like to specially thank my elder brother Sri Ravichandra Ponnaluru for providing me with spiritual and personal guidance. I am also grateful to him for teaching me valuable techniques in SQL and computer programming.

EMPIRICAL ANALYSIS OF USED CONSTRUCTION EQUIPMENT AND AUCTION HOUSE REVENUES

Abstract

by Srinivasa Sasdhar Ponnaluru, Ph.D.
Washington State University
December 2009

Chair: Thomas L. Marsh

This dissertation consists of three separate papers (as Chapters1, 2 and 3). The first chapter deals with a spatial hedonic price analysis of used excavators. Chapter 2 deals with empirical estimation of functions for auction house revenue. Chapter 3 deals with empirical analysis of price relationships in a multi-item, multi-type auction.

The objective of the first paper is to specify and estimate a spatial hedonic price function for used excavators sold by auction in North America from 1996 to 2005. The results indicate that prices of used excavators differ significantly for various reasons. Not surprisingly, prices vary by region of sale, physical condition, and brand of the equipment. We also find that prices are different between auction houses themselves. Furthermore, there exist 'within sale' spatial effects on the selling price that are statistically significant. Auction houses, besides providing auctioneering service to sellers and bidders, can influence selling prices in the auctions for used construction equipment.

The objective of the second paper is to quantify the effects of multiple units of items and to identify the influence of different types of items on auction revenue. The results indicate that auction revenues increase with an increasing rate for some items (graders) and with a decreasing rate for others (excavators and wheel loaders). Magnitude of effects varies from auction house to auction house, which, might be due to heterogeneity in the groups of bidders across auction houses. Cross quantity spillover effects also vary in magnitude and direction from auction house to auction house.

Auction houses stage events where sellers offer for sale multiple units of an item, items of different types, and items in various physical conditions. Objective of the third paper is to specify and estimate theoretically consistent inverse supply functions for multi-unit and multi-type auctions. It is hypothesized that price complementarities exist between different items being offered at an event, offering opportunity for auction houses to exploit price relationships by preselecting the number, type and condition of equipment. Normalized quadratic inverse supply functions are estimated for different types of equipment, and hypothesis are tested using transaction level, time series cross section data on equipment sales from 1996 to 2006.

Table of Contents

List of Tables

List of Figures

Dedication

This dissertation is dedicated to

my Guru

His Holiness Sri Sri Sri Ganapathi Sachchidananda Swamiji

and to

His Holiness Sri Datta Vijayananda Teertha Swamiji

Introduction

This dissertation consists of three separate papers (Chapters 1, 2 and 3). The first chapter deals with hedonic price analysis of used excavators. Chapter 2 deals with empirical estimation of functions for auction house revenue. Chapter 3 deals with empirical analysis of price relationships between different items at a multi-type auction. Each chapter is self contained with all sections including the introduction, review of relevant literature, methodology and conclusions.

An extensive panel data set was constructed for this dissertation. Data for this study was obtained from *Equipmentwatch.*[1] The raw data set comprised of 465,000 observations. The data was organized into a *SAS* database. Data management tasks such as creating new tables, adding and updating variables, deleting duplicate records, and removing corrupt data was performed by *SQL* (*SAS SQL)*. The refined data set contained 275,000 observations. The data spans over 11 years from 1996 to 2006 and comprises of records on selling price, physical condition, auction house, place (location) and date of sale, year of manufacture of the item (equipment) for various types of equipment such as excavators, trucks, crawler tractors, wheel loaders, wheel tractors and graders. Estimation of models was performed using *SAS system* by a combination of *SAS SQL* and *SAS MACROs* in *SAS IML*. Descriptive statistics of these data are presented in the studies ahead. These data provide an information basis for the current dissertation and a foundation for future research in this area.

Chapter 1:

Prices of used construction equipment have not been widely studied. Every year at least USD 100 billion worth of used construction equipment is bought and sold worldwide (RBA

[1] Equipment watch website –www.equipmentwatch.com

2007). In 2007, 5% of all used construction equipment sales were by auctions (RBA 2007). Typically a single sale at *Ritchie Brothers Auctioneers* (RBA) generates around 27 million USD in revenues and RBA holds around 130 such auctions each year. The price of used construction equipment sold at an auction ranges from USD 800 to USD 600,000 depending on its characteristics like physical condition of the equipment, brands, region of sale, auctioneer or auction house that offers it for sale. It remains to be investigated as to what factors or characteristics influence the prices. Chapter 1 addresses these questions by specifying and estimating a hedonic price function. The objective of the study in Chapter 1 is to specify and estimate a spatial hedonic pricing model for used construction equipment, in particular - excavators.

The results indicate that prices are affected by factors like geographical region, physical condition, and brand of equipment. We also test for two different spatial effects, neighborhood and within sale effects. The neighborhood effects arise due to auctions at nearby locations and 'within sale' effects due to the influence of similar items being sold at the same auction site. We find that within sale effects are predominantly significant. The results of the study also indicate that prices of equipment sold at different auction houses are significantly different after controlling for other quality effects.

Chapter 2:

Auction houses, besides offering auctioneering services, play a significant role in the sales. They might influence the price by the way of reputation effects, efficient management, economies of scale, or by the nature of auction house itself. Auction revenues differ between auction houses, as selling prices of items differ significantly between auction houses. It is yet to be investigated as to how additional units of an item and different types of items influence auction revenues. We address these questions by estimating a revenue function (generalized quadratic) for auction houses is estimated using time series cross section data from (1996 through 2006) to quantify the effects of items and to identify the influence of different types of items on auction revenue. The results indicate that auction revenues increase with an increasing rate for some items (graders) and with a decreasing rate for others (excavators and wheel loaders). Magnitude of the effects varies from auction house to auction house, which, might be due to heterogeneity in the groups of bidders across auction houses. Cross quantity spillover effects also vary in magnitude and direction from auction house to auction house.

Chapter 3:

Auctions for used construction equipment are of multi-item type where different types of equipment like excavators, trucks, crawler tractors etc., differing in characteristics is offered at a single event. Spillover effects from the sale of items of a particular type (e.g., trucks) on to items of a different type (e.g., excavators) may exist which may be exploited by auction houses, sellers and buyers. It is yet to be investigated as to whether complementary/substitute relationships exist between prices of different items. We use transaction level data on equipment auction sales from 1996 to 2006. The objectives of the study in chapter three are to empirically estimate inverse supply functions for various items (like excavators, trucks, crawler tractors, graders etc.,) and test whether cross price effects are statistically significant. Our results indicate that cross price effects are significant and unequal across different items.

Chapter 1 Spatial Price Analysis of Used Construction Equipment: The Case of Excavators

Abstract

Equipment represents one of the largest input expenditures for construction and other firms. Yet, prices of used construction equipment have not been widely studied in the economic literature. A spatial hedonic price function is specified and is estimated with an extensive data set for used excavators sold by auction in North America from 1996 to 2005. The results indicate that prices of used excavators differ significantly for various reasons. Not surprisingly, prices vary by region of sale, physical condition, and brand of the equipment. We also find that prices are different between auction houses themselves. Furthermore, there exist 'within sale' spatial effects on the selling price that are statistically significant.

Introduction

Each year at least USD 100 billion worth of used construction equipment is bought and sold worldwide. Prices of used construction equipment sold at an auction vary dramatically depending on the type of equipment and its characteristics. An important and interesting question is what factors or characteristics influence the prices for used construction equipment. Certainly, firm behavior and more well know factors could influence purchase price. For instance, do characteristics such as physical condition of the equipment or brand of equipment matter? Are prices the same across different regions of sale? But other factors may also be important. Do auction houses themselves influence the selling price of the equipment? Do neighboring auctions affect equipment prices? Are there within sale spatial effects? To address these questions, we specify a hedonic price model from the construction firm’s perspective and estimate a spatial econometric model using transaction level data on the sales of used construction equipment for different auction houses from 1996 to 2005.

The objective of this study is then to specify and estimate a spatial hedonic pricing model for used construction equipment, specifically excavators. We test for traditional factors, including geographical region, physical condition, and brand of equipment. Further results of our study indicate that prices of equipment sold at different auction houses are significantly different after controlling for other quality effects. We test for two different spatial effects, neighborhood and within sale effects significant. The neighborhood effects arise due to auctions at nearby locations and 'within sale' effects due to the influence of similar items being sold at the same auction site. Auction houses or other firms may find these results interesting as significant price differences exist, which are important for strategic marketing, business placement, and decision making.   Buyers and sellers can use such models as a tool to appraise the equipment and make more informed decisions.

The rest of the paper is organized in the following manner. First, we provide an overview of the relevant literature. Second, a theoretical model is specified. Third, background information is provided on used equipment auctions. Fourth, the data on equipment sales are discussed. Fifth, the econometric technique is outlined, followed by results. Finally, conclusions are presented.

Review of Literature

Price analysis of used construction equipment has received little or no attention in the economic literature. Lucko (2003) analyzed the residual value of used construction equipment using auction data and found that the age of the equipment, brand, physical condition and region affected the residual value. However he did not investigate spatial effects, impacts of online auctions, or differences in the effects that auction houses may have had on prices. Diekmann (2008) identified that prices are significantly different given a quality of item, between online *eBay* auctions and in-person auctions in case of agricultural tractors.

There is extensive literature on hedonic price functions. Rosen (1974), Epple (1987), and Ekeland et.al (2002) analyzed the theoretical and econometric issues related to the estimation of implicit price parameters of the supply and demand functions, when the products differ in quality. Berndt (1991) and Triplett (2006) provide an excellent overview of the methodology of hedonic price analysis including its history. Gordon (1990) considered durable goods like aircrafts, electrical and telephone equipment in his study on hedonic prices. Cole et al. (1986), Triplett (1989), Triplett (2006) and Li et al. (2006) investigated the choice of functional form for hedonic regression. Triplett (1989) noted that the most commonly used log-log specification is inconsistent with *apriori* knowledge about the computer industry. Triplett (2006) and Li (2006) found that Box-Cox models performed better.

Spatial hedonic models have been widely used in real estate economics. Anselin and Lozano (2008) provide a review of recent works in spatial hedonic models in real estate markets. Other recent works in the same field include, but not limited to, Soto (2004) (land values), Cohen (2008) (airport noise). Outside of real estate markets, spatial hedonic models are being utilized in a wide variety of studies, for example, Fanning and Marsh (1999) (income variability among veterinary clinics), Hunt et al (2005) (effects of forest management on tourism), Anselin and Lozano (2008b) (consumer willingness to pay for water supply in Indian cities). Anselin (1999) outlines Lagrange multiplier tests for spatial lag and spatial error models. Spatial weights matrix can be specified as exponential distance decay, inverse squared distance and inverse cubed distance. Getis and Aldstadt (2004) use local statistics model to estimate weights. Lima and Macedo (1999) estimate spatial weights by Bayesian sampling – importance re-sampling procedure. Garret and Marsh (2005) applied an exponential decay weighting matrix.

Theoretical Model

Used construction equipment is a quality differentiated input to the construction firm, available with a variety of characteristics. Other inputs for the construction firm may include labor, energy, materials, services, and other durable goods. We acknowledge the traditional economic literature on firm decision making and specify a dual cost function. Following Kolstad and Turnovsky (1998), the hedonic model is rationalized by illustrating the equivalence of hedonic values and marginal rates of substitution in the production or cost functions. (See also Kristofersson and Rickertsen 2004.) The intent is to use these theoretical underpinnings to guide specification of the empirical model and relevant variables from the construction firm's perspective.

Let *y* be a vector of output for the construction firm, *s* be vector of homogenous input (capital, labor, management) and *q* be the differentiated input with a vector of characteristics *x*. The production set can be expressed as:

$$g(s, q, x, y) \leq 0 \qquad \textbf{(1.1)}$$

where *g* is quasi convex with convex level sets. When *g* =0, the production possibilities frontier is defined by (1.1). The firms face prices p_s for the vector *s* and $Y(x, \beta)$ a non linear price function for the quality differentiated input, where β is a vector of parameters of the non linear price function. In the case of multiple markets, by varying β, multiple non linear price functions can be generated for each market. Multiple markets may exist due to the differences in the regions of sale, for example.

In the used construction equipment market, sellers and buyers are construction firms that differ in their needs with the equipment. The construction firm's problem is assumed to reflect cost minimization:

$$\begin{aligned} C(p_s, \beta, y) = \min_{q,s,x} & \; qY(x, \beta) + p_s s \\ s.t \quad & g(s, q, x, y) \leq 0 \\ & q, s, x \geq 0 \end{aligned} \qquad \textbf{(1.2)}$$

The objective function above identifies the least cost combination of inputs *s, q* and *x* to produce a given level of output *y*. If $Y(x, \beta)$ is convex then the objective function is convex. Above, *C* is concave in prices and over β the region where solutions exist.

First order conditions for the problem in (1.2) are:

$$\frac{\partial C}{\partial q} = Y(x, \beta) - \lambda g_x = 0$$
$$\frac{\partial C}{\partial s} = p_s - \lambda g_q = 0$$
$$\frac{\partial C}{\partial x} = qY_x - \lambda g_x = 0$$

Sellers and buyers differ from each other in marginal value product from the use of the item on sale (for example, excavator). The first order conditions can be written as:

$$Y(x, \beta) = p_s \frac{g_q}{g_s} \qquad \textbf{(1.3a)}$$

$$\nabla_x Y = p_s \frac{\nabla_s g}{q g_s} \qquad \textbf{(1.3b)}$$

Here (1.3a) indicates that the marginal rate of technical substitution (MRTS) between q and s is equal to the non linear price function. Equation (1.3b) indicates that the derivative of the non linear price function equals the MRTS between s and x.

In hedonic regressions the good is treated as bundle of characteristics that consumers sell and buy. Appropriate choice of these characteristics is vital (Triplett, 2006). Characteristics available from auction sales data are year of make, date of sale, price, place of sale, auction house that organized the sale, brand of the equipment and physical condition of equipment.

Data and Variables

The transaction level data used for the estimation of the models was obtained from *Equipment Watch.com*, which reports final sale prices of individual pieces of equipment at selected auction houses. The data spans 10 years from 1996 to 2005.[2] Background information is presented on the

[2] The observed data sample is not necessarily representative of all the auction sales in the U.S.

auction process and data itself with some basic statistics and then descriptions of the variables used in the estimation are presented.

Background

Auction, as a method of sale for construction equipment, is gaining market share (3% in 2005, 5% in 2007) (RBA 2007). For example, on an average, a single sale at *Ritchie Brothers Auctioneers* generated around USD 27 million in revenues in 2007, and *Ritchie Brothers Auctioneers* holds around 130 such auctions each year (RBA 2007). In our observed data sample from 1996 to 2005, trucks account for 22% of the total sales. However, the truck category includes some 55 different types including pickup trucks, equipment transport trucks, and dump trucks being the majority types. Excavators constitute the single largest single category of used construction equipment with approximately 21% of the total sales (wheel tractors and crawler tractors 17% each, wheel loaders, graders and scrapers account for the remaining 17%). Hence, the current study specifically deals with excavators sold in the U.S.

Descriptive statistics on the excavator sales are presented in Table 1.1. The mean selling price of excavators was approximately USD 38,000. The average age was 8.8 years. Approximately 49% were sold in the South (20% in the North East, and 14% in the West and 14%in the Midwest). Most of the equipment sold is reported to be in good condition (39% good, 7% in Excellent, 18% Fair, 35% in unknown and only 1% in poor condition). With respect to brands of equipment, Brand 1 is the most sold (42% Brand 1, 13% Brand 2, Brands 3 and 4 account for 17% together, and other brands account for the rest 28%).

Representative shares of different auction houses from 1996 to 2005 in the observed data sample are presented in Table 1.1. The largest auction house represented 45% of the sample. The second largest auction house had 28%. The auction houses offer open cry, English type, ascending bids. The highest bidder wins the item and pays the bid, which is the reported sales price.

Price

The selling price per piece of equipment at auctions reflects the buyer's willingness to pay for a particular piece of equipment. Selling price of the equipment decreases with an increase in age. Figure 1.1 suggests that the relationship between age and price to be negative.

Age of equipment

Age of a machine can be defined in terms of calendar days, in units of production or in cumulative hours of use (Mitchell, 1998). Calendar age, although a noisy measure of the machine's use, is the easiest to calculate. It is defined in years, as the difference between year of manufacture and date of sale. Manufacturers report only the year of make, but not the exact date. In this study, it was assumed that the equipment has been made on 1st of September of the previous year to the respective year of manufacture. For example, if the manufacturer reports the equipment as a 1998 model, this study would assume the date of manufacture as 1st September, 1997. This reference date of 1st of September is chosen, as the new year's models appear in the market at the beginning of the last quarter of a year.

Calendar age is used in this study due to the lack of availability of other usage measures. As the age represents the amount of machine's usable life already past, the estimated parameter is expected to be statistically significant and to have a negative sign.

Type of Excavator

Hydraulic excavators are the most common type of excavators. They are heavy machines used for digging soil and rocks. With appropriate attachments, they can be used to break concrete, steel, drilling holes in the earth, lay gravel and even mow landscapes (*Ritchie Wiki*, 2008). These excavators can be mounted on wheels, tracks or on trucks to suit their field of operation. Compact excavators are used for working and maneuvering in tighter spaces where hydraulic excavators cannot be used. Dummy variables are assigned to capture the differences of these types. For example, variable *cmhyd* takes a value of 1 if the excavator is a crawler mounted hydraulic excavator and zero otherwise.

Physical Condition

Professional equipment appraisers assess the physical condition of the equipment after examining its parts in conjunction with the hours used (Lucko, 2006). Definitions on various physical conditions are given in Table 1.2. We use dummy variables to account for the physical condition, for example, the variable excellent takes a value of 1 if the equipment is in excellent physical condition. Equipment in better condition is expected to cost more than those in poorer condition, therefore, if good condition is taken as a reference category then *poor* and *fair* are expected to have negative sign. The sign or magnitude of the parameter coefficient on *unknown* category relative to other categories is not readily predictable.

Brand of Equipment

Brand of equipment may also have significant impact on the price. Consumers value some brands more than others, given a quality of equipment. Dummy variables are defined to capture the effects brands may have on prices. For example, the variable *Brand i* takes a value of 1 if the equipment is the i^{th} brand or 0 otherwise.

Region of Sale

Differences in prices between different regions in the US are accounted for by employing dummy variables. Construction activity may differ between regions and hence the demand for equipment. The region of sale is assigned based on the U.S. census tract regions (US Census Bureau, 2007) to which the city of sale corresponds.

Auction Houses

Auction houses can have significant influence on the selling price.[3] Auction houses offer various services to buyers and sellers and the auction process itself. The services to buyer include informational and escrow in addition to services like financial lien search etc. Sellers receive services like advertising, organization of sale and escrow. In return for their services, auction houses charge a fixed percentage on sale of the item as commission. Buyers usually do not pay any premium. Buyers and sellers value these services offered by auction house. Auctions also differ in their process across auction houses. For example, Auction House 1 offers exclusively unreserved auctions while all other auction houses offer both reserved price and unreserved auctions.[4] We capture these effects by employing dummy variables for each auction house. For example, if the item is sold at *Auction House1,* the dummy variable *AH1* takes a value of 1 or 0 otherwise. The sign or the significance of these terms is not readily predictable.

Time of Sale:

Dummy variables representing the quarter of year of sale are used in the regression model to capture the changes in price after controlling for the changes in quality. The sign of the coefficients is not easily predictable.

Econometric Methods

In this section we address empirical issues in the estimation of the spatial hedonic model with Box –Cox transformations using maximum likelihood. Spatially lagged dependent variable model is estimated to account for the possible spillover effects from the sale of multiple pieces of

[3] Ong et al. (2005) identified the effect of auctioneer on the probability of sale at real estate auctions.
[4] Unreserved auctions have no reserve price or minimum acceptable bid on the item.

the same type of item at an auction event, and between neighboring auction houses. A maximum likelihood estimator is chosen, because the spatially lagged dependent variable can cause the ordinary least squares to be biased and inefficient. Box –Cox transformation is applied to satisfy the normality assumption of the models.

Spatial Econometric Model

Anselin (1988) specifies a first order autoregressive model and derives the log likelihood function as

$$Y = \rho WY + X\beta + \varepsilon$$

where W is a spatial weighting matrix; ρ is the spatial autoregressive coefficient; the remaining terms are as specified as in the linear regression model above. Because of the concern for "neighborhood" and "within sale" effects, we specify the spatial model as

$$Y = \rho_1 W_1 Y + \rho_2 W_2 Y + X\beta + \varepsilon \qquad \textbf{(1.4)}$$

where W_1 is a spatial weighting matrix for neighborhood effects (defined below); ρ_1 is the spatial autoregressive coefficient relating to neighborhood effects, while W_2 is a spatial weighting matrix for within sale effects (defined below) ; ρ_2 is the spatial autoregressive coefficient relating to within sale effects.

Baltagi and Li (2004) derive log likelihood function when dependent variable is transformed using Box Cox transformation. The log likelihood function is

$$\ln L = -\frac{N}{2}\ln\sigma^2 + \ln|A| + (r-1)\sum_{i=1}^{N}\ln Y_i - \frac{1}{2\sigma^2}\left(AY^* - X\beta\right)'\left(AY^* - X\beta\right)$$

while $Y^* = \dfrac{Y^r - 1}{r}$ when $r \neq 0$ and $Y^* = \ln Y$ when $r = 0$ where $A = (I - \rho_1 W_1 - \rho_2 W_2)$.

Following Golub and VanLoan (1996), Pace and Lesage (2004) we approximate $\ln|A|$ by Taylor Series approximation

$$\ln|(I - \rho_1 W_1 - \rho_2 W_2)| = trace[\ln(I - (\rho_1 W_1 + \rho_2 W))]$$

$$= \; trace\left(\sum_{j=1}^{\infty} \frac{(\rho_1 W_1 + \rho_2 W_2)^j}{j}\right) \qquad \textbf{(1.5)}$$

Truncating the series at *j=2*, the expression in (1.5) simplifies to

$$\rho_1 trace(W_1) + \rho_2 trace(W_2) + \frac{1}{2} trace\left((\rho_1 W_1)^2 + (\rho_2 W_2)^2 + 2(\rho_1 W_1)(\rho_2 W_2)\right)$$

As the trace of W_1 and W_2 is zero by construction, the above expression further simplifies to

$$\ln|(I - \rho_1 W_1 - \rho_2 W_2)| = \frac{1}{2} trace\left[(\rho_1 W_1)^2 + (\rho_2 W_2)^2 + 2(\rho_1 W_1)(\rho_2 W_2)\right]$$

From Pace and Lesage (2004), the traces of $W_1{}^2$ and $W_2{}^2$ can be calculated as:

$trace\left(W_1{}^2\right) = 2\sum\sum\left(L_{ij}\right)^2$ where L equals the lower triangle of elements in W_1.

Spatial Weighting Matrices

Testing for spatial effects requires the specification of weights matrices. Two types of spatial effects can be observed on the selling price of the equipment. The first type of – neighborhood effect is due to the auctions being held by other competing auction houses at nearby locations. It is hypothesized that with an increase in the distance between the given auction house and other competing locations, these effects diminish in magnitude. Bidders and sellers might treat auction houses located at different locations as different markets. In order to capture such effects, we use the exponential distance decay measure in calculating the weights.

Elements of matrix W_1 may be defined as $\hat{w}_{ij} = e^{-\left(\frac{d_{ij}}{\phi}\right)}$ where ϕ is a smoothing parameter (value fixed at 100) and d_{ij} is the distance between the auction sites *i* and *j*.[5]

The second type of spatial effect is due to influence of the other pieces of equipment being sold at the same site on auction day. The equipment auctions are multi unit in nature. During the auction, equipment on sale is often driven across a ramp. As soon as the item is sold it is driven off the ramp and its position is taken by the next item inline. This process continues until all the lots are sold. To capture these within sale effects, we specify a spatial weights matrix W_2 as $\hat{w}_{2ij} = 1$ if the item is being sold at the same site and same auction day or zero otherwise.

Following Kelejian and Prucha (2008) matrices W_1 and W_2 are standardized as

$$\tau_{1n}^{*} = \min\left\{ \max_{1 \le i \le n} \sum_{j=1}^{n} \left| w_{1ij,n} \right|, \quad \max_{1 \le j \le n} \sum_{i=1}^{n} \left| w_{1ij,n} \right| \right\}$$

$$W_1 = \frac{1}{\tau_{1n}^{*}} W_1$$

$$\tau_{2n}^{*} = \min\left\{ \max_{1 \le i \le n} \sum_{j=1}^{n} \left| w_{2ij,n} \right|, \quad \max_{1 \le j \le n} \sum_{i=1}^{n} \left| w_{2ij,n} \right| \right\}$$

$$W_2 = \frac{1}{\tau_{2n}^{*}} W_2$$

[5] The distance between two auction sites is calculated in miles by Great Circle Distance method (math forum, 2007) using the latitudes and longitudes of the city in which the auction is held. This distance measure is not a driving distance. Latitude and longitude coordinates from WGS84 datum are used. A datum is a reference for position on the surface of the Earth (National Atlas). Data on Coordinates is obtained from Census 2000 U.S. Gazetteer files (Census Bureau, 2007). The distance is calculated as

$$Dist = r * \arccos \left[\sin a * \sin c + \cos a * \cos c * \cos(b - d) \right]$$

when *r* =3963 miles, the approximate radius of the Earth; *a* and *b* are the latitude and longitude of origin city; and *c* and *d* are the latitude and longitude of destination city.

where $\hat{w}_{ij}$ is the spatial weight. This type of standardization preserves the symmetry of the spatial weights matrices even after standardization. Kelejian and Prucha (2006) discuss the advantages of this standardization in detail.

Results and Discussion

Model in (1.4) is estimated using the SAS system by combination of *SAS SQL, SAS MACROs* and *SAS IML*. Separate regressions were estimated across each year of the data from 1996 to 2006. Based on preliminary evaluation the smoothing parameter ϕ is fixed at a value of 100. A grid search is performed for Box –Cox parameter between values of -2 to 2 by an increment of 0.01 and value that maximizes the log likelihood function was chosen (value of zero was chosen for the Box –Cox parameter. See Figure A1 in the appendix).

Results from the spatial hedonic regressions for each year are presented in Table 1.3 and interpreted below. The coefficients on *age* are significant and signs are as expected (marginal effect of is negative). Controlling for other factors in the model, excavators about the age of 35 years received the minimum price.

Coefficients on brand of the equipment are significant, indicating that equipment buyers attach different values to different brands. Brand1, the most sold brand (42% of sales in our observed data sample) received higher price than other brands. Larger hydraulic excavators receive higher prices than compact excavators of similar quality and condition. Track mounted excavators received higher prices than wheel mounted or the truck mounted type in most of the years.

The signs on the coefficients of physical condition are as expected. Equipment in better condition costs more than that in a poorer condition. Equipment in fair condition received a lower price than that in excellent condition. Equipment whose condition is rated unknown received significantly higher price than that in poor condition. The coefficients on variables representing the quarter of the fiscal year of sale are not significantly different from the prices in the last quarter for most of the years. Prices differ significantly from region to region in the US. This is indicated by the significant coefficients on variables representing Mid Western US and North East for most of the years. This could be due to the differences in regional demands for equipment.

The results from the estimated models indicate that calendar age, brand of equipment, physical condition and region of sale exert a significant effect on price. These results are consistent with the findings of Lucko (2006).

The coefficients on auction houses are predominantly significant, indicating that prices received across different auction houses vary for a given quality of the equipment and other conditions *ceterus paribus*. Equipment sold at Auction house 1 (with 45% of representative share of total sales in our observed data sample) received significantly higher prices than all other auction houses. The difference in prices may be due to the influence of auction house over the selling price by the way of reputation effects, complimentary services to buyers and sellers, efficient management or other factors like economies of scale.

Likelihood ratio tests are used to test hypotheses on significance and equality of spatial autocorrelation parameters by estimating various models (see Table 1.4). Based on the test results we fail to reject the null hypotheses of $\rho_1 = 0$ for almost all years but for years 2000 and 2001. The null hypothesis $\rho_1 = \rho_2$ is rejected for years 2000 and 2001. We can also observe that spatial effects (either ρ_1 or ρ_2) are significant from year 2000 to 2003 from the test of hypothesis that $\rho_1 = 0$ & $\rho_2 = 0$ and from the year 2001 to 2004 from the hypothesis $\rho_2 = 0$. This coincides with the time that auction houses started their online bidding services.

The spatial auto correlation parameter ρ_2 captures the effects of other pieces of equipment being sold at the auction at the same site. Statistical significance of this parameter indicates that prices of similar items at an auction tend to be correlated with each other. Positive sign on the parameter indicates a positive correlation between the prices. This result is highly useful for the sellers who wish to sell their items for a premium.

The spatial parameter ρ_1 captures the effects of other auctions held at nearby locations at the same time. The parameter is predominantly insignificant. The parameter coefficient indicates the effects of auctions nearby on the selling price of the item. This result is of interest to the auction houses as it can be used in selecting newer locations for holding auctions. Given a location, the effects of competing auction houses located nearby can be calculated precisely as a product of spatial correlation coefficient and the spatial weights assigned. The sign of the spatial correlation coefficient determines if the effects are positive or negative. Conversely, given a price, the model can also be used to find an optimal site for locating the business by solving the spatial hedonic price function for distance of the new location from its competitor locations.

Conclusions

Prices of used construction equipment sold at auctions are hypothesized to be a function of the characteristics of the equipment. A spatial hedonic price function is theoretically specified and is estimated with an extensive panel/time-series data set for used excavators sold by auction in North America from 1996 to 2005. The results indicate that prices of used excavators significantly differ for various reasons. Characteristics like age, brand of the equipment, physical condition, region of sale, and auction houses significantly affect the prices.

The prices of equipment sold at different auction houses are significantly different after controlling for other quality effects. Spatial effects due to the competing auctions at nearby locations did not have a significant effect on the selling price. The 'within sale' effects are statistically significant, indicating that other pieces of equipment being sold at the same site on auction day have a significant influence on the price. Auction houses or other firms may find these results interesting and useful for strategic marketing, business placement, and decision making. Buyers and sellers can use such models as a tool to appraise the equipment and can make more informed decisions. Topics for future research would be investigation as to why prices differ across auction houses and how competition between auction houses affects the prices.

Table 1.1: Brief description of variables and descriptive statistics of excavator sales from 1996 to 2005 in the observed data sample.

Variable	Label	Mean	Std Dev	Min	Max
price	Sale Price of Excavator in USD	38429.1	33983.56	800	575000
age	Age of Excavator in Years	8.7575	5.0176	0.3671	64.2795
prime	Prime Lending Interest Rate	6.5487	1.9221	4	9.5
AH1	Binary Variable. Value=1 if Auction House 1	0.4401	0.4964	0	1
AH2	Binary Variable. Value=1 if Auction House 2	0.0517	0.2215	0	1
AH3	Binary Variable. Value=1 if Auction House 3	0.2716	0.4448	0	1
AH4	Binary Variable. Value=1 if Auction House 4	0.0350	0.1837	0	1
auct	Binary Variable. Value=1 if Auction House is any other	0.4401	0.4964	0	1
cmhyd	Binary Variable. Value=1 if Crawler Mounted. Hydraulic excavator	0.8146	0.3886	0	1
tmhyd	Binary Variable. Value=1 if Truck Mounted. Hydraulic excavator	0.0066	0.0808	0	1
wmhyd	Binary Variable. Value=1 if Wheel Mounted. Hydraulic excavator	0.0232	0.1507	0	1
cmcomp	Binary Variable. Value=1 if Crawler Mounted. Compact excavator	0.1556	0.3625	0	1
Brand1	Binary Variable. Value=1 if Brand is 1	0.4158	0.4929	0	1
Brand2	Binary Variable. Value=1 if Brand is 2	0.1276	0.3337	0	1
Brand3	Binary Variable. Value=1 if Brand is 3	0.0829	0.2758	0	1
Brand4	Binary Variable. Value=1 if Brand is 4	0.0884	0.2838	0	1
Brand5	Binary Variable. Value=1 if Brand is 5	0.0557	0.2293	0	1
mak	Binary Variable. Value=1 if Brand is Any other Maker	0.2296	0.4206	0	1
con1	Binary Variable. Value=1 if Condition is very good or excellent or new.	0.0761	0.2652	0	1
con2	Binary Variable. Value=1 if Condition is good	0.4025	0.4904	0	1
con3	Binary Variable. Value=1 if Condition is fair	0.1735	0.3787	0	1
con4	Binary Variable. Value=1 if Condition is Poor	0.0076	0.0868	0	1
con5	Binary Variable. Value=1 if Condition is Unknown	0.3403	0.4738	0	1
west	Binary Variable. Value=1 if Region of Sale is West	0.1436	0.3507	0	1
midwest	Binary Variable. Value=1 if Region of Sale is Mid West	0.137	0.3438	0	1
Neast	Binary Variable. Value=1 if Region of Sale is North east	0.1955	0.3966	0	1
south	Binary Variable. Value=1 if Region of Sale is South	0.4933	0.5	0	1
online	Binary Variable. Value=1 if Sale is done Online	0.0295	0.1693	0	1

Total Observations in all of the above variables:44630

Table 1.2:Brief definitions of physical condition of equipment as defined by *Equipment Watch* (2008)

Condition	Definition
New	New unit
Excellent	Some use, but almost new mechanically
Very Good	In above average mechanical condition; low hours or recently overhauled
Good	In average mechanical condition; may need minor repairs or replacement of worn parts soon
Fair	In below average mechanical condition; high hours or older unit
Poor	Needs major repairs
Unknown	No condition is available

Table 1.3 Spatial hedonic regression maximum likelihood estimates by each year from 1996 to 2005 in the observed data sample.

Variable	1996		1997		1998		1999	
	Parameter Estimates	**P Value**	**Parameter Estimates**	**P Value**	**Parameter Estimates**	**P Value**	**Parameter Estimates**	**P Value**
INTERCEPT	**9.8061**	**<0.0001**	**9.8705**	**<0.0001**	**9.6052**	**<0.0001**	**9.8966**	**<0.0001**
AGE	**-0.1244**	**<0.0001**	**-0.1250**	**<0.0001**	**-0.1220**	**<0.0001**	**-0.1426**	**<0.0001**
AGE2	**0.0015**	**<0.0001**	**0.0011**	**<0.0001**	**0.0018**	**<0.0001**	**0.0023**	**<0.0001**
AH1	0.0657	0.1046	**0.1186**	**0.0006**	**0.1147**	**<0.0001**	**0.1359**	**<0.0001**
AH2	0.1254	0.3068	0.0745	0.4276	-0.0369	0.6988	**0.1238**	**0.0084**
AH3	**-0.3335**	**<0.0001**	**-0.1089**	**0.0233**	**-0.0825**	**0.0237**	-0.0426	0.1267
CMHYD	**1.3620**	**<0.0001**	**1.3057**	**<0.0001**	**1.1735**	**<0.0001**	**1.0966**	**<0.0001**
TMHYD	**0.7096**	**<0.0001**	**0.9486**	**<0.0001**	**0.6007**	**<0.0001**	**0.5882**	**<0.0001**
WMHYD	**0.8968**	**<0.0001**	**0.7767**	**<0.0001**	**0.5816**	**<0.0001**	**0.5875**	**<0.0001**
BRAND1	**0.6209**	**<0.0001**	**0.5271**	**<0.0001**	**0.4659**	**<0.0001**	**0.3628**	**<0.0001**
BRAND2	**0.4766**	**<0.0001**	**0.3984**	**<0.0001**	**0.3401**	**<0.0001**	**0.2138**	**<0.0001**
BRAND3	**0.3842**	**<0.0001**	**0.3734**	**<0.0001**	**0.2720**	**<0.0001**	**0.3304**	**<0.0001**
BRAND4	**0.3588**	**<0.0001**	**0.4253**	**<0.0001**	**0.4667**	**<0.0001**	**0.2758**	**<0.0001**
BRAND5	**0.1979**	**0.0055**	**0.1944**	**0.0047**	0.0155	0.7515	**0.1170**	**0.0065**
CON1	**0.2327**	**<0.0001**	0.0683	0.0544	**0.2326**	**<0.0001**	**0.3219**	**<0.0001**
CON3	-0.0832	0.0518	**-0.2274**	**<0.0001**	**-0.1413**	**0.0002**	**-0.0918**	**0.0085**
CON4	**-0.5011**	**<0.0001**	**-0.3877**	**<0.0001**	**-0.3312**	**0.0485**	**-0.6888**	**<0.0001**
CON5	**-0.0843**	**0.0164**	-0.0189	0.6052	**-0.1219**	**<0.0001**	-0.0519	0.0516
MIDWEST	0.0837	0.0851	0.0190	0.7052	**0.1762**	**<0.0001**	**0.1445**	**0.0003**
NEAST	0.0558	0.3988	0.0209	0.7644	**0.1219**	**0.0328**	0.0856	0.0510
SOUTH	-0.0719	0.0506	-0.0331	0.4536	**0.0711**	**0.0277**	0.0531	0.0996
Q1	-0.0034	0.9388	**0.1789**	**0.0001**	**0.1741**	**<0.0001**	**0.1122**	**0.0001**
Q2	-0.0039	0.9086	**0.0937**	**0.0099**	**0.1331**	**<0.0001**	**0.0775**	**0.0018**
Q3	-0.0585	0.1236	0.0372	0.2772	-0.0273	0.3462	0.0461	0.1304
RHO1	-0.0024	0.7301	-0.0184	0.0873	0.0035	0.5282	-0.0022	0.7048
RHO2	-0.0117	0.0512	**-0.0239**	**0.0258**	-0.0009	0.8307	-0.0092	0.0726

Crawler mounted compact excavators of "other" brand sold in the Western US that are in good condition, by "other" auction house are used as the base category

Table 1.3: (.....continued)

Variable	2000 Parameter Estimates	2000 P Value	2001 Parameter Estimates	2001 P Value	2002 Parameter Estimates	2002 P Value	2003 Parameter Estimates	2003 P Value
INTERCEPT	**9.8837**	**<0.0001**	**9.9858**	**<0.0001**	**10.0589**	**<0.0001**	**10.2227**	**<0.0001**
AGE	**-0.1640**	**<0.0001**	**-0.1662**	**<0.0001**	**-0.1813**	**<0.0001**	**-0.1599**	**<0.0001**
AGE2	**0.0031**	**<0.0001**	**0.0029**	**<0.0001**	**0.0034**	**<0.0001**	**0.0025**	**<0.0001**
AH1	**0.0901**	**<0.0001**	**0.0688**	**0.0006**	**0.1332**	**<0.0001**	**0.1291**	**<0.0001**
AH2	0.1197	0.1091	**-0.1557**	**0.0001**	**-0.0958**	**0.0158**	-0.0268	0.5057
AH3	**-0.0932**	**<0.0001**	**-0.2212**	**<0.0001**	**-0.1391**	**<0.0001**	**-0.0571**	**0.0357**
CMHYD	**1.0893**	**<0.0001**	**1.1727**	**<0.0001**	**1.1869**	**<0.0001**	**1.1345**	**<0.0001**
TMHYD	**0.9485**	**<0.0001**	**0.8953**	**<0.0001**	**0.8481**	**<0.0001**	**0.9880**	**<0.0001**
WMHYD	**0.5989**	**<0.0001**	**0.8483**	**<0.0001**	**0.9205**	**<0.0001**	**0.8966**	**<0.0001**
BRAND1	**0.4791**	**<0.0001**	**0.3870**	**<0.0001**	**0.4185**	**<0.0001**	**0.4146**	**<0.0001**
BRAND2	**0.2724**	**<0.0001**	**0.3118**	**<0.0001**	**0.2881**	**<0.0001**	**0.2806**	**<0.0001**
BRAND3	**0.4127**	**<0.0001**	**0.3356**	**<0.0001**	**0.3766**	**<0.0001**	**0.3454**	**<0.0001**
BRAND4	**0.2633**	**<0.0001**	**0.3345**	**<0.0001**	**0.2613**	**<0.0001**	**0.3291**	**<0.0001**
BRAND5	**0.1882**	**<0.0001**	**0.0814**	**0.0099**	**0.0631**	**0.0391**	**0.0831**	**0.0156**
CON1	**0.0927**	**0.0009**	**-0.0734**	**0.0156**	**-0.0674**	**0.0198**	0.0028	0.9363
CON3	**-0.1364**	**<0.0001**	**-0.1343**	**<0.0001**	**-0.0806**	**<0.0001**	**-0.1470**	**<0.0001**
CON4	**-0.4481**	**<0.0001**	**-0.5800**	**<0.0001**	**-0.5079**	**<0.0001**	**-0.4656**	**<0.0001**
CON5	-0.0179	0.4219	0.0058	0.8094	**0.0505**	**0.0190**	**-0.0736**	**0.0018**
MIDWEST	**0.1438**	**<0.0001**	**0.0786**	**0.0038**	-0.0167	0.4939	-0.0325	0.2845
NEAST	**0.1072**	**0.0022**	**0.1239**	**0.0003**	-0.0096	0.7644	**-0.0915**	**0.0130**
SOUTH	**0.1044**	**<0.0001**	0.0186	0.4057	-0.0212	0.3153	**-0.1053**	**0.0001**
Q1	**0.1221**	**<0.0001**	0.0283	0.2019	-0.0237	0.2876	**-0.0659**	**0.0185**
Q2	**0.1162**	**<0.0001**	0.0467	0.0218	0.0190	0.3149	-0.0111	0.6529
Q3	**0.1213**	**<0.0001**	-0.0600	0.0058	-0.0097	0.6477	-0.0103	0.6972
RHO1	**0.0097**	**0.0165**	0.0029	0.4063	-0.0015	0.7358	0.0053	0.2139
RHO2	0.0072	0.0646	**0.0320**	**<0.0001**	**0.0240**	**<0.0001**	**0.0097**	**0.0251**

Crawler mounted compact excavators of "other" brand sold in the Western US that are in good condition, by "other" auction house are used as the base category

Table 1.3: (.....continued)

Variable	2004 Parameter Estimates	2004 P Value	2005 Parameter Estimates	2005 P Value
INTERCEPT	**10.2747**	**<0.0001**	**10.3263**	**<0.0001**
AGE	**-0.1513**	**<0.0001**	**-0.1625**	**<0.0001**
AGE2	**0.0019**	**<0.0001**	**0.0023**	**<0.0001**
AH1	**0.1589**	**<0.0001**	**0.0488**	**0.0410**
AH2	0.0405	0.2901	-0.0035	0.9617
AH3	-0.0526	0.0937	**-0.1375**	**0.0027**
CMHYD	**1.2112**	**<0.0001**	**1.2822**	**<0.0001**
TMHYD	**1.0362**	**<0.0001**	**1.4303**	**<0.0001**
WMHYD	**0.8248**	**<0.0001**	**1.1518**	**<0.0001**
BRAND1	**0.3725**	**<0.0001**	**0.4474**	**<0.0001**
BRAND2	**0.2019**	**<0.0001**	**0.2986**	**<0.0001**
BRAND3	**0.2257**	**<0.0001**	**0.3116**	**<0.0001**
BRAND4	**0.1534**	**<0.0001**	**0.2302**	**<0.0001**
BRAND5	0.0076	0.8284	0.0724	0.0913
CON1	0.0030	0.9553	**-0.1767**	**0.0076**
CON3	**-0.0784**	**0.0003**	-0.0434	0.1153
CON4	**-0.3074**	**0.0014**	**-0.2484**	**0.0293**
CON5	-0.0007	0.9769	0.0011	0.9712
MIDWEST	0.0435	0.2409	**0.1880**	**0.0001**
NEAST	**-0.1110**	**0.0086**	**-0.1792**	**0.0011**
SOUTH	-0.0167	0.5163	**-0.0881**	**0.0071**
Q1	0.0271	0.2905	0.0390	0.2040
Q2	-0.0075	0.7474	0.0472	0.1154
Q3	**0.0578**	**0.0212**	0.0519	0.1268
RHO1	0.0032	0.4330	0.0153	0.0963
RHO2	**-0.0097**	**0.0315**	0.0008	0.9325

Crawler mounted compact excavators of "other" brand sold in the Western US that are in good condition, by "other" auction house are used as the base category

Table 1.4 Likelihood Ratio test results on the significance of spatial parameters of the estimated spatial hedonic price regression models.

	Model 1	Model 2	Model 3	Model 4
		Null Hypothesis		
Year	$\rho_1 = 0$ & $\rho_2 = 0$	$\rho_1 = 0$	$\rho_2 = 0$	$\rho_1 = \rho_2$
1996	3.84	0.02	3.74	1.64
1997	6.22	1.24	3.3	1.62
1998	0.46	0.42	0.18	0.24
1999	3.14	0	2.98	1.46
2000	***7.62***	***4.2***	1.88	0.02
2001	***71.86***	***3.86***	***71.16***	***32.54***
2002	***38.4***	0.56	***38.32***	***34.16***
2003	***7.54***	2.54	***6.02***	2.12
2004	4.6	0	***3.96***	4
2005	3.24	3.24	0.46	2.94
df	2	1	1	1
$\chi^2_{0.05,df}$	5.991	3.84	3.84	3.84

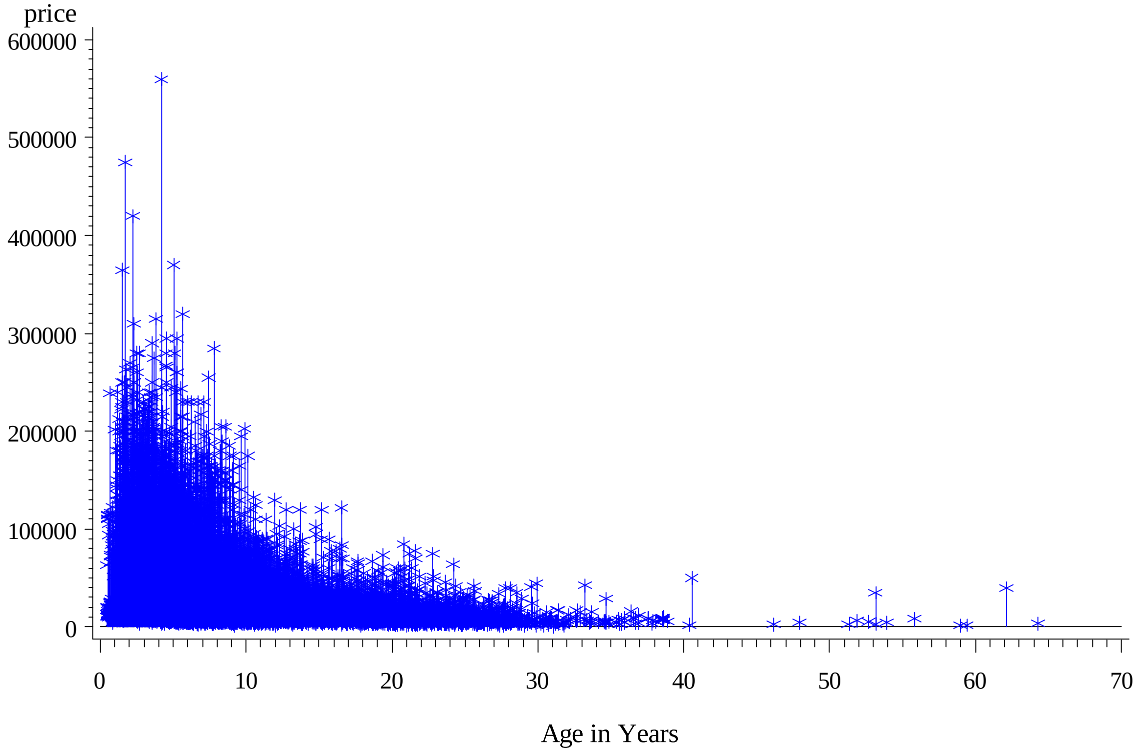
Model 1 $Y = \rho_1 W_1 Y + \rho_2 W_2 Y + X\beta + \varepsilon$

Model 2 $Y = \rho_1 W_1 Y + X\beta + \varepsilon$

Model 3 $Y = \rho_2 W_2 Y + X\beta + \varepsilon$

Model 4 $Y = \rho (W_1 + W_2) Y + X\beta + \varepsilon$

Figure 1.1: Selling price (real) of the excavators vs. age at the time of sale of excavators from the auction sales data (without controlling for any other factors in the observed data sample).



References

Anselin (1999), Luc. "Spatial Econometrics" available at: http://www.csiss.org/learning_resources/content/papers/baltchap.pdf (accessed September, 2007).

Anselin, Luc & Nancy Lozano-Gracia (2008). "Spatial Hedonic Models." Working Paper 2008-02 http://geodacenter.asu.edu/system/files/200802_AnselinLozano.pdf (accessed May, 2009).

Anselin, Luc, Nancy Lozano-Gracia, Uwe Deichmann and Somik Lall.(2008 b). "Valuing Access to Water –A Spatial Hedonic Approach Applied to Indian Cities." Working Paper 2008-08. http://geodacenter.asu.edu/system/files/200808_Anselinetal.pdf (accessed May, 2009).

Anselin. (1988). "Spatial Econometrics: Methods and Models." Kluwer Academic Publishers.1988. ISBN: 902473519.

Baltagi, Badi.and Dong Li (2004). "Testing for Linear and Log Linear Models Against Box Cox Alternatives with Spatial Lag Dependence." In *Spatial and Spatiotemporal Econometrics. Advances in Econometrics.* Vol.18, pp35-74.

Berndt (1991) "The Practice of Econometrics: Classic and Contemporary." Addison Wesley Publishing. ISBN:0-201-51489-3.

Census 2000 gazetteer http://www.census.gov/geo/www/gazetteer/places2k.html (accessed: September, 2007).

Cohen, Jeffrey P. and Coughlin, Cletus C (2008)."Spatial Hedonic Models of Airport Noise, Proximity, and Housing Prices(2007-12). *Journal of Regional Science*, Vol. 48, Issue 5, pp. 859-878, December 2008. Available at SSRN: http://ssrn.com/abstract=1292008 or DOI: 10.1111/j.1467-9787.2008.00569.x.

Cole, Rosanne, Y.C.Chen, Joan A Barquin-Stollerman, Ellen Dulberger, Nurhan Hevacian and James H. Hodge. (1986). "Quality Adjusted Price Indices for Computer Processors and Selected Peripheral Equipment." *Survey of Current Business* 66:1, January, 41-50.

Diekmann Florian, Brian E. Roe, And Marvin T.Batte.(2008). Tractors On eBay: Differences Between Internet And In-Person Auctions. *American Journal of Agricultural Economics*. 90(2) (May 2008): 306–320.

Equipment Watch (2007) http://www.equipmentwatch.com/ (accessed: January, 2007).

Equipment Watch (2008) http://www.equipmentwatch.com/Tools/LB/UserGuide/UG_ConditionSymbols.jsp (accessed: January, 2007).

Garrett, T.A and T.L Marsh (2002), "The Revenue Impacts of Cross-Border Lottery Shopping in the Presence of Spatial Autocorrelation." *Regional science and Urban Economics* 32 (2002) 501-519.

Getis, Arthur and Jared Aldstadt (2004) “Constructing the Spatial Weights Matrix Using a Local Statistic”. *Geographical Analysis*, Vol. 36, No. 2 (May 2004).

Golub, Gene H and Charles F.Van Loan (1996). "Matrix Computations." John Hopkins University press ISBN (0-8018514-8) pp 565. http://books.google.com/books?id=mlOa7wPX6OYC&printsec=frontcover&dq=golub+and+van+loan&client=firefox-a#PPA565,M1 (accessed April 2009).

Gordon, Robert J. (1990) "Measurement of Durable Goods Prices." University of Chicago Press, Chicago.

Jasper Fanning and Thomas L. Marsh (2005). "Spatial Hedonic Analysis Of Veterinarian Income" http://ageconsearch.umn.edu/bitstream/19168/1/sp05fa05.pdf (accessed May, 2009).

Kelejian, Harry H. and Prucha, Ingmar R., (2008) "Specification and Estimation of Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances" (November 2008). CESifo Working Paper Series No. 2448. Available at SSRN: http://ssrn.com/abstract=1296549.

Kolstad, C.D. and M.H.L. Turnovsky (1998). “Cost Function and Nonlinear Prices: Estimating a Technology with Quality Differentiated Inputs.” *The Review of Economics and Statistics* 80(1998):444-53.

Kristofersson, D. and K. Ricertsen (2004). “Efficient Estimation of Hedonic Inverse Input Demand Systems.” *American Journal of Agricultural Economics* 86 (2004):1127-37.

Len M. Hunta, Peter Boxallb Jeffrey Englinc and Wolfgang Haider (2005)"Remote tourism and forest management: a spatial hedonic analysis." *Ecological Economics*. Volume 53, Issue 1, 1 April 2005, Pages 101-113.

Li ,Wenzheng. Marc Prud’homme Kam Yu.(2006). "Studies in Hedonic Resale Housing Price Indexes." Paper presented to the Canadian Economic Association 40th Annual Meetings, May 26–28, 2006, Concordia University, Montr´eal.

Lima, Elcyon Caiado And Rocha Paulo Brígido Rocha Macedo (1999) "Estimation Of A Weights Matrix For Determining Spatial Effects." Ministério Do Planejamento, Orçamento E Gestão ISSN 1415-4765.

Lucko, Gunnar (2003). "A Statistical Analysis and Model of the Residual Value of Different Types of Heavy Construction Equipment." PhD Dissertation submitted to the Department of Civil Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA.

Lucko, Gunnar Christine M. Anderson-Cook and Michael C. Vorster (2006), “Statistical Considerations for Predicting Residual Valueof Heavy Equipment” *Journal of Construction Engineering and Management*, Vol. 132, No. 7, July 1, 2006. ISSN 0733-9364/2006/7-723–732.

Math forum: Using Longitude and Latitude to Determine Distance http://mathforum.org/library/drmath/view/51711.html (accessed: November, 2007).

Mitchell, Zane (1998) “A Statistical Analysis Of Construction Equipment Repair Costs Using Field Data & The Cumulative Cost Model.” Doctoral dissertation submitted to the Virginia Polytechnic institute, Blacksburg, Virginia, 1998.

National Atlas. http://www.nationalatlas.gov/articles/mapping/a_projections.html (accessed May 2007).

Ong E Seow, Lusht and Mak (2005) "Factors influencing auction outcomes and market condition." *Journal of Real Estate Research*. Vol. 27, No. 2, 2005.

Pace, Kelly and LeSage, James (2004). “Chebyshev Approximations of Log-determinants of Spatial Weights Matrices." *Computational Statistics and Data Analysis* 45 (2004) pp 179-196.

RBA (2007). Ritchie Brothers Auctioneers Annual report 2007. http://www.rbauction.com/about_ritchie_bros/2007_rba_ar.pdf (accessed October, 2008).

Ritchie Wiki (2008). Excavator Specifications. http://www.ritchiewiki.com/wiki/index.php/Hydraulic_Excavator (Accessed November, 2008).

Rosen, Sherwin.(1974). “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition.” *Journal of Political Economy*. Vol.82, No.1 pp34-55.

Soto, Patricia (2004). “Spatial Econometric Analysis of Louisiana Real Estate Values.” Doctoral Dissertation submitted to the Louisiana State University, Baton Rouge.

St.Louis FRED http://research.stlouisfed.org/fred2/series/PRIME/downloaddata?&cid=117 (accessed 10/16/07).

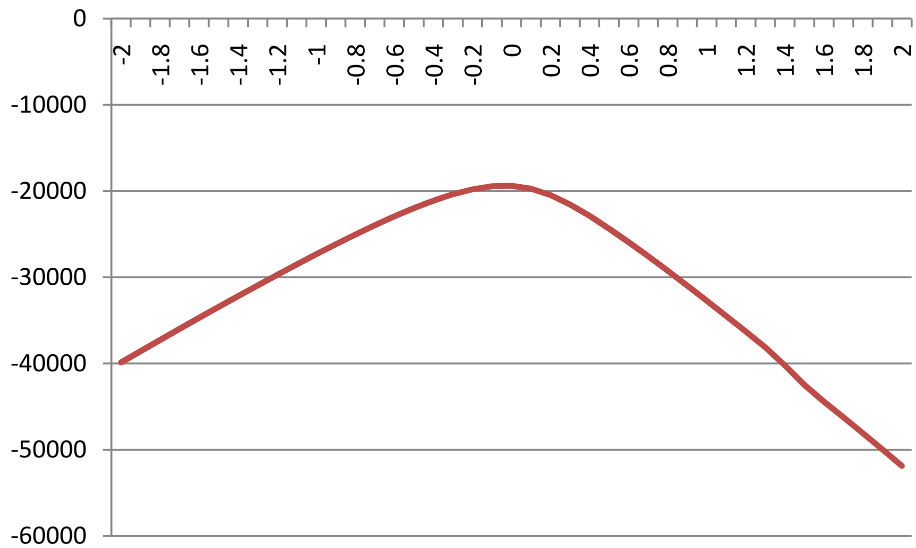
Triplett, J. (2006), "Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes: Special Application to Information Technology Products", OECD Science, Technology and Industry Working Papers, 2004/9, OECD Publishing. doi:10.1787/643587187107.

Triplett, J., (1989). "Price and technical change in a capital good: a survey of research on computers." In: Jorgenson, D., Landau, R. (Eds.), *Technology and Capital Formation*. MIT Press, Cambridge, MA, pp. 127–213.

US Census Bureau. "Census Bureau Regions and Divisions."
http://www.census.gov/geo/www/us_regdiv.pdf (accessed April, 2007).

Appendix

Figure A1. Box –Cox parameter and log likelihood values from the estimated spatial hedonic regression model, for the year 1996.



Chapter 2 Empirical Analysis of Auction House Revenue: The Case of Used Construction Equipment

Abstract

Auction houses obtain a significant part of their revenue in the form of commissions on the selling price of items offered for sale at an auction event. It is hypothesized that revenues differ between auction houses, as selling prices of items differ significantly between auction houses due to various factors. A quadratic function of revenue for auction houses is estimated using time series cross section data from (1996 through 2006) to quantify the effects of items and to identify the influence of different types of items on auction revenue. The results indicate that auction revenues increase with an increasing rate for some items (graders) and with a decreasing rate for others (excavators and wheel loaders). Magnitude of the effects varies from auction house to auction house, which, might be due to heterogeneity in the groups of bidders across auction houses. Cross quantity spillover effects also vary in magnitude and direction from auction house to auction house.

Introduction

Auction houses obtain a significant part of their revenue in the form of commissions on the selling price of items offered for sale at an auction event. Auction revenues differ between firms, as selling prices of items differ significantly between auction houses.[6] These differences may arise due to reputation effects, efficient management, auction process, nature of auction house itself or due to size of auction event. At a typical used construction equipment auction, multiple types of equipment like excavators, trucks, crawler tractors, etc. are offered in various quantities. Most auction models assume a single unit at auction, and do not investigate additional units of an item and different types of items influence auction revenues. We address these questions by estimating a quadratic function of revenue across houses using time series cross section data on equipment auction sales from 1996 to 2006 and comparing the results across different auction houses.

Market for construction equipment auction houses is fairly concentrated. Only two firms hold almost 65% of representative share of the reported data (see Figure 2.1).[7] Auction House 1, a multinational corporation (MNC) holds approximately 50% while, Auction House 3, also a MNC holds approximately 14%. The rest of 35% share is held by 68 other firms. Auction processes differ across auction houses as well. While most of the major auction houses offer both reserved price and unreserved price auctions (there is no minimum reserve price or acceptable bid), Auction House 1 offers exclusively unreserved auctions. Scale of operation and efficiency of management vary widely between firms. These and other factors may influence the revenues at auctions.

[6] Ponnaluru and Marsh (2009) find significant differences in selling prices across auction houses, after controlling for various price determinants in case of used excavators.
[7] Market share is calculated basing on our observed data sample, which may not be comprehensive of all sales during the period in the USA.

Objectives of this study are to quantify the effects of quantities of items on auction revenue and to identify the influence of different types of items on auction revenue. Results indicate that estimated revenue functions are positively linearly sloped, and that auction revenues increase with an increasing rate for some items and with a decreasing rate for others. Auction revenues are affected by cross quantity spillover effects.

The rest of the paper is organized in the following manner. First, we provide a brief overview of the relevant literature. Second, background information is provided on used equipment auctions. Third, variables used in the model estimation are discussed. Fourth, econometric technique is outlined, which is followed by results. Finally, conclusions are presented.

Review of Recent Literature

Auction houses play a significant role in the sale of construction equipment. Differences between auction houses in terms of reputation, management, size of auction, differences in between the groups of bidders in attendance at each auction house or nature of the auction house itself can influence revenues. Also, factors like numbers and types of items, physical condition of items, and time specific effects like macroeconomic effects can also affect revenues. Pinker et al (2010) found that larger lot size negatively impacts revenues in a multi-unit auction. However, Bapna et al (2001) find that lot size was not a significant factor in the case of online auctions. Kim (1996) found that offering items that act as price complements at a given auction event can maximize auction revenues. Ellison et al, (2004) find that larger markets provide greater expected surplus per participant. Higher number of bidders could increase the selling prices further due to increased competition (Menzes and Monteiro, 2005). Ponnaluru and Marsh (2009) find positive spillover effects on price due to the sale of similar items at an auction.

In exclusively online auction houses, bidders can gather information about the quality of item before choosing to attend the auction while in traditional auction house, bidders learn about the quality only after visiting an auction. Vagstad (2007) found that early information about the quality of item affects bidder entry into auction and ultimately the selling price. Diekmann (2008) found price differences between exclusively online auctions (eBay) and traditional auctions in case of agricultural tractors. D'Souza and Prentice (2002) find auction houses also influence selling price through advertisement and practices like offering items in a particular sequence during the event in the case of art auctions. Czujak (1997), Ashenfelter and Graddy (2003) used dummy variables in their analyses to account for the influence of auction house on the selling price of the item. Deltas and Jeitshcko (2007), Ginsburgh et al (2004) derive profits functions for auction houses offering single homogeneous item for sale. Parlane (2008) analyzed competing auctions with heterogeneous goods and found that auction houses exhibit monopolist like behavior with increase in the degree of heterogeneity of the items offered.

Forsund and Zanola (2006) treat sales of items as output of auction firms and the items as inputs. We follow their methodology by treating services of auction house as its output. The services include equipment sales as a major component. Auction house acts as an intermediary between buyers and sellers. Inputs would be operating capital, labor, location, auction infrastructure and items accepted from the seller. Production process involves imparting value to the items. Production by auction house involves multiple inputs and multiple outputs.

Model

Auction houses obtain a significant part of their revenue in the form of commissions on the selling price of items. The rate of commission is a fixed percentage of the selling price. Sellers pay the commission to the auction house only upon the sale of the item. Buyers usually do not pay any fee (such as buyer's premium).

Costs incurred by the auction house include fixed costs like spending on land, buildings, and infrastructure (equipment required for auction such as automobiles, computers) and variable costs like spending on labor, advertising, and security etc. Significant portion of these costs incurred are fixed (RBA 2007).

Let α represent rate of commission, p_i and q_i represent the price and quantity of service outputs, and *C* represent the costs. Profit function for an auction house can be expressed as in (2.1)

$$\Pi = \sum_{i=1}^{n} \alpha\, p_i q_i - C(q_1, \ldots q_n) \qquad \textbf{(2.1)}$$

Auction revenue is hypothesized to be a function of quantities of different items, physical condition and the year of sale. Given auction revenue is assumed to be proportional to service sales ($p_i\ q_i$) and was estimated as:

$$R_k = \beta_k + \sum_{i=1}^{n} \beta_{ik} y_i + \sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ijk} y_i y_j + \sum_{l=1}^{L} \beta_{lk}\, condition_l + \sum_{s=1}^{S} \beta_{sk}\, year_s + \varepsilon_k \qquad \textbf{(2.2)}$$

where β_{ij}'s represent the parameters to be estimated; y_i represent the number of items of each type sold:{crawler tractors, dump trucks, excavators, trucks, graders, wheel loaders, wheel tractors}; $condition_l$ represents the number of items in a particular physical condition sold at a given auction event: (excellent, good, fair, poor, unknown); $year_s$ represents dummy variables corresponding to the year at the time of sale (1996, 1997 ,.., 2006); ε_k represents the unknown error term.

Data and Variables

Data used in this study is obtained from *Equipmentwatch.com* and spans over 11 years from 1996 to 2006. In our observed data sample, trucks (mean selling price of $17,984) account for 25% of the total sales (See Table 2.1 and Table 2.2 for other descriptive statistics). However it is important to point out that the truck category includes some 55 different types including pickup trucks, equipment transport trucks, and dump trucks being the majority types. Excavators constitute 18% of the total sales (wheel tractors 18%, crawler tractors 19% each, wheel loaders, graders and scrapers account for the rest).

Other characteristics of the data are also important. Approximately 49% of the equipment were sold in the South (10% in the North East, and 19% in the West and 19%in the Midwest). Representative shares of different auction houses from 1996 to 2006 in the observed data sample are shown in Figure 2.1. The largest auction house represented 50% of the sample. The second largest auction house had 27% of the share.

The selling price per piece of equipment at auctions reflects the buyer's willingness to pay more appropriately than the marked retail prices. Prices used in the study are deflated using Producer Price Index and are expressed in 2006 US Dollars. Mean selling prices of various types of equipment at various auction houses appear to be different (see Table 2.2). Mean prices at Auction House 5 appear to be predominantly higher than at Auction House 1, and a similar trend in mean prices can be observed between Auction House 1 and 3.

Auction revenue is defined as the total amount of sales at a given auction before any deductions. It is equal to sum of prices of all the equipment sold at an event held by an auction house at a location on a given day. Auction houses obtain most of their revenue from commissions which are a fixed percentage of the final selling price of the item (RBA 2007).

Hence, their revenue is proportional to the auction revenue. Descriptive statistics on auction revenue is presented in Table 2.3. For example, Auction House 1 conducted 850 auctions with mean revenue of approximately 6 million USD. Mean revenue at Auction House 3 is 2.4 million USD (across 568 auctions) while Auction House 5 has a mean revenue of 2.6 million USD (across 113 auctions).

Auction houses may prefer to offer equipment of a particular physical condition more than those in other condition. This behavior can affect the auction revenues. Physical condition is a measure of overall physical condition of the machine. Professional equipment appraisers assess the condition of the equipment after examining all its parts such as tires, engines, under carriage, tracks etc. in conjunction with the hours used (Lucko, 2006). Definitions on various physical conditions are given in Table 2.4. We use dummy variables to account for the physical condition. Equipment in better condition is expected to cost more than the one in poorer condition. The total number of equipment in each condition is reported in Table 2.1 and Table 2.2. Most of the equipment sold is reported to be in good condition (39% good, 6% in excellent, 19% fair, 35% in unknown and only 1% in poor condition).

Prices might differ between different years due to arrival of new equipment with latest technology, changes in market conditions due to macroeconomic effects and other factors. Auction houses started offering internet bidding facilities since the year 2000. This feature allows the bidders to bid in the auction event, though they are not physically present at the auction site. This feature can have implications for auction revenues as it allows even bidders from offshore to participate in the bidding. Dummy variables are employed for each year during which the sale occurred. Coefficients on these dummy variables capture year specific effects.

Quantity of an item is calculated as the number of pieces of the item sold at an auction event held by an auction house, at a location, on a given day. For example, *s_excavator* represents the total number of excavators sold while *s_trucks* represents the number of trucks sold. Quantities of items represent the size or scale of the auction. Auctions of larger size tend to attract more bidders due to variety of items available at the auction (Ellison et.al, 2004). Increase in number of bidders increases competition for the item, thereby influencing the price and ultimately the auction revenue. Interaction terms in quantities capture spillover effects from one type of item to the other.

Econometric Methods

In this section we address empirical issues in estimation of auction revenue functions. We estimate a quadratic function of revenue using a maximum likelihood estimator, under the assumption of normally distributed error terms. Regressions were pooled over time, as to avoid sample size constraints for certain cross sections. We estimate two models- the first, a model with data pooled over all the auction houses, and the second model- estimating separate regressions for Auction Houses 1, 2, and 3, and Other (with data pooled over Auction Houses 4, 5 and all others). Likelihood Ratio test is performed to compare pooled model versus non pooled model.

Empirical issues

Quantities of items of the equipment may be endogenous as auction houses may selectively offer equipment in a particular physical condition depending on the expected selling price. Hausman's test of endogenity is performed to check for endogenity of the quantities.[8]

[8] Greene (2008) provides details on the procedure of Hausman test.

Lagged values of quantities of items (linear, and quadratic) other exogenous variables like age are used as instruments in the test. Residuals from the model (2.2) represent auction revenues after controlling for effects like amount of output (quantities of various items), condition of equipment, time specific effects etc and reflect the differences between auction houses in terms of reputation, management skills, and other effects specific to auction houses. Each auction house might have a devoted group of bidders that attend auctions only at a particular auction house. Residuals also reflect these differences.

Comparison of residuals is performed by comparing distributions and moments like mean and variance across the groups. Residuals from each of the auction houses are treated as a separate group. The nature of distribution of the groups of residuals can be compared to each other by Kruskal Wallis test and differences in means can be compared by Tukey's multiple comparison method.

Kruskal Wallis test can be used to compare if the residuals in the groups are from the same population. The null hypothesis is equality of group mean ranks i.e., the samples (groups of residuals) come from identical populations versus an alternative hypothesis that at least one of the group mean rank in not equal to others i.e., the samples (groups of residuals) come from different populations. The statistic can be calculated as:

$$H = \frac{12}{n(n+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(n+1)$$

where R_i represents the sum of ranks of residuals in the group *i*.

H is distributed as a Chi-square with *k-1* degrees of freedom where *k* is the number of groups. Dodson (2006) provides a detailed overview of Kruskal Wallis test. Tukey's pair wise multiple comparison method can be used to compare the means of the groups of residuals. Kuehl (1999) provides a detailed overview of Tukey's multiple comparison method.

Results

Results from Hausman's test of endogenity do not support endogenity of quantities or physical condition (See Table 2.5). Results from the pooled model are presented in Table 2.6. The intercept is positive but insignificant. Intercept represents mean revenue obtained from the reference category- wheel tractors. Parameter estimates on linear terms of quantities are positive and significant for each type of equipment. Quadratic terms on excavators, graders and wheel loaders are significant. For example, parameter estimates on excavators - 52607.54 (linear term) and -28.6769 (quadratic term) indicate that auction revenue increases with a decreasing rate. The same trend can be observed for wheel loaders, while, the auction revenues increase at an increasing rate for graders.

Cross quantity effects of excavators –trucks, crawler tractors – graders, and trucks – graders are negative, while, excavators –wheel loaders, crawler tractors – trucks, crawler tractors –wheel loaders and trucks – wheel loaders are positive. Trucks and crawler tractors exhibit significant cross quantity effects with all other items. Parameter estimate of the interaction term between excavators and wheel loaders is 98.457, indicating a positive interaction of wheel loaders and excavators together on auction revenue. Figure 2.2 shows the interaction effects of excavators and wheel loaders on auction revenue. Revenue maximizing combination of excavators and wheel loaders lies at top of the graphed surface. This interaction effects may not represent the functional relationships between the items in the real world.

Parameter estimates on condition of equipment are predominantly significant.

Items rated poor in condition received significantly less revenue ($57,203) than those rated unknown. Parameter estimates on dummy variables representing years 2001 through 2003 are significant. Compared to the base year of 1996, auction revenues increased until 1999 (but not significantly) and then started declining from 2001 to 2004. This period of decline coincides with a minor recession in the US.

Pooled and non-pooled models are compared using Likelihood Ratio test (calculated statistic (2206) exceeds the Chi-square table value (168.6, with 140 degrees of freedom (see Table 2.7)) indicate that the non-pooled model is a better choice than the pooled model in order to explain the variation in auction revenues across auction houses.

Results from the estimation of auction revenue function for each auction house are presented in Table 2.9. Across auction houses, the intercept terms are predominantly insignificant and positive. Parameter estimates on linear terms of quantities are all positive and predominantly significant. Parameter estimates on the coefficients of quadratic terms of quantities are predominantly negative and significant. The parameter estimates on quantities - linear terms represent slope of the estimated auction revenue function while quadratic terms represent the rate of change of auction revenues. For example, at Auction House 3, parameter estimates on crawler tractors are 58402.91 (linear) and 706.5213 (quadratic term) indicating that auction revenue from sale of crawler tractors increases at an increasing rate. A similar trend is observed across Auction House 1 and 3.

Across various auction houses, parameter estimates on cross products of quantities across auction houses are predominantly insignificant, suggesting a lack of statistically significant interaction effects between sales of different items. Parameter estimates on cross products capture the changes in auction revenue from the sale of a particular item, due to changes in the quantities of other items (interaction effects). For example, at Auction House 3, parameter estimate on cross product of excavators and wheel loaders is 486.704.

Parameter estimates on the coefficients of time of sale predominantly insignificant however, prices declined from year 2001 to 2003. This coincides with a minor recession during 2001. This period also coincides with the beginning of internet bidding facilities at auction houses.

Parameter estimates on the coefficients of condition of equipment represent shifts in the revenue between different conditions of equipment, are also predominantly insignificant across all other auction houses (except Auction House 1), indicating that condition of equipment may not be a statistically significant factor in influencing their auction revenues. At Auction House 1, all the parameter estimates on the condition of equipment are significant. We speculate that this might be due to the fact that AH 1 performs repairs and refurbishing services (for an additional fee, at seller's choice) to the equipment before sale or, due to a better system of identifying condition of items. Across most auction houses, items reported as in unknown condition received more revenue than those marked as in poor condition (for example, at auction house 1, parameter estimate on poor condition is -42195.5 while the estimate on unknown condition is 2950.627). This result is not surprising due to the fact that only less than 1% of equipment is marked as in poor condition, while 36% of equipment is reported as unknown condition.

Comparing the results from pooled model with non-pooled models (separate regression per each auction house) shows different patterns in factors that determine auction revenue across auction houses. For example, additional revenues from excavator sales from pooled model show positive slope and a negative rate of change, while across Auction Houses 1, 2 and 3, the slope is positive but rate of change is positive. Magnitude of slope also varies from auction house to auction house. This might be due to heterogeneity in the groups of bidders across auction houses.

Results from Tukey's pair wise comparison of group means of residuals from the pooled model (see Table 2.8) indicate that there is a significant difference in between group means of Auction House 1 (AH 1) and AH 2, AH 3, AH 4, and “Other” auction houses. This could be attributed to the exclusively unreserved nature of auctions offered by Auction House 1. Also, residuals from Auction House 5 differ from that of AH 1, AH3, AH 4 and “Other” auction houses. This could be due to the exclusive online nature of auction. This finding is consistent with the findings of Diekmann (2008).

Results from Kruskal Wallis test (See Table 2.10) reject the null hypothesis of equality of group mean ranks indicating that the residuals come from different populations. Residuals from represent auction revenues after controlling for effects like amount of output (quantities of various items), condition of equipment, time specific effects etc and reflect the differences between auction houses in terms of reputation, management skills, and other effects specific to auction houses. Residuals also reflect differences between groups of bidders across auction houses. Each auction house might have a devoted group of bidders that attend auctions only at a particular auction house.

Conclusion

Auction houses in addition to being an intermediary between buyers and sellers, play a significant role in the auction for used construction equipment. They provide valuable services to sellers and bidders like, besides hosting the auction event. Differences between auction houses in management efficiency, scale of operation, auction process and market conditions may influence the revenues at the auctions. A quadratic function of revenue for auction houses is estimated, using time series cross section data from 1996 to 2006. The results indicate that the estimated auction revenue function is positively sloped and auction revenues increase with an increasing rate for some items (graders) and with a decreasing rate for others (excavators and wheel loaders). Magnitude of changes in auction revenue from sale of an additional unit of an item also varies from auction house to auction house. This might be due to heterogeneity in the groups of bidders across auction houses. Estimated models assume that bidder groups are homogenous across auction houses. Auction revenues are affected by cross quantity spillover effects. Cross quantity spillover effects also vary in magnitude and direction from auction house to auction house.

Results from likelihood ratio test indicate that auction house revenues are not the same across auction houses. Auction revenues decreased from 2001 to 2003 during period of recession. Auction revenues increased albeit an in significant change, from 1996 till 2000. Auction revenues show an increasing trend from 2004 to 2006, however the change is not statistically significantly different from the revenues during 2006.

Figure 2.1: Representative share of different auction houses in used equipment sales from 1996 to 2006 in the observed data sample.

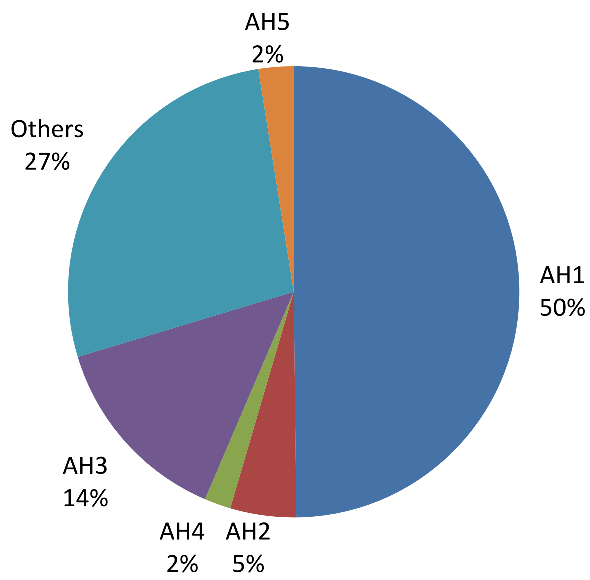


Figure 2.2: Interaction effects between excavators and wheel loaders from the pooled model

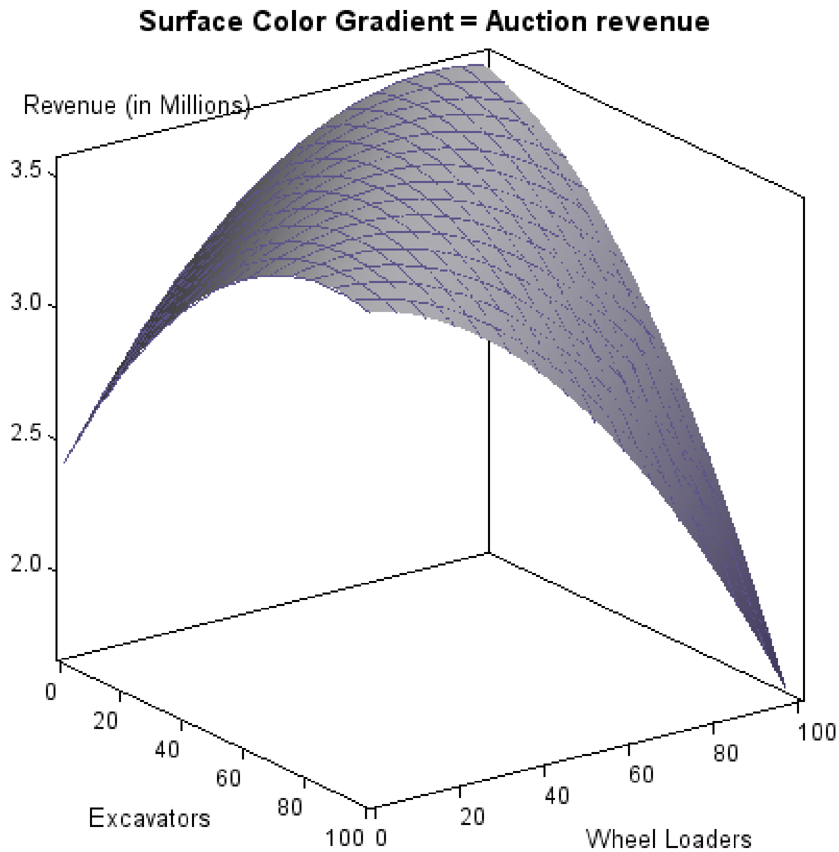


Table 2.1: Brief description of variables and descriptive statistics of used equipment sales from 1996 to 2006 in the observed data sample.

Variable		Sum	Mean	Minimum	Maximum	Std Dev
price	Sale Price of Excavator in USD		35193.94	580.4103	730000	36491.8
age	Age of Excavator in Years		11.6151	0.0767	106.2685	8.7767
AH1	Value=1 if Auction House 1	137037	0.4982	0	1	0.5000
AH2	Value=1 if Auction House 2	12992	0.0472	0	1	0.2121
AH3	Value=1 if Auction House 3	38254	0.1391	0	1	0.3460
AH4	Value=1 if Auction House 4	5206	0.0189	0	1	0.1363
auct	Value=1 if Auction House is any other Auctioneer	74675	0.2715	0	1	0.4447
excavator	Value=1 if type = Excavator	48887	0.1777	0	1	0.3823
crawlert	Value=1 if type = Crawler Tractor	49717	0.1807	0	1	0.3848
dumpt	Value=1 if type = Dump Truck	12586	0.0458	0	1	0.2090
graders	Value=1 if type = Grader	11388	0.0414	0	1	0.1992
Trucks	Value=1 if type = Truck	66035	0.2401	0	1	0.4271
wloader	Value=1 if type = Wheel Loader	30448	0.1107	0	1	0.3137
wtractor	Value=1 if type = Wheel Tractor	47181	0.1715	0	1	0.3770
con1	Value=1 if Condition = very good or excellent or new	16438	0.0598	0	1	0.2370
con2	Value=1 if Condition = good	107360	0.3903	0	1	0.4878
con3	Value=1 if Condition = fair	51409	0.1869	0	1	0.3898
con4	Value=1 if Condition = Poor	2181	0.0079	0	1	0.0887
con5	Value=1 if Condition = Unknown	97685	0.3551	0	1	0.4786
west	Value=1 if Region of Sale = West	52747	0.1918	0	1	0.3937
Neast	Value=1 if Region of Sale = North East	27762	0.1009	0	1	0.3012
south	Value=1 if Region of Sale = South	135903	0.4941	0	1	0.5000
midwest	Value=1 if Region of Sale = Mid West	51240	0.1863	0	1	0.3893
online	Value=1 if Region of Sale =Online	6908	0.0251	0	1	0.1565

Total Observations:275073

Table 2.2: Descriptive statistics of price of items in the observed data sample across various auction houses.

	Auction House 1					Auction House 3				
Variable	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**
con1	10207	63069.26	3083.68	585874.7	62752.88	2531	66291.64	2681.05	519353.97	53390.85
con2	61839	43037.95	685.1563	564378.6	41200.69	11137	41035.18	2400.27	475936.47	35066.62
con3	26393	23842.85	1811.98	409451.1	22030.46	6498	25488.08	3083.68	338710.64	20061.7
con4	1437	13130.66	1850.21	119515.5	10014.72	157	19345.47	2466.95	154184.25	20038.69
con5	37161	32024.13	966.3912	730000	37990.91	17931	34561.54	1787.36	346692.84	29426.18
Crawler tractors	24538	48004.13	685.1563	730000	45062.3	7085	40671.09	1811.98	460000	34943.61
Dump Trucks	6061	21466.11	4168.75	150000	18601.77	868	27098.63	5210.93	100702.84	21208.16
Excavators	21554	50325.2	966.3912	690745.4	43635.34	13093	39848.78	1850.21	519353.97	35966.15
Graders	6691	52017.91	1811.98	490000	41860.17	818	44298.21	1787.36	276179.44	42777.93
Trucks	32389	17719	1973.4	403918	16015.13	1903	19821.7	4759.36	165439.3	15375.44
Wheel loaders	16058	49598.39	1811.98	585874.7	40498.34	4563	52234.4	2383.15	370042.19	43516.09
Wheel tractors	23554	24353.15	1787.36	259717.6	13521.5	9546	25989.96	2085.26	220422.46	12488.33
North East	1337	36853.1	1881.97	411663.7	39451.83	16274	37824.58	1811.98	519353.97	35154.61
South	66734	40287.87	1811.98	599257.3	41029.47	15930	36730.98	1787.36	429382.96	33564.06
Midwest	23676	35048.17	1787.36	610000	37038.29	4723	36459.59	2085.26	332196.97	27956.65
West	45072	34752.89	685.1563	730000	41834.35	1285	30360.59	2085.26	247873.49	22439.99

....Continued next Page

(.......Table 2.2 continued from previous page)

	Auction House 4					Auction House 2				
Variable	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**
con1	69	75303.07	18171.54	196610.1	41830.3	508	74456.43	5073.55	345372.7	59915.35
con2	201	50940.73	7149.46	252862.2	36563	5403	43848.41	2466.95	374476.6	34882.99
con3	76	19031.94	4766.3	54812.5	9134.63	3790	24777.97	2025.68	217532.6	19479.93
con4	4	23235.73	4766.3	68515.63	30499.85	95	16879.31	2220.25	88810.13	15429.81
con5	4856	30999.22	2174.38	307445	26254.13	3196	26582.8	2415.98	460000	26031.11
Crawler tractors	860	29034.43	3651.86	252862.2	25636.4	2481	39445.23	2466.95	460000	35657.77
Dump Trucks	244	20717.88	5000	98089.34	18228.03	985	25187.58	5000	99149.39	18532.09
Excavators	1914	40725.78	4170.52	307445	31480.44	2692	44454.1	2415.98	374476.6	41486.46
Graders	63	25559.85	3908.2	81000	20768.68	530	40837.85	2025.68	223257.2	31605.64
Trucks	556	13282.45	4500	100000	11356.54	2221	19446.75	4705.57	145906.1	15119.24
Wheel loaders	830	39274.51	2174.38	196298.2	29480.12	2146	43945.33	3140.77	309125.3	33426.14
Wheel tractors	720	24436.48	3000	68251.38	13204.89	1683	23738.62	2509.3	144863.9	12513.93
North East	4926	32231.25	2174.38	307445	27647.18	1127	24584.11	3772.67	460000	25300.78
South	117	33555.05	5724.54	111169	22811.7	11391	36116.22	2025.68	374476.6	33425.64
Midwest	104	22683.38	3000	70583.5	16233.65	474	33969.12	3100	150000	25290.77
West	59	41533.14	4950.39	203226.4	40333.27	0	0	0	0	0

....Continued next Page

(......Table 2.2 continued from Previous Page)

	Auction House 5					Other				
Variable	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**	**N**	**Mean**	**Minimum**	**Maximum**	**Std Dev**
con1	253	55598.74	5000	295981	44233.56	2870	68724.17	4007.18	542246.1	49892.24
con2	794	51961.86	4500	418959	44551.02	27986	35689.62	2343.6	515208.9	31776.48
con3	452	42687.19	3000	490000	37873.56	14200	20532.19	1549.05	370719.2	17173.18
con4	19	31595.11	5315.15	84000	22550.67	469	13464.73	1881.97	76103.31	10635.46
con5	5391	41754.73	3100	370563.4	35660.38	29150	24267.64	580.4103	468984	24893.14
Crawler tractors	1734	47846.72	3000	490000	37957.07	13019	35019.48	1973.56	542246.1	33122.75
Dump Trucks	104	30239.07	5250	106000	29664.14	4324	31710.04	5000	118809.3	28294.28
Excavators	1546	53071.98	3230.78	418959	44424.78	8088	42289.64	1191.58	332482.1	34085.57
Graders	268	68781.74	4579.63	201405.7	42670.62	3018	47309.93	1787.36	297023.2	44826.39
Trucks	572	16442.34	3319.87	104218.7	15514.94	28394	20657.9	580.4103	301813.4	16217.42
Wheel loaders	797	55588.97	3319.87	295981	38354.01	6054	38342.3	1549.05	416874.6	35437.7
Wheel tractors	1717	29526.54	3100	286227.2	14334.53	9961	20794.1	1787.36	159353.9	11956.36
North East						4096	27492.07	1191.58	357575.1	28419.65
South						41731	32518.06	1549.05	515208.9	29989.27
Midwest						22263	22068.62	580.4103	463773	19876.81
West						6331	37217.53	1881.97	542246.1	46151.97

Table 2.3: Descriptive statistics on auction revenue

Auction House	No. of Auctions	Mean	Std Dev	Minimum	Maximum
AH1	850	6051171	5423793	2775.32	53616070
AH2	73	6235719	12650462	7545.33	47230542
AH3	568	2487983	4454486.6	7441.91	38337429
AH4	149	1124205	1126067.4	12393.67	5578850
AH5	113	2657880	1632585.6	20472.56	7455800
Other	1390	1583684	2437986.4	3321.97	18599305

Table 2.4: Brief definitions of physical condition of equipment as defined by Equipment Watch (2008).

Condition	Definition
New	New unit
Excellent	Some use, but almost new mechanically
Very Good	In above average mechanical condition; low hours or recently overhauled
Good	In average mechanical condition; may need minor repairs or replacement of worn parts soon
Fair	In below average mechanical condition; high hours or older unit
Poor	Needs major repairs
Unknown	No condition is available

Table 2.5: Hausman test for endogeneity of quantities in the estimated regression.

Equation	Efficient under H0	Consistent under H1	DF	Statistic	Pr > ChiSq
AH1	OLS	2SLS	41	20.55	0.9968
AH2	OLS	2SLS	41	1.73	1
AH3	OLS	2SLS	41	8.03	1
AH4	OLS	2SLS	41	0.99	1
AH5	OLS	2SLS	38	2.5	1
Other	OLS	2SLS	41	3.23	1

Table 2.6: Maximum Likelihood results from model pooled across auction houses.

Label /Brief definition	Parameter	POOLED Estimate	POOLED Approx Pr > |t|
Intercept	Intercept	9858.852	0.9333
No. of excavators	Excavator	**52607.54**	**<.0001**
No. of crawler tractors	Crawler Tractor	**45552.33**	**<.0001**
No. of graders	Graders	**126552.4**	**<.0001**
No. of trucks	Trucks	**24738.74**	**<.0001**
No. of wheel loaders	Wheel Loaders	**69169.34**	**<.0001**
Excavator * Excavator	sq ex	**-28.6769**	**0.039**
Crawler tractors * Crawler tractors	sq ct	46.00243	0.1076
Graders * Graders	sq gr	**742.9457**	**0.0363**
Trucks * Trucks	sq tr	-4.79024	0.442
Wheel loaders * Wheel loaders	sq wl	**-576.804**	**<.0001**
Excavator * Crawler tractors	ex*ct	-34.7707	0.2827
Excavator * Graders	ex*gr	221.8024	0.0767
Excavator * Trucks	ex*tr	**-116.553**	**<.0001**
Excavator * Wheel loaders	ex*wl	**98.45775**	**0.0392**
Crawler tractors * Graders	ct*gr	**-950.486**	**<.0001**
Crawler tractors * Trucks	ct*tr	**59.63902**	**0.0002**
Crawler tractors * Wheel loaders	ct*wl	**474.8137**	**<.0001**
Graders * Trucks	gr*tr	**-202.983**	**0.001**
Graders * Wheel loaders	gr*wl	57.69456	0.8108
Trucks * Wheel loaders	tr*wl	**136.9299**	**<.0001**
No. of items in condition 1	s_con1	**13972.54**	**<.0001**
No. of items in condition 3	s_con3	**2415.369**	**0.0002**
No. of items in condition 4	s_con4	**-57203.1**	**<.0001**
No. of items in condition 5	s_con5	127.3279	0.7473
Value=1 if year = 1997	d97	47120.03	0.7321
Value=1 if year = 1998	d98	74251.75	0.5744
Value=1 if year = 1999	d99	7639.043	0.9569
Value=1 if year = 2000	d00	-23650.7	0.8638
Value=1 if year = 2001	d01	**-285421**	**0.0376**
Value=1 if year = 2002	d02	**-445321**	**0.0017**
Value=1 if year = 2003	d03	**-450993**	**0.0016**
Value=1 if year = 2004	d04	-197426	0.1823
Value=1 if year = 2005	d05	32664.5	0.8243
Value=1 if year = 2006	d06	134153.4	0.422
Adj R square	0.9253		
Log likelihood	-48634		
Dependent variable : auction revenue			

Table 2.7:Likelihood Ratio test statistics for pooled vs non pooled models

model	LL
pooled	-48634
AH1	-13436
AH2	-1003
AH3	-8338
Other	-20849
LR statistic	2206
χ^2_{140}	168.6

H_0: $\beta^i_j = \beta_j$ where
$i \in \{AH1, AH2, AH3, Other\}$
and j indicates parameter

Table 2.8: Least Squares difference of means between the residuals of auction houses.

					Confidence Interval	
ahouse	**_ahouse**	**Estimate of Mean Difference**	**Pr > |t|**	**Adj P**	**Adj Lower**	**Adj Upper**
AH1	**AH2**	**416835**	**0.0015**	**0.0507**	**50362**	**921317**
AH3	AH4	148460	0.1776	0.7607	-173219	484072
AH3	**AH1**	**-246342**	**<.0001**	**0.0022**	**-496923**	**-109915**
AH3	AH2	170493	0.2414	0.8638	-261525	626366
AH4	**AH1**	**-394802**	**<.0001**	**0.003**	**-775960**	**-141731**
AH4	AH2	22033	0.8801	1	-483109	537097
AH5	**AH3**	**404902**	**0.0006**	**0.0137**	**75572**	**811146**
AH5	**AH4**	**553361**	**0.0001**	**0.0031**	**153381**	**1044189**
AH5	AH1	158559	0.2645	0.7747	-217580	497460
AH5	**AH2**	**575395**	**0.0009**	**0.0179**	**89623**	**1161936**
Other	**AH5**	**-460776**	**<.0001**	**0.0013**	**-835442**	**-136890**
Other	AH3	-55875	0.4925	0.9377	-220619	135005
Other	AH4	92585	0.2969	0.9479	-195171	420410
Other	**AH1**	**-302217**	**<.0001**	**<.0001**	**-501694**	**-190757**
Other	AH2	114618	0.3532	0.9684	-289121	568349

Degrees of freedom: 3135
Adjustment: **Tukey-Kramer**
Alpha=0.05

Table 2.9: Regression results of auction revenue by each auction house (Maximum Likelihood estimates).

Parameter	AH1 Estimate	AH1 Approx Pr > |t|	AH2 Estimate	AH2 Approx Pr > |t|	AH3 Estimate	AH3 Approx Pr > |t|	All other auctions houses "Other" Estimate	All other auctions houses "Other" Approx Pr > |t|
Intercept	531580.5	0.0766	156561.7	0.7404	-76981.5	0.5313	-134467	0.3619
Excavator	**31764.79**	**0.0012**	**-43538.1**	**0.0342**	**25091.89**	**<.0001**	**65551.73**	**<.0001**
Crawler Tractor	**51550.34**	**<.0001**	**47426.37**	**0.0578**	**58402.91**	**<.0001**	**36554.74**	**<.0001**
Graders	**117045**	**<.0001**	13430.45	0.8809	**160744.1**	**<.0001**	**73243.43**	**<.0001**
Trucks	**14954.47**	**0.0025**	17098.9	0.1956	4008.077	0.6888	**28680.74**	**<.0001**
Wheel Loaders	**56141.93**	**0.0005**	13561.36	0.5127	**44149.63**	**<.0001**	**57522.31**	**<.0001**
sq ex	**303.7917**	**0.011**	**1672.534**	**0.019**	**195.4415**	**<.0001**	**-172.788**	**0.0264**
sq ct	29.51324	0.755	937.8204	0.7362	**706.5213**	**0.0011**	-93.8719	0.2002
sq gr	362.9633	0.7245	**-34794.3**	**0.0274**	-1061.39	0.8284	-1102.27	0.0909
sq tr	**34.08483**	**0.085**	-78.5615	0.4601	**401.045**	**<.0001**	**-52.4052**	**0.0001**
sq wl	**-923.708**	**0.023**	**-5737.86**	**0.0171**	**777.9776**	**0.0236**	**2994.315**	**<.0001**
ex*ct	162.3075	0.289	**-3547.71**	**0.0343**	**-860.386**	**0.0002**	64.03115	0.6243
ex*gr	97.30313	0.8507	-7022.91	0.2652	**1608.809**	**0.023**	**1992.616**	**<.0001**
ex*tr	**-306.475**	**<.0001**	-1197.08	0.2598	205.0802	0.3064	**385.6928**	**<.0001**
ex*wl	135.2519	0.7159	1910.069	0.2659	**486.7047**	**0.0272**	**-2286.62**	**<.0001**
ct*gr	-580.118	0.3363	-6376.1	0.405	493.0441	0.7223	430.2469	0.1256
ct*tr	-70.1212	0.2024	2018.41	0.29	-476.181	0.4008	31.6831	0.5798
ct*wl	325.2853	0.2922	5012.311	0.2615	-168.896	0.6337	**-446.811**	**0.0339**
gr*tr	**-532.792**	**0.0008**	5602.411	0.2863	-1948.35	0.1958	**920.1802**	**<.0001**
gr*wl	899.3795	0.233	**23974.94**	**0.0232**	**-7642.95**	**<.0001**	**-1414.42**	**0.0115**
tr*wl	**551.0432**	**<.0001**	-2086.97	0.1695	231.8548	0.6395	**-946.641**	**<.0001**
s_con1	**10167**	**<.0001**	**103070.6**	**0.0006**	**40123.81**	**<.0001**	**36947.29**	**<.0001**
s_con3	**6817.573**	**0.0002**	50336.21	0.2839	-1556.33	0.3365	**6034.276**	**<.0001**
s_con4	**-42195.5**	**0.0191**	25955.3	0.8799	-3890.35	0.8812	-12974.1	0.2773
s_con5	**2950.627**	**0.0094**	**24063.28**	**<.0001**	**6141.076**	**<.0001**	852.6761	0.2182
d97	208488	0.4988	-113997	0.985	135061.6	0.4018	-13132.4	0.9409
d98	362380.5	0.2293	6395002	0.3285	24532.39	0.8734	-85180	0.6381
d99	371067.9	0.2623	8932.278	0.9991	-53397.9	0.7323	39810.73	0.8265
d00	-174644	0.6497	-74787.9	0.8799	135543.8	0.3394	124216.2	0.4069
d01	**-747154**	**0.0485**	-123460	0.8031	37510.33	0.7965	-13420.7	0.9309
d02	**-944701**	**0.0286**	-262725	0.5961	-48558.6	0.7361	-131933	0.4073
d03	**-841422**	**0.0415**	-247887	0.6238	-145421	0.3792	-48057.4	0.759
d04	-285429	0.5021	-132393	0.7904	146132.4	0.3436	1618.636	0.9921
d05	-128911	0.7609	-222724	0.6454	**474107.9**	**0.002**	213112.7	0.186
d06	255867.7	0.5369	-88777.7	0.856	453744.1	0.1101	-96719.7	0.7005
Adj Rsquare	0.8887		0.9994		0.9823		0.8922	
Log likelihood	-13436		-1003		-8338		-20849	

Dependent variable : auction revenue

Table 2.10: Kruskal Wallis test for equality of group mean ranks of residuals in the observed data sample.

Kruskal-Wallis Test	
Chi-Square	77.6343
DF	5
Pr > Chi-Square	<.0001

References

Ashenfelter and Graddy (2003). "Auctions and the price of art". *Journal of Economic Literature*. Vol 41 pp 763-87

Bapna, Ravi. Paulo Goes,and Alok Gupta (2001). "Insights and Analyses of Online Auctions". *Communications of the ACM.* Vol.44, No.11, Nov 2001.

Czujack, C. (1997) "Picasso paintings at auction".*Journal of Cultural Economics*. Vol.21 pp 229-247

D'Souza, Claire and David Prentice. (2002). "Auctioneer Stategy and Pricing: Evidence from Art Auction." *Market Intelligence and Planning.*Vol.20, Issue 7, pp 417-427.

Deltas, George and Thomas D. Jeitschko (2007). "Auction host site pricing and market equilibrium with endogenous bidder and seller participation." *International Journal of Industrial Organization* 25(2007) 1190-1212.

Diekmann Florian, Brian E. Roe, And Marvin T.Batte.(2008). Tractors On eBay: Differences Between Internet And In-Person Auctions. *American Journal of Agricultural Economics*. 90(2) (May 2008): 306–320.

Dodson, Bryan (2006). "The Weibull Analysis Handbook" ISBN 087389667X, 9780873896672 http://books.google.com/books?id=5GzgBpdJkHwC&pg=PA115&dq=anderson+darling+test&client=firefox-a#PPA115,M1 (accessed May 2009).

Ellison Glenn, Markus Mobius and Drew Fundenberg (2004). "Competing Auctions." *Journal of the European Economic Association* March 2004 2(1):30 – 66.

Equipment watch https://www.equipmentwatch.com/HomePage.jsp (accessed January, 2007)

Forsund, Finn and Roberto Zanola (2006). "The Art of Benchmarking: Picasso Prints and Auction house performance". *Applied Economics*. Vol.38 Issue 12, pp 1425-1434.

Ginsburgh Victor, Patrick Legros and Nicolas Sahuget (2004). "How to win twice at an auction: On the Incidence of Comissions in Auction Markets." *The Fondazione Eni Enrico Mattei Note di Lavoro Series Index:* http://www.feem.it/Feem/Pub/Publications/WPapers/default.htm accessed (Nov. 2007)

Greene, William (2008). "Econometric Analysis". Prentice Hall, 6th edition, 2008

Kim, Hee-Su. (1996). "Equilibrium and Efficiency in Auctions of Complementary goods without bundling." *Economics Letters.* Vol 52, pp49-54.

Kuehl Robert (1999), "Design of Experiments: Statistical Principles of Research Design and Analysis" (2nd edition). Duxbury Press.ISBN-13: 9780534368340.

Lucko, Gunnar Christine M. Anderson-Cook and Michael C. Vorster (2006), "Statistical Considerations for Predicting Residual Valueof Heavy Equipment" *Journal of*

Construction Engineering and Management, Vol. 132, No. 7, July 1, 2006. ISSN 0733-9364/2006/7-723–732.

Lucko, Gunnar Christine M. Anderson-Cook and Michael C. Vorster (2006), “Statistical Considerations for Predicting Residual Valueof Heavy Equipment” *Journal of Construction Engineering and Management*, Vol. 132, No. 7, July 1, 2006. ISSN 0733-9364/2006/7-723–732.

Menezes and Monteiro, (2005). *An Introduction to Auction Theory.* Oxford press.

Ong E Seow, Lusht and Mak (2005). "Factors influencing auction outcomes and market condition". *Journal of Real Estate Research*. Vol. 27, No. 2, 2005.

Parlane, Sarah (2008). "Auctioning Horizontally differentiated items." *Review of Industrial Organization*. December 2008 (print) Springer.

Pinker, Edieal.,Abraham Seidmann and Yaniv Vakrat (2010). " Using bid data for the management of sequential, multi-unit, online auctions with uniformly distributed bidder valuations." *European Journal of Operational Research*. Vol.202 Issue 2, April 2010, pp574-583.

Ponnaluru, Srinivasa and Thomas Marsh (2009). "A Spatial Hedonic Price Analysis of Used Construction Equipment - the Case of Excavators." Manuscript. School of Economic Sciences, Washington State Univeristy, Pullman.

RBA (2007). Ritchie Brothers Auctioneers Annual report 2007. http://www.rbauction.com/about_ritchie_bros/2007_rba_ar.pdf (accessed October, 2008).

Vagstad, Steinar(2007)." Should auctioneers supply early information for prospective bidders?" *International Journal of Industrial Organization* 25 (2007) 597–614.

Chapter 3 Price Relationships in Multi-Item Construction Equipment Auctions

Abstract

Auction houses stage events where sellers offer for sale multiple units of an item, items of different types, and items in various physical conditions. Theoretically consistent inverse supply functions are specified for multi-unit and multi-type auctions. It is hypothesized that price complementarities exist between different items being offered at an event, offering opportunity for auction houses to exploit price relationships by preselecting the number, type and condition of equipment. Normalized quadratic inverse supply functions are estimated for different types of equipment, and hypothesis are tested using transaction level, time series cross section data on equipment sales from 1996 to 2006.

Introduction

Auctions for used construction equipment differ in their process from their well known counterparts like single item auctions (e.g., art auctions, collectibles etc.), multi item auctions (Treasury Bills, Telecom 3G etc.) or combinatorial auctions (e.g., bus routes, industrial procurement). A typical used equipment auction involves many buyers and sellers, offering for sale various types of equipment (e.g., excavators, trucks, or wheel tractors) with varying characteristics (e.g., brand, age, or condition). In addition, sellers may offer and buyers may purchase one or more units of various types of equipment. It is hypothesized that this multi-item and multi-unit nature of an auction can affect price formation, by the way of spillover effects from the sale of items of a particular type (e.g., trucks) on to items of a different type (e.g., excavators). To address these issues and tests hypotheses, we use transaction level data on equipment auction sales from 1996 to 2006.

Price relationships in equipment auctions may arise due to a variety of factors. Presence of different types of items at a single event reduces transaction costs (shipping costs, search costs, informational costs, and other opportunity costs of time) to both sellers and bidders (prospective buyers). Multi-type and multi-unit equipment auctions attract a diverse group of bidders. Some of the bidders may be interested only in a specific item, while others might bid on more than one item. Presence of significant cross quantity effects could indicate that bidders bid on more than one type of item.

Auction houses might exploit price relationships between different types of equipment for several reasons. It has been argued that offering items that act as price complements at a given auction event can maximize auction revenues (Kim, 1996). These price spillover effects can have direct and feedback effects on revenue and profits of auction houses. Positive spillover effects bring higher selling price on items, directly increasing auction revenues. Higher selling prices attract more future sellers and thereby more future bidders creating feedback effects (Deltas and Jeitschko, 2007).

The objectives of this study are to theoretically specify and empirically estimate inverse supply functions for various items (such as excavators, trucks, crawler tractors, graders etc.,) and test whether cross quantity effects are statistically significant. Our results indicate that cross quantity effects are significant and unequal across different items. Auction houses may find these results interesting for planning and marketing purposes. Buyers and sellers can also benefit from these results by making better informed decisions.

The rest of the paper is organized in the following manner. First, we provide a brief overview of the relevant literature. Second, a theoretical model is specified. Third, background information is provided on used equipment auctions. Fourth, the data and variables used in the estimation are discussed. Fifth, the econometric technique is outlined, which is followed by results. Finally, conclusions are presented.

Review of Recent Literature

Auctions for used construction equipment are multi-unit and multi-type in nature. Recent developments in auction literature focused on multi-unit auctions. Pinker et al (2010) found that larger lot size negatively impacts revenues in a multi-unit auction. However, Bapna et al (2001) find that lot size was not a significant factor in the case of online auctions. Kim (1996) found that offering items that act as price complements at a given auction event can maximize auction revenues.

Selling price of an item can be influenced by various factors such as age of the item (equipment), auction house, presence of multiple pieces of the same type of item, number of bidders etc. Lucko (2006) analyzed the residual value of used construction equipment using auction data and found that the age of the equipment and physical condition affected the residual value. Ponnaluru and Marsh (2009) found significant differences in prices across auction houses controlling for quality of the item. They also report statistically significant spillover effects on prices, arising from the sale of similar type of items (excavators) at an auction event. Positive spillover effects increase the selling prices at a given auction. Existence of price premiums can attract sellers. Price premiums can set off a positive chain reaction described by Deltas and Jeitshcko (2007) as 'feedback effects', where an increase in the seller attendance triggers an increase in bidder attendance which in turn influences the future seller attendance. Ellison et al (2004) find that larger markets provide greater expected surplus per participant. Higher number of bidders could increase the selling prices further due to increased competition (Menzes and Monteiro, 2005).

Kristofersson and Ricertsen (2004) estimate inverse demands from the parameters of hedonic price function of quality differentiated inputs. As the equipment can also be treated as inputs to the auction house, a similar approach of deriving inverse demands is not appealing to our problem at hand for two reasons: first, the variables representing quality characteristics (construction equipment) are qualitative in nature, and interpretation of parameter estimates on these quality characteristics as marginal effects (marginal prices) is not accurate, as the parameters would represent shift effects (from the mean price); and the second, the input demands may not be identifiable, as the auction house does not actually pay for procuring the inputs from the sellers (auction house accepts the items for sale on behalf the seller). .

Forsund and Zanola (2006) treat sales of items as output of auction firms and the items as inputs. We follow their methodology by treating equipment sales as output. Treating the equipment as an output, we specify an output distance function. Fare and Premont (1995) provide a detailed treatment of the relationships between output distance functions and revenue functions. Holt and Bishop (2001) derive normalized quadratic distance functions to estimate theoretically consistent inverse demands.

Background and Model

At a used equipment auction, multiple pieces of different types of equipment are sold. Buyers can buy one or more types of items. In many auction houses, the equipment on sale is driven across a ramp in the auction theatre. Bidders seated in the theatre can watch and bid on the item on display. As soon as the item is sold it is driven off the ramp and its position is taken by the next item in line. This process continues until all the lots are sold. Auction houses usually organize the event at their location. Bidders (prospective buyers) can view and physically inspect the item immediately before or on the date of sale. Often bidders who are unable to be present physically at the auction site can still participate in the bidding by using the online bidding facility of the auction house's website. Bidders are required to pre-register before the auction.

Some auction houses require a security deposit at the time of bidder registration. Bidders get unique identification numbers after their registration. Most of the buyers (about 80%) are end users with some resale (RBA 2005).

Auction houses offer a wide range of services to bidders (prospective buyers) and sellers. The services for sellers include appraisal of the equipment, advertising, organization of sale, and collection and secure transfer of sale proceeds. The services provided for prospective buyers include informational (catalog), financial, and escrow service. Prior to the auction event, auction houses often publish an auction catalog online or in hard copy and then distribute it to the bidders. Some offer in-house financing for the purchase for the buyers who need special payment arrangements. Auction houses hold the money paid by the buyers in an escrow account. Upon the transfer of title to the buyer, the money is released to the seller.

Auction houses obtain most of their revenue from commissions which are a fixed percentage of the final selling price of the item (RBA 2007). Hence, their revenue is proportional to the auction revenue. Auction houses can maximize their revenue by choosing an optimal rate of commission and by achieving a higher selling price for an item. Relationships between prices of different types of items can be exploited to maximize the auction revenues by suitably offering items that act as price complements at a given auction event. Price premiums at an auction house attract sellers. An increase in seller attendance could mean wider variety of items and larger auction size. These features could attract more bidders and higher number of bidders could increase the selling prices further.

Auction houses acts as an intermediary between buyers and sellers and their actual output is services for buyers and sellers. Forsund and Zanola (2006) treat sales of items as output of auction firms and the items as inputs. We follow their methodology by treating equipment sales as output. Inputs would be operating capital, labor, location, auction infrastructure and items accepted from the seller. Production by auction house involves multiple inputs and multiple outputs.

Assuming profit maximization of the auction house as an approximation to firm behavior, we apply duality theory in the form of the output distance function to derive price relationships. Let $x \in \Re_{+}^{N}$, and $y \in \Re_{+}^{M}$ denote vectors of inputs, outputs respectively. *T* denotes technology set where $T = \{(x, y): x \;\; can\ produce\, y\}$.and θ is a positive scalar.

Output distance function represents the maximal proportional expansion of output when an input vector is exogenously given. It represents a revenue function of a profit maximizing firm under duality theory. Following Fare and Premont (1995) output distance function for an auction house under perfect competition can be set up as:

$$D_o(x, y) = \inf_{\theta}\{\theta > 0 : (x, y/\theta) \in T\} \qquad \textbf{(3.1)}$$

$\dfrac{\partial D_o(x, y)}{\partial y_k} = p_k^*$ where $p_k^* = \dfrac{p_k}{R}$ represents revenue normalized price of output k , α represents auction house's rate of commission and R is revenue from a given auction event.

We specify output distance function as normalized quadratic function:

$$\begin{aligned} D_o(x, y) = b_0 &+ \sum_{i=1}^{n-1} b_i y_i^* + \frac{1}{2}\sum_{j=1}^{n-1}\sum_{i=1}^{n-1} b_{ij} y_i^* y_j^* + \sum_{i=1}^{n-1}\sum_{k=1}^{K} \beta_{ik} A_k y_i \\ &+ \sum_{i=1}^{n-1}\sum_{l=1}^{L} \gamma_{il} C_l y_i + \sum_{i=1}^{n-1}\sum_{m=1}^{M} \delta_{im} R_m y_i + \sum_{i=1}^{n-1}\sum_{s=1}^{S} \tau_{is} T_s y_i \end{aligned} \qquad \textbf{(3.2)}$$

with $n-1$ outputs y_i and homogeneity is imposed by normalizing the quantities $y_i^* = \left(\dfrac{y_i}{y_n}\right)$ for i=1,..n-1.

Price flexibilities are given by the equation:

$$\varepsilon_{ij} = \frac{\partial \ln p_k}{\partial \ln y_j} = \frac{b_{ij}^* y_i^*}{\hat{p}_i}$$ for i, j=1..n-1 using estimated b_{ij}^* and predicted $\hat{p}_i$

Data and Variables

Data used in this study is obtained from *Equipmentwatch.com* website and spans over 11 years from 1996 to 2006. In our observed data sample, trucks (mean selling price of $16,913) account for 25% of the total sales (See Table 3.1 and Table 3.2 for other descriptive statistics). The truck category includes some 55 different types including pickup trucks, equipment transport trucks, and dump trucks being the majority types. Excavators (mean selling price of $39,700) constitute 18% of the total sales. Wheel tractors constitute 18%, crawler tractors 19% each, wheel loaders, graders and scrapers account for the rest. (For mean selling prices of various types of equipment, see Table 3.2).

Approximately 49% were sold in the South, 10% in the North East, and 19% in the West and 19%in the Midwest. Most of the equipment sold is reported to be in good condition, 39% good, 6% in Excellent, 19% Fair, 35% in unknown and only 1% in poor condition. Representative shares of different auction houses from 1996 to 2006 in the observed data sample are as follows: The largest auction house (Auction House 1) holds 45% of the share; the second largest auction house holds 28%, Auction House 2 holds 6% and Auction House 4 holds 4% of the share.

Price

Price of an item reflects the highest bid at which the item is sold. The prices are nominal and are in US dollars.

Total Revenue per auction

Total revenue per auction is defined as the total amount of sales at a given auction before any deductions etc. It is equal to sum of prices of all the equipment sold at an event held by an auction house at a location on a given day.

Age of equipment

Age of a machine is calculated as a period between date of manufacture and date of sale. As manufacturers report only the year of make but not the exact date, we assumed that the equipment has been made on 1st of September of the previous year to the respective year of make. For example, if the manufacturer reports the equipment as a 1998 model, this study would assume the date of manufacture as 1st September, 1997. This reference date of 1st of September is chosen, as the new year's models would start appearing in the market at the beginning of the last quarter of a year. Calendar age is used in this study due to the lack of availability of other usage measures such as hours of usage on the machine. Age represents the amount of machine's usable life already past. Newer machines have more usable life than the older ones.

Physical condition

This measures the overall physical condition of the machine. Professional equipment appraisers assess the condition of the equipment after examining all its parts such as tires, engines, under carriage, tracks etc. in conjunction with the hours used (Lucko, 2006). Definitions on various physical conditions are given in Table 3.3. The proportions of equipment in various physical conditions sold at auctions in our sample period can be seen in Figure 3.1. We use dummy variables to account for the physical condition, for example, the variable *excellent* takes a value of 1 if the equipment is in excellent physical condition. Equipment in better condition is expected to cost more than one in poorer condition. The sign or relative magnitude of the parameter on *unknown* condition is not readily predictable. Total number of equipment in each condition is reported in Table 3.1.

Region of Sale

Prices might differ between different regions in the US due to variation in construction activity hence the demand for equipment. The region of sale is defined based on the U.S. census tract regions (US Census Bureau, 2007) to which the city of sale corresponds. Regional distribution of various excavator sales is presented in Table 3.1. Dummy variables representing West, Midwest, South and Northeast were assigned accordingly.

Auction Houses

Auction houses can have significant influence on the selling price[9]. Descriptive statistics on price across various auction houses are given in Table 3.2. Auction houses differ from each other in scale of operation, management efficiency, number of locations, reputation etc. We capture these effects by employing dummy variables for each auction house. For example, if the item is sold at Auction House1, the dummy variable *AH1* takes a value of 1 or 0 otherwise. The sign or the significance of these terms is not readily predictable.

Quantities of items

Quantity of an item is calculated as the total number of items of identical type being offered at an auction event at a given day. Quantity of items can affect the price in multiple ways. The number of pieces of the same type of equipment being offered at a sale can exert a “sales effect” on the prices. Also, when a bidder buys multiple pieces of equipment in a single lot, the selling price is affected. As the type of sale is an auction, the quantities of items available are fixed *ex ante* and prices form during the event, one might expect the quantities of items to be exogenous. However, this reasoning may not hold in practice, as auction houses determine the actual quantities put on

[9] Ong et al. (2005) identified the effect of auctioneer on the probability of sale at real estate auctions.

sale based on the expected prices during the event, and sellers might also choose to list with an auction house based on recent sales (time series nature of the data) and expected prices.

Estimation

In this section we address empirical issues in the estimation of the supply functions using iterated two stage least squares (IT2SLS). Preliminary regressions were estimated by Ordinary Least Squares and Hausman test for endogenity of quantities is performed. IT2SLS is estimated to account for endogenity. Separate regressions were estimated for each type of equipment, allowing the parameter estimates to vary freely across equations over observed data sample from 1996 to 2006 in *SAS* using *PROC MODEL* procedure.

Homogeneity (of degree zero) is imposed by normalizing the quantities of an item by sum of quantities of all the items at the sale. Variables such as lags (first and second) of quantities, and other exogenous variables like prime lending interest rates, age, dummy variables for auction houses, condition are used as instruments in the IT2SLS estimation. Check for multicollinearity was done by calculating variance inflation factors (VIFs). (See Kutner et.al (2005) for a detailed description of VIF calculation.). Basing on VIFs multicollinearity was not an issue (see Table A3.1 in the appendix).

From the output distance function inverse input supply functions are derived as:

$$p_k^* = b_k + \sum_{i=1}^{n-1} b_{ik} y_i^* + \sum_{k=1}^{K-1} \beta_{ik} A_k + \sum_{l=1}^{L-1} \gamma_{il} C_l + \sum_{m=1}^{M-1} \delta_{im} R_m + \sum_{s=1}^{S-1} \tau_{is} T_s$$

for k=1,..n-1, where, b_i and b_{ij}, β, γ, δ and τ represent the parameters to be estimated.Here, p^* represents revenue normalized price, y^* represent normalized quantities of various type of equipment {excavators, crawler tractors, trucks, graders, and wheel loaders}, A represents auction houses {AH1, AH2, AH3, AH4, others}, C represents condition of equipment {con1, con2, con3, con4 and con5},*R* represents region of sale {West, Midwest, Northeast and South} and *T* represents time of sale {quarter 1-q1, q2, q3 and q4}.

Results

Results from IT2SLS estimation of inverse supply functions are presented in Table 3.5. Intercepts are significant and positive across all the equations estimated. The intercept represents mean normalized price of the reference category –equipment sold at the "Other" auction house, in good condition, in the West during fourth quarter of the year of sale. The coefficients on quantity of item ("own item quantity") are positive (except for trucks) and significant (insignificant only in the case of crawler tractors), indicating a positive relationship between the price and the quantity of an item supplied. For example, in the case of excavators, own quantity parameter estimate is 0.2237, indicating that normalized price (real price to auction revenue ratio) increases by 0.2237 with a unit increase in the quantity of excavators. Cross quantity parameter estimates are all significant in the case of excavators and wheel loaders. In the case of trucks, cross quantity parameter estimates are predominantly significant while they are predominantly insignificant in the case of crawler tractors and graders.

The coefficients on *age* are significant except for the case of excavators (insignificant in the case of excavators) and signs are as expected (marginal effect is negative). Among the types of equipment considered in the observed data sample, trucks experienced rapid decline in the price with age, but crawler tractors experienced slower decline in prices. Controlling for other factors in the model, crawler tractors of age 70 years, graders of 46 years old and trucks of about 20 years old received the minimum price. Past this age, equipment may be sold as an antique.

Parameter estimates on linear and quadratic terms on age are insignificant in the case of excavators. Also, in the case of graders and wheel loaders, the quadratic terms are insignificant.

The coefficients on auction houses are predominantly significant, indicating that prices received across different auction houses vary for a given quality of the equipment and other conditions *ceterus paribus*. Prices of a given type of equipment (except trucks and graders) sold at Auction House 1 are significantly higher than the prices at all other auction houses. The parameter estimate representing an auction house represents the shift in the normalized price from the reference category - “Other” auction house. The negative sign arises due to the fact that AH1 has higher auction revenues (hence, smaller price to revenue ratio) compared to the reference category. These results are consistent with the findings of Ponnaluru and Marsh (2009).

The signs on the coefficients of physical condition are as expected. Equipment in better condition costs more than that in a poorer condition. Equipment whose condition is unknown received significantly higher price than that in poor condition (except the case of trucks and graders). In the case of graders, the all the parameters on the physical condition are insignificant. The category – *Poor* was not statistically significant in any of the estimated equations.

Prices differ significantly from region to region in the US. This is indicated by the significant coefficients on variables representing Mid Western US and North East. Crawler tractors, wheel loaders and excavators received higher prices in the North East than other regions. Trucks received higher prices in the West compared to the West. These results are consistent with the findings of Ponnaluru and Marsh (2009).

The coefficients on variables representing the quarter of the fiscal year of sale are predominantly insignificant in the case of crawler tractors, graders, and wheel loaders. Prices in all the three quarters are different from the fourth in the case of excavators and trucks, while they are all insignificant in the case of wheel loaders. Excavators received higher prices during second quarter of the year, while trucks and graders received higher prices during the first quarter of the year of sale.

The responsiveness (flexibility) of price to quantities- own quantity flexibility and cross quantity flexibilities are given in Table 3.6. Own quantity flexibilities are positive for all the items except trucks. Own quantity flexibilities for crawler tractors and trucks are inflexible (0.1922, -0.0474 respectively), while they are flexible for graders (2.5819), wheel loaders (1.462), and excavators (1.169). This indicates that, for example, if the quantity of graders supplied increases by 1%, the price of graders increases by 2.58%. Cross quantity flexibilities for all items except for excavators are inflexible.

Cross quantity flexibilities between a pair of items are not equal. For example, cross quantity flexibility of excavators with respect to trucks is -0.4042, while cross quantity flexibility of trucks with respect to excavators is -0.5918. This asymmetry in flexibilities could indicate the presence of differences among groups of bidders that are interested in particular items. It is to be noted that the flexibilities are reported at the means and the flexibilities at other points (locations) may be different. The flexible nature of the results implies that by appropriate combination of different items, higher revenues (prices) may be achieved at an auction.

Statistical significance on quantity terms (own item quantity) indicates that multiple units of an item significantly influences its price formation. This result is consistent with the findings in multi unit auction literature. Cross quantity terms capture the influence of different types of items on a given item. Statistical significance on the cross quantity terms indicates presence of significant price relationships between different items. Hence, multi - unit multi -type auctions cannot be treated as a collection of multi-item auctions.

Conclusion

Auctions for used construction equipment differ in their process from their well known counterparts like single item auctions, multi item auctions, or combinatorial auctions. At a typical auction event, different types of equipment like excavators, trucks, wheel tractors etc. with different characteristics are sold. This (multi-item) nature of auction can affect price formation, by the way of spillover effects from the sale of items of a particular type (e.g., Trucks) onto items of a different type (e.g., excavators). We use transaction level data on equipment auction sales from 1996 to 2006 to estimate inverse supply functions. Results indicate that multiple units of an item significantly influence its price formation. Multiple items of all equipment except trucks showed positive influence on the price formation. Cross quantity terms capture the influence of different types of items on a given item. Statistical significance on the cross quantity terms indicates presence of significant spillover effects between different items.

Prices significantly differ between auction houses. Items (except trucks and graders) sold at Auction House 1 received significantly higher prices than any other auction house. Prices also vary significantly from region to region in the US. Prices also vary across quarters of the year of sale. Auction houses may find these results interesting for planning and marketing purposes. Buyers and sellers can also benefit from these results by making better informed decisions. Topics for further research would include derivation of optimal bidding strategies for bidders and commission rate schedules for auction houses that offer multi -unit multi- type auctions.

Figure 3.1: Proportion of items in various physical conditions in the observed data sample

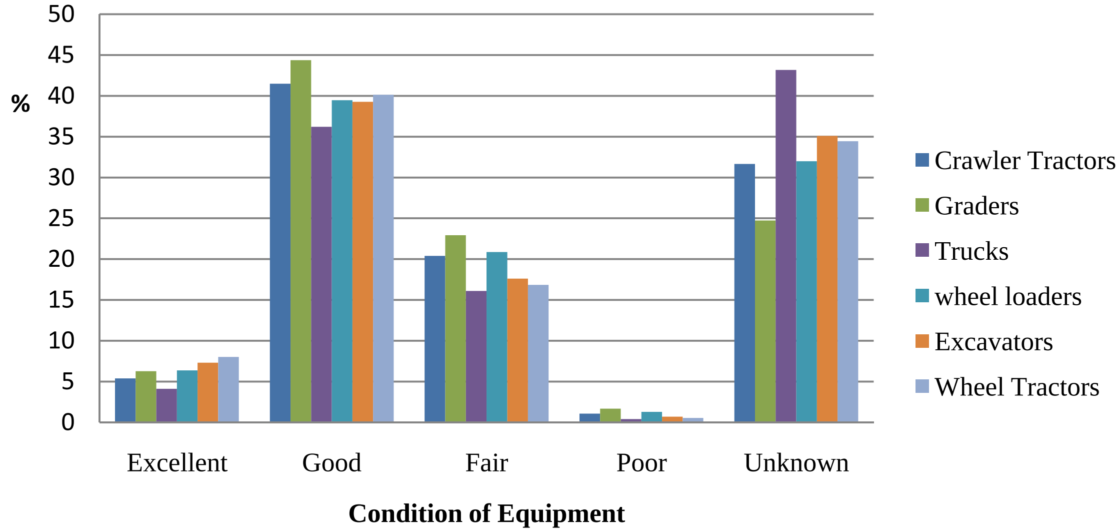


Figure 3.2: Proportions of various types of used construction equipment sold at auctions in the US from 1996 to 2006 in the observed data sample

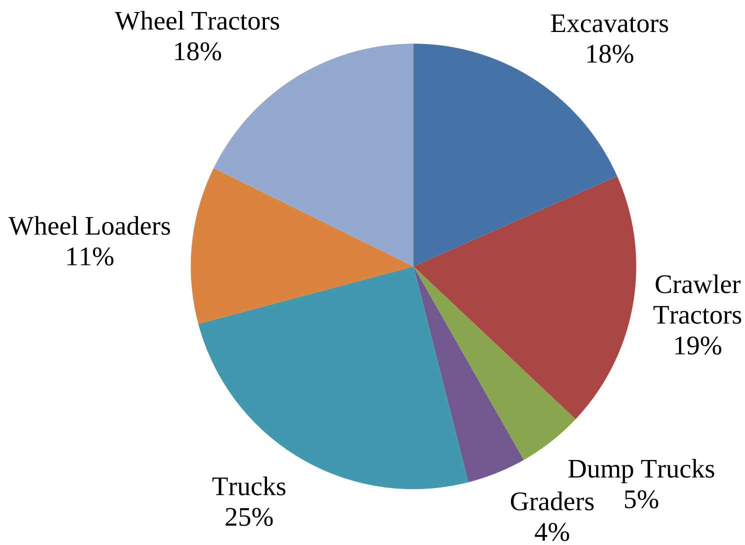


Table 3.1: Brief description of variables and descriptive statistics of all sales from 1996 to 2006 in the observed data sample.

Variable		Sum	Mean	Minimum	Maximum	Std Dev
price	Sale Price of Excavator in USD		35193.94	580.4103	730000	36491.8
age	Age of Excavator in Years		11.6151	0.0767	106.2685	8.7767
AH1	Value=1 if Auction House 1	137037	0.4982	0	1	0.5000
AH2	Value=1if Auction House 1	12992	0.0472	0	1	0.2121
AH3	Value=1 Auction House 1	38254	0.1391	0	1	0.3460
AH4	Value=1 if Auction House 1	5206	0.0189	0	1	0.1363
auct	Value=1if Auction House is any other	74675	0.2715	0	1	0.4447
excavator	Value=1if type of item = Excavator	48887	0.1777	0	1	0.3823
crawlert	Value=1if type = Crawler Tractor	49717	0.1807	0	1	0.3848
dumpt	Value=1if type = Dump Truck	12586	0.0458	0	1	0.2090
graders	Value=1if type = Grader	11388	0.0414	0	1	0.1992
Trucks	Value=1if type = Truck	66035	0.2401	0	1	0.4271
wloader	Value=1if type = Wheel Loader	30448	0.1107	0	1	0.3137
wtractor	Value=1if type = Wheel Tractor	47181	0.1715	0	1	0.3770
con1	Value=1 if Condition = very good or excellent or new	16438	0.0598	0	1	0.2370
con2	Value=1 if Condition = good	107360	0.3903	0	1	0.4878
con3	Value=1 if Condition = fair	51409	0.1869	0	1	0.3898
con4	Value=1 if Condition = Poor	2181	0.0079	0	1	0.0887
con5	Value=1 if Condition = Unknown	97685	0.3551	0	1	0.4786
west	Value=1 if Region of Sale = West	52747	0.1918	0	1	0.3937
Neast	Value=1 if Region of Sale = North East	27762	0.1009	0	1	0.3012
south	Value=1 if Region of Sale = South	135903	0.4941	0	1	0.5000
midwest	Value=1 if Region of Sale = Mid West	51240	0.1863	0	1	0.3893

Total Observations:275073

Table 3.2: Descriptive statistics of price across different variables in the observed data sample.

Variable	N	Mean	Minimum	Maximum	Std Dev
AH1	137037	32744.94	575	730000	35412.49
AH2	12992	30839.15	1700	460000	28823.07
AH3	38254	32074.18	1500	460000	29110.77
AH4	5206	28659.36	1800	295000	24420.61
'Other' Auction	74675	25481.73	500	490000	25746.92
Crawler Tractors	49717	37130.47	575	730000	35331.12
Dump Tucks	12586	22948.65	4000	150000	20698.72
Excavators	48887	39700.44	800	575000	34785.19
Graders	11388	43367.08	1500	490000	37598.87
Trucks	66035	16913.73	500	365000	14354.25
Wheel Loaders	30448	41005.3	1300	485000	34370.74
Wheel Tractors	47181	20933.49	1500	250000	11591.76
Con1	16438	55094.99	2250	490000	49807.14
Con2	107360	35292.95	575	525000	32961.88
Con3	51409	20586.99	1300	490000	18531.77
Con4	2181	12163.45	1500	125000	10290
Con5	97685	27241.74	500	730000	29412.6
North East	27762	30060.18	1000	460000	28781.25
Mid West	51240	25666.69	500	610000	26680.81
South	135903	32304.42	1300	575000	31765.06
West	52747	30596.77	575	730000	36862.5

Table 3.3: Brief definitions of physical condition of equipment as defined by Equipment Watch (2008).

Condition	Definition
New	New unit
Excellent	Some use, but almost new mechanically
Very Good	In above average mechanical condition; low hours or recently overhauled
Good	In average mechanical condition; may need minor repairs or replacement of worn parts soon
Fair	In below average mechanical condition; high hours or older unit
Poor	Needs major repairs
Unknown	No condition is available

Table 3.4: Hausman's test for endogenity of quantities of items.

Equation	Efficient under H0	Consistent under H1	DF	Statistic	Pr > ChiSq
Crawler Tractors	OLS	IT2SLS	21	41.72	0.0046
Graders	OLS	IT2SLS	21	18.63	0.609
Trucks	OLS	IT2SLS	21	30.76	0.0777
Wheel Loaders	OLS	IT2SLS	21	43.09	0.0031
Excavators	OLS	IT2SLS	21	47.13	0.0009

Table 3.5: Parameter estimates of inverse supply function from Iterative Two Stage Least Squares estimation from 1996 to 2006.

	Crawler Tractors		Graders		Trucks		Wheel Loaders		Excavators	
Parameter	Estimate	Approx Pr > |t|	Estimate	Approx Pr > |t|	Estimate	Approx Pr > |t|	Estimate	Approx Pr > |t|	Estimate	Approx Pr > |t|
Intercept	**0.0407**	**<.0001**	**0.0626**	**0.0015**	**0.0337**	**<.0001**	**0.0467**	**<.0001**	**0.2074**	**<.0001**
Excavators	0.0090	0.5688	-0.0561	0.074	**-0.0576**	**<.0001**	**0.0429**	**0.0326**	**0.2237**	**<.0001**
Crawler Tractors	0.0118	0.2573	0.0040	0.8088	**0.0122**	**0.0194**	**-0.0856**	**<.0001**	**-0.4460**	**<.0001**
Graders	**-0.0605**	**<.0001**	**0.1402**	**<.0001**	**-0.0610**	**<.0001**	**-0.1551**	**<.0001**	**-0.8628**	**0.0001**
Trucks	**-0.0332**	**<.0001**	**-0.0342**	**0.0496**	**-0.0116**	**<.0001**	**-0.0403**	**<.0001**	**-0.2232**	**<.0001**
Wheel Loaders	-0.0066	0.3375	**-0.1148**	**0.0035**	-0.0093	0.098	**0.1455**	**<.0001**	**0.1967**	**0.0211**
age	**-0.0005**	**<.0001**	**-0.0010**	**0.0002**	**-0.0011**	**<.0001**	**-0.0005**	**0.0016**	0.0002	0.8161
age^2	**3.7E-06**	**<.0001**	1.1E-05	0.0516	**2.7E-05**	**<.0001**	-3.4E-06	0.4799	-4.0E-05	0.2521
AH1	**-0.0147**	**<.0001**	0.0018	0.6465	-0.0005	0.6191	**-0.0300**	**<.0001**	**-0.1219**	**<.0001**
AH2	**-0.0155**	**0.0009**	**0.0196**	**0.0409**	**0.0087**	**0.0001**	**-0.0495**	**<.0001**	**-0.1776**	**<.0001**
AH3	**-0.0277**	**0.0109**	**0.0380**	**0.0182**	**0.0279**	**<.0001**	**-0.0708**	**<.0001**	**-0.3254**	**<.0001**
AH4	-0.1820	0.1366	**1.2861**	**0.0137**	**0.5138**	**<.0001**	**-0.3718**	**0.0013**	**-1.6772**	**0.0004**
con1	0.0013	0.1469	0.0003	0.9224	0.0008	0.3004	**0.0049**	**0.002**	**0.0190**	**0.0064**
con3	-0.0001	0.9059	-0.0004	0.8369	**-0.0022**	**<.0001**	-0.0001	0.9569	-0.0008	0.8689
con4	-0.0012	0.4994	0.0001	0.9876	-0.0007	0.7662	0.0071	0.0518	-0.0024	0.8996
con5	**0.0106**	**<.0001**	-0.0006	0.8959	**-0.0027**	**<.0001**	**0.0134**	**<.0001**	**0.0266**	**0.0003**
midwest	**0.0074**	**<.0001**	-0.0035	0.3463	0.0004	0.4243	**0.0132**	**<.0001**	**0.0509**	**<.0001**
neast	**0.0301**	**0.0166**	-0.0614	0.0521	**-0.0579**	**<.0001**	**0.0655**	**<.0001**	**0.2510**	**0.0007**
south	**-0.0108**	**<.0001**	**-0.0154**	**<.0001**	**-0.0023**	**<.0001**	0.0014	0.4942	**0.0249**	**0.0033**
q1	-0.0009	0.4994	**-0.0105**	**0.0002**	**-0.0035**	**<.0001**	0.0017	0.4229	**0.0470**	**0.0019**
q2	0.0021	0.1995	-0.0077	0.0074	**-0.0036**	**<.0001**	0.0038	0.0542	**0.0256**	**0.0045**
q3	0.0010	0.5292	-0.0056	0.1341	**-0.0041**	**<.0001**	0.0013	0.4303	**0.0221**	**0.0015**
Correlation Coeff. between actual and predicted values		0.3013		0.1981		0.0816		0.3005		0.2927
No. of obs		34208		8371		48893		20755		31937

Dependent Variable: Revenue normalized price

Equipment sold at “Other” Auction House, in good condition, in the West during quarter 4 is used as reference category

Table 3.6: Price flexibilities of inverse supply functions at the mean

Equation	Crawler Tractors	Graders	Trucks	Wheel Loaders	Excavators
Crawler Tractors	0.1922	-1.2202	-0.1394	-0.0686	0.0892
Graders	0.0594	2.5819	-0.2367	-1.4031	-0.6405
Trucks	0.1812	-0.9251	-0.0474	-0.7674	-0.5918
Wheel Loaders	-1.2039	-2.2019	-0.1503	1.4620	0.4724
Excavators	-5.6989	-7.4488	-0.4042	1.0635	1.1699

References

Bapna, Ravi. Paulo Goes,and Alok Gupta (2001). "Insights and Analyses of Online Auctions". *Communications of the ACM.* Vol.44, No.11, Nov 2001.

Deltas, George and Thomas D. Jeitschko (2007). "Auction host site pricing and market equilibrium with endogenous bidder and seller participation." *International Journal of Industrial Organization* 25(2007) 1190-1212.

Ellison Glenn, Markus Mobius and Drew Fundenberg (2004). "Competing Auctions." *Journal of the European Economic Association* March 2004 2(1):30 – 66.

Equipment watch https://www.equipmentwatch.com/HomePage.jsp (accessed January, 2007)

Fare, Rolf and Daniel Primont (1995). “Multi-output production and duality: Theory and applications.” Kluwer academic publishers. Boston. 1995.

Forsund, Finn and Roberto Zanola (2006). “The Art of Benchmarking: Picasso Prints and Auction house performance”. *Applied Economics*. Vol.38 Issue 12, pp 1425-1434.

Holt, Matthew and Richard Bishop (2002). “A semi flexible normalized quadratic inverse demand system: an application to price formation of fish.”*Empirical Economics*. Vol.27, pp23-47, 2002.

Kim, Hee-Su. (1996). "Equilibrium and Efficiency in Auctions of Complementary goods without bundling." *Economics Letters.* Vol 52, pp49-54.

Kristofersson, D. and K. Ricertsen (2004). “Efficient Estimation of Hedonic Inverse Input Demand Systems.” *American Journal of Agricultural Economics* 86 (2004):1127-37.

Kutner, Michael., Nachtsheim, Chirstopher., Neter and Li “Applied Linear Statistical Models.” McGraw-Hill. Singapore. 5th edition, 2005.

Lucko, Gunnar Christine M. Anderson-Cook and Michael C. Vorster (2006), “Statistical Considerations for Predicting Residual Valueof Heavy Equipment” *Journal of Construction Engineering and Management*, Vol. 132, No. 7, July 1, 2006. ISSN 0733-9364/2006/7-723–732.

Menezes and Monteiro, (2005). *An Introduction to Auction Theory.* Oxford press.

Ong E Seow, Lusht and Mak (2005). "Factors influencing auction outcomes and market condition". *Journal of Real Estate Research*. Vol. 27, No. 2, 2005.

Pinker, Edieal.,Abraham Seidmann and Yaniv Vakrat (2010). " Using bid data for the management of sequential, multi-unit, online auctions with uniformly distributed bidder valuations." *European Journal of Operational Research*. Vol.202 Issue 2, April 2010, pp574-583.

Ponnaluru, Srinivasa and Thomas Marsh (2009). "A Spatial Hedonic Price Analysis of Used Construction Equipment - the Case of Excavators." Manuscript. School of Economic Sciences, Washington State Univeristy, Pullman.

RBA (2005). Ritchie Brothers Auctioneers Annual report 2005. http://www.rbauction.com/about_ritchie_bros/2005_rba_ar.pdf (accessed October, 2008).

RBA (2007). Ritchie Brothers Auctioneers Annual report 2007. http://www.rbauction.com/about_ritchie_bros/2007_rba_ar.pdf (accessed October, 2008).

US Census Bureau. “Census Bureau Regions and Divisions.” http://www.census.gov/geo/www/us_regdiv.pdf (accessed Apr2007).

Appendix

Table A3.1 preliminary OLS estimates and variance inflation factors

Parameter	Crawler Tractors			Grader			Trucks		
	Estimate	Approx Pr > |t|	VIF	Estimate	Approx Pr > |t|	VIF	Estimate	Approx Pr > |t|	VIF
Intercept	0.0361	<.0001	0.0000	0.0231	<.0001	0.0000	0.0229	<.0001	0.0000
Excavator	0.0005	0.7141	1.5698	0.0239	<.0001	1.4694	-0.0022	0.0660	3.1358
Crawler Tractor	0.0510	<.0001	2.4347	-0.0332	<.0001	2.6342	-0.0137	<.0001	6.4092
Graders	-0.0290	<.0001	1.3415	0.2772	<.0001	1.5878	-0.0298	<.0001	2.4619
Trucks	-0.0198	<.0001	3.1237	0.0009	0.8079	3.7426	-0.0006	0.5846	14.9197
Wheel Loaders	-0.0294	<.0001	1.6553	-0.0515	<.0001	1.7823	-0.0077	0.0010	4.0571
age	-0.0006	<.0001	5.3468	-0.0008	<.0001	13.8852	-0.0009	<.0001	9.2672
age^2	0.0000	<.0001	4.7717	0.0000	0.0310	12.9316	0.0000	<.0001	8.6451
Ritchie	-0.0129	<.0001	1.4985	-0.0065	<.0001	1.4591	-0.0060	<.0001	1.9046
yoder	-0.0093	<.0001	1.3061	0.0012	0.5255	1.3521	-0.0041	<.0001	1.4443
lyon	-0.0150	<.0001	1.9587	0.0032	0.0984	1.5482	-0.0012	0.1015	1.3757
Petrow	-0.0004	0.8818	1.1553	0.0486	<.0001	1.0443	0.0050	0.0094	1.1587
con1	0.0017	0.0751	1.1197	-0.0006	0.7212	1.1830	0.0029	<.0001	1.1317
con3	-0.0003	0.6476	1.3645	-0.0018	0.0811	1.4579	-0.0031	<.0001	1.3736
con4	-0.0008	0.6725	1.0457	0.0009	0.7801	1.0927	-0.0013	0.3996	1.0140
con5	0.0100	<.0001	1.5181	0.0108	<.0001	1.3776	-0.0014	<.0001	1.3729
midwest	0.0060	<.0001	2.0316	0.0039	0.0053	1.6435	-0.0008	0.0098	2.6595
neast	0.0122	<.0001	1.7623	0.0159	<.0001	1.2179	0.0294	<.0001	1.3485
south	-0.0159	<.0001	2.3592	-0.0066	<.0001	2.0755	-0.0010	0.0011	2.5982
q1	-0.0032	<.0001	1.8598	-0.0083	<.0001	1.9823	-0.0014	<.0001	1.8827
q2	0.0002	0.7377	1.6913	-0.0046	<.0001	1.8399	0.0001	0.7407	1.7706
q3	-0.0009	0.1629	1.5181	0.0013	0.2975	1.5706	-0.0010	0.0002	1.6516
No. of obs		34208			8371			48893	

Table A3.1 continued

Parameter	Wheel Loaders			Excavators		
	Estimate	Approx Pr > |t|	VIF	Estimate	Approx Pr > |t|	VIF
Intercept	0.0246	<.0001	0.0000	0.0556	<.0001	0.0000
Excavator	-0.0025	0.2946	1.7316	0.2497	<.0001	1.5032
Crawler Tractor	-0.0354	<.0001	2.5939	-0.1940	<.0001	2.0789
Graders	-0.0577	<.0001	1.3971	0.0532	0.1701	1.4136
Trucks	-0.0111	0.0004	3.5174	-0.0667	<.0001	3.0052
Wheel Loaders	0.1814	<.0001	1.8593	-0.1001	<.0001	1.6137
age	-0.0006	<.0001	17.6812	-0.0007	0.3996	7.5846
age^2	0.0000	0.8355	16.4151	0.0000	0.9471	6.9370
Ritchie	-0.0218	<.0001	1.6899	-0.0336	<.0001	1.8889
yoder	-0.0350	<.0001	1.4626	-0.0301	<.0001	1.4629
lyon	-0.0251	<.0001	2.1492	-0.1017	<.0001	2.2929
Petrow	-0.0067	0.0813	1.2329	-0.0155	0.3032	1.2769
con1	0.0062	<.0001	1.2028	0.0122	0.0547	1.1970
con3	-0.0013	0.1580	1.4350	-0.0033	0.4735	1.3454
con4	0.0029	0.3490	1.0540	0.0032	0.8630	1.0453
con5	0.0111	<.0001	1.5736	0.0069	0.1103	1.5674
midwest	0.0155	<.0001	1.7254	0.0345	<.0001	1.8196
neast	0.0197	<.0001	1.9568	-0.0047	0.5678	2.3268
south	-0.0011	0.2474	2.1621	0.0014	0.7759	2.3938
q1	-0.0060	<.0001	1.9509	-0.0066	0.1592	1.9335
q2	-0.0026	0.0075	1.7054	-0.0034	0.4583	1.5907
q3	-0.0027	0.0115	1.5209	0.0066	0.1781	1.4747
No. of obs		20755			31937	