# READDRESSING PRICE MODELS IN BID RIGGING DETECTION: A TRANSACTION COST MODEL PORTLAND PROCUREMENT AGENCIES

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**ABSTRACT:** Past research has provided a variety of model approaches to detecting improprieties in the bidding process with public procurement auctions. Recent literature has moved beyond traditional bid price models and seeks to incorporate various non-price factors, such as vendor utility, into bid rigging modeling efforts. In response, this research aims to incorporate specific non-price factors such as vendor distance to site, vehicles owned, etc. to demonstrate, while using Transaction Cost Economic [TCE] Theory, that these complex price models can be used in an effort to address bid rigging in public procurement auctions. Future implications of these techniques are also discussed with regards to their potential usefulness both in the aggregate and in specific contract areas. Data which contains bids accused of collusion were collected and coded to include variables omitted from other OLS models. The price models tested were found to improve upon modeling capabilities of standard OLS models opening the possibilities for more extensive research into detailed price modeling focusing on bidding improprieties.

## INTRODUCTION

Within the United States, the need for provision of goods and services by governments at all levels – federal, state and local – is a response to both voter preference and the presence of market failure (Samuelson 1954). The resulting market failure leads to potential problems including the lack of information and capacity of that government to be the sole providers for the necessary goods and services. Governments reverted to private sector vendors for the purpose of supplying those goods and services – via public procurement auctions – which the government cannot and does not wish to provide (Coase 1937).

Public procurement auctions can be conducted in a variety of ways. The most common are request for proposals [RFPs] and invitations to bid [ITBs]. Auctions are seeking to obtain private sector assistance with the provision of those goods and services the government is not willing to supply. Therefore, the auction becomes the primary mechanism for ensuring a competitive market for the government to obtain those goods and services while maintaining a level of control over the supply chain (Pitzer and Thai 2009). However, public procurement auctions face problems pertaining to oversight and control. Procurement agencies are charged with making a variety of purchases for different levels of government and are only given a limited number of tools with which to ensure those purchases are in the best interests of the governmental organization as well as the constituency which they serve. Therefore, these limitations may lead to a lack of institutional control (Tanzi 1999) over detecting bidding improprieties in public procurement auctions. Determining whether a bid has a significant level of suspicion for deeper investigation then becomes critical for the procurement agency and its employees. Different attempts were made to model bidding improprieties. They include studies of bid prices (Abrantes-Metz et al 2006; Bolotova et al 2008; Harrington and Chen 2006; Maskin and Riley 2000), winning bid price (Baldwin et al 1997; Brosig and Reib 2007; Lundberg 2005), winners (Aoyagi 2003; Lang and Rosenthal 1991; Lengwiler and Wolfstetter 2006), bid price-to-reserve price ratios(Ishii 2009; Kagel and Levin 2008; Skrzypacz and

Hopenhayn 2004) and winning bid price-to-reserve-price ratios(Bajari and Ye 2003; Bajari and Summers 2002; Porter and Zona 1993,1999). None have been able to generate a practical tool to reduce bid rigging in procurement.

This research seeks to fill a void left by previous models. It addresses similar questions raised by the bid rigging literature, but forwards a model to detect bid rigging in the future. However, the current research will also seek to determine if other influential conditions might be present in the bids such as: – vendor experience, vendor location, additional cost factors such as travel, etc. – or within vendor demographics – size, scope, etc. – which could lead to a better understanding of improprieties in the bidding process. Finally, potential implications for procurement agents, future scholarly endeavors through a demonstration of the usefulness of price modeling, and the rationale for not abandoning its potential will be discussed.

In order to address these additional questions, the research draws upon transaction cost economics [TCE] as a theoretical frame. By incorporating transaction cost theory, the limitations placed on public procurement auction research may be corrected. A more detailed examination of the reality of procurement auctions can provide a broader understanding of the behaviors taking place. Furthermore, it will address the use of a price models built on bids incorporating this new information, collected from three separate procurement agencies in Portland, Oregon. The model specifics, bids and collection will be discussed in greater detail in the sections below.

Before detailing the theoretical framework and model, it is imperative to offer a brief review of the development of the literature in two major areas impacting the current study. First, the literature focusing on cartels within public procurement auctions provides the backdrop for the opportunistic behavior of private vendors. Second, a brief description of each of the previous model-building theories is given in order to illustrate how they have closed themselves off from acceptance of the more complex reality of public procurement auctions.

## CARTEL FORMATION

The detection of cartels in procurement auctions has become a popular area of research across disciplines. A cartel is comprised of a group of bidders coming together for the purpose of driving up the bid prices with the additional cost being placed on the agency charged with conducting the auction (Bajari and Summers 2002; Leyton-Brown et al 2002). Cartels can either be classified as strong cartels – those that have the ability to control bidding among its members – or weak cartels – those that have difficulty controlling bidding due to the inability of members to make side payments – payments which act as unofficial alleviation for cartel members who are expected to win with the lowest bid in a system where their production cost is not able to be revealed to the other cartel members (McAfee and McMillan 1992). As such, much of the research on cartels has developed from studying first-price auctions – auctions which are based on awarding and paying the vendor the price they bid – (Blume and Heidhues 2006; Brosig and Reib 2007; Leyton-Brown et al 2002; Lopomo et al 2011; Marshall and Marx 2007; McAfee and McMillan 1992; Menezes and Monteiro 2006; Pesendorfer 2000) against second-price auctions – auctions which are based on awarding the bidder, then paying them the next lowest price bid rather than the price they bid – (Marshall and Marx 2007) in order to differentiate cartel control.

Cartels are able to act in various ways which further illustrate their strength. Pesendorfer (2000) weighs the method of preventing certain members from bidding against the divided market approach – splitting the market for a given good or service for the purpose of having vendors bid within those different markets. By keeping members from bidding, cartels are able to reduce rivalry (Gupta 2001) and achieve the sought-after gains (Lopomo et al 2011).

However, dividing the market (Pesendorfer 2000), or rotating the bidding – a scheme with members of a cartel always bidding, but alternating which member will be the lowest for different contracts – (Porter and Zona 1993), allows for lower bidding due to the repeating nature of the contracts (Gupta 2001). Although arguments have been made that bid rotation cannot be considered collusion (Skrzypacz and Hopenhayn 2004), it can still be labeled as an unethical practice whereby it will fit in the category of an impropriety this research is aiming to address.

## MODELS OF DETECTION

Past research has used numerous models for detecting collusion procurement auctions(Padhi and Mohapatra 2011). These models have been categorized into 1) bid price (Abrantes-Metz et al 2006; Bolotova et al 2008; Harrington and Chen 2006; Maskin and Riley 2000), 2) winning bid price (Baldwin et al 1997; Brosig and Reib 2007; Lundberg 2005), 3) winners (Aoyagi 2003; Lang and Rosenthal 1991; Lengwiler and Wolfstetter 2006), 4) bid price-to-reserve price ratio (Bajari and Summers 2002; Bajari and Ye 2003; Ishii 2009; Kagel and Levin 2008; Porter and Zona 1993,1999; Skrzypacz and Hopenhayn 2004), and 5) winning bid-to-reserve price ratio with non-price attributes (Bajari and Ye 2003; Porter and Zona 1993,1999). Each model builds upon the other as they attempt to correct model shortcomings. A brief explanation of each will be given followed by the results of its use.

*Bid Price:*

Research focusing on bid price has come with the belief that there can be a set of patterns detected in the prices themselves which would lead to observing collusive behavior (Harrington and Chen 2006; Maskin and Riley 2000). When seeking detection, researchers have found that observing the variance (Abrantes-Metz et al 2006; Bolotova et al 2008; Harrington and Chen 2006) as well the mean and standard deviation (Abrantes-Metz et al 2006) are acceptable measures for modeling the bid price. A major finding using such a model was that prices do not tend to respond immediately to economic shocks in the case of cartel-driven bidding (Harrington and Chen 2006).

Bid price research does fail to account for heteroscedasticity of the data (Padhi and Mohapatra 2011). When auctions of different natures – good versus services – or auctions of different quantities arise, the distributions will fail the test of normality and variances can be erratic.

*Winning Bid Price:*

Similar to that of bid price research, winning bid price research attempts to use game theory to compare potentially collusive bidding with competitive bidding processes (Baldwin et al 1997; Brosig and Riley 2007; Lundberg 2005). Examinations were made into the descriptive statistics to find whether elevated cost levels occurred when the collusive models were analyzed against competitive models. Furthermore, relationships could be detected with regards to number of bidders, volume of procurement (Lundberg 2005), and supply effects (Baldwin et al 1997).

The problem of heteroscedasticity exists within the winning bid price models as well as regular bid price models. However, the bigger problem is the necessary data containing winning bid prices and the potential lack of predictive validity even when those data are made available. There is a need for alternative non-price factors to be present in the data along with the price in order to generate a model with more predictive capabilities.

*Winner:*

Drawing on the essence of the cartel literature, models have been generated based solely on the winners – particular bidders – in procurement auctions (Aoyagi 2003; Lang and Rosenthal 1991; Lengwiler and Wolfstetter 2006). These models draw on the concept of repeat bidding and a cyclical nature of cartels found through the use of bid rotation.

Theoretically, the understanding that the same bidders constantly bid on similar contracts does provide procurement agents with a good starting point to being on the lookout for bidding improprieties. However, with regards to winning models, the large amount of bidding data from the vendors being studied necessary for determining if cycles do exist among assumed 'competitive' firms becomes impractical.

*Bid Price-to-Reserve Price Ratio:*

In response to the models using just bid price to detect collusive efforts, researchers have decided that other factors may need to be included. Specifically, through the use of a ratio test between the bid price and the reserve price – minimum acceptable price – they will be able to remove the problems of heteroscedasticity of the data (Bajari and Summers 2002; Bajari and Ye 2003; Kagel and Levin 2008; Ishii 2009; Porter and Zona 1993,1999; Skrzypacz and Hopenhayn 2004) as the data moves towards a normal distribution of the variance. Along with removing the heteroscedasticity problem, data also moves towards normality because of the common ratio for analysis (Padhi and Mohapatra 2011) as opposed to larger scaled differences caused by contract budgets.

*Winning Bid Price-to-Reserve Price Ratio with Non-Price Attributes:*

Using the ratio of bid price to reserve price to generate normal data may prove worthwhile. However, most of the authors did not just focus on the ratio itself as a sole predictor. Instead, the need for non-price attributes such as distance to the site, overall utility of the winning firm, experience of the winning firm, the free capacity of rivals and the minimum distance of the rival firms (Bajari and Summers 2002; Kagel and Levin 2008) were shown to be necessary. By adding these non-price mechanisms, researchers attempted to use OLS regression techniques for detection of collusion and the approach was found to be most credible.

A major flaw in the use of winning bid-price-to-reserve price ratios is the need for winning bids and bids found to be collusive to exist within the data. However, this does not prevent testing or using this model or similar ones. Instead, it suggests a model by which detection can be undertaken largely in part due to the normality of the bid price-to-reserve price ratios among competitive bidding and collusive bidding (Beck and Barefield 1986; King and Mercer 1991; Paarsch et al 2006; Rasmusen 2007).

## LIMITATIONS OF PREVIOUS RESEARCH

The past attempts at modeling bidding improprieties have fallen short on a number of different aspects. Some of those include failing to move beyond means (Abrantes-Metz et al 2006) and variance (Abrantes-Metz et al 2006; Bolotova et al 2008; Harrington and Chen 2006) when analyzing price models, providing sufficient a priori data illustrating bids suspected of improprieties in order to model predictively (Bajari and Ye 2003; Padhi and Mohapatra 2011), incorporating the complexity of the transaction into a simplified model (Solow 2001), and increasing the scope of potential factors which could potentially explain bid price beyond those presented by Bajari and Summers (2003) and Kagel and Levin (2008).

Within price models, a simple analysis of variance and means of price assumes that the rigging will use a simplified model among the colluders in which the number of goods or services as well as the unit pricing will not be affected. However, within the research itself, conclusions by Abrantes-Metz et al (2006) and Bolotova et al (2008) conflict. Abrantes-Metz et al (2006) find that variance is less in bids where collusion is present. Bolotova et al (2008) find that the variance is actually higher in collusive bidding. This illustrates the susceptibility of limiting analysis to means and variance of price to detect collusion and other improprieties.

Finding a priori data tends to be a problem in various areas of research. For detecting collusion, it becomes critical in order to provide a comparative analysis. Unfortunately, identifying those particular bids requires extensive research in itself. As such, use of tools such as ordinary least squares regression begins to lose the capability to remain unbiased as the data collected must be pre-screened.

Complexity and unaccounted for factors within the model are also major limitations of previous research. Researchers have purposely limited the use of particular variables for the sake of adhering to assumptions of linear regression. Doing so can ignore variables which might be scaled differently assuming they lack any explanatory power. It leads to simplification of a potential factor through incorporation or exclusion thus eliminating any significance it might have.

Each of the previous limitations is aimed to be addressed in the present research. In order to address these limitations, a hedonic price model, which will address a multitude of potential factors found within bid submissions, will be used. Use of hedonic modeling will build on the assumption of modeling complexity which can be found in transaction cost economics. Therefore, a discussion of transaction cost economics will follow.

## TRANSACTION COST ECONOMICS [TCE]

Oliver Williamson (2002) describes transaction cost theory as focusing on the governance of contractual relations. In such terms, Williamson is describing governance as a way to accomplish order and structure for the purpose of a mutual benefit to the parties involved. Issues of contracting out draw on such an understanding with the proposed mutual benefits for both the public and private sector entities involved. TCE is directly concerned with the transaction itself (Commons 1932). It draws upon the premise that minimizing the visible and unseen costs associated with the transaction will lead to the desired beneficial outcome. The basis for TCE derives from

Coase theorem (1960) arguing that low transaction costs allow rational parties to bargain in order to seek that efficient outcome. For TCE, the ability to adjust to meeting the conditions set by Coase theorem incorporates bounded rationality (Simon 1947). Simon (1947) contends that in the absence of perfect information, a rational decision can still be made by focusing on what *is* known.

Use of Simon (1947) and Coase (1960) have been applied to local government negotiations claiming that economies of scale might be produced with proper conditions in place (Feiock 2007; Lubell et al 2002; Ostrom 1990). Feiock (2007) argues this is particularly important with regards to local governments and their ability to capitalize on opportunities which provide both goods or services as well as create additional benefits over time. The decision-making of procurement officials and complexity of local government contracting can be demonstrated under such a framework. Local governments seek to address their needs and become more willing to accept decisions made through bounded rationality generated from the lack of complete or perfect information. This makes them more susceptible to accepting the bargaining position of the private sector organization if they are able to present the appearance of long-term benefits for the public sector organization. Resulting problems with oversight (Tanzi 1999) place the public agency at an immediate disadvantage. Detecting unethical behavior from private sector vendors is one example of such a disadvantage.

With particular regard for the transaction itself, modeling the transaction becomes critical with providing a simplified view of a complex situation (Solow 2001). TCE permits complex situations to be housed in a simpler model contingent on that model being in line with the data provided. Attempts were made to incorporate non-price attributes into a model for bid rigging (Bajari and Ye 2003; Porter and Zona 1993,1999). However, those scholars used overall utility variable was used instead of exploring specific elements of that vendor's utility. This ignores the complexity of elements of vendor utility and prevents calculation of their individual influences. The present study is attempting to incorporate these potential factors which were previously ignored due to issues of operationalization and generalizability.

Furthermore, the implication towards bid improprieties within the transaction can be addressed by TCE from both the vendor – private sector – and agency – public sector – sides. According to Williamson (1975,1985,2002), rational self-interest will lead individuals to behave opportunistically rather than within the frame of cooperation. This helps demonstrate the formation of cartels. As mentioned, cartels form to maximize their individual benefit over time. By forming cartels, individual vendors are able to reduce the transaction costs incurred prior to the actual auction process. Their behavior allows the development of a strategic approach to the procurement auction regardless of the strength of the cartel.

It also helps demonstrate the behavior of local governments as they reach out to the private sector in order to attempt to maximize their power of provision. Local governments rarely desire to use sole sourcing as a means of procurement (Pitzer and Thai 2009). Instead, the local government's willingness to make a decision pertaining to major purchasing, regardless of the lack of complete information, is placed under the guise of *competition*. The avenue pursued becomes evaluation rather than cooperation. Procurement officials are trained to generate a method of review instead of focusing on a more time-consuming path of information exchange between procurement agents and private vendors.

Lastly, as TCE concerns itself with the transaction, the current research and model will be centered on the transaction. A transaction is not just the agreement of a contract. Rather, it is from the start of the process until its conclusion. Collusive behavior has been demonstrated to take place both before bidding through meetings of cartels (McAfee and McMillan 1992; Pesendorfer 2000) as well as during the bidding process (Gupta 2001; Porter and Zona 1993,1999). The latter will be the basis of the construction of the model. In keeping with the aim of producing a model which is usable for both scholars and procurement agents, the bidding process becomes the only stage in which agents are active. Initial model construction and test for fit allows for a movement back to the game theoretic used in previous research (Baldwin et al 1997; Brosig and Riley 2007; Lundberg 2005) with the aim of developing a predictive scenario under which the various visible and unseen costs are represented.

Before detailing the data and methodology which will be used in conjunction with TCE, a brief overview of the limitations of previous research will be described in order to illustrate the differences of the model being developed as well as the direction of the analysis which will take place following the description of that model.

## DATA

The data collected for the given model was collected in August 2011 at the various agency offices housing the various contracts. Through the use of specific NIGP contacts, snowball sampling and information requests, the data became available. Examination was solely focused on hard copies of the various bids. In the following section, specifications regarding the data and the requirements for its collection will be described. Furthermore, the dataset characteristics will also be provided.

For the purpose of analysis, the dataset used a set of limitations in order to prevent major case modifications.

1. Only the use of RFPs or ITBs will be acceptable.

A Request for Proposal requires bidders to describe details of various aspects of their company as well as the means by which they will be able to complete the necessary tasks. An Invitation to Bid simply focuses on the provision of prices for given goods or services while still remaining open to adding documentation which may be thought to demonstrate the vendor as being 'responsible' (Pitzer and Thai 2009). The rationale for limiting the type of solicitation was largely based on keeping with the most common types of solicitations. While procurement agencies do use Request for Qualifications [RFQs], they do not illustrate a price element and simply qualify a vendor to submit a bid for upcoming projects which fit into the category for which the RFQ was provided.

2. Data was collected using one of three local procurement agencies in Portland, Oregon.

The reason is threefold. First, Oregon Solicitation Procedure requires ITBs to award specific contracts to the lowest bidder. As such, incorporation of a complex model, like the one used in this research, can account for non-price factors with the knowledge that collusive behavior might seem simpler for bidders in an ITB. It also allows a direct comparison between ITBs and RFPs. Second, the same elements making the model complex also permit the use of a variety of contracts. By using an area as diverse as Portland, contracts are not going to be limited to metropolitan contracts. Finally, the research is aimed at local governments. Therefore, by keeping within the same city as well as evaluating contracts from different agencies allows for uniform evaluation without concern for demographic differences.

3. The RFPs and ITBs were limited to August 2010 – August 2011.

In order to eliminate the need for value and price corrections, a one year limit was placed on the cases within the data. This also allows for certain variables, such as vendor characteristics, to remain relatively constant.

With regards to the data itself, no limitations were placed on types of contracts in order to maintain consistency with regards to transaction cost theory. Included in these contracts were waste removal and management contracts, construction contracts and park management contracts. No restriction was placed on goods or services. Furthermore, use of consultation with procurement agents was acceptable in the selection of the various bids to analyze. This allowed for a correction of the a priori knowledge regarding the bids which contained accusations of improprieties.

The data contain a set of 170 bid submissions for 19 different contracts. Of the 19 contracts, 15 were RFPs and 4 were ITBs. Contract types were categorized as goods, services or goods and services. There were 4 contracts labeled as goods, 14 as services and 1 as goods and services. Bid submissions for the various contracts ranged from 1 bidder to 25 bidders. Bidders were labeled based on various characteristics including experience in the particular contract area, company scope – the breadth of the work throughout the world – and the number of employees or company size.

Bid variables were coded only by the principal investigator and author on the basis of a code sheet which was designed following the examination of the first ten bids. Furthermore, this limited potential questions surrounding intercoder reliability. The code sheet includes a total of 48 variables. These variables include vendor characteristics, bid contract information, awarding and collusion variables, price and non-price attributes including detailed utility variables. For a complete list and description of variables, please refer to Table 1.

## MODEL, METHOD AND JUSTIFICATION

In order to analyze the relationships between variables, implementation of hedonic price modeling techniques will be used. While hedonic modeling is typically used in land, housing and water pricing (Mohayldin et al 2009), it provides unique functionality with regards to public procurement auctions in general. Hedonic modeling allows for the integration of a large quantity of variables. Past research also indicates a preference towards variable specific to each situation (Hoehn et al 2006; Harrison Jr. and Rubinfeld 1978). To illustrate the incorporation of such variables, a brief discussion of the variables coded in the present research follows.

## Table 1 – Variables and Their Descriptions

| Variable | Variable Code | Description | Variable | Variable Code | Description |
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| Exclusivity | EXC | Variable used to describe whether the contract is exclusive to the company awarded or if it permits multiple suppliers | Recycled Material Requirements | RMR | Does the bid require use of recycled products (when possible) |
| Contract Period | PER | Dedicated to the months for which the contact is in effect | Percentage of Recycled Materials | PRM | How much material is proposed to be used as recycled |
| Product/Service | TYP | Descriptive variable to categorize whether the purchase is a good/service | Award Dispute | AD | Was the bid award challenged by another contractor following award announcement |
| Amount | AMT | Outlines the amount of the good or service which is contracted | Per Unit Markup | PUM | Amount of markup per unit of product/service (if specified) |
| Bid Type | BTP | Categorical variable to define whether it is an ITB, RFP, etc. | Total Markup | TMU | Amount of total markup for all units of work to be completed |
| Submittal Instruction | INS | Dummy variable to determine whether the bid submittal has strict instructions for bidders which can cause automatic | Additional Per Unit Cost | APUC | Amount of additional cost incurred for each unit of product/service to complete |

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| Equal Opportunity | EQU | Variable describing whether the bid is open to all contractors or require pre-approval | Total Additional Unit Cost | TAUC | Total additional costs for completion of all units |
| Bid Number | BN | Variable used for grouping bid submittals for the same project | Total Cost | TC | Bid Price for the vendor to complete all work |
| Transportation Travel Requirements | TTR | Distance variable in miles which would be required per unit for completion/delivery of a good/service | Locations | LCS | Number of locations the contractor must work on in order to complete the job |
| Minimum Daily Requirements | MDR | Describes how much of the good/service must be completed in a single day (if one exists) | Extra Processes | EPS | Will the contractor be required to perform extra services in order to complete a project task |
| Refunding | RFD | Variable indicating whether any cost of bidding will be refunded | Completeness | COM | Will the contractor be required to complete the entire job? Or, will the procurement office subsidize some of the cost/production |
| Post-award Modifications | PAM | Details any permissible alteration to a bid from the awarded contractor after the awarding of | Security Feature | SEC | Are there security features at the sites? Ex. Card lock entry |

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| | | the bid | | | systems |
| Partnerships Permitted | PPT | Corporations ability to submit a bid with partners | Number of Vehicles owned | NVO | How many vehicles (or machines) does the contractor already have in possession to help complete the task |
| License/Permit Cost | LPC | Cost variable which describes costs fronted as a result of obtaining any necessary permits or licenses for proper completion | Lighting Available | LAV | If lighting is necessary (such as a contract requiring nighttime action), is it provided by the contractor? |
| Material Substitutes | MSS | Describes whether the contractor may use a substitute material other than those specified in the Call | Hours Per Day | HPD | Number of hours per day the contract permits/requires work |
| Stations | STS | Number of pieces of equipment (such as pumps or building) which permit work | Weather Facility | WFC | If the job requires, are weather facilities provided by the contractor for the safety or their workers? |
| Max Units Completed at 1 time | MUC | How many units of work can be completed at the same time? This can be partial units, so it should be ratio? | Service Facilities Available | SFA | Are service facilities (i.e. bathrooms, water fountains/rooms, phone access, etc.) available if necessary? |

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| On-site Vehicles | OSV | How many vehicles or machines used to work on the project can be stationed at each location at one time? | Time Expected for 1 Unit Completion | TEUC | Number of hours it will take to complete a unit of the task involved |
| Extra Security Provisions | ESP | Are there additional security measures being taken by the contractor for the sites or access | E-Reporting | ERP | Will the contractor communicate electronically with the Procurement Office to maintain updates |
| Company Name | CN | States the name of the bidder (will remain anonymous upon analysis) | Investigation | INV | Tells whether or not an investigation was performed regarding the integrity of the bid |
| Bidders | BDS | How many bidders are involved for the submittal? | Experience | EXP | Number of years of experience the bidder has for the given call |
| Company Size | CS | Number of company personnel | Questioned | QUE | Is the bid under question by either another vendor or by the procurement office? |
| Company Location | CL | States the headquarters for the company by city, state, country | Awarded | AWD | Was the bid awarded to this company? |
| Company Scope | CSP | Describes whether the company has international status, remains | Disqualified | DQ | Was the bid disqualified for |

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| | | domestic, or just stays regional | | | any reason? |

*VARIABLES:*

Within the present model, *bid price* is the dependent variable. A breakdown of the other types of variables and specific variables collected are as follows:

*Vendor Characteristics:*

Vendor characteristics are comprised of five variables which are all designed as company identifiers. There are three nominal variables include vendor name, location and scope. The location variable is geographic while scope relates to where the company operates – local, regional, national or international. Finally, there are two other scale variables. Company size is measured by the number of employees while experience is measured in years the company has dealt with work relating to the particular contract.

*Bid Contract Information:*

Bid contract information variables are all found in the agency advertisement documents related to the contract. Most of these variables are dummy variables labeled 0 or 1. Those include completeness, extra processes, recycled material requirements, material substitutes, partnerships permitted, post-award modifications, refunding, equal opportunity, submittal instruction and exclusivity – refer to Table 1 for details of each. Non-dummy variables within this category include the number of job sites required, bid numbers, the number of bidders, minimum daily required work, travel requirements for the contractor, the contract period, bid type – ITB or RFP – and the type of contract – good, service, good and service.

*Award/Collusion Variables:*

Variables found in the award/collusion category are dummy variables labeled 0 or 1. These variables are designed to create categories for comparative analysis. They include award dispute, questioned awards, investigated awards, bid awarded and bidder disqualification. The dispute, question and investigated variables provide different levels of analysis with regards to determining collusion as disputed awards derive from other bidders while questioned and investigated come from the agency itself. Investigated bids are those accused of actual collusive behavior while questioned merely show signs of, but are not actually determined to possess bidding improprieties. External documentation within the bid files provides the distinction for these categories as memorandum and external letters identify whether or not awards and investigations took place.

*Price Variables:*

Variables which relate to price, other than total cost – the dependent variable, are measured on a ratio scale. These include licensing cost, per unit markups, total markups, additional per unit costs and total additional unit costs. Often these variables are not found in RFPs, but do sometimes exist when details are provided by the vendor as to specific operations costs as well as costs of equipment and production.

*Non-price/Utility Attributes:*

The variables found in the non-price category are largely based on the functional capabilities of the vendor. Typically these variables are not found in bid submissions, but can be provided without request if a vendor is attempting to demonstrate their capacity and responsible nature. These variables are either scaled as a dummy of 0 or 1 or can be ratio variables. Dummy variables coded include lighting, security features, extra security provisions, service facilities, weather facilities, and e-reporting capabilities. Ratio variables include vehicles owned, vehicles for use on-site, maximum unit of work capability, time to complete one unit of work, pieces of equipment available at one time, hours which can be worked daily and percentage of recycled material used for production.

*THE MODEL:*

In order to determine the proper form for the model, a review of previous uses of hedonic price modeling were analyzed. Typical hedonic models use of linear, log-linear, semi-log linear, reciprocal or log-inverse regression techniques (Mallios et al 2009; Triplett 2004). As previously discussed, concerns regarding use of standard OLS regression has led to the exploration of hedonic modeling. Therefore, in order to demonstrate the opportunities using alternative price models, the data will compare OLS with a log-linear model using the same independent variables. A natural log transformation was performed on all ratio variables maintained for model comparison.

### Table 2 – Variable Cases for Models

| Variable | Valid Cases (N) | Mean (μ) | Standard Deviation (σ) | Variable – Natural Log Transformed | Valid Cases (N) | Mean (μ) | Standard Deviation (σ) |
|---|---|---|---|---|---|---|---|
| Number of bidders (BDS) | 170 | 17.86 | 8.62 | Ln(BDS) | 170 | 2.65 | .83 |
| Experience in the field (EXP) | 162 | 22.69 | 21.02 | Ln(EXP) | 160 | 2.84 | .79 |
| Number of employees for vendor (CS) | 150 | 2221.48 | 25882.29 | Ln(CS) | 150 | 2.39 | 1.85 |
| Contract period (PER) | 163 | 22.58 | 7.27 | Ln(PER) | 163 | 3.04 | .45 |

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| Number of tasks or goods to complete (AMT) | 168 | 18418.12 | 99871.08 | Ln(AMT) | 168 | 3.23 | 3.44 |
| Travel distance for completion from vendor site (TTR) | 158 | 70.47 | 263.20 | Ln(TTR) | 157 | 2.96 | 1.62 |
| Minimum daily requirements requested (MDR) | 170 | .02 | .22 | Ln(MDR) | 2 | .69 | .00 |
| Cost of a license for the vendor (LPC) | 170 | .59 | 7.67 | Ln(LPC) | 1 | 4.60 | n/a |
| Percentage of recycled material used by vendor (PRM) | 23 | 59.61 | 46.82 | [redacted] | | | |
| Per unit of work markup (PUM) | 2 | .00 | .00 | [redacted] | | | |
| Total markup (TMU) | 2 | .00 | .00 | [redacted] | | | |
| Average cost per unit of work completed | 50 | 28754.20 | 107165.25 | Ln(APUC) | 34 | 6.17 | 4.07 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (APUC) | | | | | | | |
| Total cost of work completed (TAUC) | 50 | 121342.05 | 274011.81 | Ln(TAUC) | 32 | 9.46 | 3.31 |
| Price bid/proposed (TC) | 170 | 299133.85 | 907233.00 | Ln(TC) | 170 | 8.27 | 3.40 |
| Locations where work must be completed (LCS) | 168 | 4.57 | 14.58 | Ln(LCS) | 168 | .97 | .70 |
| Number of vehicles owned by vendor (NVO) | 42 | 136.29 | 386.11 | | | | |
| Number of vehicles dedicated to site use (OSV) | 63 | 12.78 | 11.11 | Ln(OSV) | 63 | 2.24 | .82 |
| Hours to work per day (HPD) | 17 | 12.12 | 6.81 | | | | |
| Time to complete one unit (TEUC) | 22 | 28346.53 | 47237.57 | | | | |
| Number of work stations on site (STS) | 11 | 1.36 | .51 | | | | |
| Maximum units of work vendor can | 26 | 321.46 | 884.28 | | | | |

| | | | | |
|---|---|---|---|---|
| complete at one time (MUC) | | | | |

a. Variables in the second set of columns which were omitted resulted from the initial observation that they contained less than 50 valid cases (N).

Before analyzing the models, substantive variables were derived. In order to eliminate variables which would be of no use, assumption of a minimum of fifty observations for each variable was required. Based on Table 2, which displays all non-categorical independent variables, only 13 of the variables meet the fifty minimum. Following the natural log transformation, Table 2 also shows an additional four variables which can be eliminated for not meeting the fifty observation minimum. From the remaining nine variables – eight independent and one dependent – two models were constructed based on collusion variable which provides an a priori categorization to the models. Therefore, the final model constructions are as follows:

[1]*OLS Model:* $TC = \alpha_i + \beta_{i1}*BDS + \beta_{i2}*EXP + \beta_{i3}*CS + \beta_{i4}*PER + \beta_{i5}*AMT + \beta_{i6}*TTR + \beta_{i7}*LCS + \beta_{i8}*OSV + \beta_{i9}*BTP + \beta_{i10}*TYP + \beta_{i11}*CSP + \varepsilon_i$

[2]*Hedonic Model:* $ln(TC) = \alpha_j + \beta_{j1}*ln(BDS) + \beta_{j2}*ln(EXP) + \beta_{j3}*ln(CS) + \beta_{j4}*ln(PER) + \beta_{j5}*ln(AMT) + \beta_{j6}*ln(TTR) + \beta_{j7}*ln(LCS) + \beta_{j8}*ln(OSV) + \beta_{j9}*BTP + \beta_{j10}*TYP + \beta_{j11}*CSP + \varepsilon_j$

The upcoming sections will include an analysis on the models and their fit as well as a discussion of the ability of the Hedonic Model to remain the best, linear, unbiased estimator [BLUE] possible. Furthermore, a discussion pertaining to TCE and the findings will be given with final concluding remarks addressing the implications of those findings.

## ANALYSIS

In the following section, a brief look into the results of the models will be undertaken. Particular interest will be paid to goodness of fit tests to determine the usefulness of hedonic models. Further analysis will cover issues of multicollinearity and potentially harmful outliers of the hedonic model.

Table 3 – Model Comparisons

| | OLS Aggregate | OLS Non-Rigged | OLS Rigged | Hedonic Aggregate | Hedonic Non-Rigged | Hedonic Rigged |
|---|---|---|---|---|---|---|
| R-Squared | .567 | .795 | .994 | .733 | .701 | .995 |
| Adjusted R-Squared | .537 | .781 | .988 | .714 | .680 | .988 |
| Std. Error | 617118.16 | 213400.59 | 246893.99 | 1.82 | 1.74 | .14 |
| F-Statistic | 18.841 | 56.347 | 153.088 | 39.392 | 33.978 | 158.901 |

a. Note: Rigged and Non-Rigged models used identical model structure as the Aggregate models. Their identifier was based on the AD variable with 0 = Not rigged, 1 = Rigged.

A summary of the model fit is provided for the six models in Table 3. Of particular interest is the performance of the aggregate models. The hedonic model outperforms the standard OLS model used in past research. Alternate models also indicate viable performance with regards to fit, but must be cautioned due to the limited availability of a priori cases expressly identifying rigged bids. Specifically, the Hedonic Rigged Model shows promise with an adjusted $R^2$ = .988. The Aggregate Hedonic Model has an adjusted $R^2$ of .714 in comparison to only .537 for the OLS Model. Due to the small N for Rigged Models, additional data is necessary to draw any solid conclusions from the various analyses presented in the tables. Further discussion regarding the significance of these models will be provided in conclusion.

### Table 4 – OLS Model Comparisons

| | OLS Aggregate | | | OLS Non-Rigged | | | OLS Rigged | | |
|---|---|---|---|---|---|---|---|---|---|
| Variables | *Standardized Coefficients* | *t Statistic* | *VIF* | *Standardized Coefficients* | *t Statistic* | *VIF* | *Standardized Coefficients* | *t Statistic* | *VIF* |
| (Constant) | | -7.335*** | | | -9.513*** | | | -4.594*** | |
| CSP | .196 | 2.710*** | 1.921 | .068 | 1.278 | 2.005 | .02 | .459 | 2.139 |
| BTP | .718 | 8.703*** | 2.483 | | | | | | |
| TYP | .321 | 3.602*** | 2.908 | .919 | 9.908*** | 6.093 | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| BDS | -.706 | -6.654*** | 4.114 | -1.062 | -15.771*** | 3.213 | -1.736 | -21.79*** | 6.838 |
| EXP | .089 | 1.202 | 1.989 | .073 | 1.370 | 2.005 | .016 | .346 | 2.32 |
| CS | .011 | .175 | 1.426 | .041 | .896 | 1.469 | -.023 | -.48 | 2.547 |
| PER | .883 | 6.381*** | 7.000 | .680 | 10.73*** | 2.846 | | | |
| AMT | -.913 | -7.049*** | 6.133 | .439 | 4.65*** | 6.33 | -3.037 | -21.45*** | 21.606 |
| TTR | .086 | 1.398 | 1.368 | .192 | 3.87*** | 1.742 | .007 | .167 | 1.825 |
| LCS | -.007 | -.117 | 1.376 | -.035 | -.755 | 1.556 | | | |
| OSV | .085 | 1.585 | 1.039 | .036 | .956 | 1.013 | 2.331 | 18.79*** | 16.585 |

a. Models dependent variable is price bid/proposed (TC); Rigged and Non-rigged models are separated by variable AD = 0 for Non-rigged and 1 for Rigged
b. Significance levels: * = p<.10, ** = p<.05, *** = p<.01
c. Insufficient data provided for variables BTP in Non-rigged model and BTP, TYP, PER, & LCS in the Rigged model

### Table 5 – Hedonic Model Comparisons

| | **Hedonic Aggregate** | | | **Hedonic Non-Rigged** | | | **Hedonic Rigged** | | |
|---|---|---|---|---|---|---|---|---|---|
| Variab | *Standardized Coefficie* | *t Statist* | *VIF* | *Standardized Coefficie* | *t Statist* | *VIF* | *Standardized Coefficie* | *t Statisti* | *VIF* |

| les | *nts* | *ic* | | *nts* | *ic* | | *nts* | *c* | |
|---|---|---|---|---|---|---|---|---|---|
| (Constant) | | 4.453*** | | | 1.351 | | | 37.686*** | |
| Ln(BDS) | -.445 | -6.364*** | 2.893 | -.549 | -7.68*** | 2.898 | | | |
| Ln(EXP) | .101 | 2.105** | 1.362 | .092 | 1.722* | 1.37 | -.028 | -.723 | 1.622 |
| Ln(CS) | .165 | 2.823*** | 2.024 | .168 | 2.444** | 2.282 | .004 | .098 | 2.026 |
| Ln(PER) | -.074 | -1.163 | 2.397 | .1 | 1.459 | 2.274 | 3.128 | 19.79*** | 27.941 |
| Ln(AMT) | .311 | 2.867*** | 6.969 | .605 | 4.848*** | 7.538 | -3.378 | -22.65*** | 24.887 |
| Ln(TTR) | -.112 | -2.406** | 1.28 | -.083 | -1.522 | 1.448 | -.073 | -1.792 | 1.869 |
| Ln(LCS) | -.158 | -2.727*** | 1.98 | -.244 | -3.662*** | 2.156 | | | |
| Ln(OSV) | .095 | 2.07** | 1.25 | .041 | .87 | 1.078 | -.343 | -6.136*** | 3.489 |
| BTP | .087 | 1.215 | 3.021 | | | | | | |
| TYP | .042 | .409 | 6.219 | .41 | 2.914*** | 9.582 | | | |
| CSP | .017 | .26 | 2.379 | .071 | .951 | 2.674 | -.037 | -.816 | 2.295 |

a. Models dependent variable is the natural log of price bid/proposed (Ln(TC)); Rigged and Non-rigged models are separated by variable AD = 0 for Non-rigged and 1 for Rigged
b. Significance levels: * = p<.10, ** = p<.05, *** = p<.01
c. Insufficient data provided for variables BTP in Non-rigged model and BTP, TYP, Ln(BDS), & Ln(LCS) in the Rigged model

The hedonic model and OLS model both show signs of minor multicollinearity. The Variance Inflation Factors [VIFs] are just about acceptable level (<5) for two variables. Table 5 shows the *lnAMT* and *TYP* variables in the Hedonic Aggregate Model are above that level with values of 6.97 and 6.22 respectively. Table 4 demonstrates that PER and AMT have high VIFs with values of 7.0 and 6.13. However, as Triplett (2006) alludes to, multicollinearity in hedonic modeling is often the result of the sample. Alleviation of multicollinearity in hedonic modeling can come with expansion of the sample. Triplett (2006) also warns against variable reduction in these models as it can remove potentially important variables and cause inflated significance levels for the resulting reduced model. Thus, for the hedonic model, multicollinearity is not necessarily seen as a major problem. However, OLS is bound by much stricter standards with regards to finding an unbiased estimator (Berry and Feldman 1985). This makes the problem of multicollinearity presented more troubling in the case of the OLS model.

Table 6 also shows Durbin-Watson scores for both models to be a bit on the low side. This is an indicator that the model needs to be attended to in order to correct for potential problems of autocorrelation or autoregression. However, indications are that the OLS model suffers greatly from heteroscedasticity while the Hedonic model does not. Goldfeld-Quandt test results are presented in Table 6 and identify the Hedonic model as retaining the assumption of homoscedasticity to the .05 level. The OLS model produced a value well above the critical which does not allow for rejecting heteroscedasticity within the model.

Various identifying characteristics are also discussed with regards to both the OLS and Hedonic models in Table 6. Most important are the residual plots provided which illustrate an eye test for heteroscedasticity. As Table 6 and Figures 1 and 2 indicate, the scatterplot from the Hedonic model is spread whereas the OLS Model demonstrates a narrow set of points which funnels outward. This funneling is a greater sign of heteroscedasticity – unequal variance (Berry and Feldman 1985).

### Table 6 – Regression Assumption Tests

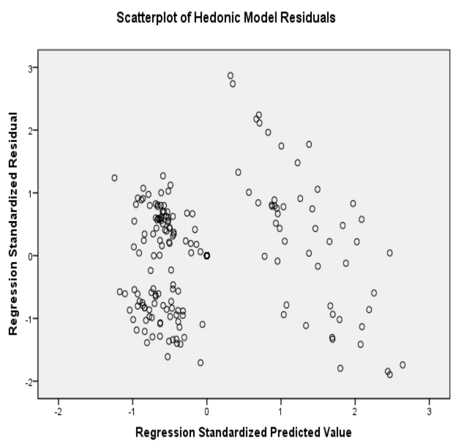
| Tests | OLS Model | Hedonic Model |
|---|---|---|
| Cook's Distance | Mean = .052 | Mean = .004 |
| Durbin-Watson | .860 | .617 |
| Variables with high VIFs | PER (7.00) & AMT (6.133) | LnAMT (6.969) & TYP (6.219) |
| Residual Plot | Funnel | Spread |
| One-Way ANOVA F-Stat | 18.841*** | 39.392*** |
| Goldfeld-Quandt Test Statistic[b] | 11.09[c] | 1.36[d]** |

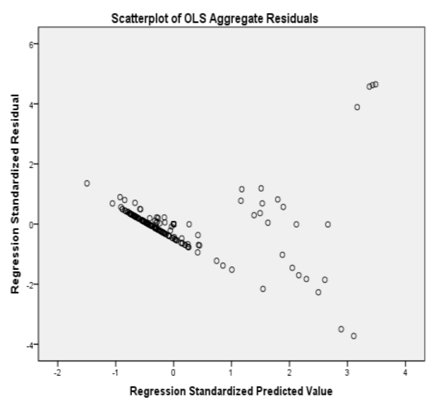
a. * = p<.10, ** = p<.05, *** = p<.01
b. X = AMT for OLS and ln(AMT) for Hedonic models
c. df = 27, 66
d. df = 48, 41

A final look into the hedonic model is testing for any outlier problems. In reference to the Hedonic Aggregate Model Residual Statistics in Table 6, Cook's Distance is highlighted. This identifies when it might be acceptable to remove a given data point. The generally accepted rule is if the distance ($d_i$) is greater than 1, problems of outliers may exist (Cook and Weisberg 1982). As can be observed, in the hedonic model the maximum $d_i$ = .199 indicating minimal problems with outliers.

Figure 1

Figure 2




Specific variable results from the Hedonic Model indicate multiple significant variables with regards to their impact on the price. Vendor variables such as the company size, experience of the company, travel requirements and the number of vehicles the company can bring to the site all show high levels of significance at the $p<.02$ level. Each variable except for the travel requirements shows a positive relationship to price indicating that price will rise as along with those variables. Furthermore, other significant variables included the number of bidders, the amount of work and the number of jobsites. The amount of work was the only variable with a positive relationship to price. Implications of these findings will be provided in the discussion section.

Concluding remarks will summarize the findings and significance of the uses of hedonic models in local public procurement auctions with respect to helping identify rigged bids as well as the implications on the previous literature.

## DISCUSSION

General observations from the model analyses identify the Hedonic model as a more appropriate model for the current scenario of identifying key variables which help identify price. However, the model is not limited to its fit. A brief look into the importance for examining behavior of vendors will be discussed with the implications deriving from TCE presented.

First, from the assumptions of TCE, the variables used in the analysis were given credence for their situational significance. This prevented the need to generate indices through factor analysis or separate multivariate regressions prior to generating a specific model. Furthermore, the model itself fit with the assumption of TCE as a framework built on complexity. Hedonic models, which are also built on such an assumption, presented an obvious fit which has been overlooked in previous literature.

Second, in continuing with the desire to model complexity, TCE opens the door to acknowledging the various actors and their different roles within public procurement auctions. The Hedonic model was better suited to incorporate representative variables from both the agency (i.e. amount of work required, bid type, site locations, and type of tasks) and vendor (i.e. company scope, company size, travel requirements, vehicles owned, experience, and unit completion capabilities) for the purpose of demonstrating their different potential impacts on price.

From the findings, the relationship of bid price to vendor experience, vendor size, amount of work and vendor utility all drove price up. However, there was also a significant finding that the number of bidders, travel and worksite locations drives bid price down. In examining the specific coefficients, the two most impactful variables were the amount of work to be completed and the number of bidders.

The finding surrounding the number of bidders is of particular interest for the purpose of discussion. Given the inferences from this, the perceived goals of the public sector as discussed early with regards to transaction costs might be surfacing. The results indicate competition does drive price down which identifies a winning situation for the public procurement agencies. Further research into the differences in rigged and non-rigged scenarios might provide a better demonstration.

Finally, in using the assumption of TCE, this research was able to demonstrate that a wide variety of elements within the bidding process and hidden within the bid documents themselves provide a better understanding of how procurement officials might be able to model the price to be expected from a particular bidder. Using such knowledge, procurement officials can seek to enhance their oversight and the body of information available to them for the purpose of preventing bidding improprieties.

A brief conclusion will follow. It will discuss the potential future impact of the findings from this research as well as discuss the holes which still need to be addressed.

## CONCLUSION

Based on the findings of both the Rigged and Aggregate Hedonic Price Models, it can be concluded there is still usefulness for price modeling in efforts to detect bidding improprieties. There is still a need for more research to refine the models and a priori knowledge regarding bids which have been rigged is difficult to find (Padhi and Mohapatra 2011).

Some shortcomings of the current model include the limited number of bids which had been concluded to possess improprieties as well as the limited number of overall cases. However, the intention was not to demonstrate a permanent model with fixed coefficient values demonstrating an overarching knowledge of collusive behavior. Rather, the model achieves two primary objectives. First, it provides a broader base by which research may identify elements within and outside of procurement auctions through the use of hedonic models which had not been previously addressed. Second, it illustrates the significance of price as an underlying indicator by which vendors and the information they provide when submitting for a potential contract may be understood.

With the model pushing for hedonic modeling and price as the critical variable, future research should target more precise models within specific contract areas. Having demonstrated that hedonic price models stand up to OLS regression, a new wave of research could be opened with regards to collusion detection. Moreover, hedonic models allow for a more realistic approach. Understanding the theoretical framework provided by transaction cost theory, hedonic models allow for the complexities of reality to be addressed in ways that OLS does not permit. Finally, future endeavors into hedonic modeling for the purposes of predictive capacity should be undertaken.

## NOTES

[1]Table 1 details the list of variables and should be consulted for reference both for general discussion as well as for description of the variables which remain for testing of the different models.

[2]Both models represented were given different subscripts to denote that the constants, error terms and coefficients produced were not to be considered interchangeable and for model uniformity. Furthermore, both the OLS Model and Hedonic Model were investigated on the aggregate and through separation based on the

*Award Dispute [AD]* variable in an effort to demonstrate model comparisons with a priori knowledge of suspected bidder collusion.

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