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ANURUDDHA D. H. K. KANKANAMGE
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ESSAYS IN AUCTIONS AND INFORMATION

A Dissertation APPROVED FOR THE
DEPARTMENT OF ECONOMICS

By

Dr. Timothy Dunne
(Co-Chairperson)

Dr. Georgia Kosmopoulou
(Co-Chairperson)

Dr. Indranil Chakraborty
(member)

Dr. Jiangdong Ju
(member)

Dr. Gregory Parker
(member)

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Abstract

This dissertation investigates the impact of information release in auctions and the change in auction organization on participant behavior. The first two essays examine how the release of information affects the aggressiveness of bidding in highway contract procurement auctions. The last study examines how changes in the auction format impacts bidding behavior and state revenue. All three essays utilize data obtained from the Oklahoma Department of Transportation (ODOT) on highway procurement auctions, let from January 1997 through November 2003.

The first essay in chapter 3 examines the impact of a policy change by ODOT on the bidding behavior of firms participating in the auctions. In January 2000, the ODOT changed its policy regarding the release of the state's engineering estimate. Prior to that date, the state only released the engineering estimate after the bids were opened. The policy change allowed for the release of the state's engineering cost estimate to potential bidders prior to the bid letting. Papers by Milgrom and Weber (1982) and Goeree and Offerman (2003) argue that such information release by the seller should result in more aggressive bidding. This essay empirically examines the response of auction participants to this change in policy. Using data on bids and winning bids, the paper shows that the release of the additional information results in more aggressive bidding. These results are further confirmed by the analysis conducted pooling Oklahoma and Texas procurement auction data. In Texas, bidders are aware of the engineering cost estimate pre-bid letting during the entire sample period. The comparison between Oklahoma and Texas indicates a significant decline in bids in Oklahoma after the information release. This study

concludes that this decrease in the level of bids is consistent with predictions of the theoretical models.

The second essay in chapter 4 examines information release in auctions but in a different situation. In ODOT auctions, a significant number of projects fail to be auctioned off the first time. These projects are subsequently re-auctioned off at a later date. For these auctions, potential bidders can observe the results of the first round of bidding for a project. That is, potential bidders can observe the number of bidders, the bids submitted, the rejected low bid and the state's estimate of the engineering cost for the project. Given the substantial release of information in these auctions, I examine the difference in bidding between the first and second round auctions. The results indicate bidding appears to be only modestly affected by such information release. The additional information leads to somewhat lower average bids while the effect on the variance of bids is quite weak.

The last essay in chapter 5 examines how a specific change in the bid letting procedures affects bidding. Before April 2002, projects were auctioned off in both a morning and afternoon session (a sequential auction format). The results of the morning session were announced before the afternoon session bids were due. In March 2002 the department changed its auction format to a single session or simultaneous format. Evidence from the theoretical literature suggests that seller revenue may vary between sequential and simultaneous auction formats depending on several factors including the possibilities of synergies across projects. Considering different levels of synergies, this paper compares the bidding behavior and seller revenue between the simultaneous and sequential auction formats. The results indicate more aggressive bidding behavior after the policy change occurred. Bidders bidding on multiple projects bid more aggressively in the simultaneous auction format. The results do not provide consistent supportive evidence to the theories that compare the revenue performance of the two auction formats.

Chapter 1

Introduction

1.1. Importance of the Study

Goods and services exchanged by means of government procurement auctions account for more than 10% of the United States GDP.[1] Therefore government policies related to the design and implementation of these auctions are of vital importance to the sellers (or auctioneers) and to the buyers (or bidders). Because the price discovery process in these auctions depends on the policies set forth by the government, it is evident that the final resource allocation also depends on these policies. The motivation for studying auctions is largely due to the various policy concerns (Porter, 1995). For example the literature examines how the government should optimally lease mineral or timber rights and procures various services. The empirical literature that addresses government policy impacts on procurement auctions is relatively small and often confined to experimental studies. This study contributes to the auction literature by investigating some key policy changes which have occurred in the procurement processes of the Oklahoma Department of Transportation.

The focus of this study is on two major policy changes relevant to the procurement auctions of the Oklahoma Department of Transportation (ODOT) in auctioning off road construction contracts. In every month ODOT auctions off around 35-40 projects, worth around $44 million. These auctions are conducted as first-price sealed-bid auctions and the lowest bidder is awarded the contract. Chapter 3 of this study addresses a change in the information release policy by ODOT, which occurred in

[1] Bajari and Tadelis (2001), and McAfee and McMillan (1987).

January 2000. For every project auctioned off, ODOT prepares a cost estimate known as the engineering cost estimate. Before January 2000 the engineering cost estimate was made available only after the auctions concluded. However, beginning in January 2000 ODOT changed its policy and started to reveal this estimate prior to the bid letting. The theoretical auction literature suggests that when more information is available to bidders it increases the competition among the bidders and benefits the seller (Milgrom and Weber, 1982; Goeree and Offerman, 1999, 2003). Chapter 3 examines the impact of this policy change on the subsequent bidding behavior and the seller's revenue (in this context the procurement costs of ODOT) using ODOT auction data.

Chapter 4 further investigates how information availability affects bidding in a selected sample of re-auctioned off projects. For a variety of reasons projects in this sub-sample were not awarded in the first letting. These projects are subsequently auctioned off in a later month. At the end of the first auction, ODOT releases the results of the first round which includes all the bids submitted, together with the names of the bidders and the engineering cost estimate (since January 2000 ODOT revealed this estimate pre-bid letting as mentioned above). Thus bidders in the second round have the ability to learn about their rivals' bidding behavior in the first round and bid accordingly. Chapter 4 investigates the impact of the information made public after the first round on subsequent bidding behavior.

Chapter 5 focuses on another policy change implemented by ODOT that altered the auction format. Until March 2002, ODOT had conducted monthly auctions in two sessions, one in the morning and another in the afternoon. At the end of the morning session ODOT gave out the results of the morning session, i.e., winning bidders' names and their winning bids, as well as other bids with the names of the bidders. Bidders in the afternoon session can take this information into account before they submit bids. However beginning of April 2002 ODOT switched to a single session auction format. Therefore bidders must submit all their bids simultaneously. The auction literature suggests that such a change in the auction format affects bidding behavior and the seller's revenue. Chapter 5 examines the impact of the change in the auction format on subsequent bidding behavior in ODOT auctions.

1.2. Objectives of the Study

The first objective of the study is to examine the impact of revealing the engineering cost estimate prior to bid letting on bidding behavior and test theories developed by Milgrom and Webber (1982) and Goeree and Offerman (1999, 2003). Second this study examines the impact of additional information revealed after the conclusion of the first round of auctions, on projects that are not awarded. The effect of the additional information revealed on the mean and the variance of bids is examined. Finally, this study compares the revenue performance between the two session and single session formats and test theories developed by Krishna and Rosenthal (1996) and Hausch (1986).

1.3. Results of the Study

Chapter 3 provides supportive evidence for the theories by Milgrom and Weber (1982) and Goeree and Offerman (1999, 2003) that predict more aggressive bidding behavior with the release of additional information to the bidders. The results indicate a significant decrease in the overall bids and in the winning bids after the policy change occurred in January 2000. This in turn implies a decrease in procurement costs (which implies an increase in the seller's revenue) which is consistent with the theories. The results of chapter 4 indicate that the impact of the additional information revealed after the first round of auctions about the rivals has only a moderate effect on the average bid. There is a moderate increase in the competition in the subsequent rounds of auctions. The information effect on the variance of bids is weak. The results of chapter 5 indicate a decrease in the overall bids and in the winning bids after the change in the auction format.

1.4. Organization of the Study

Chapter 2 of this study reviews the basic auction literature. Chapter 3 investigates the change in the information release policy on bidding behavior and tests related theories. Chapter 4 further examines the release of additional information on projects that were not awarded in the first round and the impact of this information on the subsequent rounds of auctions. Chapter 5 examines the change in the auction format from two sessions to one session and tests the impact of the change in the auction format on the seller's revenue. Chapter 6 presents the main conclusions of this study together with limitations and future research implications.

Chapter 2

Literature Review

2.1. Importance of Auctions

Governments use auctions in a wide range of transactions including defense contracts, selling timber rights, federal offshore oil and gas drainage lease sales, government construction contracts, and the sale of the right to use the electromagnetic spectrum for communications. Also former socialist countries in Eastern Europe and the countries of the former Soviet Union use auctions in the process of privatizing government enterprises (Krishna, 2002). In addition to governments, large numbers of private institutions use auctions to sell goods such as antiques, art work, wine, automobile products[2] and agricultural products (Dutch flower auctions, live cattle auctions, etc.). With the recent developments in e-commerce, web-based auctions conducted by private institutions have grown at a rapid rate, since the birth of these auctions in 1995. For example the largest internet base auction site, eBay, had reached 3 billion dollars in transactions by 1999 with over 3 million items selling through its web site during a typical week (Lucking-Riley, Bryan and Reeves, 2000). With these developments, auctions have become an important mechanism to exchanges of goods and services.

It is important to examine why the seller (auctioneer) selects the auction as a selling mechanism. The answer primarily lies with the uncertainty of the value of the object being auctioned off to the bidders as well as the seller. All parties have different pieces of information about the value of the object. The seller is interested to know the

[2] Business-to-business auto parts auctions among firms like General Motors, Ford and Daimler-Chrysler expect to handle $250 million transactions a year (Klemperer, 2000).

maximum amount that a buyer would be willing to pay for an object. Instead of the seller putting a price tag on the object with limited information, auctions allow sellers to accept bidders' individual valuations as bids. Every bid submitted by a bidder summarizes the information available to a given bidder about the value of the object.[3] Therefore, auctions may provide a good mechanism to the seller to lessen the information asymmetry problems that exists between buyers and the seller.

For economists, auctions provide a vital testing ground to investigate the strategic behavior of economic agents and price formation under information asymmetry. McAfee and McMillan (1987) point out the perfect information assumption in standard economic models between the buyer and the seller would not hold in all transactions, particularly in auctions. As such, the price determined by a given selling mechanism would not give the "right" signal to allocate resources which in turn would lead to economic inefficiencies. Auctions provide a good framework for researchers to investigate the price discovery process under information asymmetry. In addition to the information issues, Klemperer (2000) discusses in detail the applicability of auction-theoretic tools in economics that are not necessarily auctions.

2.2. Auction Forms

There are four main forms (types) of auctions identified in the literature. They are an English auction, a Dutch auction, a first-price sealed-bid auction and a second-price sealed-bid auction (McAfee and McMillan, 1987; Milgrom, 1989; Krishna, 2002). In the English auction, the oldest auction type (Krishna, 2002), the auctioneer calls out prices (also known as oral ascending auction) and raises the value until only one bidder remains in the auction. When the second highest bidder drops out from the auction, the highest

[3] This may not be the case under collusive behavior.

valuation bidder wins the auction at the second to last bidder's price. Unlike other auction types, in English auctions participants know the current bid and therefore bidders can bid accordingly. In the Dutch auction, the auctioneer starts the auction with an initial high bid and then the price is lowered. The first bidder who stops the price will win the auction. In the first-price sealed-bid auction, bidders submit sealed-bids and the highest bidder is awarded the item at the amount he bids. Similarly in the second-price sealed-bid auction, bidders submit sealed bids but the highest bidder wins the auction at the second highest bidder's price. One of the main differences between the sealed-bid auction and the English auction is that, in the English auction bidders observe the bids submitted by other interested bidders in the auction. This is not possible in the sealed-bid auction since all bidders submit only one bid. The ODOT auctions are conducted using the first-price sealed-bid auction format. Variations of the above four types of auctions are widely used, i.e., imposing a reserve price,[4] royalty payment[5] etc.

2.3. The Value of the Object

The auction literature identifies two polar cases in classifying the value of objects. These are independent private value objects (and IPV models) and common value objects (and CV models). In the case of IPV, the bidder knows the value of the object to him and his value does not depend on the value to the other bidders. Examples are flower auctions in the Netherlands and buying objects for personal use and consumption.

CV objects have a re-sale value and bidders have a certain amount of uncertainty about the value of the item. An example is when the government is selling mineral rights

[4] An auctioneer can set up a minimum acceptable bid and if the highest bid is lower than the reserve price, the seller can decide not to sell the item.

[5] In government auctions to award mineral rights, the government can impose a royalty payment where the winning bidder is suppose to pay a royalty fee for every unit of output produced by using the resource he bought at the auction.

to explore for underground oil, the value to a bidder depends on the amount of oil that can be extracted. Also, if a bidder participates in an auction with the idea of re-selling the item, then the object has a common value. However, in real-world auctions, objects will not have pure CV characteristics. The majority of objects will have both private value components as well as common value components. Milgrom and Weber (1982) have introduced a model, where objects have both private and common value elements, known as the Affiliated Value model (AV). With affiliation, bidders' valuations are correlated. That is, when a bidder has a higher value for the object, he expects the other bidders to have higher values on average. For example, the road construction contracts considered in this study can be identified as AV objects. These contracts have both private value and common value cost components. Firms may know their own cost estimate (depending on their efficiency levels) for a given project while it may have some uncertainty about the prices of inputs they may have to buy from the open market (concrete, iron etc.). Thus bidders' valuations are correlated through the common cost components in these contracts.

2.4. Revenue Equivalence Theorem

From the seller's perspective, it is an important question to ask which auction type generates the highest revenue. Milgrom (2004) points out that the answer to this question depends on the specific circumstances. Under a specific set of assumptions, the standard auction model[6] predicts that revenue is the same on average, across auction types (English, Dutch, first-price or second-price auctions). The standard auction model assumes a symmetric framework of analysis within which bidders are risk neutral and have independent private values (McAfee and McMillan, 1987; Engelbrecht-Wiggans,

[6] The standard auction model is explained in detail by McAfee and McMillan (1987).

1980). Deviations from these assumptions do not guarantee the revenue equivalence among different mechanisms. However, when it comes to choosing the appropriate auction type, revenue may not be the only concern. For example, in the design of the Federal Communications Commission's radio spectrum auctions, efficiency has been given a priority over revenue in order to benefit the bidders who may bid on adjacent projects (Krishna and Rosenthal, 1996).

When there are multiple objects, the question "what auction format would be preferred by the seller" again depends on specific circumstances, since it is more complex than the single object case. The revenue performance depends on many factors, such as whether they are sold sequentially[7] or simultaneously, whether the goods are substitute or complementary goods, the value of the objects, etc. The design of the FCC spectrum auctions is an example that allows bidders to derive complementarities by winning adjacently located service areas (Krishna and Rosenthal, 1996). Beside these concerns, Milgrom (2004) points out that, multi-unit auctions can also lead to phenomenon like collusive behavior.

2.5. Procurement Auctions

Procurement is a process where bidders compete for the right to sell their goods or services. The government sector spends around \$30-\$40 billion every year on road construction alone through the procurement process (Krasnokutskaya, 2003). Milgrom (2000) points out the procurement process can be complex in certain instances where the procurer accounts not only the price but also the other aspects such as the quality, e.g., government defense contracts. In this literature, the revenue and efficiency performance

[7] In standard sequential auctions units are sold one at a time and in a short enough time, in such a way that bidders do not discount future payoffs (Krishna, 2002).

of procurement auctions have been investigated under a number of different assumptions. This literature has explored the presence of asymmetric information among the buyers[8], bid rigging and collusive behavior between the bidders,[9] the entry of firms,[10] and the presence of synergies across objects.[11]

2.6. Summary

This section highlights the importance of auctions as selling mechanisms, their importance to sellers and its importance to economists. Also this section provides basic information about auction types, the value of the object(s), the revenue equivalence theorem, the use of multi-unit object auctions, and a brief description about the procurement auction literature. The specific theoretical and empirical literature related to the topics that I investigate will be discussed in detail in the corresponding chapters.

[8] See Hendricks and Porter (1988), Hendricks, Porter and Tan (1993).
[9] See Bajari and Ye (2001), Pesendorfer (2000), Poter and Zona (1993, 1999).
[10] See De Silva, Dunne and Kosmopoulou (2003).
[11] See De Silva (2005), Moreton and Spiller (1998), Ausubel et al (1997), and Gandal (1997).

Chapter 3

The Impact of Public Information on Bidding in Highway Procurement Auctions

3.1. Introduction

This study investigates how a change in the information available to bidders affects the outcomes of road construction procurement auctions held by the Oklahoma Department of Transportation (ODOT). The change examined deals with the release of ODOT's internal estimate of the cost of a project. This is referred to as the "engineer's cost estimate." Prior to January 2000, ODOT did not reveal the engineering cost estimate to bidders before the bid letting. However, they did release the engineer's estimate after the bids were opened. In January of 2000, this policy was changed and bidders could now request the engineering cost estimate for a project from ODOT prior to the bid letting. This paper empirically examines whether this change in information available to bidders affects the bidding behavior of firms and likewise ODOT's payments to contractors. The theoretical literature suggests that such a release of seller information to bidders should increase competition among bidders and thus increase seller revenue. The empirical literature that investigates the impact of the release of sellers' information is largely confined to experimental studies. Hence, the data on changes in the information release in ODOT procurement auctions should provide a natural testing ground to explore these issues.

In the theoretical literature there are a few key studies that analyze the impact of information on bidding behavior and seller revenue. Milgrom and Weber (1982) theoretically demonstrate that a release of seller's information[12] about the value of the object in first-price affiliated value auctions can raise the expected price (in ascending auctions). Another study by Goeree and Offerman (2003) develops an auction model where the value of the object has both private value and common value components. They show that the release of sellers' information regarding the value of an object reduces the uncertainty of the common value component of the object. This reduction in uncertainty leads to more aggressive bidding by bidders with a higher private value (in ascending auctions). Thomas (1996) compares bidding with full information and partial information in first-price auctions. With full information all bids are revealed ex post. With partial information only the winning bids are revealed. He demonstrates ex post revelation of all bids by the seller leads to stronger competition and an increase in seller revenue**.**

The empirical literature that analyzes the impact of information in auctions is limited to experimental studies, as mentioned earlier. Kagel, Harstad and Levin (1987) experimentally analyze the impact of the release of sellers' information on the bidding behavior in auctions with affiliated private values. In the case of first-price sealed-bid auctions, they find that ex ante revealing public information about the value of the object increases sellers' revenue. This result is consistent with the theoretical findings of Milgrom and Weber (1982) and Goeree and Offerman (1999, 2003) in first-price sealed-bid auctions.

This study examines the influence of information release on bidding and seller revenue in first-price sealed-bid auctions. Bidding behavior in the periods before and

[12] For example, Milgrom and Weber (1982) discuss in the sale of a work of art, the seller can reveal appraisals obtained by him to the bidders.

after the change in information policy is modeled. Overall this study finds a significant decrease in the average bid and average winning bid level after the release of the engineer's estimate to bidders by ODOT. A decrease in the average winning bid implies an increase in the seller revenue in descending price auctions. Thus this analysis is consistent with the theoretical predictions by Milgrom and Weber (1982) and Goeree and Offerman (1999, 2003) related to first-price auctions and information release by the seller. The rest of this paper is organized as follows. An overview of the theoretical and empirical literature related to this study is given in section 3.2. A discussion of data sources is presented in section 3.3. The empirical model is presented in section 3.4 and section 3.5 reports the results of the empirical analysis. Section 3.6 concludes.

3.2. Literature Review

The role of information in auctions has been an important topic in both the theoretical and empirical literatures on auctions. While much of this literature has focused on asymmetries in information across bidders, a smaller literature has examined the release of information by the seller. This section summarizes some key studies that investigate the impact of the release of seller information in auctions on seller revenue and bidding behavior.

3.2.1. Theoretical Literature

Milgrom and Weber (1982) develop a model of competitive bidding with affiliated values that generates predictions about seller revenue.[13] A specific feature of the affiliated value model is that the higher the value of the item for one bidder the more likely it is that the value will be higher for other bidders. Typically when values are affiliated, the value of the object to the bidder depends on observed private value

[13] These predictions are related to first price, second price and English auctions.

components and the unobserved common value components. In ODOT auctions, there are unobserved common value elements (common costs) as well as observed private value elements (private costs). Observed private cost components may include material and labor costs observed by the firms. Unobserved common cost components may include cost components that were uncertain at the time of bidding. For example, in a given project the soil properties of the construction site may vary depending on the location of the project. The relevant properties of the soil may not be fully known until the project is started and excavation begun. Such costs can be treated as common costs that were uncertain at the time of bidding. Therefore the total cost of a project to a bidder is a mix of private and common cost components.

Milgrom and Weber (1982) examine the impact of information on sellers' revenues in affiliated value auctions. In their model, they introduce an additional public information signal given by the seller to help bidders estimate the value of the object. Therefore this signal is affiliated with the bidders' estimates and the common value components bidders observe. Considering first-price auctions, Milgrom and Weber (1982) predict that a policy of publicly revealing the seller's information cannot lower, and may raise the expected price. Revealing the seller's information reduces the uncertainty of bidders. This leads them to revise the common cost elements in their own estimates. As a result their estimated value gets closer to the true value of the object causing them to bid more aggressively. This is because a rational bidder, in a sealed-bid auction with the object having a common value component, always sets his bid equal to what he estimates to be the second highest bidder's valuation given that all bidders are making the same presumption. This bidding behavior is a result of bidders trying to avoid becoming a victim of the winner's curse (McAfee and McMillan, 1987; Smith, 1981). Therefore with more information available to bidders, there should be an upward revision in bids (on average) and an increase in the seller's revenue.

Goeree and Offerman (1999, 2003) analyze a first-price sealed-bid auction model that generates predictions about seller's revenue**.** A key difference in Goeree and Offerman's modeling framework compared with Milgrom and Weber (1982) is that bidders receive multiple signals. That is, every bidder will receive different pieces of information related to the common value and private value components. Hence, the value of the object to the bidder is a summary statistic of the two pieces of information. Goeree and Offerman (1999, 2003) argue that when the seller releases additional information, it will reduce the uncertainty of the common cost components. This reduction in uncertainty will lead to more aggressive bidding behavior, particularly**,** among risk averse bidders that are trying to avoid the winner's curse. Thus when the uncertainty of the common cost component is reduced, the private cost component weighs more heavily in their decision and bidders with lower private cost have an advantage over the other bidders. Therefore aggressive bidding behavior leads to an increase in efficiency as well as revenue.[14] Goeree and Offerman's predictions are consistent with the predictions of the first-price auctions by Milgrom and Weber (1982) despite the differences in the modeling frameworks.

[14] Goeree and Offerman (1999, 2003) use the total expected surplus to show how the seller's revenue increases with the release of information. The total expected surplus is defined as the common value minus the winner's expected cost; see Goeree and Offerman (1999, 2003) for details.

Thomas (1996) analyzes the impact of ex-post information in first-price sequential auctions[15] where bidders submit bids for multiple objects. The value of the objects is identical to all bidders. Thomas argues that when bidders bid for multiple objects, bidding behavior in a subsequent auction is different from the initial auction. The difference in bidding behavior depends on what bidders learn from the revealed seller's information and the outcome of the first auction (whether a given bidder wins or loses). The ex-post information in the model includes all bids submitted by other firms, the winning bid, and the identity of the winning bidder. Thomas (1996) points out that when the seller reveals such information, bidders learn about their rivals' private information. Thomas examines the bidding behavior at different levels of information. First, he describes a situation where only the winning bidder is revealed ex-post (and no other bid information is revealed). He then compares this to another situation where bids and names of bidders are revealed including the identity of the winning bidder. Here, he shows that a policy of revealing full information leads to stronger competition among the bidders and to greater revenue for the auctioneer, versus a policy of revealing only the identity of the winning bidder. The ex-post information received by the bidders in Thomas's study is different from the ex-ante information received by the bidders in Milgrom and Weber (1982) and Goeree and Offerman (1999, 2003). But despite such differences in the nature of the information, his predictions are generally consistent with the other two studies. The next section summarizes several key experimental studies that analyze the impact of information on seller revenue and on bidding behavior

[15] Thomas calls these auctions "repeated auctions" rather than sequential auctions. The difference is that, in a standard sequential auction the utility of the second object is zero due to unit demand. Thomas assumes bidders would like to acquire all of the items and these items have identical values to all bidders.

3.2.2. Empirical Literature

Kagel and Levin (1986) emphasize the presence of the winner's curse by analyzing the impact of public information in common value auctions with affiliated values (using first-price sealed-bid procedure). Because the true value of the object is unknown to bidders and all bidders have the same value of the object, winning bidders may experience the winner's curse due to judgmental failures about the true value of the object. In this paper, private information signals are drawn for bidders from a uniformly distributed interval. Here, two types of public information are employed separately. First, a common signal is given that helps the bidders to estimate the true value of the object. This signal is an additional value drawn from the same interval from which the private information signals were drawn, and it can reduce the uncertainty of the bidders' estimates. The second type of public information reveals the lower bound of the interval of which the private signals were drawn. In both cases, bidders have common knowledge about the information available to others. Due to the common value component, bidders may experience the winner's curse. In order to avoid the winner's curse, bidders will discount their bids. Kagel and Levin (1986) show the size of the bid discount increases with the increase in the number of bidders and the dispersion of rival bids (or the size of the interval on which the bidders' private information signals were drawn). The authors examine how the variations in the number of bidders and the width of the interval affect the winner's curse. The results of this study show that in the *absence* of the winner's curse the release of seller's information increases seller revenue. However, they also observe that in the *presence* of the winner's curse public information reduces seller's revenue. They argue -- that when the number of bidders is large, the additional seller information will cause optimistic bidders to make downward revisions in their bids (in ascending price auctions) which will offset the upward revision of less optimistic bidders and vice versa.

Kagel, Harstad and Levin (1987) test a key implication of the theory developed by Milgrom and Weber (1982) that is relevant to the first-price sealed-bid auctions with affiliated private values. Using experimental methods, they examine the impact of the release of the seller's information on revenue. In their experiment, two series of auctions are conducted. In the first auction, bidders submit bids based on the private values they receive,[16] and in the second auction they bid both with the public information and the private value. The profit received by a bidder is the value of the object minus the bid he/she submits at the auction. With respect to public information, two types of signals are employed in the experiment. First an additional signal is given to the bidders, which is drawn from the same interval from which the bidders' private values were drawn. This signal gives an indication of the private values received by the other bidders. Bidders are then asked to bid again for the same object but with the additional signal they observed. Second, bidders are informed about the center and the two boundaries of the interval from which the private values were drawn (in this case no additional signal is given). They report that revealing the seller's information increases seller revenue and the revenue increases further with a higher level of public information.

Following the above two experimental studies, Goeree and Offerman (2002) experimentally analyze some key predictions of the theoretical model they developed in their in 1999 and 2003 papers. The experimental setting is a first-price sealed-bid auction

[16] Bidders' private values are determined in the following manner: A value (x_0) is randomly drawn from the interval of \$25-\$125 which has a uniform distribution. Then bidders' private values are drawn from an interval within this interval where x_0 is the center of the interval**.**

with both private and common value components. In the experiment, subjects are given both private and common value signals. By combining these two pieces of information, bidders then determine their bids. Both signals are drawn from two different uniformly distributed intervals. At the end of each set of auctions, all bids and the common value of the object are revealed to the bidders. However, the private and common value signals and the winner's profits are not revealed. In a second set of auctions, a seller's signal regarding the common value component is provided to bidders. The signal is drawn from the same interval where the common value signals are drawn. With the disclosure of the seller's information (an additional signal given to the bidders), the uncertainty about the common value component is reduced. The authors show that a decrease in the uncertainty of the common value component is accompanied by an increase in the seller revenue and a decrease in the winning bidder's profits.

Some characteristics of the auctions analyzed by Kagel and Levin (1986), Kagel, Harstad and Levin (1987) and Goeree and Offerman (2002) are similar to the characteristics of ODOT auctions. The ODOT auctions are first-price sealed-bid auctions. Bidders participate in ODOT auctions have their cost estimates prepared based on the private information as well as the public information about the common cost components available to them. Affiliation occurs through the project-specific common cost components. The above experimental studies compare bidding situations where different amounts of public information are available to bidders. In the analysis that follows, the difference in public information will depend upon the release of ODOT's estimate of the cost of a project. The ODOT auction setting is most closely related to the situation modeled by Goeree and Offerman (2002).

In a previous study directly related to ODOT auctions, De Silva, Dunne and Kosmopoulou (2002) examine the impact of the release of information on the results of a set of morning auctions on the bidding behavior in the afternoon auctions. These auctions are held once every month in two sessions, a morning and afternoon session held on the same day. At the end of the morning session, ODOT releases the results from the morning session including the name of the winning bidder, winning bid and bids submitted by other firms with their names. This is the case where the seller reveals information ex-post. In the afternoon session, participants are thus informed about the results from the morning session. De Silva, Dunne and Kosmopoulou (2002) point out that bidding in the afternoon auctions can be affected by the outcome of the morning auctions due to the information released concerning the morning session. They find that bidding is more competitive in the afternoon session when more information is available.

In conclusion, regardless of the nature of information released in the above theoretical and empirical studies, the studies generally indicate increased competition among bidders and increased seller revenue when more information is available to bidders. In the situation studied herein, if the ODOT's policy of revealing the engineering estimate (prior to bid letting) affects bidding behavior, a decline in the average bids and the average winning bids should be observed. The decline in average bid implies an increase in competition while the decline in average winning bid implies an increase in seller revenue.

3.3. Data

This study employs data obtained from ODOT, on auctions for construction projects for the period of January 1997 to March 2002.[17] For every project, detailed information regarding bidder and project characteristics has been obtained. This includes the engineer's estimate of the project prepared by ODOT, names of the contractors that purchased project plans from ODOT (project plan holder list), bids submitted by contractors with their names, winning bidder's name and the winning bid (for the projects that are awarded), and the number of calendar days specified by ODOT to complete a project. In order to submit a bid, a firm has to be pre-qualified[18] and also has to be a plan holder[19] for a particular project. The lowest bidder is almost always awarded the contract if they satisfy the state's reserve price. ODOT may reject low bids that are 7% above the engineer's estimate of ODOT, though they do not always enforce this reserve rule.

A key variable of interest in this study is the state's engineering cost estimate prepared by ODOT. The estimate contains cost items specified in terms of material requirement[20] or description of work[21]. For each item, the unit cost and the estimated total costs are given in the estimate. However the estimate does not identify the labor cost separately. For example in an asphalt project, the quantity of asphalt required and the unit cost are specified in the estimate. The unit cost of asphalt incorporates both the material and the labor costs for paving a unit of asphalt. Adding across all individual items gives the total estimate for a project. As discussed above, ODOT changed its

[17] The data comes from three reports in the ODOT web site, namely the as read bid report, the low bid report and the award notice.
[18] In order to pre qualify; firms have to submit certified financial statement to ODOT.
[19] A firm submitting a bid must purchase the project plan from the ODOT. Firms purchasing plans are known as plan holders. The project plan gives a detailed description of the project design features.
[20] For example, quantities of asphalt, concrete, steel, different pipe types etc.
[21] For example removal of asphalt paving, construction traffic control, culvert end treatment, removal of guard rail, sediment removal etc.

policy with regard to the release of this information (the estimates prepared by ODOT for the projects) in January 2000.

In order to analyze the impact of releasing the cost estimate prior to bid letting, this study identifies three time periods in the data where the information regarding the cost estimate or the use of the information regarding the cost estimate may differ. The period from January 1998 to December 1999 is identified as the period of *Info-1*.[22] During this period ODOT did not reveal the engineering cost estimate to the contractors. *Info-2a* is a six month period from January 2000 to June 2000. The period *Info-2b* is from July 2000 to March 2002. In the *Info-2a* and *Info-2b* periods bidders are aware of ODOT's cost estimate of the project. The *Info-2a* period is included as a separate period to observe bidders' immediate response to the change in ODOT's information release policy. This flexibility on the specification is allowed since it may take time for bidders to learn how to incorporate the state's cost estimate into their estimation procedures and to learn how other bidders incorporate the information into their bids. This specification allows for such a period of transition.

In order to show how bidding differs across the three periods, plots of the distribution of bids for the *Info-1*, *Info-2a* and *Info-2b* periods is shown in Figure 3.1. Figure 3.1 presents the kernel density plots for the bid distributions for the three periods. All bids are normalized by the engineer's estimate of the project which allows comparing bids across auctions of different project size. The relative bid indicates the proportion a bid is above (more than one) or below (less than one) the engineer's estimate for a

[22] In order to construct the variables that control bidder history, and rival history (described in the next section), empirical analysis is started from January 1998 even though data is available from January 1997.

project. The left most, curve in Figure 3.1 represents the *Info-2b* period indicating a downward shift in the distribution of bids compared to the *Info-1* period.

Table 3.1 presents summary statistics of the data from January 1998 to March 2002 for the full sample and the sample broken out by the three sub-periods. This table includes statistics on the number of auctions, number of plan holders, number of firms, average number of plan holders per auction, number of bidders, average number of bidders per auction, number of auctions with bids, the average relative bid and the average winning bid. A total of 5092 bids coming from 1611 auctions during the sample period have been employed in the analysis. Notice that the numbers of bids are far lower than the number of plan holders (9190) meaning that not all plan holders bid. The total number of firms participating in these auctions over the entire period is 263. On average there are 5.7 plan holders and 3.2 bidders per auction. Notice the decreasing pattern in the mean relative bids and mean relative winning bids starting from the period of *Info-1* and in the two subsequent periods. This is the same pattern that is observed in Figure 3.1.

3.4. Empirical Analysis

This section presents an empirical model to analyze the impact of the change in the information policy by ODOT on bidding behavior. First the overall bid level is examined in order to observe whether there is a decrease in the bids due to the information release. Then the impact of information on seller revenue is investigated. The winning bids are used as a measure of the seller's revenue.

The dependent variable for both the bid and the winning bid regressions is measured relative to the engineer's estimate (the same as the relative bid variable seen in Figure 3.1). The relative bid is used in order to be able to compare bidding across auctions of different project size. A mean equation and a standard deviation equation is estimated in the analysis. The objective is to examine the impact of the information released on both the mean and the variance of bids and winning bids. The regression equation takes the following form

$$y_i = \beta_0 + \beta_1 Info2a_i + \beta_2 Info2b_i + \gamma X + \varepsilon_i$$

with an error structure

$$\varepsilon_i \sim (0, \sigma_i^2).$$

The standard deviation equation (sigma) takes the following form

$$\sigma_i = \varphi_0 + \varphi_1 Info2a_i + \varphi_2 Info2b_i + \varphi_3 \log(\#\_of\_bidders)_i .$$

In the mean equation, *Info-2a* and *Info-2b* represent the controls for informational differences and bidders reaction to information over time across the time periods. The other control variables can be grouped into four major categories and are contained in the matrix *X*. They are auction characteristics variables, bidder characteristics variables, rival characteristic variables, and variables that controls for aggregate time varying factors.

Info-2a and *Info-2b* are two dummy variables that control for the time periods -- the six month period immediately after the change in information policy and the subsequent period thereafter. The omitted group is the period where the engineering cost estimate was not released prior to the bid letting. The hypothesis is that the revelation of engineer's estimate by ODOT prior to bid letting will lower the overall bids and the winning bids during the periods of *Info-2a* and *Info-2b.* A decrease in the relative winning bids in *Info-2a* and *Info-2b* periods implies an increase in the seller's revenue.

It is very unlikely that all firms would respond equally to the information release. One possibility is that large and small firms may respond differently to the information release since they have different levels of expertise in bid preparation and may have different levels of past experience. As a measure of firm size, the maximum backlog of a firm during the sample period is used.[23] Porter and Zona (1993) have used this variable to measure firm capacity as well. In this study, a firm with a maximum backlog of more than 7 million dollars is considered as a large firm.[24] If the maximum backlog is less than or equal to 7 million dollars, the firm is considered as a small firm. To allow for differences in the response to the information release between these two size groups, the firm size variable is interacted with the information variables (time period controls). This yields six different time period-project size dummy variables -- large firms during the period of *Info-1 (Info-1 LF)*, small firms in the period of *Info-2a (Info-2a SF)*, large firms in the period of *Info-2a (Info-2a LF)*, small firms in the period of *Info-2b (Info-2b SF)*, and large firms in the period of *Info-2b (Info-2b LF).* Small firms in the period of *Info-1 (Info-1 SF)* are the omitted group in this specification of the empirical model.

The remaining variables in the model are represented by the matrix *X*. There are four auction characteristics variables -- project types, project size, source of funding for the project and the number of bidders. In case of the project type variables, all projects are grouped into six main categories based on the description of the project. This includes asphalt paving projects, clearance and bank protection projects, bridge projects, grading and draining projects, concrete work and traffic signals and lighting projects. All the other projects are considered as miscellaneous projects[25] and it is the omitted group in

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[23] Backlog is computed for the firms that won contracts. Details of the construction of this variable are in the next section. For the firms that have not won any contract the engineering estimate of the largest project they bid is considered as the firm size.
[24] Maximum backlog of firms vary from a minimum of $801 to $48 million. The $7 million cut off point includes 15% of the all firms in the sample in the large firm group.
[25] Miscellaneous projects include landscaping, water line adjustments, intersection modification, parking etc.

the regression. Project type variables control the variability in these broad classes of projects. With respect to project size, large (Large Projects=1) and small projects (Large Projects=0) are identified based on the distribution of engineering cost estimate. Large projects are different in complexity and work requirement (such as Disadvantaged Business Enterprise[26] program requirements). Therefore bidding behavior may vary by project size. All projects with an engineering cost estimate over one million dollars are considered as large projects which includes approximately 20% of all projects in the sample.

With respect to project financing, there are two major sources--projects that are funded by the U.S. federal government and the projects that are funded by the Oklahoma state government. In the projects funded by the Federal government, the contractors have to abide by the guidelines set forth by the U.S. government.[27] Therefore a dummy variable is included to identify the projects funded by the federal government. Federal Projects=1 if the project is funded by the U.S. federal government, otherwise it is zero. The next auction characteristic variable is a measure of auction-level competition among the bidders. As in the literature the number of bidders (*Log of Number of Bids*) is used as a control for the degree of competition in the auctions (Hendricks, Pinske and Porter 1999; De Silva, Dunne and Kosmopoulou 2002, 2003).

Bidder characteristic variables include a firm's past winning to bid ratio and utilization of a firm's capacity. As in De Silva, Dunne and Kosmopoulou (2003), this

[26] Disadvantaged Business Enterprise is defined as an enterprise with more than 51% ownership by socially and economically disadvantaged groups as defined by the Federal Government. It also must be a small business defined by the Small Business Administration regulations. If it is a general contractor the firms gross receipts averaged over a three years period cannot exceed $17.40 millions.

[27] The main contractor of a U.S. government funded project is responsible to provide equal opportunity to disadvantaged business groups, when assigning sub-contracts.

study employs the winning-to-bid ratio to measure past success rate in auctions for a given firm. It is the past number of wins divided by the past number of bids submitted by a firm at the time of bidding. Second, the utilization rate is the backlog of a firm divided by the maximum backlog of that firm during the sample period.[28] This indicates the capacity utilized by a given firm for the contracts already won. Backlog[29] is the dollar value of the unfinished amount of work for the contracts that a firm has won. Similar capacity measures have been used in the empirical auction literature analyzing highway procurement auctions.[30]

As in De Silva, Dunne and Kosmopoulou (2002, 2003) this study employs a variable that controls for rival heterogeneity. This measures the rivals past success in auctions to control for the toughness of competition. This variable is constructed as follows. For every firm in an auction (all plan holder firms in an auction), the number of auctions won in the past was counted and divided by the number of plans held by that firm for the same period. These ratios were then averaged across the rivals of a given firm in an auction to obtain an overall measure of the competitiveness of the rivals.

In the analysis that follows, it is important to control for factors that change over time other than the information. Four variables are included that control for monthly variation in the amount of projects being let, the distribution of projects being let, the number of potential bidders, and the economic climate.

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[28] For firms that never won a contract, the utilization rate is zero meaning that these firms have full capacity available for utilization.

[29] The backlog variable and the project type variables described earlier are the same variables that have used in De Silva, Dunne and Kosmopoulou (2002, 2003).

[30] For example, Porter and Zona (1993) have used the utilization rate (defined as the backlog of a firm at a particular time divided by the maximum backlog of the firm) as a measure of firm capacity. Bajari and Ye (2002) have used firm capacity defined as a given firm's used capacity (measured as the total winning bids amounts up to that time) over the firms' total winning bids for a season (one year period).

The first variable controls for differences in the amount of projects auctioned off across time. Such variations occur due to budgetary conditions and seasonal factors in the State of Oklahoma. The monthly variation in the total value of estimates is shown in Figure 3.2. It measures monthly fluctuations in real dollars (millions) for all projects. These monthly fluctuations in the available project dollars could affect average bidding behavior. The second variable measures the number of projects auctioned in a month relative to the number of firms participating in the bidding. This variable controls for two aspects of the distribution of projects being let. First it controls the number of projects auctioned off in a given month. Second it also controls for the number of firms interested in bidding in a given month. This is important since the real value of monthly estimate total does not control for the actual number of projects in a month. The third measure is a variable that controls for the distribution of project sizes in a given a month. A measure is included to account for project size inequality and is constructed in the same manner as a Herfindhal index – the sum of the project shares squared in a month. A larger value indicates a more concentrated project mix. Bidding behavior could be affected in a given month when a large portion of the project funds in a month are allocated to a few projects. Finally, the state unemployment rate is included to control for cyclical factors that may affect the Oklahoma economy. Summary statistics of the regression variables discussed above are presented in Table 3.2.

In the standard deviation equation, σ_i is allowed to vary with the information variables and the number of bidders in an auction. The theoretical literature suggests that the uncertainty about the value of the object decreases when more information is available to bidders. This is due to a reduction in the uncertainty in the common value components of the object. In this case, the release of engineering cost estimate may reduce uncertainty of the common cost components of the projects. This would lead to a reduction in the variance in the overall bid level. The mean equation together with the standard deviation equation is estimated using maximum likelihood methods.

3.5. Results and Discussion

The regression results for different specifications of the model are given in Table 3.3 through Table 3.7. The upper half of the main tables report the results of the mean equation while the lower section of each table reports the results of the standard deviation equation. Table 3.3 presents the overall bid level (Relative Bid) regression results for three specifications. The first column of Table 3.3 includes the information variables (time period variables), auction characteristics, bidder characteristics, rival characteristics and time varying control variables. In the mean equation, the results indicates a systematic reduction in the overall bid level during the periods of *Info-2a* (January, 2000 to June 2000) and *Info-2b* (July 2000 to March 2002) relative to the period of *Info-1* (period before January 2000). This result is consistent with the predictions by Milgrom and Weber (1982), about the release of seller information on bidding behavior in first-price auctions. The standard deviation equation in the first column indicates a significant decrease in the variance in the *Info-2b* period which is consistent with decrease in the uncertainty among bidders.

In column (2) of Table 3.3, the firm size interaction terms are included in order to see the effect of the release of information on large and small firms. The results in the mean equation indicate that large firms appear to alter the bids more in response to the additional information. In case of the large firms, results indicate approximately 0.058

and 0.082 reduction in the relative bids in the two subsequent periods after January 2000 compared to the period before January 2000. The decrease in bids for smaller firms is considerably more muted. The result observed here is different from the initial explanation about differential impacts of the release of information between large and small firms. The standard deviation equation does not show a systematic reduction in variance when the firm size-time period interactions are included. A likelihood ratio test was conducted between the models in column (1) and column (2) in order to test the statistical significance of the interaction terms. The test supports the inclusion of interaction terms in the model in column (2).

Column (3) of Table 3.3 is an alternative specification to column (1). It presents the results of the relative bid regression without the time varying monthly variables. The results from this column can be compared with column (1) to see how sensitive the results are to the exclusion/inclusion of the other monthly variables. The results indicate that exclusion of these monthly variables does not change the coefficients in a significant manner and it is consistent with the insignificance of these four variables in column (1) and column (2).

Among the other results in Table 3.3, the large projects variable is significant in all three models and bidders bid relatively low for larger projects indicating more competition for larger projects. The same is true when examining the federal projects – bidders bid somewhat more aggressively for these projects. With regards to firm characteristics, firms with higher winning-to-bid ratios and lower capacity utilization submit, on average, lower relative bids. These results are consistent with the results reported in De Silva, Dunne and Kosmopoulou (2002, 2003). Also, the negative and significant coefficient on the *Log Number of Bidders* variable indicates there is more competition as the number of bidders increase. The monthly variables do not have a significant impact on the bidding behavior in any of these models.

Table 3.4 presents the results of the winning relative bids models. The winning relative bid regression will tell us how the seller revenue is affected by the change in the information release policy. Columns (1), (2) and (3), have the same specification for the models as in Table 3.3. The mean equation in Column (1) of Table 3.4 indicates a decline in the winning relative bids in the *Info-2*a and in the *Info-2b* periods relative to the period before January 2000. Winning relative bids decrease by 0.041 in the *Info-2b* period. The lower winning bid is consistent with the improvement in seller revenue predicted by Milgrom and Weber (1982) and Goeree and Offerman (2003). Also our results are consistent with the experimental results by Kagel and Levin (1986), Kagel, Harstad and Levin (1987) and Goeree and Offerman (2002) about the disclosure of seller information. These studies show an increase in the seller's revenue when more public information is available to the bidders. Column (2) shows the winning bid level of large firms in *info-2b* period have declined by 0.04 relative to large firms in the period before January 2000 (*Info-1)*. Also small firms show a 0.04 decline in the winning bid level relative to small firms in the period before January 2000 (*Info-1)*. The expectation that large firms would be less responsive (relative to the small firms) to the information release is not supported by the relative winning bid regression. Looking at the other variables, the rivals' previous winning to plan holder ratio has a negative and significant impact as in De Silva, Dunne and Kosmopoulou (2003). A likelihood ratio test between the models in column (1) and column (2) indicates that the firm size and information interaction terms are not statistically significant in the relative winning bid regression.

Table 3.5 presents robustness checks for the results in Tables 3.3 and 3.4 respectively. Recall that the relative bid tells us the proportion above or below the engineer's estimate of a particular bid. The project size (measured in term of engineer's estimate) varies from a minimum of $2400 to a maximum of $32 million. The relative importance of the project is not captured by the relative bid since it treats all projects of different size equally. Therefore weights are assigned to the model based on the project size (using the engineer's estimate of a project as the weighting variable) so that the relative bid of a larger project has more weight in the regression than a smaller project. Clearly, from a cost perspective, the State of Oklahoma will be more concerned with bidding on a large project than a small project. Table 3.5 column (1) and column (2) present the results of the weighted relative bid regression and weighted winning relative bid regressions, respectively. The results show that in the *Info-2b* period there is a 0.091 decline (columns (1)) in the relative bids and 0.069 declines (column (2)) in the winning relative bids relative to the period before January 2000. Notice that there is a larger decrease in the bid level and the winning bid level compared to the results in Table 3.3 and Table 3.4. There is also a significant decrease in the variance of all bids in the period after June 2000 (*Info-2b)*.

In addition to the weighted model a fixed effects model is estimated to control for unobserved firm heterogeneity. In doing so, this study identifies the 50 firms in the sample that submit the greatest number of bids. All the other firms are grouped together under one group. Bajari and Ye (2001) have adopted this approach identifying the 11 largest firms in the sample when they estimate their fixed effects model. In this study, the fixed effects capture the heterogeneity across the top 50 firms (identified in terms of participation, i.e. submitting bids). The remaining firms in the sample are modeled with a common fixed effect as in Bajari and Ye's (2001). In this sample the top 50 firms have won approximately 70% of the total value of projects awarded during the sample period.

Table 3.6 reports results of the fixed effects model. It reports three models with firm fixed-effects -- column (1) overall bid level, column (2) the winning bid, and column (3), the weighted model for winning bid regression. Results in column (1) and (2) of Table 3.6 are consistent with the previously estimated models. Column (1) indicates a 0.062 decline in the overall bid level in the period after June 2000 (*Info-2b).* There is a significant decrease in the variance of all bids (column (1)) in the period after June 2000 (*Info-2b).* A likelihood ratio test between the two models in column (1) of Table 3.6 and column (1) of Table 3.3 indicates that fixed effects matter in the model. The results in column (2) indicate that the winning bids decline in the period after January 2000. Column (3) indicates a 0.058 decrease in the winning bid in the *Info-2b* period when the model incorporates both weights and fixed effects. The results of this table are consistent with the previous results in Tables 3.3 to 3.6.

The standard deviation equations reported in Tables 3.3-3.6 show a significant decline in the variances of relative bids in the *Info-2b* period at the overall bid level. The reduction in the variance with more information is more consistent with a reduction in the uncertainty. It is also consistent with the theory of Goeree and Offerman (1999) that predicts a reduction in the uncertainty when more information is available to the bidders.

As in the literature, I also examined the changes that occur in the money left on the table. Bajari and Ye (2001) define money left on the table as the difference between the second lowest bid and the winning bid. They argue that if firms had complete information about their competitors' cost (in road construction projects) then the amount of money that should be left on the table would be near zero. Money left on the table is defined as the proportional difference between the reserve price and winning bid or the proportional difference between the second lowest bid and the winning bid which ever is smaller. In cases where the second lowest bid exceeds the engineer's estimate, this study considers the difference between the reserve price and the winning bid. A significant amount of money left on the table implies significant differences in the private information among the bidders.

Table 3.7 reports the results of money left on the table for the three models. The first column shows the un-weighted regression results. The second column shows the weighted results and the third column shows the weighted model incorporating firm fixed effects. The results in column (1) indicate that there appears to be more money left on the table in the latter two periods than in the period before January 2000. However, these results are quite sensitive to specification. Columns (2) and (3) show this. In both the weighted model, and the weighted model with fixed effects, the information variables are not statistically significant meaning that there is no significant differences in the amount of money left on the table after January 2000. According to Bajari and Ye's (2001) argument, this implies bidders have more or less the same knowledge of their rivals' private cost information (before and after January 2000).

One concern in interpreting the above results is that the information period variable may be picking up some other factor that is uncontrolled for in the regression. This is the classic omitted variable bias problem. In order to examine this possibility, the study use data on Texas auctions to compare with Oklahoma auctions. In Texas, the engineering cost estimate has been revealed prior to bid letting during the entire sample period from January 1998 to March 2002). Therefore there is no informational difference as in Oklahoma across time periods. However, by comparing across Oklahoma and Texas, common shocks hitting both states can be controlled that might affect bidding behavior. Clearly, the common shock that is most concerned about is the recession that occurred in 2001.[31]

The analysis is conducted pooling Oklahoma and Texas samples together. The objective is to examine whether there is a significant difference in bidding across the periods in Texas as compared to Oklahoma. The sample considered is from January 1998 to March 2002 time period for both Oklahoma and Texas data. The Texas data consist of 27,422 plan-holder observations with 16,685 bids. A total of 4088 auctions have been auctioned off during the period considered. The average relative bid for the Texas sample before January 2000 is 1.111 and for the sample after it is 1.063. Table 3.8 provides summary statistics.

The same procedure is used to measure the variables in Texas as in Oklahoma. Separate time period dummies are included for Texas bidding in order to compare the bidding pattern across states. The results from the pooled model are presented in Table 3.9. Again, the results indicate that in Oklahoma bids are lower in post January 2000

[31] This recession has occurred for a period of eight months between March, 2001 and November 2001. These recession dates are provided in the National Bureau of Economic Research web site.

period. A statistical test of the difference between the Oklahoma base period and Oklahoma post 2000 period and Texas base period and Texas post 2000 period (the difference-in-difference of the estimates) indicates that the decline in relative bids is larger in Oklahoma for the *Info-2b* period, as compared to Texas.[32] There is also a decline in the variance of bids on Oklahoma in period *Info-2b.*

As a robustness check for the results in Table 3.9 two models are re-estimated using the weighting procedure discussed above. The results of the weighted models are presented in Table 3.10. The results indicate that the decline in Oklahoma is significantly greater than the decline in Texas at the overall bid level. The results also show a similar pattern at the winning bid level but at the 10% significance level. The variance of bids also declined more in Oklahoma relative to Texas while there is no statistical difference in the variance of winning bids between the two states. Overall the Oklahoma-Texas results further supports the findings of this study.

3.6. Conclusion

This study investigates a change in the release of information to bidders prior to bid letting in road construction auctions. The impact of this policy change on the overall bid level and the winning bid level is investigated. The results indicate a strong effect on the overall bid level with a 0.066 decline in the period after June 2000 (Table 3.6 column (1)). This implies that competition among the bidders has increased. Looking at the winning bids there is a 0.063 decline in the average winning bids in the period after June 2000 (Table 3.6, column (3)). The reduction in the winning bid level implies a significant reduction in the procurement costs of ODOT after the change in the

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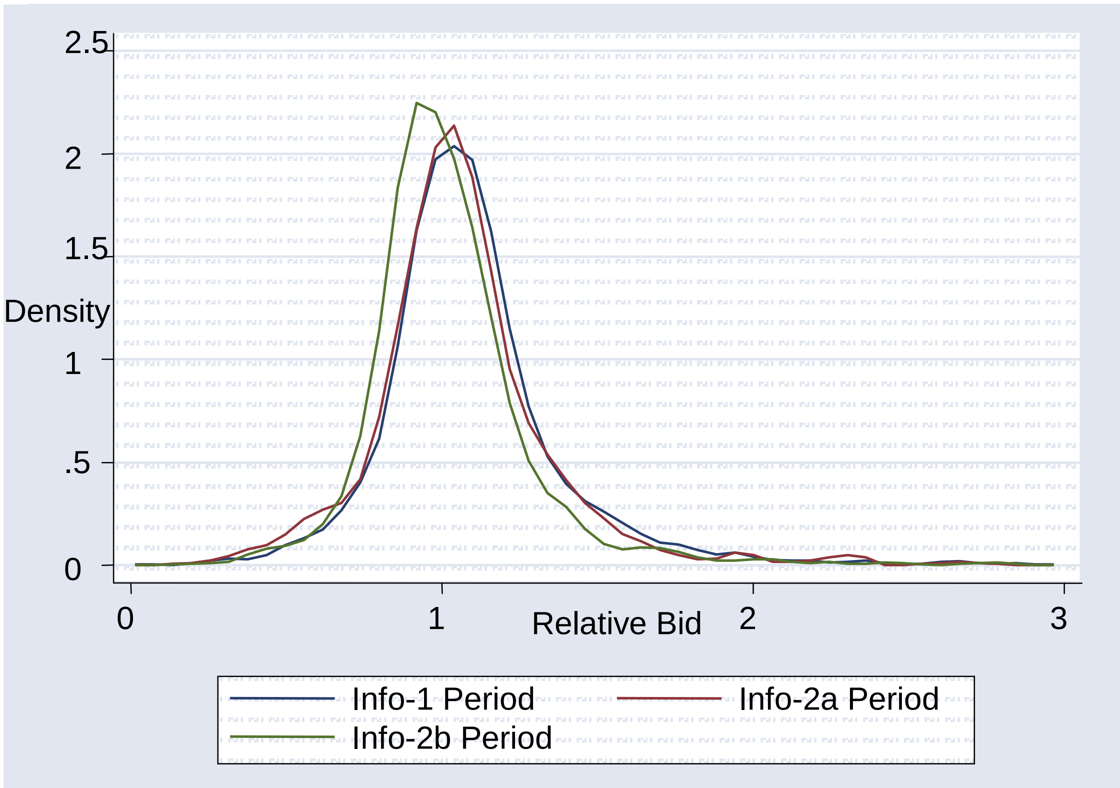
[32] A coefficient test is performed after estimating the models in Table 9. The null hypothesis for the test is the difference between *OK-Info1* period and *OK-Info-2b* period is same as the difference between *TX-Info-1* period and *TX-Info-2b* period. This was rejected with 5% significance for the overall bid level analysis.

information policy. These results are further supported by the analysis conducted by pooling data for Oklahoma and Texas. Only in Oklahoma is this dramatic decline at the overall bid level during the post January 2000 period observed. Further this study shows a significant decline in the variance of relative bids in the post January 2000 period which is consistent with a reduction in uncertainty when more information is available to bidders. These results are in general agreement with the auction literature that predicts an increase in competition that benefits seller and a reduction in uncertainty among the bidders when more public information is available.

Figure 3.1: Distributions of Relative Bids (bids normalized by the engineer's estimate) for the Three Time Periods.



The right most curve represents the period before January 2000 (represented by *Info-1*) followed by the middle curve for the six months transition period represented by *Info-2a* period and the left most curve for the period after June 2000 represented by *Info-2b* period.

Figure 3.2: Real Value of Monthly Project Estimate Totals

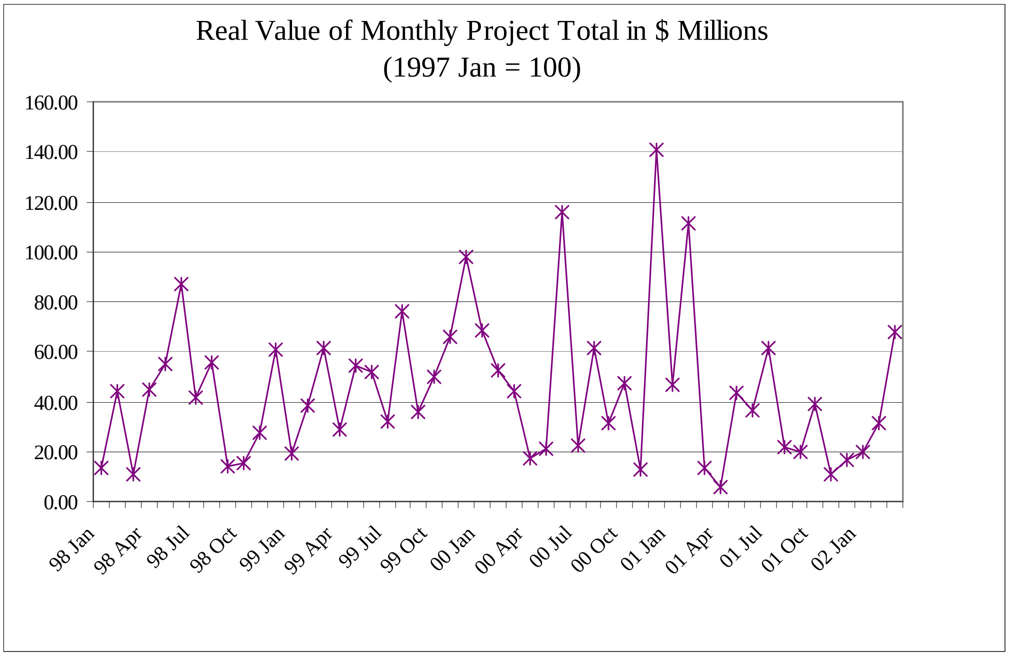


Table 3.1: Summary Statistics of Auctions

	Full Sample	January 1998-December 1999 *(Info-1)*	January 2000-June 2000 *(Info-2a)*	July 2000-March 2002 *(Info-2b)*
Number of Auctions	1611	798	196	617
Number of Plan Holders	9190	4421	1116	3653
Number of Firms	263	196	129	181
Average Number of Plan Holders per Auction	5.7213 (3.416)	5.70 (3.547)	5.938 (3.747)	5.721 (3.416)
Number of Bids	5092	2445	597	2050
Average Number of Bidders per Auction	3.3851 (1.693)	3.2626 (1.599)	3.443 (1.678)	3.352 (1.910)
Number of Auctions with Bids	1531	754	186	591
Mean Relative Bid	1.062 (0.282)	1.095 (0.293)	1.065 (0.293)	1.021 (0.260)
Mean Relative Winning Bid	0.939 (0.216)	0.963 (0.205)	0.923 (0.211)	0.912 (0.228)

Standard deviations are in the parenthesis.

Table 3.2: Means of the Regression Variables

Variables	Mean	(Std)
Relative Bid	1.062	(0.282)
Money Left on the Table (MLT)	0.071	(0.094)
Info-1	0.498	(0.500)
Info-2a	0.115	(0.319)
Info-2b	0.388	(0.487)
Info-1 LF	0.208	(0.406)
Info-1 SF	0.290	(0.454)
Info-2a LF	0.040	(0.195)
Info-2a SF	0.075	(0.264)
Info-2b LF	0.147	(0.354)
Info-2b SF	0.241	(0.428)
Large Projects	0.234	(0.424)
Federal Projects	0.543	(0.498)
Log of Number of Bids	1.087	(0.533)
Rivals Previous Winning to Pan Holder Ratio	0.149	(0.062)
Firm’s Own Winning to Bid Ratio	0.261	(0.144)
Utilization Rate	0.237	(0.282)
Log Real Value of Monthly Total of Engineering Estimates	17.391	(0.698)
Monthly Number of Firms per Project	2.076	(0.695)
Project Concentration Ratio	0.143	(0.081)
Unemployment	3.772	(0.680)

Table 3.3: Relative Bid Regressions for Three Specifications

Independent Variable	(1)		(2)		(3)	
Constant	1.252*	(0.136)	1.225*	(0.136)	1.310*	(0.033)
Info-2a	-0.042*	(0.015)			-0.032*	(0.013)
Info-2b	-0.074*	(0.009)			-0.072*	(0.008)
Info-1 LF			0.044	(0.012)		
Info-2a SF			-0.022	(0.022)		
Info-2a LF			-0.023	(0.017)		
Info-2b SF			-0.042*	(0.013)		
Info-2b LF			-0.070*	(0.012)		
Project-1	-0.120	(0.029)	-0.119*	(0.029)	-0.119*	(0.029)
Project-2	-0.082	(0.047)	-0.078	(0.047)	-0.080	(0.047)
Project-3	-0.113*	(0.029)	-0.110*	(0.029)	-0.110*	(0.029)
Project-4	-0.132*	(0.029)	-0.131*	(0.029)	-0.126*	(0.029)
Project-5	0.171*	(0.063)	0.175*	(0.063)	0.168*	(0.063)
Project-6	-0.163*	(0.032)	-0.157*	(0.032)	-0.159*	(0.032)
Large Projects	-0.074*	(0.010)	-0.076*	(0.010)	-0.073*	(0.010)
Federal Projects	-0.024*	(0.010)	-0.024*	(0.010)	-0.024*	(0.010)
Log of Number of Bids	-0.016	(0.008)	-0.013	(0.008)	-0.018*	(0.008)
Rivals' Previous Winning to Plan Holder Ratio	-0.038	(0.069)	-0.041	(0.070)	-0.038	(0.069)
Firms' Own Winning to Bid Ratio	-0.203*	(0.033)	-0.200*	(0.033)	-0.205*	(0.033)
Utilization Rate	0.052*	(0.014)	0.054*	(0.014)	0.058*	(0.013)
Log Real Value of Monthly Total of Engineering Estimates	0.006	(0.007)	0.006	(0.007)		
Monthly Number of Firms per Project	0.008	(0.009)	0.007	(0.009)		
Project Concentration Ratio	-0.077	(0.071)	-0.077	(0.071)		
Unemployment	-0.012	(0.007)	-0.012	(0.007)		
Sigma						
Constant	0.285*	(0.021)	0.287*	(0.021)	0.285*	(0.021)
Info-2a	0.000	(0.017)	0.000	(0.017)	0.000	(0.017)
Info-2b	-0.034*	(0.013)	-0.034*	(0.012)	-0.034*	(0.012)
Log of Number of Bids	0.001	(0.014)	-0.001	(0.014)	0.001	(0.014)
Number of Observations	5092		5092		5092	
Wald χ^2	377.86		452.82		360.82	
Log Likelihood	-594.325		-584.341		-597.457	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.4: Relative Winning Bid Regressions for Three Specifications

Independent Variable	(1)		(2)		(3)	
Constant	0.670*	(0.196)	0.673*	(0.196)	1.108*	(0.039)
Info-2a	-0.049*	(0.020)			-0.051*	(0.018)
Info-2b	-0.040*	(0.013)			-0.046*	(0.012)
Info-1 LF			0.005	(0.015)		
Info-2a SF			-0.059*	(0.028)		
Info-2a LF			-0.024	(0.022)		
Info-2b SF			-0.035	(0.020)		
Info-2b LF			-0.043*	(0.016)		
Project-1	-0.025	(0.034)	-0.025	(0.034)	-0.026	(0.034)
Project-2	-0.174*	(0.063)	-0.174*	(0.063)	-0.178*	(0.063)
Project-3	-0.030	(0.035)	-0.028	(0.035)	-0.031	(0.035)
Project-4	-0.025	(0.036)	-0.024	(0.036)	-0.021	(0.036)
Project-5	0.201*	(0.063)	0.201*	(0.063)	0.192*	(0.062)
Project-6	-0.051	(0.037)	-0.049	(0.037)	-0.049	(0.037)
Large Projects	-0.026	(0.015)	-0.028	(0.016)	-0.020	(0.015)
Federal Projects	-0.010	(0.015)	-0.010	(0.015)	-0.011	(0.015)
Log of Number of Bids	-0.074*	(0.010)	-0.074*	(0.010)	-0.073*	(0.010)
Rivals' Previous Winning to Plan Holder Ratio	-0.222*	(0.081)	-0.225*	(0.081)	-0.228*	(0.082)
Firms' Own Winning to Bid Ratio	-0.009	(0.039)	-0.007	(0.039)	-0.008	(0.038)
Utilization Rate	0.064*	(0.021)	0.061*	(0.022)	0.061*	(0.021)
Log Real Value of Monthly Total of Engineering Estimates	0.023*	(0.009)	0.023*	(0.009)		
Monthly Number of Firms per Project	0.029*	(0.013)	0.029*	(0.013)		
Project Concentration Ratio	-0.161	(0.099)	-0.165	(0.099)		
Unemployment	0.001	(0.010)	0.001	(0.010)		
Sigma						
Constant	0.169*	(0.018)	0.169*	(0.018)	0.171*	(0.018)
Info-2a	0.014	(0.018)	0.014	(0.018)	0.012	(0.018)
Info-2b	0.026	(0.025)	0.026	(0.025)	0.027	(0.025)
Log of Number of Bids	0.024	(0.015)	0.023	(0.016)	0.022	(0.015)
Number of Observations	1426		1426		1426	
Wald χ^2	189.07		200.18		160.82	
Log Likelihood	231.486		232.154		226.550	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.5: Relative Bids and Relative Winning Bids Weighted by the Engineer's Estimate

Independent Variable	(1) Weighted Relative Bid		(2) Weighted Relative Winning Bid	
Constant	1.453*	(0.159)	1.072*	(0.269)
Info-2a	-0.028	(0.015)	-0.032	(0.026)
Info-2b	-0.099*	(0.010)	-0.074*	(0.018)
Project-1	-0.005	(0.027)	0.059	(0.047)
Project-2	-0.028	(0.051)	-0.127*	(0.059)
Project-3	-0.025	(0.027)	0.028	(0.046)
Project-4	-0.051	(0.027)	0.029	(0.047)
Project-5	0.183*	(0.065)	0.191*	(0.059)
Project-6	-0.052	(0.037)	0.034	(0.057)
Large Projects	-0.061*	(0.010)	-0.034*	(0.016)
Federal Projects	0.024*	(0.010)	0.025	(0.016)
Log of Number of Bids	-0.015	(0.010)	-0.052*	(0.013)
Rivals' Previous Winning to Plan Holder Ratio	-0.062	(0.089)	-0.120	(0.119)
Firms' Own Winning to Bid Ratio	-0.092*	(0.032)	-0.088	(0.047)
Utilization Rate	0.047*	(0.017)	0.062*	(0.025)
Log Real Value of Monthly Total of Engineering Estimates	-0.011	(0.008)	0.000	(0.014)
Monthly Number of Firms per Project	0.005	(0.009)	0.012	(0.016)
project Concentration Ratio	0.015	(0.078)	-0.038	(0.117)
Unemployment	-0.031*	(0.006)	-0.016	(0.011)
Sigma				
Constant	0.188*	(0.010)	0.125*	(0.014)
Info-2a	-0.011	(0.010)	0.005	(0.017)
Info-2b	-0.028*	(0.006)	-0.004	(0.011)
Log of Number of Bids	-0.014*	(0.006)	-0.002	(0.009)
Number of Observations	5092		1426	
Wald χ^2	418.69		141.07	
Log Likelihood	3.751e+10		1237e+09	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.6: Firm Fixed Effects Models

Independent Variable	(1) Relative Bid		(2) Relative Winning Bid		(3) Weighted Relative Winning Bid	
Constant	1.228*	(0.134)	0.710*	(0.196)	1.085*	(0.229)
Info-2a	-0.035*	(0.015)	-0.033	(0.020)	-0.018	(0.022)
Info-2b	-0.066*	(0.009)	-0.039*	(0.013)	-0.063*	(0.015)
Project-1	-0.110*	(0.028)	-0.023	(0.035)	0.058	(0.044)
Project-2	-0.071	(0.046)	-0.186	(0.063)	-0.137*	(0.055)
Project-3	-0.080*	(0.029)	-0.041	(0.038)	0.025	(0.043)
Project-4	-0.112*	(0.028)	-0.022	(0.036)	0.038	(0.042)
Project-5	0.158*	(0.064)	0.188*	(0.065)	0.131*	(0.064)
Project-6	-0.147*	(0.038)	-0.064	(0.045)	0.047	(0.062)
Large Projects	-0.083*	(0.010)	-0.032*	(0.016)	-0.045*	(0.017)
Federal Projects	-0.022*	(0.010)	-0.016	(0.015)	0.028	(0.015)
Log of Number of Bids	-0.014	(0.008)	-0.069*	(0.010)	-0.050*	(0.014)
Rivals' Previous Winning to Plan Holder Ratio	-0.035	(0.074)	-0.268*	(0.091)	-0.171	(0.120)
Firms' Own Winning to Bid Ratio	-0.066	(0.047)	0.098	(0.054)	0.046	(0.050)
Utilization Rate	0.025	(0.015)	0.036	(0.024)	0.024	(0.027)
Log Real Value of Monthly Total of Engineering Estimates	0.005	(0.006)	0.020*	(0.009)	-0.002	(0.012)
Monthly Number of Firms per Project	0.004	(0.009)	0.024	(0.013)	0.008	(0.015)
Project Concentration Ratio	-0.073	(0.070)	-0.113	(0.098)	-0.132	(0.108)
Unemployment	-0.014*	(0.007)	-0.002	(0.009)	-0.016	(0.010)
Sigma						
Constant	0.277*	0.021	0.014*	(0.017)	0.130*	(0.013)
Info-2a	0.005	0.018	0.031	(0.027)	-0.005	(0.021)
Info-2b	-0.033*	0.013	0.013	(0.017)	-0.010	(0.011)
Log of Number of Bids	0.003	0.014	0.014	(0.017)	-0.009	(0.009)
Number of Observations	5092		1426		1426	
Wald χ^2	621.05		325.81		541.92	
Log Likelihood	-518.97		283.903		1.386e+09	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.7: Money Left on the Table Models

Independent Variable	(1) Un-weighted model		(2) Weighted Model		(3) Weighted Model with Firm Fixed Effects	
Constant	0.309*	(0.098)	0.080	(0.085)	0.056	(0.085)
Info-2a	0.019*	(0.008)	0.003	(0.009)	0.003	(0.009)
Info-2b	0.012*	(0.005)	0.006	(0.005)	0.004	(0.005)
Project-1	-0.031*	(0.012)	-0.048*	(0.018)	-0.044*	(0.017)
Project-2	0.078*	(0.027)	0.015	(0.025)	0.013	(0.024)
Project-3	-0.018	(0.012)	-0.054*	(0.017)	-0.049*	(0.017)
Project-4	-0.035*	(0.013)	-0.064*	(0.017)	-0.062*	(0.016)
Project-5	-0.117*	(0.023)	-0.083*	(0.018)	-0.059*	(0.021)
Project-6	-0.030*	(0.014)	-0.052*	(0.020)	-0.053*	(0.021)
Large Projects	0.000	(0.006)	0.001	(0.006)	0.007	(0.006)
Federal Projects	0.002	(0.006)	-0.008	(0.005)	-0.008	(0.005)
Log of Number of Bids	-0.017*	(0.006)	-0.019*	(0.005)	-0.020*	(0.005)
Rivals' Previous Winning to Plan Holder Ratio	0.055	(0.038)	-0.060	(0.051)	-0.054	(0.048)
Firms' Own Winning to Bid Ratio	0.023	(0.017)	0.005	(0.019)	-0.039	(0.025)
Utilization Rate	-0.035*	(0.010)	-0.020*	(0.009)	-0.012	(0.010)
Log Real Value of Monthly Total of Engineering Estimates	-0.010*	(0.005)	0.004	(0.004)	0.005	(0.004)
Monthly Number of Firms per Project	-0.017*	(0.005)	-0.001	(0.005)	0.003	(0.005)
Project Concentration Ratio	0.068	(0.041)	-0.005	(0.035)	0.012	(0.040)
Unemployment	-0.002	(0.004)	0.001	(0.004)	0.002	(0.004)
Sigma						
Constant	0.114*	(0.011)	0.078*	(0.006)	0.077*	(0.007)
Info-2a	0.005	(0.011)	-0.001	(0.007)	0.000	(0.009)
Info-2b	-0.001	(0.009)	0.000	(0.004)	-0.001	(0.005)
Log of Number of Bids	-0.023*	(0.008)	-0.022*	(0.004)	-0.023*	(0.005)
Number of Observations	1426		1426		1426	
Wald χ^2	120.77		75.01		672.39	
Log Likelihood	1443.195		2.986e+09		3.087e+09	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.8: Summary Statistics for the Texas Sample

	All Auctions	January 1998-December 1999 *(Before)*	January 2000-March 2002 *(After)*
Number of Auctions	4088	1968	2120
Number of Plan Holders	27422	12844	14598
Number of Firms	1110	712	831
Average Number of Plan Holders per Auction	6.648 (3.258)	6.449 (3.051)	6.832 (3.430)
Number of Bids	16685	7426	9259
Average Number of Bidders per Auction	4.062 (1.988)	3.754 (1.777)	4.348 (2.127)
Mean Relative Bid	1.085 (0.229)	1.111 (0.232)	1.063 (0.224)
Mean Relative Winning Bid	0.981 (0.179)	1.011 (0.180)	0.954 (0.172)

Standard deviations are in parenthesis.

Table 3.9: Pooled Analysis for Oklahoma and Texas

Independent Variable	(1) Relative Bid		(2) Relative Winning Bid	
Constant	1.361*	(0.092)	1.049*	(0.134)
OK-Info-1	-0.042*	(0.011)	-0.035*	(0.016)
OK-Info-2a	-0.075*	(0.016)	-0.079*	(0.023)
OK-Info-2b	-0.129*	(0.012)	-0.093*	(0.018)
TX-Info-2a	-0.027*	(0.005)	-0.032*	(0.008)
TX-Info-2b	-0.034*	(0.004)	-0.038*	(0.007)
Project-1	-0.022*	(0.006)	0.020*	(0.008)
Project-2	-0.021	(0.026)	-0.078	(0.041)
Project-3	-0.014*	(0.006)	0.022*	(0.009)
Project-4	0.001	(0.007)	0.045*	(0.011)
Project-5	-0.065*	(0.010)	-0.030*	(0.015)
Project-6	-0.045*	(0.007)	-0.006	(0.010)
Large Projects	-0.090*	(0.004)	-0.041*	(0.005)
Federal Projects	0.037*	(0.003)	0.033*	(0.005)
Log of Number of Bids	-0.044*	(0.004)	-0.097*	(0.005)
Rivals' Previous Winning to Plan Holder Ratio	-0.194*	(0.033)	-0.261*	(0.043)
Firms' Own Winning to Bid Ratio	-0.181*	(0.012)	-0.068*	(0.016)
Utilization Rate	0.024*	(0.005)	0.016	(0.009)
Log Real Value of Monthly Total of Engineering Estimates	-0.004	(0.004)	0.007	(0.006)
Monthly Number of Firms per Project	-0.010*	(0.004)	-0.005	(0.005)
Concentration Ratio	0.089*	(0.037)	0.034	(0.055)
Unemployment	0.002	(0.003)	0.000	(0.004)
Sigma				
Constant	0.232*	(0.007)	0.193*	(0.008)
OK-Info-1	0.070*	(0.009)	0.039*	(0.011)
OK-Info-2a	0.070*	(0.016)	0.049*	(0.016)
OK-Info-2b	0.025*	(0.009)	0.028*	(0.011)
TX-Info-2a	0.001	(0.006)	-0.003	(0.010)
TX-Info-2b	-0.005	(0.005)	-0.004	(0.006)
Log of Number of Bids	-0.008	(0.004)	-0.021*	(0.006)
Number of Observations	21743		5486	
Wald χ^2	1655.28		774.03	
Log Likelihood	1111.303		1853.693	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 3.10: Oklahoma and Texas: Weighted Regression Models

Independent Variable	(1) Relative Bid		(2) Relative Winning Bid	
Constant	1.353*	(0.086)	1.059*	(0.127)
OK-Info-1	-0.042*	(0.010)	-0.034*	(0.015)
OK-Info-2a	-0.074*	(0.015)	-0.075*	(0.021)
OK-Info-2b	-0.130*	(0.011)	-0.094*	(0.017)
TX-Info-2a	-0.028*	(0.005)	-0.033*	(0.008)
TX-Info-2b	-0.035*	(0.004)	-0.038*	(0.006)
Project-1	-0.021*	(0.005)	0.018*	(0.008)
Project-2	-0.030	(0.025)	-0.082*	(0.039)
Project-3	-0.014*	(0.006)	0.020*	(0.009)
Project-4	-0.001	(0.006)	0.040*	(0.010)
Project-5	-0.064*	(0.010)	-0.031*	(0.014)
Project-6	-0.042*	(0.007)	-0.007	(0.010)
Large Projects	-0.088*	(0.004)	-0.040*	(0.005)
Federal Projects	0.037*	(0.003)	0.034*	(0.005)
Log of Number of Bids	-0.044*	(0.004)	-0.095*	(0.005)
Rivals' Previous Winning to Plan Holder Ratio	-0.196*	(0.031)	-0.258*	(0.041)
Firms' Own Winning to Bid Ratio	-0.182*	(0.012)	-0.070*	(0.015)
Utilization Rate	0.024*	(0.005)	0.016	(0.008)
Log Real Value of Monthly Total of Engineering Estimates	-0.003	(0.004)	0.006	(0.006)
Monthly Number of Firms per Project	-0.009*	(0.003)	-0.005	(0.005)
Concentration Ratio	0.090*	(0.035)	0.041	(0.053)
Unemployment	0.002	(0.003)	-0.000	(0.004)
Sigma				
Constant	0.229*	(0.007)	0.190*	(0.008)
OK-Info-1	0.061*	(0.008)	0.031*	(0.010)
OK-Info-2a	0.060*	(0.015)	0.044*	(0.016)
OK-Info-2b	0.019*	(0.008)	0.024*	(0.010)
TX-Info-2a	0.002	(0.006)	-0.002	(0.010)
TX-Info-2b	-0.004	(0.005)	-0.003	(0.006)
Log of Number of Bids	-0.009*	(0.004)	-0.021*	(0.008)
Number of Observations	21743		5486	
Wald χ^2	1768.22		813.47	
Log Likelihood	24781.272		27153.707	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Chapter 4

An Empirical Study of the Release of Information in Repeated Procurement Auctions

4.1. Introduction

This study empirically investigates the impact of information release on bidding behavior in procurement auctions. The situation that I am studying here concerns the re-auctioning off of items that failed to be successfully auctioned off in an initial auction. For example, in highway construction auctions a project may fail to be auctioned off because the state rejects the submitted bids as not meeting the reserve price or because there were no bids submitted at the auction. The state often re-auctions off these projects in a later auction. In such a circumstance, a great deal of information is released to potential bidders about the specific auction that may be used in the later round. In Oklahoma, the bids of the unsuccessful bidders are revealed, as is the state's estimate of the costs of the project. This information is available to potential bidders when the project is re-auctioned off in a subsequent letting. In this study, I investigate how the release of this type of information impacts the average bid and the variance of bids in highway procurement auctions in Oklahoma.

In this study, I consider the release of information by the state about the project's costs and the rivals' bidding behavior. Milgrom and Weber (1982) consider auctions with affiliated values and show that, in first price auctions, a policy of revealing the seller's information cannot lower and in fact it may raise the expected price. In this study, I examine whether the information released from the initial round rejected auctions results in more aggressive bidding. In a related paper, Goeree and Offerman (1999, 2003) develop a model where the objects that are auctioned off have both private and common value characteristics. In that case, the public disclosure of the auctioneer's information increases expected revenue. By releasing information, the auctioneer reduces uncertainty in the auction.

The empirical literature on auctions that examines the effect of the release of information by the seller is more limited in scope. Using experimental methods, Kagel, Harstad and Levin (1987), find that the release of information raises the seller's revenues. In a repeated auction setting, bidders are provided with some information prior to each auction period about the true value of the object being auctioned off. They conclude that an increase in the observed average revenue corresponds to the availability of public information to the bidders. Other empirical research has examined asymmetries in information available to bidders and asymmetries in costs across bidders in a range of auction settings. For example, papers by Bajari and Ye (2002) and Jofre-Bonet and Pesendorfer (2000) examine how differences in rival costs affect bidding behavior. These papers find that as rivals' project backlogs increase or as rivals' distance to projects increase (both presumed to increase rivals' costs) bidders bid less aggressively. In common value settings, the role of asymmetries in bidder information has been examined with the focus on how asymmetries may affect the "winner's curse" (Hendricks and Porter, 1988). The nature of information release considered in this paper is quite different than that examined in prior work. Here, I examine how information released by the seller regarding their estimate of the cost of performing a project and the release of information about how bidders bid for a project affect subsequent bidding for the project when it is re-auctioned.

The data used for this study comes from the Oklahoma Department of Transportation (ODOT) procurement auctions. These auctions are held monthly in the form of first-price sealed-bid auctions and the data are available from January 1997 through March 2002. For each project, the data set includes information about the date at which the auction was held, a list of all firms that purchased the plans, a list of bids received, the states engineering cost estimate, and a detailed description of the project. I use a sub sample of the entire data set that includes all auctions, which were not awarded the first time around and were re-auctioned off in a later round. This allows to compare the bidding in the first round (where the information available to bidders is more limited) to the bidding behavior in the second round where bidders know more about their potential rivals' valuation of the project and about how the state values the project. In addition, the data allow us to make one additional comparison. In the middle of the data set, the state changed its policy related to the release of the engineering cost estimate. Beginning in early 2000, the state began releasing the engineering cost estimate to the general contractors association before the bid letting. Thus, I can also compare the bidding behavior of firms in first round auctions before and after the change in this policy, as well.

The chapter is organized as follows. Section 4.2 describes the relevant theoretical and empirical literature. Section 4.3 discusses the data set and presents summary statistics of the auctions under study. Section 4.4 presents the results of the empirical analysis. Section 4.5 concludes.

4.2. Literature Review

4.2.1. Empirical work on sequential auctions

Hendricks and Porter (1988) analyze data from OCS oil lease auctions from 1959 to 1969. In these auctions, informational asymmetries exist between bidders who are already engaged in drilling activities on neighboring tracts and the non-neighboring firms who obtain their information through their own surveys. They find that the bidding strategies of these two bidder groups are consistent with the predictions of the Bayesian – Nash equilibrium model of bidding in first-price sealed-bid auctions. Neighboring firms won more than one half of the drainage tracts with a positive net profit. The average net profit for the non-neighboring firms was approximately zero.

Kagel, Harstad and Levin (1987) find experimental evidence in support of a theoretical model developed by Milgrom and Weber (1982) in first-price sealed-bid auctions with affiliated values. The model predicts that revealing public information raises expected revenues. Kagel, Harstad and Levin (1987) adopt a dual market procedure by allowing bidders to bid for the same object twice. After observing the bids from an initial auction and before re-auctioning off the same items, they reveal either partial or full information that help bidders to guess the true value of the object. Then bidders are asked to bid again for the same objects. Bids are revealed under both market designs separately at the conclusion of both auction periods. They find that the release of public information brings about an increase in revenue which is consistent with the predictions of a risk averse Nash equilibrium bidding model.

De Silva, Dunne and Kosmopoulou (2002) study procurement auctions in the state of Oklahoma. These auctions are held in two sessions every month, one session is held in the morning and another in the afternoon. Bidders in the afternoon auctions can take into account the information released during the morning session. In particular, this study focuses on the bidding behavior in the afternoon sessions of winners and losers of the auctions that took place in the morning. In this framework, bidders can bid for more than one project. This allows winners and losers from the morning session to participate again in the afternoon session. Therefore, the asymmetry among bidders in the afternoon session is due to the differences in the opportunity cost of completing a contract between winners and losers. They find that firms that won in the morning bid more aggressively in the afternoon. Also, firms that lost in the morning bid aggressively relative to their morning bids.

In a related study following the theoretical predictions from Maskin and Riley (2000), De Silva, Dunne and Kosmopoulou (2003) examine the bidder asymmetry that could be attributed to experience in construction contracts using the data from ODOT. Bidder asymmetry could arise due to inexperience in these projects and lack of confidence about the cost estimates. This is a different flavor of information compared to seller information addressed by other studies. They identify two types of bidder groups, incumbents and entrants based on their experience. They find that entrants' cost dispersion is larger than incumbents and that entrants bid more aggressively than incumbents and leave more money on the table.

4.2.2. Theoretical evidence of impact of information in sequential auctions

Milgrom and Weber (1982) considered auctions with affiliated values and show that, in first price auctions, a policy of revealing the seller's information cannot lower, and may raise the expected price.

Thomas (1996) develops a model to analyze the effect of the public release of seller information on bidding behavior. He focuses on the amount of information shared between the auctioneer (such as a distributor) and the bidders (such as the manufacturers). In this framework, bidders are demanding multiple objects and their values are correlated. He compares the policy of fully revealing information (the winning bid and all other bids), against a policy where bidders are allowed to see only the identity of the winner ex post. He finds that when more information is released it raises expected profits to the seller and increases competition among the bidders which is consistent with the existing theory.

Goeree and Offerman (1999, 2003) develop a model where the objects that are auctioned off have both private and common value characteristics. In this case, the public disclosure of the auctioneer's information increases expected revenue. They also show that more uncertainty about the common value reflects higher levels of inefficiency. They find that the profit of the winning bidder is higher with greater uncertainty since bidders want to avoid the winner's curse and bid more cautiously. On the other hand, with less uncertainty bidding is more aggressive.

4.3. Data

4.3.1. Repeating Auctions

This study utilizes data from ODOT highway procurement auctions. These auctions are carried out monthly and are first-price sealed-bid auctions where the lowest bidder is awarded the contract. The study uses data from January 1997 to March 2002 and focuses on a specific set of construction projects. The specific construction projects under study are projects that fail to be auctioned off in an initial auction and are subsequently placed up for auction in a later bid letting. There are several reasons, as to why these auctions have not been awarded in the first round. First, ODOT has a reserve rule that allows it to reject the lowest bid if it exceeds ODOT's engineering estimate by more than seven percent. Second, in some auctions there are no bids submitted by any of the contractors. In this case, the state often resubmits the project in a later auction. The third reason could be due to submission of unbalanced bids by contractors. In this case, while the lowest bid may meet reserve requirements, the composition of the bids on the underlying project components may not have met state requirements.[33] These are the major reasons for not awarding contracts.

Overall, the data include 146 construction projects that were not successfully auctioned off in the first round and were subsequently re-auctioned off. These initial auctions are identified as R_1 auctions. The corresponding second round auctions are identified as R_2 auctions. Of the 146 R_1 auctions, 119 were awarded in the second round while 10 construction projects were auctioned off for a third time and these are denoted R_3. From these R_3 auctions, 9 auctions have been awarded and one project was auctioned off in the fourth round R_4. Of the initial 146 projects offered for re-bidding, 16 were not awarded during the time period of analysis. Table 4.1 summarizes these auction statistics for each bidding round. The table reports the number of auctions, the average number of plan holders per auction,[34] the average number of bidders per auction, number of auctions with bidders and the number of awarded auctions. In addition, the table provides some

[33] If the cost components of the bid significantly deviate from the cost components of ODOT's engineering estimate the bid is known as an unbalanced bid. Unbalanced bids may be rejected even when a bid is lower than the engineering estimate.

[34] Firms that are willing to bid in a given project can obtain a project plan from ODOT which contains a detailed description about the project. All firms that bid in these auctions are required to purchase the project plan from ODOT. However all plan holders are not necessarily bidders.

population statistics for comparison purposes. Overall, the data show that in the initial round the average number of bidders per auction is quite low both compared to the population total and to the average number of bidders in later rounds.

Table 4.2 presents data on the relative bids in the initial auctions, “repeated” auctions and for non-repeated auctions over the time period of analysis. The relative bid is measured as the bid divided by the engineering cost estimate and it allows for the comparison of bids across auctions since it normalizes each auction by an auction specific estimate of cost. The first two rows present the average relative bid and the average relative low bid respectively for the sample of “repeated” auctions. The next two rows present the same information but for all other highway auctions let during the same period. The data show in the first round of the repeating auctions (R_1) on average bids are 32 percent higher than the engineering estimate. In the second and third rounds they are 19 percent above the engineering estimate.

4.3.2. Classification of Auction Information

The sample design allows for the classification of auctions based on differences in the information available to auction participants. There are two main distinctions made with regards to information release. The first main distinction is made as to whether an auction is a first round or a subsequent round auction (R_2, R_3, or R_4). Participants in the subsequent rounds can observe what happened in the initial auction. This information includes the engineering cost estimate of the state, the number of plan holders and bidders, the list of submitted bids and the rejected low bid (if bids were submitted). The second main distinction deals with when the auction takes place. ODOT changed its policy regarding the release of the state’s engineering cost estimate early in 2000 resulting in the engineering estimate being made available to potential bidders before the bid letting. Thus, after January 2000, bidders have access to the state's engineering cost estimate prior to the bid letting. However, note that after January 2000, initial round bidders still do not have all the information that later round bidders have. Bidders in subsequent rounds see the rejected bids and the participation decisions of potential rivals from the first round. Using these two pieces of information I classify auctions into four broad information groups – (1) first round auctions where the state engineering estimates are not known, (2) first round auctions with knowledge of the state engineering estimate, (3) subsequent round auctions with knowledge of the prior round bidding behavior and the state's estimate of the project cost in the prior round; and (4) subsequent round auctions with knowledge of the state's current engineering estimate and of prior round bidding action.

In addition to these broad classifications of available information, measures are constructed based on the specific outcome of the prior round auction. It is likely that bidders in subsequent rounds will be influenced by participation patterns and the aggressiveness of bidding in the first round. To that end, I distinguish between three outcomes depending upon the bidding patterns in the first round. First, if the previous round lowest bidder bid lower than seven percent of the engineering estimate (the stated reserve price), I group these auctions together (denoted as I_1). These are auctions that were rejected for a reason other than a failure to receive a bid that met the reserve bid. This is most likely due to the fact that the low bid was "unbalanced". Second, if the previous round lowest bid was above the reserve bid, then these are auctions likely rejected because the low bid did not meet the reserve price (denoted as I_2). Finally, if there were no bids submitted in the previous round, I denote these auctions as I_3.

The final measurement issue I address concerns the information content of the engineering cost estimate released in the first round. When the state re-auctions off a project, it often changes the engineering cost estimate (45% of the time). It may raise, keep the same, or even lower the cost estimate in the subsequent rounds. The prior round engineering estimate is thus a noisy signal of the current engineering estimate for all auctions that occur prior to January 2000 (before the state began releasing the current estimate). One way, bidders may identify whether the state is likely to change the estimate is to look at whether there are changes in the project descriptions or changes in work/composition lists that accompany each project. In general, these changes to the projects are not major changes that would mutate the project into an effectively new project. I make sure the projects are in the same location and are for similar kinds of work. To control for these changes in the analysis below, I simply classify all projects depending upon whether there are changes to the project (denoted as S_2) or not (denoted as S_1) – a zero-one variable.

The classification scheme allows for a rich set of interactions based on the information available to bidders. For initial round auctions the classification scheme is simple, auctions that occur before January 2000 and auctions that occur after January 2000. Hence, there are only two types of initial round auctions. For the subsequent auctions the interactions are more complex and are illustrated in Figure 4.1. Figure 4.1 groups the data into two time periods, three groups that describe the bidding in the previous round, and two groups that describe whether the re-auctioned off project is the same in description or differs somewhat. This classification scheme defines twelve (2x3x2) possible auction information states based on prior auction information and changes in the information released by the state.

4.3.3. Regression Variables

Besides the auction information variables and the relative bid data that have been described above, I also construct a number of control variables that will be used in the estimation procedure that follows. The variables can be broadly classified into three groups of control variables -- project characteristics, bidder characteristics and rival characteristics.

The project characteristics include measures of project size, project type, whether the project is under Federal or State financing, and the number of plan holders. To measure the overall size of the project, I use the state's engineering estimate. I include a dummy variable to indicate projects whose value exceeds $1 million. I include this variable because larger projects are different in complexity and work requirements (e.g., large projects are more likely to be subject to disadvantaged business programs requirements). Also, I distinguish between projects that have federal funding vs. state only funding. These projects will be subject to federal guidelines.[35] If a project has federal funding, this dummy variable (FEDST) is set equal to one. As in the previous literature, I control for the number of bidders. Since, the actual number of participants may be endogenous (Hendricks, Pinkse and Porter, 2001), I proxy the potential competition in the auction by the number of plan holders. In Oklahoma, only firms

[35] For example the main contractor is responsible to avoid any discrimination among the sub contractors in terms of residence requirements for labor, in terms of segregated facilities (separate dinning areas, rest rooms etc.) and alike. Main contractor must provide equal opportunity to disadvantaged business groups to compete and undertake sub contracts.

buying plans may bid in an auction and the plan holder list is made available to bidders prior to the auction. Thus, the number of plan holders, acts as upper bound on the actual number of bidders in an auction. Finally, I control broadly for the type of project being auctioned. Projects are classified into seven different categories -- including asphalt paving, clearance and bank protection, bridgework, grading and draining, concrete work, signals and lighting and miscellaneous work.

To control for differences in bidder efficiency, I employ two variables following De Silva, Dunne and Kosmopoulou (2002, 2003) that measure bidder performance.[36] First, I look at a firm's success in previous auctions. For each firm, a winning to bid ratio is constructed that measures the winning percentage of the firm in past auctions (WINRATIO). This variable should proxy well for differences in firm efficiencies. Second, a variable that measures the backlog (BACKLOG) of projects a firm under contract is constructed. Previous papers by Porter and Zona (1993), Jofre-Bonet and Pesendorfer (2000), and Bajari and Ye (2002) have used the backlog variable to proxy for capacity constraints facing bidders. It is argued that as the backlog rises a firm will bid less aggressively. A variable is also constructed to control for the "toughness" of rivals that a firm faces in an auction. For each bidder, the set of potential rivals is provided by the plan holder list for an auction. For each rival on the plan holder list, the ratio of rival's past winning to plans held is constructed. This variable summarizes the likelihood that a rival bids and wins in an auction where "tough" rivals would have high winning percentages in previous auctions. I then average this variable over all rivals in an auction to create a rival toughness variable (RIVAL).

[36] Project type variables and backlog variable are the same variables that were used in De Silva Dunne and Kosmopoulou (2002, 2003) and I thank the authors for allowing me to use those variables in the current study.

The final variable I construct attempts to control for differences in the total amount of project value auctioned off in a month. Over the entire time period I examined, the dollar value of contracts awarded fluctuated. In particular, the dollar value of projects awarded falls as the Oklahoma economy and the state budget worsened in 2001 and 2002. Hence, I included a variable that measures the real dollar value of all projects let in each month. This should control for differences in bidding that may be due to differences in the number and value of projects that occur over time.

4.4. Estimation and Results

In this section, I present the results of the empirical model that examines the relationship between bidding behavior and information asymmetries across auctions. My goal is to see how differences in the information available to bidders affect the mean and variance of bids. I start by specifying a simple reduced-form bidding model.[37] The dependent variable in all the regressions is the relative bid and it is modeled as a function of auction specific information variables, project characteristics, bidder characteristics, rival characteristics and availability of projects. The regression equation is given as

$$Rbid_i = \beta_0 + \beta_1 R_{1i} T_{2i} + \sum_{h=1}^{2}\sum_{j=1}^{3}\sum_{k=1}^{2}\beta_{hjk} T_{hi} I_{ji} S_{ki} + \sum_{m=14}^{19}\beta_m PROJECT_{mi} + \beta_{20} BIGEST_i$$
$$+ \beta_{21} FEDST_i + \beta_{22} RIVAL_i + \beta_{23} WINRATIO_i + \beta_{24} LBACKLOG_i + \beta_{25} LNPH_i +$$
$$\beta_{26} LRALLET_i + \varepsilon_i$$

The error structure of the model takes the following form:

$\varepsilon_i \sim N(0, \sigma_i^2)$

where σ_i is modeled as

[37] There are 13 auction specific information variables in the model according to above classification. Out of these, three variables ($RT_1I_1S_2$, $RT_1I_3S_2$, and $RT_2I_3S_2$) did not have any observations and was not included in the regression. Therefore total number of coefficients estimated in the mean equation is 23 (Table 4.5).

$$\sigma_i = \gamma_0 + \gamma_1 R_{1i} T_{2i} + \sum_{h=1}^{2} \sum_{j=1}^{3} \sum_{k=1}^{2} \gamma_{hjk} T_{hi} I_{ji} S_{ki} \ .$$

The first three terms in the relative bid (Rbid) equation characterize the information differences across auctions. The omitted group, represented by the intercept, is all first round auctions where the state engineering estimate is not known. The second term represents first round auctions where the state engineering estimate is known. The third term represents 12 dummy variables that measure differences in information available to second round bidders. These correspond to classification system described in Figure 4.1. The remaining variables describe auction characteristics (project dummies, bigest, fedst, lnph), bidder characteristics (winratio, lbacklog), rival characteristics (rival) and a control for the amount of projects auctioned off in a month (lrallet). Summary statistics of the variables used in the estimation are presented in Table 4.3.

σ_i is also allowed to vary with the variables the measure differences in information release across auctions. The motivation for this modeling of the standard deviation equation (sigma) comes from the theory that suggests that the release of information should reduce the uncertainty about the value of the object (Goeree and Offerman, 2003) and hence may impact the variance of bids. The model was estimated using the maximum likelihood estimation procedures.

Before I present the individual coefficient estimates, I test a number of restrictions regarding the information variables to see if the interaction terms can be simplified. These are presented in Table 4.4. The first row presents the results of a likelihood ratio test of whether the same and different classification scheme matters. The test rejects the null hypothesis that there is no difference between the two groups of auctions and the restrictions are imposed on both the mean and variance components of the model. The next row examines whether there is a difference in bidding between the periods when the information regarding the state engineering cost estimate available to bidders and when it is not. The test rejects the null hypothesis that there is no difference between bidding between the two time periods. The last row of the table reports the test of whether bidding in later round auctions depends on the level of the observed bidding in the previous auction. Again, the likelihood ratio test rejects the null hypothesis that there is no difference in bidding among auctions with different levels of rejected previous round low bids. The conclusion here is that the interaction terms in the regression equation cannot be estimated in a more parsimonious fashion.

The regression results are presented in Table 4.5. The top half of the table reports the coefficients from the regression of the mean of the relative bid and the bottom half reports the coefficients from the standard deviation equation. The first group of coefficients represents the information variables. Note that while there are 12 possible interactions only nine occur in the data. First, the coefficients on the information are all negative indicating more aggressive bidding in subsequent rounds as compared to the first round auctions. However, note that the observation of simply lower bids in the subsequent rounds is not a test of the theory -- as one would expect this pattern because of the states application of the reserve rule. The bid levels and variance must differ systematically by the information available in the subsequent auctions. Second, it is also not surprising that the most aggressive bidding occurs in auctions that had relatively aggressive bidding in the first round (I_1 auctions). Though, it appears that there is little difference in the aggressiveness of bidding between I_1 auctions and I_3 auctions. Third, there does not appear to be a strong pattern in the coefficients due to whether the project description changed (S_1 versus S_2 auctions). However, recall the likelihood ratio test indicates that there is a statistical difference between these auction types. Examining the effect of information on the variance, no strong patterns emerge across different groups of information variables. In fact, I generally see a rise in the variance of bids after the release of the engineering cost estimate. This pattern does not support the notion that increases in this type of information reduce the variance of bids. In general, the results do not indicate a strong role for these types of information differences as affecting auction outcomes.

Of the remaining variables in the model, only the project variables and the variable that measures project size are statistically significant at the 5% level. With respect to the project size variable, larger projects have more aggressive bidding than smaller projects.

4.5. Conclusion

This study investigates bidding behavior in auctions where there is a substantial release of information prior to the auction letting. In general, I find little systematic correlation between the release of information and the aggressiveness of bidding or the variance of bids. An overall view of what is happening in these auctions can be seen in Figure 4.2. Figure 4.2 presents the kernel density for the distribution of relative bids for three samples of firms – R_1 Auctions, R_{234} Auctions (repeated auctions), and all non-repeating auctions. The later group of auctions has not been used in the regression analysis presented above. Comparing these groups of auctions, this study shows that there is a substantial difference in the mean of R_1 auctions (the rightmost distribution) and it appears that there is greater dispersion, reflected especially in the shape of upper tail. The R_{234} distribution is shifted left (reflecting the lower bids) and the spread appears to be reduced. This pattern generally agrees with the priors about information release. However, the empirical work was unable to make the link between information release and the reduction in variance and the reduction in average bids. Finally, note that while the mean of the R_{234} auction distribution is lower than the R_1 auction it remains above the mean of the auction that are successfully auctioned off in the first round. This suggests that there remains a systematic difference between these auctions (R_{234}) and auctions successfully auctioned off in the first round.

Figure 4.1: Auction Information Classification

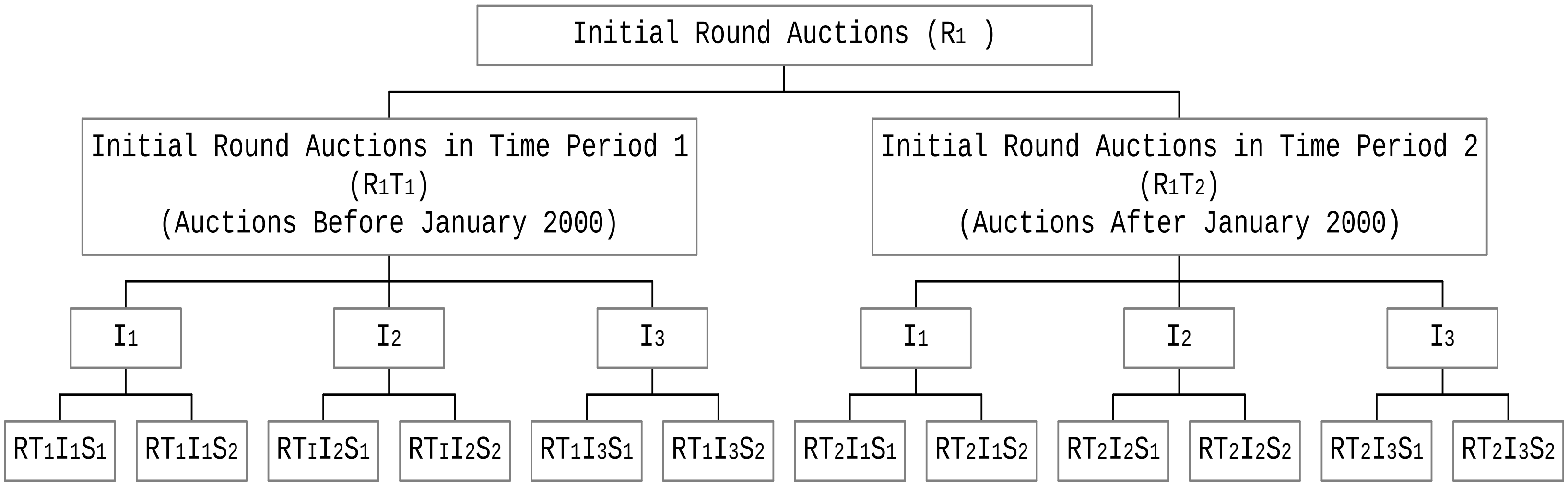


Figure 4.2: Kernel Density of Relative Bid Distribution of Auctions not Repeating (Left most curve), Initial Round Auctions (R_1: Right most curve), and Subsequent Auctions (R_{234}: Middle curve).

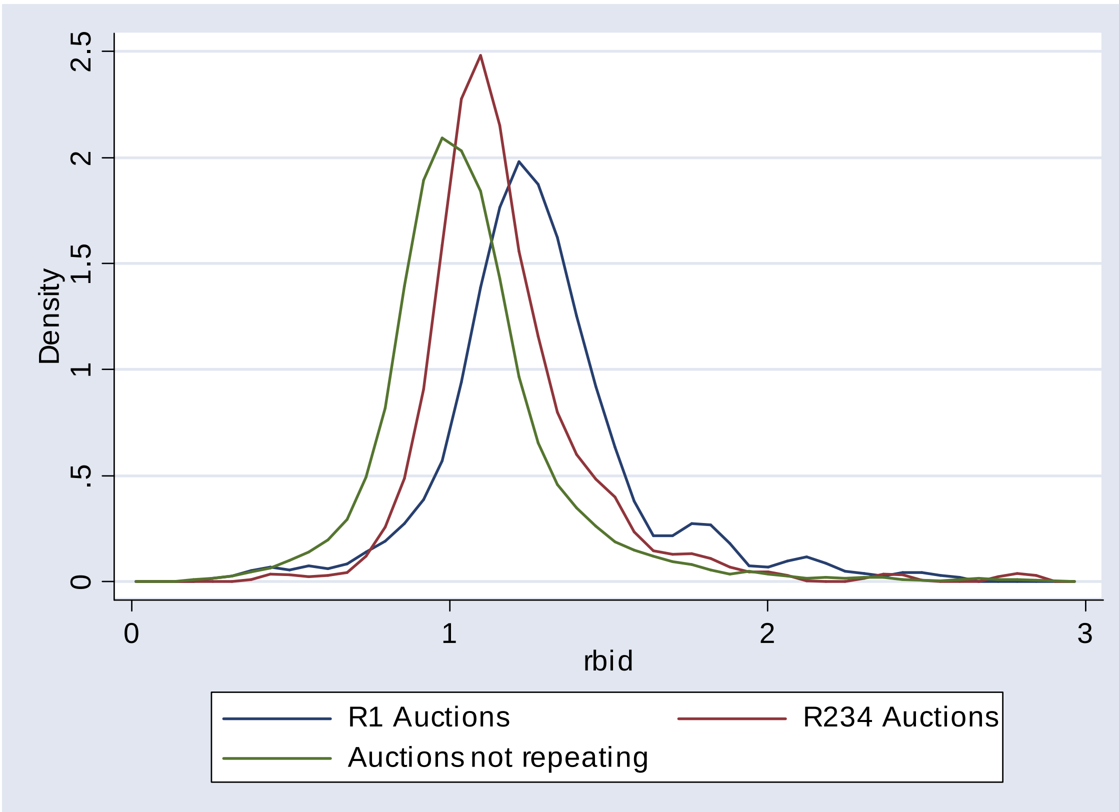


Table 4.1**:** Summary Statistics of Auctions

	Full Sample	*Repeating Auctions*			
		R_1	R_2	R_3	R_4
Number of Auctions	2338	146	146	11	1
Number of Plan Holders	13132	708	757	58	3
Average Number of Plan Holders per Auction	5.617 (3.248)	4.849 (2.419)	5.185 (2.546)	5.273 (1.954)	3.000 (.)
Number of Bids	7246	232	401	37	2
Average Number of Bidders per Auction	3.102 (1.862)	1.596 (1.407)	2.740 (1.563)	3.364 (0.924)	2 (.)
Number of Auctions with Bids	2174	108	139	11	1
Number of Auctions Awarded	1922	0	119	10	1
Number of Auctions Not Awarded	419	146	27	1	0
Number of Auctions with a Change in the Engineering Estimate					
No change in the estimate			79	5	1
Decrease in the estimate			17	1	0
Increase in the estimate			48	5	0
Total			144[38]	11	1

Note: Standard deviations are in the parenthesis.

[38] The total of these auctions is 144. Of the total 146 R_2 auctions engineering estimate for two previous round auctions (R_1 auctions) were not available. Therefore the change in the estimate is unknown.

Table 4.2: Mean Relative Bid and Mean of the Low Relative Bid for Repeated Auctions and Auctions that are not repeated

	Auctions Not Repeated	R_1	R_2	R_3	R_4
Mean Relative Bid	1.091	1.321	1.188	1.193	1.095
	(0.432)	(0.342)	(0.314)	(0.202)	(0.020)
Mean of the Low Relative Bid	0.948	1.261	1.045	1.062	1.080
	(0.234)	(0.380)	(0.169)	(0.203)	(.)

Note: Standard deviations are in the parenthesis.

Table 4.3: Means of the Regression Variables

Variable	Mean (Std.)
Relative Bid	1.217 (0.289)
R_1T_1	0.230 (0.421)
R_1T_2	0.128 (0.334)
$RT_1I_1S_1$	0.028 (0.165)
$RT_1I_2S_1$	0.092 (0.289)
$RT_1I_2S_2$	0.072 (0.259)
$RT_1I_3S_1$	0.090 (0.286)
$RT_2I_1S_1$	0.060 (0.238)
$RT_2I_1S_2$	0.022 (0.147)
$RT_2I_2S_1$	0.148 (0.355)
$RT_2I_2S_2$	0.094 (0.292)
$RT_1I_1S_1$	0.036 (0.186)
Rivals Previous Winning to Plan Holder Ratio (RIVAL)	0.140 (0.057)
Large Projects (BIGEST)	0.216 (0.413)
Federal / State Projects (FEDST)	0.643 (0.480)
Firm's Previous Wining to Bid Ratio (WINRATIO)	0.259 (0.147)
Log of the Firm's Backlog (LBACKLOG)	10.122 (6.537)
Log Number of Plan Holders in an Auction (LNPH)	1.521 (0.516)
Log of the Real Value of Monthly Engineering Estimate totals for the auctions (LRALLET)	17.456 (0.644)

Table 4.4: Likelihood Ratio Test Results

The Null Hypothesis	Likelihood Ratio (χ^2)
There is no difference between the auctions that underwent a change in work/composition and those did not (S_1 and S_2)	30.92*
There is no difference between the auctions that were held before January 2000 and after January 2000 (T_1 and T_2).	37.67*
There is no difference between the auctions based upon previous round outcomes (I_1, I_2 and I_3).	31.47*

* Denotes 5% significance.

Table 4.5: Relative Bid Regression

Independent Variable		
Constant	1.852*	(0.376)
R_1T_2	-0.008	(0.054)
$RT_1I_1S_1$	-0.225*	(0.080)
$RT_1I_2S_1$	-0.140*	(0.054)
$RT_1I_2S_2$	-0.168*	(0.035)
$RT_1I_3S_1$	-0.106*	(0.041)
$RT_2I_1S_1$	-0.210*	(0.051)
$RT_2I_1S_2$	-0.092	(0.056)
$RT_2I_2S_1$	-0.018	(0.044)
$RT_2I_2S_2$	-0.130*	(0.043)
$RT_2I_3S_1$	-0.179*	(0.048)
PROJECT-1	0.026	(0.056)
PROJECT-2	0.085	(0.110)
PROJECT-3	-0.056	(0.043)
PROJECT-4	-0.049	(0.051)
PROJECT-5	0.144	(0.096)
PROJECT-6	0.019	(0.072)
Large Projects Dummy(BIGEST)	-0.095*	(0.037)
Federal / State Projects (FEDST)	0.029	(0.028)
Rivals Previous Winning to Plan Holder Ratio (RIVAL)	-0.007	(0.214)
Firm's Previous Winning to Bid Ratio (WINRATIO)	-0.023	(0.075)
Log Backlog of the Firm (LBACKLOG)	0.0005	(0.002)
Log Number of Plan holders (LNPH)	0.043	(0.030)
Log Real Value of Monthly Project Totals (LRALLET)	-0.034**	(0.020)
Sigma		
Constant	0.234*	(0.016)
R_1T_2	0.152*	(0.038)
$RT_1I_1S_1$	0.046	(0.056)
$RT_1I_2S_1$	0.084*	(0.038)
$RT_1I_2S_2$	-0.087*	(0.025)
$RT_1I_3S_1$	-0.016	(0.029)
$RT_2I_1S_1$	0.004	(0.036)
$RT_2I_1S_2$	-0.108*	(0.037)
$RT_2I_2S_1$	0.075*	(0.032)
$RT_2I_2S_2$	0.005	(0.030)
$RT_2I_3S_1$	-0.068*	(0.030)
Number of Observations	500	
Wald χ^2	82.25	
Log Likelihood	-21.336	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance and ** denotes 10% significance. Omitted group is R_1T_1.

4.6. Appendix: Table 4.1: Auction Information Variables

Variable Name	Description
R_1T_1	Initial round auctions (R_1 auctions) that were held before January 2000. These auctions are not successfully awarded and bidders in these auctions do not observe the current engineering estimate.
R_1T_2	Initial round auctions (R_1 auctions) that were held after January 2000. These auctions are not successfully awarded and bidders in these auctions observe the current engineering estimate.
$RT_1I_1S_1$	Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000, which had a lowest bid below 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auctions) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and do not observe the current estimate.
$RT_1I_1S_2$	Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000, which had a lowest bid below 7% of the engineering estimate in the initial round. The current auction (R_2, R_3, or R_4 auction) different from the initial round auction in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate. They do not observe the current estimate.
$RT_1I_2S_1$	Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000, which had a lowest bid above 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auction) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and do not observe the current estimate.
$RT_1I_2S_2$	Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000, which had a lowest bid above 7% of the engineering estimate in the initial round. The current auction (R_2, R_3, or R_4 auction) different from the initial round auction in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate. They do not observe the current estimate.
$RT_1I_3S_1$	Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000. No bids have been submitted in the corresponding initial round auction. Also the current auction (R_2, R_3, or R_4 auction) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions do not observe the current engineering estimate.

$RT_1I_3S_2$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held before January 2000. No bids have been submitted in the corresponding initial round auction. Also the current auction (R_2, R_3, or R_4 auction) has undergone changes in terms of materials used or work composition. The bidders in these auctions do not observe the current engineering estimate.

$RT_2I_1S_1$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000, which had a lowest bid below 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auctions) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and observe the current estimate.

$RT_2I_1S_2$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000, which had a lowest bid below 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auctions) has undergone changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and observe the current estimate.

$RT_2I_2S_1$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000, which had a lowest bid above 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auctions) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and observe the current estimate.

$RT_2I_2S_2$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000, which had a lowest bid above 7% of the engineering estimate in the initial round. Also the current auction (R_2, R_3, or R_4 auctions) has undergone changes in terms of materials used or work composition. The bidders in these auctions observe the previous round bids and engineering estimate and observe the current estimate.

$RT_2I_3S_1$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000. No bids have been submitted in the corresponding initial round auction. Also the current auction (R_2, R_3, or R_4 auction) has not undergone any changes in terms of materials used or work composition. The bidders in these auctions observe the current engineering estimate.

$RT_2I_3S_2$ Subsequent auctions (R_2, R_3, or R_4 auctions) that were held after January 2000. No bids have been submitted in the corresponding initial round auction. Also the current auction (R_2, R_3, or R_4 auction) has undergone changes in terms of materials used or work composition. The bidders in these auctions observe the current engineering estimate.

Chapter 5

The Impact of a Change in the Auction Format on Bidding Behavior

5.1. Introduction

This chapter investigates the impact of change in the format of the auctions held by the Oklahoma Department of Transportation (ODOT) on the bidding behavior and the seller revenue. Every month ODOT calls sealed-bids from prospective bidders to auction off road construction contracts. Until March of 2002, ODOT auctioned off these contracts in two separate sessions on a single day. One session was held in the morning and the other in the afternoon. A number of projects were auctioned off simultaneously within each session. At the end of the morning session, ODOT revealed all the information that was generated in the morning auctions to the bidders. That included the names of the winning bidders, winning bids and the bids submitted by other firms. Therefore, for those auctions offered in a sequence, interested bidders could take into account available information on the bidding behavior of others when submitting their bids in the afternoon session. After March 2002, ODOT started auctioning these contracts in a single session holding simultaneous first-price auctions. The auction literature suggests that such a change in the auction format can have a significant impact on the seller's revenue. Using ODOT auction data, this study investigates the impact of this format change on the bidding behavior and the State's revenues.

The attempts to compare directly the simultaneous with the sequential auction format have been very limited in the theoretical literature. The recent work was essentially motivated by the success of the Federal Communication Commission (FCC) in selling its PCS[39] licenses in a multi-round auction format in the early 1990's. The FCC's primary goal was to promote efficiency. In that effort, a number of auction theorists designed a simultaneous multiple round auction format (McMillan, 1994; Krishna and Rosenthal, 1996; Moreton and Spiller, 1998). One of the key reasons for this design of auction is to allow bidders to realize synergies that arise due to the proximity in the location of those licenses. Krishna and Rosenthal (1996) point out that there was no sufficient theoretical literature to support the FCC’s decision at the time. Their theoretical work came later to address issues of revenue in the presence of potential synergies. Krishna and Rosenthal (1996) compare the seller revenue across two formats, the simultaneous and the sequential auction formats, and find that the revenue is higher in simultaneous auctions when the bidders have the potential to realize higher level of synergies. In a related study, Rosenthal and Wang (1996) observe higher seller revenue when bidders have potentially higher synergies. Hausch (1986) on the other hand compares the seller revenue between the two auction formats without considering synergies. He finds that, in common value auctions, the revenue is higher in sequential auctions due to existence of the winner's curse.

There are no empirical studies that compare directly the seller revenue between sequential and simultaneous auctions. The literature mainly focuses on the effect of synergies on the seller's revenues within a single auction format. Ausubel et al (1997), Moreton and Spiller (1998), show that generally, bidders holding adjacent licenses in FCC spectrum auctions are willing to bid more aggressively. Also De Silva (2005)

[39] Personnel Communication Systems (PCS) include portable phones, paging devices etc. See Moreton and Spiller (1998) for details.

observes aggressive bidding behavior due to the presence of geographic synergies in road construction auctions in Oklahoma. His analysis is restricted in the sequential auction format.

The goal of this study is to examine the relative performance of the sequential and simultaneous auction formats in the road construction auctions held in Oklahoma. The empirical analysis of this study captures the potential for some synergies and compares the revenue performance between the two auction formats. This study finds a decrease in overall bids and in winning bids after the policy change occurred. However results do not support theories developed by Krishna and Rosenthal (1996).

In the next section I describe the relevant literature to this study. Section 5.3 and 5.4 describe the data and empirical analysis respectively. The results are presented in section 5.5 and section 5.6 concludes.

5.2 Literature Review

5.2.1. Theoretical Literature

Krishna and Rosenthal (1996) analyze simultaneous second-price sealed-bid auction model in an independent private value setting. Multiple objects are auctioned off to two types of bidders called local and global bidders. Local bidders have privately known valuation for the object and enjoy no synergies (no increasing returns). Global bidders observe a signal about the value of the object and enjoy synergies. That is, if a global bidder wins two objects, the total value of the objects together is more than the sum of the individual values.[40] Krishna and Rosenthal (1996) compare revenues between simultaneous and sequential auction formats. The comparison is done with varying

[40] The model assumes that the synergy is always a positive synergy and it is public knowledge.

levels of synergy and with varying number of global bidders (one and two global bidders). Their results suggest that when global bidders enjoy higher level of synergies, the simultaneous auction format generates higher seller revenue than the sequential auction format. The opposite is true with a lower level of synergies, i.e. the sequential auction format generates higher seller revenue with lower level of synergies. Using second-price, simultaneous ascending bid auction format Albano, Germano and Lovo (2001) compare the revenue performance of simultaneous ascending bid auction[41] to three other auction formats. They are sequential auctions, VCG auctions[42] and simultaneous one-shot auctions. They use a second-price auction format in a similar modeling framework to Krishna and Rosenthal (1996). They find that the sequential auction format performs poorly relative to the two simultaneous auction formats. Aggressive bidding behavior in simultaneous auctions is due to exploitation of synergies by global bidders.

Rosenthal and Wang (1996) analyze simultaneous auctions when the objects have common values. They consider a first-price sealed-bid auction format. Like Krishna and Rosenthal (1996) they distinguish between global and local bidders. They observe aggressive bidding behavior among global bidders with a higher level of synergies.

Hausch (1986) develops a first-price sealed-bid auction model to compare seller revenue between sequential and simultaneous auction formats. He considers a two-object auction model with common values. Bidders receive a high or a low signal about the value of the object. He argues that in sequential sales if a high signal bidder mimics the

[41] Bidders can simultaneously submit bids on multiple objects. Then the auctioneer starts raising the price. The authors point out that the format is similar to the Japanese auction for multiple objects.

[42] In VCG auction mechanisms (Vickrey-Clark-Groves mechanisms) a bidder's optimal strategy is to always submit bids according to his/her true value of the object regardless of the information received from others.

low signal bidder there will be an overall reduction in the winner's curse. Therefore on average higher seller revenues can be expected in sequential auctions relative to the simultaneous auctions when bidders do not reveal their actual values. However, if bidders signal their true values when bidding, he finds that the simultaneous auction format performs better in revenue than the sequential format. Notice that, this study draws its conclusions without considering synergies like in other previously discussed studies. The higher revenue from sequential auctions is attributed to the presence of winner's curse.

Benoit and Krishna (2001) analyze a multiple object, simultaneous English auction with budget constrained bidders. Thus they incorporate strategic behavior which is different from previous studies. The objects have common values but not identical as in other common value models. The budget constraints faced by the bidders and the values of the objects are publicly known. Benoit and Krishna (2001) consider both positive synergies (complementary goods) and negative synergies (substitute goods) in the model. This study compares the revenue obtained from simultaneous and *optimal sequential auction*[43] formats. The study shows that the *optimal sequential auction* generates higher revenue than the simultaneous format under the following two conditions.[44] (a) When the value of the two objects is significantly different, and (b) when there are large positive synergies (in the case of complementary goods) to the bidders. In ODOT auctions projects are not systematically ordered in a particular way. Even though the sequential auction format adopted by ODOT does not match with the

[43] They show that, the optimal sequential auction, of two objects with different values requires that the more valuable object is sold first and the less valuable second.
[44] Goeree, Offerman and Schram (2003) find evidence for higher seller revenue when the objects are sold in a decreasing order of quality in a sequential first price auctions compared to the first price simultaneous auctions (when the objects are heterogeneous and there is unitary demand for the objects.).

optimal sequential auction format used by Benoit and Krishna (2001), theoretical evidence like this reflects the complex nature of the revenue comparison between the two auction formats.

Goeree, Plott and Wooders (2003), compare the revenues generated by "Ascending right to choose auctions" (ARTC) with the standard simultaneous ascending (SA) auctions. ARTC auctions are commonly used in the sale of real estate auctions which is in a sequential format in this study. In the ARTC format after the winner is selected he has the right to choose the preferred item.[45] Both ARTC and SA auctions are conducted as English auctions in this study and the objects have private values. This study shows that when the bidders are risk averse, selling items via the ARTC auction format raises more revenue than simultaneous auction format. With risk neural bidders both auction formats raise the same revenue.

Feng and Chatterjee (2003) also compare the performance of sequential and simultaneous auctions. They consider a second-price sealed-bid auction in the independent private value framework. Bidders have unit demand and the objects are identical. They compare the revenues between a one period simultaneous format and a two period sequential format. They find that the revenue from the two period auction format depends largely on market competition. They define the intensity of market competition in the auction as the number of objects for sale divided by the number of bidders. They show that, if the competition is higher (a lower number of objects for a given number of bidders), simultaneous auctions generate more revenues than sequential auctions. When the market is less competitive the sequential format performs better.

[45] Then the remaining bidders bid on the next item.

5.2.2. Empirical Literature

Ausubel et al (1997) analyze synergies in PCS auctions. They identify two types of synergies as local and global. This terminology is used differently here than in the theoretical work cited above. Local synergies are defined as the synergies that arise from holding two or more licenses in adjacent locations. Global synergies arise from holding two or more licenses that are not in adjacent locations. In particular, this study focuses on the effect of local synergies. This is because local synergies are more likely to give rise to the "exposure problem".[46] They point out that when there are two or more bidders in an auction who would take advantage of local synergies in a particular area the final auction price would reflect the local synergies to the winning bidder and to the second highest bidder (marginal bidder). Their results indicate that the variables used to capture synergies have a positive and significant impact on the final bidding price.[47] Also they find that when marginal bidder anticipates synergies it tends to push the price up significantly.

Moreton and Spiller (1998) analyze the synergies in the PCS[48] spectrum auctions conducted by the FCC. Synergies arise either by the ownership of adjacent licenses (local synergies) or by the ownership of several licenses that are not located adjacently (global synergies). They identify the value of a license using the total network value[49] of

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[46] If a given bidder bids aggressively in an early auction anticipating to win a subsequent auction and does not win, he ends up with an incomplete set of objects. This adverse outcome is identified as the "exposure problem" in the literature.
[47] They include both absolute and relative synergy variables in their models. The potential for synergy is identified using a dummy variable. It is also weighted by the population in the area (which reflects the demand for telephones in a given area). See Ausubel et al (1997) for details.
[48] At the time this paper was written the FCC included the following devices under PCS: communication devices that will include multifunction portable phones and other imaging devices, new types of codeless phones and paging devices.
[49] Network value is the total value of all licenses held by a given bidder in adjacently located areas. Authors approximate the value of a license by the number of subscribers in the license area, the median

the license considering several factors. Synergies arise from the total value of these licenses. They consider synergies for the winning bidders as well as synergies for the second lowest bidder. Local synergies are measured by the size (number of subscribers) of the local wireless network that a bidder holds. Global synergies occur when bidders hold multiple licenses in the nationwide wireless network. This study is different from Ausubel et al (1997) in two ways. First, Moreton and Spiller (1998) include additional control variables in their reduced form winning bid regression. These variables can identify the state level regulatory environment, which affects the issuing of these licenses. Secondly, Moreton and Spiller (1998) consider synergies between PCS to PCS as well as PCS to cellular synergies.[50] Their results indicate that the winning bidder's and second to lowest bidder's local PCS license coverage has a positive and significant effect on the winning bid. This result is consistent with the result of Ausubel et al (1997). The effect of global synergies was moderate in their study.

Cramton (1997) descriptively analyzes the first six spectrum auctions conducted by the FCC from July 1994 to May 1996. He points out that one of the primary goals in the design of FCC spectrum auctions was efficiency[51] and not revenue maximization. With this objective FCC adopted simultaneous, multiple round, open, ascending bid auctions. Cramton (1997) discusses the pros and cons of the sequential and simultaneous auction formats. He points out that one of the disadvantages of sequential auctions is that

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family income, the geographic area, and variables that capture economic activity in the area. The number of subscribers reflects the demand. The median family income for the residents in the area is included as a control for wealth. The economic activity is measured by including the percentage of population employed by financial, insurance and real estate sectors.

[50]Authors point out that, some state level cellular telephone regulations makes PCS licenses more attractive to service providers. These regulations affect the intensity of synergies that a bidder could derive.

[51] Cramton points out that, high auction prices are consistent with efficiency i.e. high prices in these auctions are coming from firms that have higher values (due to synergies assuming that these firms can provide better services to the customers at lower prices).

bidders can not switch back and change their bids. In the simultaneous format bidders can do such changes whenever they needed since these are open bid auctions. Bidders have been able to win their desired set of licenses and Cramton (1997), points out this is an efficient outcome achieved by the auction format adopted by the FCC.

De Silva (2005) examines the impact of bidding behavior in spatially correlated projects auctioned off by the Oklahoma Department of Transportation with the emphasis in geographic synergies. His analysis is purely in the sequential framework. He finds aggressive bidding behavior and higher winning probability in spatially correlated projects. Neil Gandal (1997) examines the competition for licenses in Israeli Area Cable Television which were awarded in sequential auctions. He finds aggressive bidding behavior overtime when the licenses are interdependent. These findings are consistent with the existing literature relevant to synergies in auctions.

5.3. Data

This study uses ODOT auction data from January 1997 to November 2003[52] to study differences in bidding behavior between sequential and simultaneous auctions in the presence of synergies. As mentioned earlier, ODOT auctions off 30-35 projects every month. The total value of these projects is around forty three million dollars. Before April 2002 the auctions were held in two sessions within a day of the month. At the end of each session, ODOT released information about the concluded auctions. After April 2002 all projects were offered simultaneously in a single session. This study attempts to capture differences that can be attributed to the sequential nature of earlier auctions.

The ODOT data were obtained from four reports, namely the project *plan holder list, as read bid report, low bid report* and *award notice*s which are available on the

[52] There were no projects auctioned off in December 2003.

ODOT web site. The project *plan holder list* includes names of the firms that have purchased project plans. For every project the ODOT prepares a project plan that includes some of the design features of the project. In order to submit bids at ODOT auctions firms have to go through a pre-qualification process[53] set forth by ODOT and must purchase the project plan. Bid information of every project is available through the *as read bid report*. It contains all bids submitted by the firm together with their names. This is a vital piece of information for the firms to learn about their rivals in the bidding process. Also the *as read bid report* contains the county where the project is located and the project description. The project description gives information about the type of project i.e. asphalt paving, bridge work, traffic lighting etc. The *low bid report* was used to obtain the project engineering cost estimate and the number of calendar days required to complete a given project. The project engineering cost estimate is prepared by the ODOT engineer's office; it contains a detailed estimate of different cost components. The low bid report includes only the total value of the project cost estimate. This estimate was not revealed by the ODOT prior to bid letting until January 2000. After January 2000 ODOT started revealing the cost estimate prior to bid letting and this study consider that policy change in the analysis. The name of the winning bidder and his location were recorded from the *award notice* report. In addition, the project identification number, the month and the session of the project (relevant for auctions held in morning and afternoon sessions) were also recorded.

[53] In the pre-qualification process, the ODOT scrutinizes the financial statements, working capital available at the time of bidding and the firm history related to successful completion of projects.

The regression analysis uses data from January 1998 to November 2003.[54] The auction statistics for the full sample as well as the sub-samples before and after the change in the auction format are given in Table 5.2. The period before the change is from January 1998 to March 2002, which consists of 51 months of auction data. The period after the change in the auction format is from April 2002 to November 2003, which consists of 20 months of auction data. The full sample consists of 2318 auctions, while the sub sample before has 1709 auctions, and the sample after has 609 auctions. The total number of bids in the full sample is 6261, and the sample before has 4476 bids while the sample after has 1785 bids. In the analysis, the bids are normalized by the engineering cost estimate of the project and are called relative bids. Mean relative bids for the full sample and sub samples are given in the Table 5.2. Notice the slight decline in the mean relative bids in the period after the change in auction format compared to the period before. The analysis in this study is focused on empirical testing of this difference. The next section presents the empirical model and variables used in the analysis.

5.4. Empirical Analysis

The goal in the empirical analysis is to examine the impact of the change in the auction format on the seller's revenue and the bidding behavior in the presence of potential synergies among projects. The study identifies sequentially placed bids and simultaneously placed bids. Then it identifies within a given month which projects have a potential for synergies that could lower their cost if won by a single bidder and

[54] This study uses the information from the year 1997 to create historical information and control for bidder and rival history in the analysis. The definition and details about the construction of these variables are in the following sections.

characterize them as high and low synergy projects. Then the empirical model and the variables are explained in detail.

5.4.1. Bidder group classification

As in Krishna and Rosenthal (1996) and Rosenthal and Wang (1996), this study identifies global bidders. In this study, a global bidder is defined as a bidder who bids on two or more projects in a given month.[55] Global bidders submitted bids before and after April 2002. They are classified as follows:

1. *Sequential Bids* (submitted only before April 2002).
2. *Simultaneous Bids* (since April 2002).

5.4.1.1. Classification of Sequential Bidders

Single- Session and Two –Session Bidders

Due to the sequential nature of the ODOT auctions before April 2002, one must be careful identifying the sequentially placed bids. Under this auction format, bidders can bid both in morning and afternoon sessions. All global bidders who bid before April 2002 grouped into two groups, S*ingle-Session Bidders* who bid only in morning or afternoon sessions and *Two-Session Bidders* who bid in both sessions.

Two-Bid Group and Multiple-Bid Group

The *Two-Session Bidders* are used to identify those who place sequential bids. All *Two-Session Bidders* are separated into two groups: *Sequential Two-Bid Group* and *Sequential Multiple-Bid Group*. The bidders in the first group have placed one bid in each session, sequentially to a total of two bids in a given month. The bidders in the second group have placed multiple bids in one or both sessions. For those bidders some

[55] Any bidder who places one bid in a given month is not included in the analysis since the focus is on global bidders.

bids are simultaneously placed without any knowledge of the bidding outcome in other auctions held that day and some are placed sequentially and the bids in the afternoon session can be adjusted strategically based on the morning outcome. The purpose of this distinction is to isolate purely sequential effect from mixed bidding effects.

AM-Bidders and PM-Bidders

Single session bidders are grouped into two groups considering whether they place bids in the morning or afternoon session. If bidders bid only in the morning session they are identified as *AM-Bidders*. If the bids are placed only in the afternoon they are called *PM-Bidders*.

Bidders bidding for High Synergy and Low Synergy Projects

All bids submitted by multiple bidders within a month are grouped according to the intensity of synergies. Partly for simplicity and partly because there is no continuous way to do the identification, two synergy levels are considered: *High Synergy* and *Low Synergy*. A bidder bidding on two projects can benefit from high synergies if: 1) the bids submitted by a bidder in a given month are placed within the same field division[56], and 2) those bids in the same field division (Figure 5.2 presents ODOT field divisions) are of the same project type[57]. Therefore if multiple bids placed by a bidder are within the same field division and within the same project type, it is assumed those bidders can benefit from potentially higher level of synergies, relative to other bidders. If the bids on projects do not belong to the high synergy group, they are classified as *Low Synergy bids*. With

[56] There are eight field divisions in Oklahoma identified by the ODOT (Figure 2 represents ODOT field divisions). A field division consists of several adjoining Oklahoma counties. When bidders place several bids within the same field division, this study assumes bidders can realize synergies due to close location of these projects.

[57] Considering the project description (such as asphalt, bridgework, traffic lighting, grading and draining etc.) this study groups all the projects into seven main project types. These project types are explained in detail in the section describing the empirical model.

the classification of High and Low Synergy groups there are total of eight groups of multiple bids under the *Sequential* auction format (see Figure 5.1).

All groups of bids can be summarized as follows.

Bids in two sessions (before the auction format change):

AM-Bids High (low) synergy projects

PM-Bids High (low) synergy projects

Two-Bids in high (low) synergy projects

Multiple-Bids in high (low) synergy projects

Bids in a single session (after the auction format change):

Am-Bids in high (low) synergy projects

PM-Bids in high (low) synergy projects

5.4.1.2. Classification of Simultaneous Bidders

A similar approach is taken as in the previous section to group simultaneous bidders and their bids. All simultaneous bidders are divided into two groups as *Simultaneous Two-Bid Group* and *Simultaneous Multiple-Bid Group.* Bidders in the *Two-Bid Group* have submitted only two bids in a given month while the bidders in the multiple-bid group have submitted more than two bids. The two-bid group is identified as the analogous group to *Sequential Two-Bid* group for comparison purposes.

The bids submitted by those groups are further classified as bids that are in projects with the potential for High or Low synergies. Thus there are four bid groups under the simultaneous auction format (See Figure 5.1).

These groups can be summarized as follows.

Two-Bids in high (or low) synergy projects

Multiple-Bids in high (or low) synergy projects

There are twelve variables altogether that identify the groups as depicted in Figure 5.1. The number of bids and wins for each of these variables are given in Table 5.3.

5.4.2. Empirical Model

The dependent variables in the regression analysis are *relative bid* and *relative winning bid.* Bids and winning bids are normalized by the engineering cost estimate of the project to obtain these dependent variables. The explanatory variables identify the intensity of existing potential synergies. Reduced form regression model that is considered as the base model in the analysis, takes the following form.

$$y_i = \alpha + \beta X + \gamma Z + \varepsilon_i$$

where,

$$\varepsilon_i \sim (0, \sigma_i^2).$$

The first set of variables consists of eleven dummy variables[58] represented by ***X*,** and identifies bids based on whether there are synergies across different projects offered. The second set of variables consists of other qualitative and quantitative variables and is represented by *Z* in the model. These variables can be broadly categorized into variables representing auction characteristics, bidder characteristics, rival characteristics, and the variables that control for time variant factors.

Variables representing auction characteristics include project types, project size, the source of funding for the project, and the number of bidders in an auction. As in De Silva, Dunne and Kosmopoulou (2002, 2003) and De Silva (2005) all projects are grouped into seven broad project types based on the project descriptions given in the

[58] Of the twelve dummy variables that identify different bidder groups multiple-bid simultaneous bidders with lower synergies group is omitted in the regression.

reports available on the ODOT web site. These project types are asphalt paving projects, clearance and bank protection projects, bridge projects, grading and draining projects, concrete work, traffic signals and lighting projects, and miscellaneous projects.[59] Miscellaneous projects were omitted in the regression so that there are six project type variables.[60] These variables control for variation of bidding behavior across these project types.

Large projects variable is used to identify project size (*Large Projects*--projects with engineering estimate over one million dollars). The project engineering cost estimate is used to identify large and small projects. In general, large projects are subject to different work requirements, such as Disadvantaged Business Enterprise Programs[61] requirements. This variable captures the variability between large and small projects. All projects costing over one million dollars are defined as large projects. This includes the largest 24% of the projects in the sample.

Also a variable is used to identify the funding source of projects that represents another auction characteristic. ODOT projects are funded by the federal government and the state government. Federally funded projects are subject to Federal guidelines.[62] Such differences between federal and state projects can have an impact on the bidding behavior. The next variable relates to the number of bids in an auction. It is actually the *log of the Number of Bids*. In the auction literature, this variable has been used as a

[59] Miscellaneous projects are landscaping, waterline adjustments, intersection modification, parking etc.
[60] Recall that, these project type variables and the field division variable are used to identify bidders with high synergies.
[61] A Disadvantage Business Enterprise is defined as an enterprise with more than 51% ownership by socially and economically disadvantaged groups as defined by the Small Business Administration regulations. If the firm is a general contractor, the firm's gross receipts averaged over a three years period cannot exceed $17.4 million.
[62] For example the main contractor of a federally funded project must provide equal opportunity to disadvantaged business groups in the allocation of any sub-contracts. Also, the main contractor must avoid any sort of discrimination among the sub-contractors.

control for the degree of competition in the auction.[63] In this study the number of bids submitted by both global and local bidders is included.

The next group of variables in *Z* represents bidder characteristics. These variables include *Firm's Past Winning to Bid Ratio* and the *Capacity Utilization* of a firm. A given firms past number of wins divided by the past number of bids submitted is used as the measure of the firms past success rate *(Winning to Bid Ratio)*. A higher *Winning to Bid Ratio* implies a higher success rate in the past. This study considers only the last twelve months of bidding and winning statistics since a given bidder's current success rate is mostly likely to be represented by his immediate past bidding and winning history. [64] Capacity utilization *(Capacity Utilization)* of a firm is the backlog of a firm divided by the maximum backlog[65] of that firm during the sample period. Similar capacity utilization measures have been used by Porter and Zona (1988) and Bajari and Ye (2002). The backlog of the firm is the dollar value of the unfinished work from previously won contracts.[66] The capacity utilization of the firm reflects how much of the firm's capacity is being utilized by already won contracts. Firms with a larger capacity utilized would have a relatively lower capacity left for further projects.

This study also employs a variable that captures toughness of rivals. Any given bidder is faced with a set of rivals in every auction except those auctions that have only one bid. If a given bidder is faced with a tougher set of rivals, then the bidder is expected

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[63] See Gandal (1997), Hendricks, Pinske, and Porter (1999), De Silva, Dunne and Kosmopoulou (2002, 2003), and De Silva (2005).
[64] *Winning to Bid Ratio* and *ARWP Ratio* (describe in the following paragraph) have been used in De Silva, Dunne and Kosmopoulou (2002, 2003) considering the bidding and winning statistics from the beginning of the sample (bid counts and win counts start from 1997).
[65] The maximum backlog of a firm that has won contracts but never had a backlog (if the project was completed within the same month there will not be a backlog left for the next month) is the largest project the firm won. Also firms that never won any contact will have zero capacity utilization since full capacity is available to use at the time of bidding.
[66] The backlog of a firm is computed as in De Silva, Dunne and Kosmopoulou (2002, 2003).

to bid more aggressively in that auction in order to win.[67] This is not the case if the same bidder faces a relatively weaker set of rivals. To construct this variable, rivals' previous success in winning auctions is computed. This is computed as the number of previous successes divided by the number of plans purchased for every bidder in an auction. The history of the last twelve months is considered when counting the past number of successes and past number of plans held. Then these ratios were averaged across the set of rivals for any given bidder to obtain the average rivals' winning to plan holder ratio *(ARWP Ratio)*. A higher *ARWP Ratio* implies a tougher set of rivals.

A variable is also included (*After January 2000*) that identifies the difference in the two time periods due to another policy change that occurred in January 2000. Before January 2000 ODOT did not reveal the engineering cost estimate of the projects (prepared by the ODOT), before bidders submitted bids. ODOT changed this policy so that it now reveals its estimate to the bidders pre-bid letting. This policy change was investigated in chapter 3 and observed aggressive bidding behavior after the policy change. Therefore this variable is included to identify this change in the time period.

The next set of variables in *Z* controls for aggregate measures such as business activity that varies with time. These are four monthly variables. The first variable controls for the volume of projects auctioned off in a month measured in terms of dollars. A higher dollar value reflects a higher volume of projects. Bidding behavior could be affected by the volume of projects in a month. The sum of the engineering cost estimate total of a month for all the projects is used as the project volume measure. Then that dollar value is converted to a real value using 1997 as the base year (*Real Value of*

[67] From the plan holder list available to the bidders from ODOT (before bid letting) bidders have the knowledge of potential bidders in advance.

Monthly Engineering Estimate Total). In the regression, the log of the real value is included. The monthly total value of the estimates could vary depending on the budgetary conditions in the state of Oklahoma.

The second monthly variable in the *Z* matrix is the *Number of Projects per Firm* in a given month. This variable captures two factors that change every month: the number of projects auctioned off and the number of firms that bid in a month.[68] The bidding behavior could be affected by the availability of projects per firm in a given month. The third monthly variable is the *Concentration Ratio*. This is constructed similarly to the Herfindhal Index. First, the share of every project is computed. That is, the engineering cost estimate of a project is divided by the sum of the engineering cost estimate of the month. This value is then squared and summed across all the projects in a month to obtain the concentration ratio. A higher concentration ratio implies a concentrated market. Bidding behavior could be affected by the monthly value of this ratio. The fourth monthly variable is a measure of business activity in Oklahoma, the Oklahoma General Business Index[69] *(OKGBI).* This variable would be an indicator of the performance of the construction industry in a month. Means of all variables in the empirical model are presented in Table 5.4.

The model is estimated using OLS method followed by post estimation coefficient tests to test the differences across the bidder groups. Further, several robustness checks are carried out on the results of the base model. The next section

[68] Note that a given firm can purchase several plans for different projects. The number of firms therefore is different from the number plan holders in a given month. The number of firms in a month is counted in this case.
[69] The index provides a relative measure for judging the level of economy today based on the benchmark year 1987. Further details about this index can be obtained from www.origins.ou.edu/databases/.

presents main results and comparisons among different bid groups when bidders are faced with different synergy levels.

5.5. Results and Discussion

As a first step in the estimation process, and before making the distinction between projects with high or low potential for synergies, overall differences in the bidding behavior between the two time periods is examined (due to the change in the auction format). The initial model identifies the time period before and after the change in the auction format through a variable called *Simultaneous.* That variable takes the value of 1 in the period after March 2002**.** The results from the initial model indicate a 0.03 significant decline in the overall bidding level and a 0.03 significant decline in the winning bid level after the change in the auction format. The results of the initial model are given in columns (1) and (2) of Table 5.5. This raises the question, is this decline in the bid level caused by the change in the auction format? If the answer is yes, what causes this change? Is it the potential for synergies or other factors? In order to answer these questions, the differences in bidding behavior between the bidder groups in the two formats of auctions are tested.

First the base model and the winning bid model are estimated. Different bidder groups in these models are distinguished depending on the level of synergy. These results are given in the Table 5.6, columns (1) and in (2) respectively. The omitted group is the *Sequential Multiple-Bid Low Synergy* group. Considering the behavior across auction formats, this study finds more aggressive bidding behavior in the simultaneous auctions than the sequential. The results of the comparisons between bidder groups for the base model and winning bid model are summarized in the following table.

Table 5.1: Comparisons for Base Model and Winning Bids Model

COMPARISON BETWEEN SEQUENTIAL AND SIMULTANEOUS AUCTION FORMATS	BASE MODEL	WINNING BIDS
<u>TWO-BID GROUPS</u>		
(1) HIGH SYNERGY	No difference	No difference
(2) LOW SYNERGY	No difference	No difference
<u>MULTIPLE BID GROUPS</u>		
(3) HIGH SYNERGY	Aggressive bidding in the simultaneous auction format	No difference
(4) LOW SYNERGY	Aggressive bidding in the simultaneous auction format	Aggressive bidding in the simultaneous auction format

In the Table 5.1 above, in the first two comparisons *Sequential Two-Bid Groups* are compared to the *Simultaneous Two-Bid Groups* both with high and low potential for synergies. These groups allow isolation of purely simultaneous and purely sequential effects. The results indicate that there is no significant difference in the bidding behavior across the auction formats in the overall bids and in the winning bids. The third and fourth comparisons in both models indicate aggressive bidding behavior by simultaneous *Multiple-Bid* groups. Notice that the third comparison in the base model is consistent with Krishna and Rosenthal (1996) theory while the fourth comparison is not, in both models. Thus, this study does not find consistent evidence to support Krishna and Rosenthal (1996) theory that predicts higher revenue in simultaneous auctions when bidders have higher level of synergy.

Of course, there are differences between the empirical work and the theory developed by Krishna and Rosenthal (1996) that may be responsible for the difference in the outcome. For example, the model by Krishna and Rosenthal (1996) examines private values while the construction contracts considered in this study have both private and common value components. This can make a difference in the ranking of auctions as Hausch (1986) suggested. Also as Feng and Chatterjee (2003) suggest that the intensity of competition can have an effect on the outcome. ODOT auctions off its contracts to a relatively small number of competing bidders that could face the potential for synergies.

Several other specifications are considered to allow further comparisons between the groups of bidders identified in the analysis. First, firm fixed effects are incorporated to the base model and to the winning bids model. Fixed effects results are presented in Table 5.7, columns (1) and (2) for the overall bid level and the winning bid level. The results do not indicate any significant difference across the four comparisons either at the overall bid level or at the winning bid level.

Since the dependent variable relative bid is the bid normalized by the estimate, it does not reflect the project size differences. In an attempt to take that into account, the relative bid regression model is weighted by the project engineering cost estimates so that relative bids of larger projects would have larger weight than relative bids of smaller projects. Three models are re-estimated with the weights: the base model, fixed effects model and the winning bids model with fixed effects. Results for the weighted models are presented in Table 5.8 columns (1), (2) and (3).

The results of the overall bid regression with weights are presented in Table 5.8 column (1). The results indicate when competing for high synergy projects the *Simultaneous Multiple-Bid group* bid more aggressively than the *Sequential Multiple-Bid group* which is consistent with the base model result. Also in the low synergy projects, *Simultaneous Multiple-Bid* group bid aggressively relative to *Sequential Multiple-Bid* group. This is again consistent with the base model result. The other comparisons between sequential and simultaneous *Two-Bid* groups; both high and low synergy are not significant.

The weighted relative bid regression with fixed effects and the weighted relative winning bid regression with fixed effects are presented in Table 5.8 columns (2) and (3) respectively. The results indicate that there is no significant difference in the four comparison groups (as in the Table 5.1) at the overall bids and the winning bids levels.

Among the variables in the *Z* matrix the variable identifying *Large Projects* was significant in all the models except in the winning bid regression (Table 5.6 column (2)). Bidders show aggressive bidding in larger projects relative to the smaller projects indicating more competition for larger projects. The *log number of bidders* was significant in all models indicating aggressive bidding behavior as the number of bidders increase in the auctions. The *Winning to Bid Ratio* that measures the bidders' previous success rate, was significant at the overall bid level and had the expected effect. A higher *Winning to Bid Ratio* leads to more aggressive bidding. The *ARWP Ratio* variable that measures toughness of the rivals was negative and significant in all winning bid regression models except for the weighted winning bid regression indicating that a tougher set of rivals would lead to more aggressive bidding behavior.

A variable is used to represent the difference in the bidding behavior due to revelation of the engineering cost estimate since January 2000. The coefficient of this variable is negative and significant in all the models. It indicates on average the *Relative Bids* have declined by about 0.05 after ODOT started revealing the engineering cost estimate prior to bid letting. Among the other time variant variables the *Real Value of*

Monthly Estimate Total was significant only in the winning bid regressions and in weighted models but does not show a systematic sign for the coefficient. The number of projects per firm in a month was significant in the two initial models, base model, winning bid model and in the fixed effects models. The results indicate more aggressive bidding behavior with a higher number of projects per firm.

The *Concentration Ratio* was significant in two of the weighted regression models (base model and fixed effects models with weights). The coefficient on the *Concentration Ratio* indicates more competition when the projects are concentrated. A higher *Concentration Ratio* indicates that funds are allocated to a relatively smaller number of projects. The aggressive bidding observe with the concentration ratio could be due to the competition among large firms.

The variable that measure the overall economic activity, *OKGBI* had a positive and significant effect at the overall bid regression indicating relatively lesser competition for road construction projects when there is a lot of other economic activity in the state. The variables describing *Capacity Utilization* and *Federal Projects* did not show a systematic significance in the analysis**.**

This study also tested whether more aggressive bidding behavior in high synergy bidder groups can be observed than low synergy bidder groups (within the same auction format). These tests present an opportunity to compare the results with other evidence in the literature. In particular, after estimating all models, comparisons are made between: *AM* high and low synergy groups, *PM* high and low synergy groups, *Sequential Two-Bid* high and low synergy bidder groups, *Sequential Multiple-Bid* high and low synergy bidder groups, *Simultaneous Two-Bid* high and low synergy bidder groups and

Simultaneous Multiple-Bid high and low synergy bidder groups. The F-test statistics for these tests are presented in Table 5.9. The study finds some weak evidence of aggressive bidding by the *Multiple-Bid* group with high synergy (relative to the corresponding low synergy group). The remaining comparisons between high and low synergy groups at the winning bid level did not show a significant difference.

In addition to the above analysis, this study considers the effect of the format of auction and the competition on different types of projects. This study introduces the dummy variable *Simultaneous Auction Format* to capture the period after March 2002. Within each project type, this variable identifies differences in bidding due to the auction format. Also this study included a variable capturing the intensity of competition and its interaction with the auction format and a synergy variable that identifies same division bids for a given firm. It is examined whether there is evidence that ODOT benefits with the simultaneous auction format when auctioning off more uncertain projects (projects with common value elements and potentially higher winner's curse) such as bridgework relative to more certain projects (less uncertainty) such as traffic signals. Project wise regression results are presented in Table 5.10 and 5.11. The results are not conclusive for every project type. It seems that the simultaneous auction format performs better in auctions of bridge projects (common value) and worse in auctions of asphalt related projects (private value). The results for the rest of the project types are insignificant. This study also examines the relative performance of the two formats of auctions in light of Hausch's (1986) predictions. He predicts that in the presence of winner's curse the simultaneous auction format generates higher revenues (when bidders signal their true values). When bidders try to mimic each other, there is less overall winner's curse and the sequential format generates higher revenue. Among different project types, bridgework has in general higher cost uncertainty and fits better the framework of common value auctions. Results indicate that in this framework the simultaneous auction format performs better (evident by the negative coefficient in project type 3 presented in Table 5.10). Despite the fact that there is some variation in the bids, suggestive of the fact that the bidders probably don't mimic each other, there is no hard evidence to conclude that they indeed signal their true values. In that sense, this is not a direct test of Hausch's results. Hausch just provides a possible explanation for the observed outcome.

This study also attempts to find supportive evidence for Feng and Chatterjee (2003) who predicts that, in private value auctions, under intense competition the simultaneous format performs better in terms of revenue. The intensity of competition is identified by the number of projects per firm. This variable is interacted with the *Simultaneous* variable to distinguish between different effects of competition in the two auction formats (*Projects per Firm under the Simultaneous Auction Format*). The interaction effect should be positive and significant in simultaneous auctions at least for auctions of asphalt and signal type projects. The results do not show a significant pattern.

5.6. Conclusion

Overall, this study finds some evidence of aggressive bidding behavior in the simultaneous auction format. There is a 3% decrease overall in the level of bids as well as winning bids after the state adopted the simultaneous auction format. The decrease in the bid level implies a benefit to ODOT. The results provide some evidence of aggressive bidding by *Multiple-Bid* groups facing potentially high synergies in the simultaneous auction format, in the overall bid regression but not in the winning bid regressions.

However the results do not provide consistent support to the theory by Krishna and Rosenthal (1996).

Comparisons between high and low synergy bidder groups within the same auction format indicate some weak evidence of more aggressive bidding behavior among the multiple bidders with higher level of synergy in the overall bid regression.

Figure 5.1: Classification of Bids According to the Synergy Levels

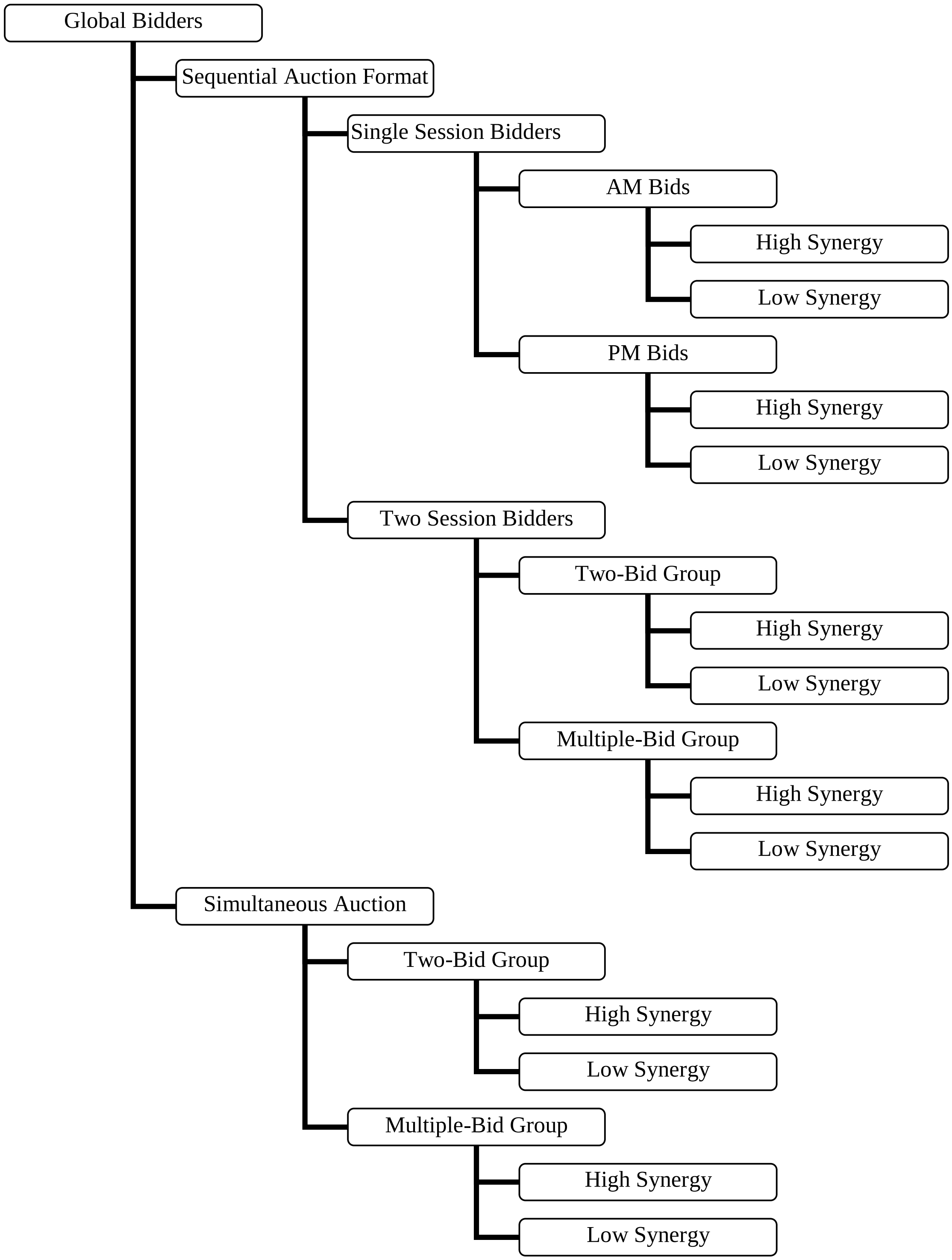

Figure 5.2: ODOT Field Divisions (Source: Oklahoma Department of Transportation web site).

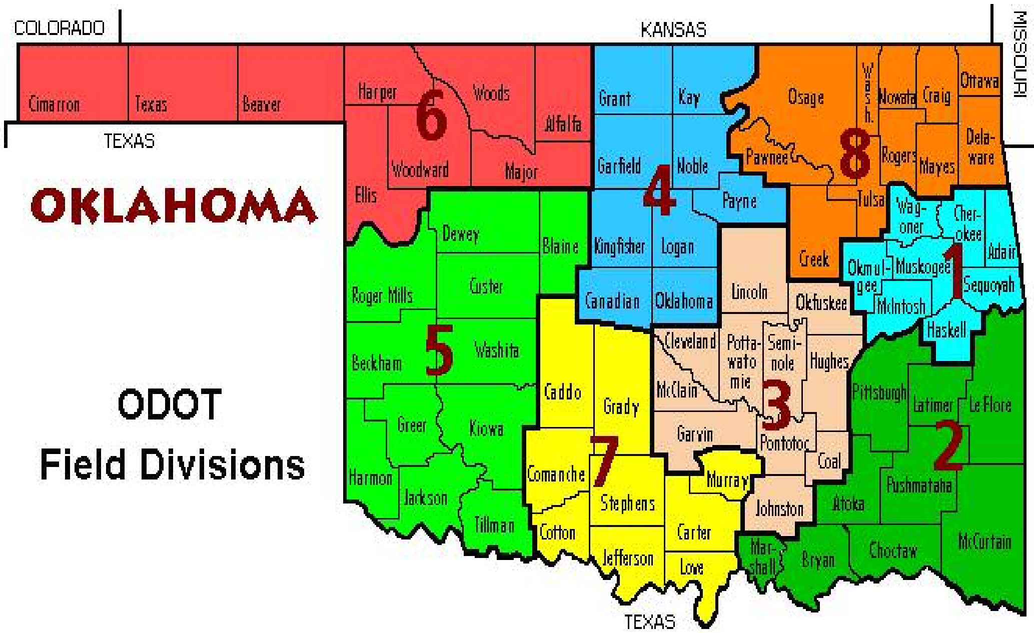

Table 5.2: Summary Statistics for the Regression Sample

	Full Sample	Before the change in the Auction Format	After the change in the Auction Format.
Number of Auctions	2318	1709	609
Number of Plan Holders	8852	6238	2614
Number of Plan Holders per Auction	7.036 (3.851)	7.201 (3.206)	8.296 (3.964)
Number of Firms	156	139	98
Number of Bids	6261	4476	1785
Number of Bids per Auction	3.395 (1.703)	3.334 (1.684)	3.563 (1.744)
Mean Relative Bid	1.058 (0.278)	1.077 (0.300)	1.011 (0.263)
Mean Winning Relative Bid	0.935 (0.208)	0.950 (0.211)	0.895 (0.194)

Standard deviations are in the parenthesis

Table 5.3: Bid Counts and Win Counts for Different Synergy Levels

Bidder Group Variables	Number of Bids	Number of Wins	Percentage of Wins
Before the Change in the Auction Format			
Number of Bidders bid only in morning	552	156	28.3%
Number of bidders bid only in afternoon	337	92	27.3%
Sequential Two-Bids with High Synergy	130	37	28.5%
Sequential Two-Bids with Low Synergy	441	136	30.8%
Sequential Multiple-Bids with High Synergy	1077	309	28.7%
Sequential Multiple-Bids with Low Synergy	1964	509	25.9%
After the Change in the Auction Format			
Simultaneous-Two Bids with High Synergy	64	19	29.7%
Simultaneous-Two Bids with Low Synergy	311	78	25.1%
Simultaneous-Multiple Bids with High Synergy	667	156	23.4%
Simultaneous-Multiple Bids with Low Synergy	748	196	26.2%

Table 5.4: Means of the Regression Variables

Variable	Mean	
Relative Bid	1.056	(0.278)
Relative Winning Bid	0.934	(0.204)
Simultaneous Auction Format	0.297	(0.457)
AM-Bidders-High Synergy	0.023	(0.150)
AM-Bidders-Low Synergy	0.063	(0.243)
PM-Bidders-High Synergy	0.016	(0.124)
PM-Bidders-Low Synergy	0.037	(0.189)
Sequential Two-Bid Group-High Synergy	0.020	(0.142)
Sequential Two-Bid Group-Low Synergy	0.069	(0.253)
Sequential Multiple Bid Group-High Synergy	0.169	(0.374)
Simultaneous Two-Bid Group-High Synergy	0.012	(0.107)
Simultaneous Two-Bid Group-Low Synergy	0.051	(0.219)
Simultaneous Multiple-Bid Group-High Synergy	0.114	(0.318)
Simultaneous Multiple-Bid Group-Low Synergy	0.121	(0.326)
Project-1	0.212	(0.409)
Project-2	0.012	(0.110)
Project-3	0.469	(0.499)
Project-4	0.158	(0.365)
Project-5	0.023	(0.151)
Project-6	0.087	(0.282)
Large Projects	0.247	(0.431)
Federal Projects	0.630	(0.483)
Log of Number of Bids	1.571	(0.362)
ARWP Ratio	0.131	(0.072)
Winning to Bid Ratio	0.236	(0.168)
Capacity Utilization	0.278	(0.387)
After January 2000	0.666	(0.472)
Log Real Value of Monthly Total of Engineering Estimate	17.495	(0.619)
Monthly Number of Projects per Firm	0.568	(0.142)
Concentration Ratio	0.128	(0.070)
OKGBI	128.886	(1.951)

Note: Standard deviations are in parenthesis.

Table 5.5: Relative Bid Regression for the Initial Model without Synergy Variables

Independent Variable	(1) Relative Bid		(2) Relative Winning Bid	
Constant	0.034	(0.237)	0.229	(0.328)
Simultaneous Auction Format	-0.033*	(0.008)	-0.026*	(0.012)
Project-1	-0.034	(0.031)	0.113*	(0.038)
Project-2	0.158*	(0.059)	0.180	(0.112)
Project-3	0.038	(0.031)	0.076*	(0.038)
Project-4	-0.061*	(0.030)	0.087*	(0.038)
Project-5	-0.019	(0.037)	0.099*	(0.047)
Project-6	-0.072*	(0.032)	0.084*	(0.041)
Large Projects	-0.066*	(0.009)	-0.022	(0.012)
Federal Projects	-0.010	(0.010)	0.004	(0.014)
Log of Number of Bids	-0.075*	(0.010)	-0.116*	(0.013)
ARWP Ratio	-0.070	(0.052)	-0.144*	(0.065)
Winning to Bid Ratio	-0.146*	(0.023)	-0.047	(0.032)
Capacity Utilization	0.018	(0.010)	0.015	(0.016)
AfterJanuary 2000	-0.054*	(0.009)	-0.039*	(0.012)
Log Real Value of Monthly Total of Engineering Estimates	0.001	(0.007)	0.024*	(0.010)
Monthly Number of Projects per Firm	-0.083*	(0.032)	-0.135*	(0.041)
Concentration Ratio	-0.086	(0.069)	-0.130	(0.088)
OKGBI	0.010*	(0.002)	0.004	(0.003)
Number of Observations	6261		1685	
R-Squared	0.065		0.100	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 5.6: Relative Bid Regression: Base Model and Winning Bids

Independent Variable	(1) Relative Bid-Base Model		(2) Relative Winning Bid	
Constant	0.011	(0.241)	0.256	(0.326)
AM-Bidders-High Synergy	-0.027	(0.023)	-0.003	(0.038)
AM-Bidders-Low Synergy	-0.026	(0.015)	0.021	(0.022)
PM-Bidders-High Synergy	-0.033	(0.024)	-0.020	(0.022)
PM-Bidders-Low Synergy	-0.024	(0.019)	0.038	(0.032)
Sequential Two-Bid Group-High Synergy	-0.056*	(0.021)	-0.022	(0.034)
Sequential Two-Bid Group-Low Synergy	-0.034*	(0.015)	-0.012	(0.018)
Sequential Multiple Bid Group-High Synergy	-0.043*	(0.010)	-0.007	(0.015)
Simultaneous Two-Bid Group-High Synergy	-0.052	(0.037)	-0.025	(0.044)
Simultaneous Two-Bid Group-Low Synergy	-0.032	(0.020)	-0.042	(0.028)
Simultaneous Multiple-Bid Group-High Synergy	-0.082*	(0.011)	0.001	(0.017)
Simultaneous Multiple-Bid Group-Low Synergy	-0.035*	(0.013)	-0.042*	(0.019)
Project-1	-0.020	(0.031)	0.113	(0.039)
Project-2	0.160*	(0.059)	0.179	(0.112)
Project-3	-0.029	(0.031)	0.074	(0.039)
Project-4	-0.055	(0.030)	0.087*	(0.038)
Project-5	-0.012	(0.037)	0.102*	(0.047)
Project-6	-0.066*	(0.032)	0.082*	(0.041)
Large Projects	-0.066*	(0.009)	-0.021	(0.012)
Federal Projects	-0.010	(0.010)	0.004	(0.014)
Log of Number of Bids	-0.075*	(0.010)	-0.116*	(0.013)
ARWP Ratio	-0.060	(0.052)	-0.152*	(0.065)
Winning to Bid Ratio	-0.143*	(0.023)	-0.048	(0.032)
Capacity Utilization	0.016	(0.010)	0.014	(0.016)
After January 2000	-0.055*	(0.009)	-0.039*	(0.012)
Log Real Value of Monthly Total of Engineering Estimates	0.001	(0.007)	0.023*	(0.010)
Monthly Number of Projects per Firm	-0.079*	(0.033)	-0.135*	(0.043)
Concentration Ratio	-0.086	(0.069)	-0.127	(0.088)
OKGBI	0.011*	(0.002)	0.004	(0.003)
Number of Observations	6261		1685	
R-Squared	0.070		0.100	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 5.7: Fixed Effects

Independent Variable	(1) Relative Bid		(2) Relative Winning Bid	
Constant	1.361	(0.238)	0.142	(0.331)
AM-Bidders-High Synergy	-0.016	(0.027)	-0.021	(0.043)
AM-Bidders-Low Synergy	-0.029*	(0.014)	-0.001	(0.022)
PM-Bidders-High Synergy	-0.007	(0.025)	-0.031	(0.024)
PM-Bidders-Low Synergy	-0.029	(0.019)	0.019	(0.033)
Sequential Two-Bid Group-High Synergy	-0.055*	(0.020)	-0.041	(0.037)
Sequential Two-Bid Group-Low Synergy	-0.033*	(0.015)	-0.021	(0.018)
Sequential Multiple Bid Group-High Synergy	-0.040*	(0.010)	-0.034*	(0.015)
Simultaneous Two-Bid Group-High Synergy	-0.029	(0.040)	-0.026	(0.049)
Simultaneous Two-Bid Group-Low Synergy	-0.025	(0.020)	-0.066*	(0.028)
Simultaneous Multiple-Bid Group-High Synergy	-0.055*	(0.011)	-0.017	(0.018)
Simultaneous Multiple-Bid Group-Low Synergy	-0.016	(0.014)	-0.038*	(0.019)
Project-1	-0.030	(0.030)	0.052	(0.040)
Project-2	0.140*	(0.059)	0.063	(0.108)
Project-3	-0.022	(0.031)	0.012	(0.044)
Project-4	-0.037	(0.028)	0.041	(0.040)
Project-5	-0.018	(0.034)	0.046	(0.045)
Project-6	0.009	(0.033)	0.096*	(0.044)
Large Projects	-0.087*	(0.009)	-0.042*	(0.013)
Federal Projects	-0.001	(0.010)	0.002	(0.014)
Log of Number of Bids	-0.069*	(0.011)	-0.109*	(0.014)
ARWP Ratio	-0.009	(0.055)	-0.160*	(0.071)
Winning to Bid Ratio	0.044	(0.033)	0.085	(0.048)
Capacity Utilization	0.005	(0.013)	-0.028	(0.022)
After January 2000	-0.063*	(0.009)	-0.032*	(0.013)
Log Real Value of Monthly Total of Engineering Estimates	-0.003	(0.007)	0.016	(0.010)
Monthly Number of Projects per Firm	-0.067*	(0.033)	-0.091*	(0.044)
Concentration Ratio	-0.063	(0.065)	-0.082	(0.090)
OKGBI	0.011*	(0.002)	0.005	(0.003)
Number of Observations	6261		1685	
R-Squared	0.167		0.254	

Note: Standard errors are in parenthesis. * Denotes 5% significance.

Table 5.8: Regression Models Weighted by the Engineering Cost Estimate of the Project

Independent Variable	(1) Base Model		(2) Fixed Effects		(3) Relative Winning Bids with Fixed Effects	
Constant	0.405	(0.247)	0.372	(0.248)	0.446	(0.349)
AM-Bidders-High Synergy	0.021	(0.019)	0.031	(0.022)	0.026	(0.034)
AM-Bidders-Low Synergy	0.007	(0.015)	0.006	(0.015)	0.014	(0.030)
PM-Bidders-High Synergy	-0.031	(0.024)	-0.032	(0.023)	-0.004	(0.033)
PM-Bidders-Low Synergy	-0.001	(0.020)	0.000	(0.021)	-0.041	(0.023)
Sequential Two-Bid Group-High Synergy	-0.046*	(0.023)	-0.020*	(0.024)	-0.015	(0.032)
Sequential Two-Bid Group-Low Synergy	-0.030*	(0.014)	-0.037	(0.014)	-0.046*	(0.018)
Sequential Multiple Bid Group-High Synergy	-0.009	(0.014)	-0.012	(0.014)	-0.045*	(0.020)
Simultaneous Two-Bid Group-High Synergy	-0.053*	(0.023)	-0.048	(0.025)	-0.045	(0.029)
Simultaneous Two-Bid Group-Low Synergy	-0.051*	(0.015)	-0.039*	(0.016)	-0.063*	(0.022)
Simultaneous Multiple-Bid Group-High Synergy	-0.042*	(0.012)	-0.028*	(0.012)	-0.010	(0.025)
Simultaneous Multiple-Bid Group-Low Synergy	-0.029*	(0.011)	-0.025*	(0.012)	-0.034	(0.020)
Project-1	0.024	(0.023)	0.019	(0.024)	-0.013	(0.032)
Project-2	0.087	(0.048)	0.061	(0.045)	-0.032	(0.064)
Project-3	0.009	(0.021)	0.013	(0.023)	-0.037	(0.031)
Project-4	-0.008	(0.021)	-0.004	(0.021)	-0.031	(0.026)
Project-5	0.019	(0.032)	0.003	(0.034)	-0.027	(0.040)
Project-6	-0.013	(0.026)	0.042	(0.031)	0.019	(0.039)
Large Projects	-0.065*	(0.009)	-0.067*	(0.009)	-0.035*	(0.014)
Federal Projects	0.030*	(0.009)	0.031*	(0.010)	0.012	(0.013)
Log of Number of Bids	-0.064*	(0.011)	-0.062*	(0.011)	-0.087*	(0.016)
ARWP Ratio	-0.077	(0.067)	-0.074	(0.069)	-0.059	(0.092)
Winning to Bid Ratio	-0.095*	(0.024)	0.000	(0.034)	0.070	(0.059)
Capacity Utilization	0.027*	(0.010)	0.035*	(0.012)	-0.001	(0.017)
After January 2000	-0.059*	(0.009)	-0.066*	(0.010)	-0.045*	(0.013)
Log Real Value of Monthly Total of Engineering Estimate	-0.014	(0.008)	-0.018*	(0.008)	-0.003	(0.011)
Monthly Number of Projects per Firm	-0.044	(0.032)	-0.024	(0.032)	-0.057	(0.045)
Concentration Ratio	-0.240*	(0.062)	-0.231*	(0.068)	-0.127	(0.100)
OKGBI	0.009*	(0.002)	0.007*	(0.002)	0.005	(0.003)
Number of Observations	6261		6261		1685	
R-Squared	0.138		0.214		0.370	

Note: Robust standard errors are in parenthesis. * Denotes 5% significance.

Table 5.9: F Statistics for the Coefficient Tests between High and Low Synergy Groups

The Null Hypothesis for the Coefficient tests performed after estimating each model	Base Model	Wining Bids Model	Fixed Effects Model	Winning Bids with Fixed Effects	Weighted Base Model	Weighted Model with Fixed Effects	Weighted Winning Bids Model with Fixed Effects
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No difference between high and low synergy *AM-Bid Groups*	0.000 (0.986)	0.340 (0.561)	0.210 (0.648)	0.180 (0.675)	0.350 (0.554)	0.940 (0.334)	0.090 (0.758)
No difference between high and low synergy *PM-Bid Groups*	0.100 (0.755)	2.510 (0.114)	0.540 (0.465)	1.740 (0.187)	0.950 (0.324)	1.140 0.287)	1.010 (0.315)
No difference between high and low synergy *Sequential Two-Bid Groups*	0.910 (0.340)	0.090 (0.762)	0.940 (0.333)	0.240 (0.625)	0.440 (0.506)	0.430 (0.512)	0.840 (0.360)
No difference between high and low synergy *Sequential Multiple Bid Groups*	18.82* (0.000)	0.230 (0.630)	16.450* (0.000)	5.040* (0.025)	0.390 (0.533)	0.690 (0.407)	4.980* (0.026)
No difference between high and low synergy *Simultaneous Two-Bid Groups*	0.230 (0.629)	0.110 (0.735)	0.010 (0.922)	0.550 (0.457)	0.000 (0.950)	0.100 (0.757)	0.330 (0.568)
No difference between high and low synergy *Simultaneous Multiple-Bid Groups*	12.40* (0.000)	5.080* (0.024)	8.530 (0.004)	1.140 (0.285)	1.120 (0.289)	0.040 (0.845)	1.000 (0.317)

P-values are in the parenthesis. * Denotes 5% significance.

Table 5.10: Relative Bid Regressions for Project Types

Independent Variable	(1) Project Type 1		(2) Project Type 2		(3) Project Type 3	
Constant	0.322	(0.425)	17.818*	(5.921)	-0.355	(0.387)
Simultaneous Auction Format	0.122*	(0.058)	1.938	(0.989)	-0.220*	(0.053)
Bids in the Same Division	-0.005	(0.012)	-0.119	(0.113)	-0.040*	(0.011)
Large Projects	-0.059*	(0.016)	-0.332	(0.292)	-0.041*	(0.020)
Federal Projects	-0.052*	(0.015)	-0.049	(0.218)	-0.022	(0.014)
Log of Number of Bids	-0.031	(0.017)	-0.342	(0.228)	-0.092*	(0.017)
ARWP Ratio	-0.090	(0.063)	-2.848	(1.856)	0.033	(0.102)
Winning to Bid Ratio	-0.168*	(0.029)	-0.531	(0.381)	-0.136*	(0.039)
Capacity Utilization	0.048*	(0.014)	-0.057	(0.252)	-0.012	(0.017)
After January 2000	-0.057*	(0.014)	-0.297	(0.176)	-0.071*	(0.014)
Log Real Value of Monthly Total of Engineering Estimates	-0.018	(0.010)	0.321*	(0.123)	0.011	(0.010)
Monthly Number of Projects per Firm	0.083	(0.059)	-1.700	(1.058)	-0.202*	(0.059)
Projects per Firm under the Simultaneous Auction Format	-0.138	(0.093)	-2.351	(1.550)	0.292*	(0.093)
Concentration Ratio	-0.013	(0.134)	-1.907	(2.913)	-0.209*	(0.092)
OKGBI	0.009*	(0.003)	-0.153*	(0.051)	0.013*	(0.003)
Number of Observations	1322		79		2941	
R-Squared	0.084		0.432		0.068	

Note: Project 1: asphalt; project 2: bank protection, shoulder work; Project 3: bridge work

Standard errors are in parenthesis.
Denotes 5% significance

Table 5.11: Relative Bid Regressions for Project Types

Independent Variable	(1) Project Type 4		(2) Project Type 5		(3) Project Type 6		(4) Project Type 7	
Constant	0.162	(0.368)	4.353	(2.215)	0.038	(0.810)	-0.870	(2.898)
Simultaneous Auction Format	0.017	(0.043)	0.065	(0.216)	-0.201	(0.133)	0.173	(0.278)
Bids in the Same Division	-0.010	(0.010)	-0.011	(0.047)	0.016	(0.023)	-0.049	(0.070)
Large Projects	-0.085*	(0.017)	-0.034	(0.052)	-0.111*	(0.037)	-0.177	(0.096)
Federal Projects	0.049*	(0.011)	-0.024	(0.048)	0.045	(0.038)	0.099	(0.092)
Log of Number of Bids	-0.072*	(0.014)	-0.062	(0.067)	-0.126*	(0.048)	-0.063	(0.122)
ARWP Ratio	0.010	(0.116)	-0.321	(0.392)	-0.238	(0.126)	0.204	(0.457)
Winning to Bid Ratio	-0.061	(0.036)	0.015	(0.129)	-0.152*	(0.065)	-0.196	(0.152)
Capacity Utilization	0.018	(0.013)	0.035	(0.093)	0.073*	(0.030)	0.011	(0.063)
After January 2000	-0.058*	(0.013)	-0.222*	(0.061)	0.052	(0.029)	0.010	(0.110)
Log Real Value of Monthly Total of Engineering Estimates	-0.019	(0.011)	-0.026	(0.062)	0.014	(0.018)	0.097	(0.073)
Monthly Number of Projects per Firm	-0.015	(0.049)	-0.111	(0.240)	0.028	(0.093)	-0.531	(0.438)
Projects per Firm under the Simultaneous Auction Format	-0.089	(0.076)	-0.100	(0.374)	0.205	(0.233)	-0.574	(0.530)
Concentration Ratio	-0.207*	(0.099)	0.202	(0.347)	-0.287	(0.192)	0.332	(0.450)
OKGBI	0.011*	(0.003)	-0.020	(0.016)	0.008	(0.006)	0.005	(0.022)
Number of Observations	992		149		546		211	
R-Squared	0.124		0.221		0.077		0.120	

Note: Project 4: Grading and drainage projects; Project 5: concrete and pavement projects; Project 6: Signals; Project 7: Miscellaneous work

Standard errors are in parenthesis.
* Denotes 5% significance

Chapter 6

Conclusions, Limitations and Further Research

6.1. Conclusions

This study investigates the impact of two key policy changes that were implemented by ODOT with respect to the procurement auctions in road construction contracts. The first policy change that occurred in January 2000 dealt with the release of the engineering cost estimate and is examined in chapter 3. The results of this study indicate a strong effect due to this policy change with a 0.066 decline in the overall relative bids and a 0.063 decline in the winning relative bid level. The decline in the overall bids implies an increase of competition among bidders, and the decline in the winning bid level implies a decrease in the procurement costs after the policy change. These results are further confirmed by the analysis conducted pooling Oklahoma and Texas samples. The results indicate that the decrease in bids in Oklahoma is significantly larger than the decrease in bids in Texas. These findings are consistent with the theories proposed by Milgrom and Weber (1982) and Goeree and Offerman (1999, 2003) and the existing experimental work by Kagel, Harstad and Levin (1987), Goeree and Offerman (2002) and Kagel and Levin (1986).

Chapter 4 investigates the impact of additional information revealed by ODOT from the auctions for projects that were not awarded in the first round. The impact of this information on bidding behavior in repeating auctions is examined. The results indicate that the information revealed after the first round has led to only a moderate decline in the overall bid level in the subsequent auctions. The effect of the information that was released on the variance of the bids is also weak.

Chapter 5 investigates the second policy change implemented by ODOT, namely, the change from the two-session auction format (sequential format) to the one-session auction format (simultaneous format). The results indicate a 3% decrease in the overall bids and in the winning bid level due to this change. Comparisons between bidder groups in the two auction formats find evidence of aggressive bidding among the bidders who bid on multiple projects with potentially high synergies after the policy change. Comparisons between high and low synergy groups within the same auction format provide some weak evidence of more aggressive bidding among the multiple bidders with high synergy.

6.2. Limitations of the Study

There are number of limitations contained in this dissertation. First, throughout this study, the firm capacity was approximated by the maximum backlog of a firm. This measure is not ideal because it does not control for firm growth in capacity or capture economic activity of the firm outside of road procurement. A more appropriate measure would be the firms' annual total revenue that includes activities outside of the road procurement. Unfortunately, such a measure is unavailable in the state procurement data.

In chapter 5, the comparison of the two auction formats has several limitations. First, the ODOT auctions are not conducted in a sequential auction format (before the change in auction format) as specified in the theoretical literature (one object after the other within a sufficiently short interval). Therefore, comparing sequential and simultaneous effects was limited to specific bidder groups. Second, in the case of multiple bids, both sequentially placed bids and simultaneously placed bids exist as mentioned earlier. As a result, it is not possible to isolate one or the other effect in multiple bid groups. In addition, the model in Krishna and Rosenthal (1996) uses a second-price sealed-bid mechanism while ODOT auctions use a first-price sealed-bid mechanism. Also Krishna and Rosenthal (1996) consider a private value model while the construction contracts are more appropriately classified under the affiliated value framework. This makes the link between the theory and the empirical test weaker.

6.3. Implications for Future Research

In the three essays of this study, the effect of the policy changes on bidders' participation decisions in auctions was not examined. This is important since it affects the number of bidders that participate in auctions and, thereby, the degree of competition in the auction. Investigating which policies favor more bidder participation would be useful in formulating future policies related to procurement auctions.

In order to consider high synergy in chapter 5, this study considered bids placed within the same ODOT field division by a given bidder. This could be further narrowed down to the county level in order to identify bids placed within the same county. It will eliminate the projects that are not within the same county from the high synergy group leading to a closer set of projects (relative to the projects within the same field division). This will refine the high synergy definition that might affect the results of this chapter.

The paper by Benoit and Krishna (2001) predicts that optimal sequential auction format generates higher seller revenue than the simultaneous auction format. Under the optimal sequential auction format they consider selling the more valuable object first. The order of sale could be investigated in ODOT auctions before April 2002. It would be interesting to investigate the patterns in order of sales in ODOT auctions and its effect on the procurement costs (seller's revenue). Future procurement policies can be tailored based on the understanding of these issues.

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