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ASYMMETRIES IN PROCUREMENT AUCTIONS

A Dissertation APPROVED FOR THE
DEPARTMENT OF ECONOMICS

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ABSTRACT

This study investigates bidder behavior in road construction procurement auctions held by the Oklahoma Department of Transportation (ODOT) in the period January 1997 to August 2000. The first essay, "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," deals with differences in bidding behavior between incumbent and entrant firms in procurement auctions. The study finds that entrants bid more aggressively and win auctions with significantly lower bids than do incumbents. As a result, the forgone surplus is greater for entrants than for incumbents. The differences in bidding patterns are consistent with an asymmetric model of auctions, in which the distribution of an entrant's costs exhibits greater dispersion than that of an incumbent. The characteristics of rival bidders also have an effect on bidding behavior. The tougher the average rival, the lower the bid and the lower the winning bid.

The second essay, "Sequential Bidding in Road Construction Auctions," investigates differences in bidding patterns between morning and afternoon auctions. Empirical evidence from construction contracts suggests that prices are not statistically different between morning and afternoon sessions and that there is no statistically significant difference in the probability of submitting a bid between winners and losers of morning auctions. In afternoon auctions, a large part of the adjustment in bidding behavior is induced by additional asymmetries that arise due to release of information about prices and bids in morning auctions. As expected, the more competitive the set of rivals a firm faces, the more aggressively it bids. Even though the difference in the probability of submitting a bid is not statistically

significant between winners and losers of early auctions, losers make a much larger adjustment in their afternoon bids relative to winners.

In the third essay, "Synergies in Recurring Procurement Auctions: An Empirical Investigation," I examine the impact of synergies on bidder behavior in recurring road construction procurement auctions. The projects are spatially correlated. When bidders with potential synergies participate, their probability of bidding and winning increases and they bid more aggressively. Further, firm efficiencies increase the probability of bidding and winning, as does the aggressiveness of bids. Finally, a firm that is capacity unconstrained will bid more aggressively than one that is capacity constrained.

CHAPTER I

INTRODUCTION

I.1. Auctions

Auctions have entered the economics literature relatively recently, although they have been an integral part of economic life for more than 2500 years.[1] McMillan (1994), Cramton (1997), Klemperer (1999), and Kagel and Levin (2001) identify the various organizations and contexts in which auctions play a predominant role today, including nontraditional commodities like radio spectrum licenses, electricity, and transport.

Vickrey (1961) first discussed the game-theoretic aspects of auctions and made enormous progress in analyzing them theoretically. However, only after the 1970s did the practical, empirical, and theoretical aspects of auctions begin to be studied in greater detail with critical contributions from Wilson (1977), Milgrom and Weber (1982a), Maskin and Riley (1984, 1985), and Samuelson (1986).

As Klemperer (1999), and Kagel and Levin (2001) point out, auctions are well-defined economic environments and can provide unique opportunities to test various economic theories, especially game theory, with incomplete information. Major empirical research efforts have focused on auctions for mineral rights, timber, and road construction. There has also been increasing interest in experimental work on auctions.[2] Chapter II of this study provides a more extensive theoretical and empirical literature review of auction research.

[1] See Cassady (1967) for a history of auctions.
[2] See Kagel and Roth (1995).

I.2. Importance of the Study

Theoretical and empirical economists have explored, to some extent, asymmetries due to collusion, differences in information, and capacity constraints. However, empirical studies have not examined bidder behavior due to asymmetries caused by differences in experience with a focus on entrants and incumbents. Further, researchers have not considered learning as it arises from the release of new information about winners and losers in a sequence of auctions, nor have they looked at synergies gained by winning multiple projects in road construction auctions. In my thesis, I empirically investigate the bidding behavior of firms due to these asymmetries using the Oklahoma Department of Transportation (ODOT) data on road construction project auctions. The data set utilized in this study allows for testing the validity of several existing theoretical predictions regarding rivals, firm efficiency, and capacity constraints. In short, this study will fill several gaps in the literature on asymmetric auctions by empirically testing several existing theoretical predictions.

Most of the theoretical literature on auctions has investigated bidding behavior in two polar cases, private-value and common-value models. Some researchers have considered asymmetries among bidders in models focusing on differences in private costs.[3] Other studies have investigated informational asymmetries in common-value auctions focusing on the value of information and the winner's curse.[4] One of the significant features of this study is the incorporation of informational asymmetries in a model that retains the basic theoretical structure introduced by Maskin and Riley (2000b) but makes sufficient modifications to allow for private and common value components.

[3] See Lebrun (1999) and Maskin and Riley (2000a, 2000b).
[4] See Milgrom and Weber (1982) and Engelbrecht-Wiggans et al (1983).

Then, using a non-structural estimation procedure, this model investigates those asymmetries caused by differences in experience. I consider, at one extreme, the group of least experienced bidders (entrants) and compare their behavior to that of bidders with some experience (incumbents). The third chapter shows that entrants behave differently from incumbents. We attribute their behavior to the fact that entrants lack bidding experience (a private-value component) and information about the auction process (a common-value component). Understanding bidding behavior under these circumstances is important as entry or the threat of entry can increase competition in auctions. Therefore, this chapter provides new insights into bidder behavior when bidders face asymmetries from private and common-value components.

The empirical literature on sequential auctions has focused mainly on the direction of expected prices. However, experience and learning have an important effect on these bidding patterns. Information that is released earlier auctions can significantly influence the behavior of bidders in subsequent auction sessions. In the fourth chapter, I examine bidding behavior due to asymmetries in relation to the sequential nature of auction markets. This type of bidder heterogeneity has not been addressed in auction research. I examine the effect of the release of information on bidder behavior in road construction auctions.

When considering recurring auctions, McMillan (1994) and Cramton (1997) point to two major issues: extraction of synergies between goods and more efficient distribution of goods. Theoretical studies have shown that, in recurring auctions, bidders trying to acquire multiple objects are more aggressive in their bidding than those bidding on single objects.[5] The empirical research on recurring procurement auctions shows that firms may experience geographic synergies when they win two or more adjacent projects and bidders trying to acquire multiple projects display more aggressive bidding behavior.[6] Further, studies have also shown that project location has a significant influence on bidding behavior.[7] Hence, in road construction contracts, asymmetries arise when firms win multiple projects or develop competitive advantages due to their familiarity with regional resource markets. The fifth chapter examines the effect of such synergies in road construction procurement auctions and empirically tests the predictions of Jeitschko and Wolfstetter's (2001) theory.

I.3. Objectives of the Study

In spite of a large number of empirical studies on auctions[8], there are still many gaps, especially when considering asymmetric auctions. The bidding behavior of new entrants, the sequential nature of auction settings, and synergies are some areas that empirical economists have not studied extensively. I, therefore, examine these types of asymmetries in procurement auctions. Bidder asymmetry is defined as follows: (1) *entrants*, firms submitting a bid for the first time, and *incumbents*, firms who have submitted at least one bid; (2) firms that have won in the morning session and firms that have lost in the morning session; and (3) firms with synergies[9] and firms with no

[5] See Krishna and Rosenthal (1995), Branco (1997), and Jeitschko and Wolfstetter (2001).
[6] See Gandal's (1997), Ausubel et al (1997), and Rusco and Walls (1999).
[7] See Porter and Zona (1999) and Bajari (2001).
[8] See Chapter II for a more comprehensive literature review.
[9] In this study, synergies are defined as economic advantages that bidders gain through complementarities associated with winning multiple projects in a particular geographic area.

competitive advantages[10]. Three separate essays present analyses of the bidding behavior of firms under the above circumstances.

I.4. Delimitation of the Study

Government contracts, like State of Oklahoma Department of Transportation's (ODOT) road construction contracts, are typically awarded through procurement auctions. This study uses ODOT data for auctions held from January 1997 to August 2000. These data are unique due to the variables they include such as plan-holder information, engineers' cost estimates, number of days to complete projects, locations of projects and firms, and winning firms and their locations, all of which are favorable to realize the objectives of this study.

I.5. Results of the Study

The third chapter, "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," deals with differences in bidding behavior between incumbent and entrant firms in procurement auctions.[11] The results indicate that entrants bid and win more aggressively compared to incumbents. As a result, entrants tend to leave more 'money on the table' compared to incumbents. Further, entrants' costs exhibit greater dispersion than incumbents' costs, a finding that is consistent with an asymmetric model of auctions. Finally, the results indicate that, when firms face tougher rivals, they tend to bid and win aggressively.

[10] A firm may have economic advantages (no competitive advantages) due to bidder's familiarity (lack of familiarity) with local market resources, and inherent firm efficiencies (inefficiencies).
[11] This chapter is based on the working paper entitled "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," written in collaboration with Timothy Dunne and Georgia Kosmopoulou.

The fourth chapter, "Sequential Bidding in Road Construction Auctions," investigates differences in bidding patterns between morning and afternoon auctions.[12] This chapter demonstrates that construction contract prices are not statistically different between morning and afternoon sessions and that there is no statistically significant difference in the probability of submitting a bid in the afternoon by morning winners and losers. Even though the difference in the probability of submitting a bid is not statistically significant between winners and losers of early auctions, losers make a much larger adjustment in their afternoon bids relative to winners. This bidding behavior is induced by the additional asymmetries that arise due to the release of information about prices and bids in morning auctions. Similar to the findings in the first essay, the second essay also suggests that firms tend to bid more aggressively when they face tougher rivals.

The fifth chapter, "Synergies in Recurring Procurement Auctions: An Empirical Investigation," empirically investigates the impact of synergies and competitive advantages (or no-advantages) on bidder behavior in recurring road construction procurement auctions. This chapter reveals that projects are spatially correlated. When bidders with synergies or competitive advantages participate in procurement auctions, their probability of bidding and winning increases and they bid more aggressively. Finally, the study shows that a firm that is capacity unconstrained will bid more aggressively than one that is capacity constrained.

[12] This chapter is based on the paper entitled "Sequential Bidding in Road Construction Auctions," written in collaboration with Timothy Dunne and Georgia Kosmopoulou that is forthcoming in Economics Letters

I.6. Organization of the Study

Chapter II presents a summary of the existing theoretical and empirical literature pertaining to auctions. Chapter III presents the first essay, "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions." Chapter IV presents the second essay, "Sequential Bidding in Road Construction Auctions." The third essay, "Synergies in Recurring Procurement Auctions: An Empirical Investigation," is presented in Chapter V. Finally, Chapter VI lays out a summary of the study and suggests possible extensions of this line of research. In the next chapter, I summarize the theoretical and empirical literature pertaining to this study.

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CHAPTER II

AUCTION LITERATURE

II.1. Introduction

This chapter provides an overview of the landmark theoretical and empirical studies of auctions with a focus on the bidding behavior due to asymmetries. Section II.2 introduces the standard types of auctions that provide the conceptual background for this study. Section II.3 describes the basic models of auctions on which auction research is based. Section II.4 outlines the theoretical literature, and Section II.5 examines the empirical literature on auctions.

II.2. Standard Auction Types

There are four basic types of auctions: 1) ascending-bid auctions, also called open, oral, or English auctions; 2) descending-bid auctions, also called Dutch auctions; 3) first-price sealed-bid auctions; and 4) second-price sealed-bid auctions. What follows is a description of their rules in terms of single-object auctions. McAfee and McMillan (1987) discuss these rules in greater detail.

In English auctions, the price is raised until a single bidder remains. In these auctions, the seller may announce the prices, the bidders may call out prices themselves, or bids may be submitted electronically with the highest current bid posted (e-Bay auctions). In Dutch auctions (used to sell flowers for export in the Netherlands), an auctioneer initially calls for a very high price and then continuously lowers it until a bidder stops the auction and claims the object for that price. In first-price sealed-bid auctions, each bidder independently submits a single bid without observing others' bids.

The object is sold to the bidder who makes the highest bid. In procurement auctions, however, the lowest bidder wins the object. In second-price sealed-bid auctions, commonly called Vickery auctions after the theorist who first analyzed them in 1961, the highest bidder claims the object but pays only the amount of the second-highest bid.

II.3. Basic Models of Auctions

Information is a crucial element of auction theory (Klemperer 1999). Each player's best strategy is a function of his own information, and he tries to maximize his payoff conditional upon other players' strategies and his beliefs about their information. Accordingly, the Bayesian-Nash equilibrium is best suited to such theory. Depending upon the information gathering process of bidders, there are two polar cases: private-value[13] and common-value auctions.[14]

In most auctions, there are both private-value and common-value components. For example, bidders for antiques may want to buy them for their own pleasure (a private-value element) but they may also bid for investment and eventual resale (a common-value element) (Milgrom and Weber 1982a). Therefore, analyzing these auctions becomes somewhat complicated even though they are well-defined economic environments. Hence, when analyzing auctions, theorists tend to emphasize these polar cases for ease in exposition.

[13] In private-value models, every bidder values the object privately and independently of other bidders.
[14] In common-value models, the value of the object is same for all bidders but they are unaware of its actual value when preparing to submit bids. A key feature of common-value auctions is the possibility of "winner's curse." Another bidder's information may help a bidder to determine more accurately the value of the object being auctioned. This information can be 'good' or 'bad' and the individual who wins the auction often does not take into account the fact that winning implies that he has the most optimistic estimate and, as a result, faces winner's curse.

II.4. Theoretical Literature

This section outlines some of the theoretical literature on auctions that form the theoretical framework for this study, particularly those concepts that impinge upon bidder behavior contingent upon asymmetries. First, asymmetric information models with private values are outlined. Then, common-value auction models are described in terms of asymmetries. Finally, recurring auction models are considered.

Private-Value Models

The literature on asymmetries in private-value auctions is considerably smaller than that on symmetric auctions. Recently, Lebrun (1999) and Maskin and Riley (2000a, 2000b) have shown that differences in private costs will shape the bidding distribution function. Maskin and Riley (2000b) say that these cost asymmetries can arise due to different technologies and managerial efficiencies. They define 'strong' bidders as those who are very efficient, and 'weak' bidders as those who are less efficient. To be more precise, the cost distribution of a strong bidder is skewed to the right relative to that of the weak bidder. They show that, in this case, a bidder of any kind who faces a 'strong' bidder tends to bid more aggressively and, when facing a 'weak' bidder, tends to bid less aggressively.

Common-Value Models

Milgrom and Weber (1982a) show that, in common value models, a bidder's expected profit depends more on the privacy of his information than on its accuracy. Moreover, even if a bidder makes unbiased estimates of the true value of an object, the winner will find that he faces the winner's curse. In common-value auctions with an infinite number of bidders, the price will converge to the true value of the object

(Klemperer 1999). Further, Milgrom and Weber (1982a) and Engelbrecht-Wiggans, Milgrom, and Weber (1983) consider informational asymmetries in a common-value auctions setting and show that 'informed' bidders are less likely to face the winner's curse.

Levin and Smith (1994) show that, when considering endogenous entry with symmetric information, a seller should charge an entry fee or a reservation price (socially optimal) to maximize revenues. Chakraborty and Kosmopoulou (2001) consider endogenous entry with asymmetric information (unlike Levin and Smith's results) and argue that social planners should not discourage entry.

Recurring Auctions

Equilibrium models of recurring auctions have appeared in the literature only recently. Two concerns in recurring auctions are bidders' extraction of synergies between goods and enhanced efficiency in the distribution of goods (McMillan, 1994 and Cramton, 1997). Motivated by these concerns, Krishna and Rosenthal (1995) and Branco (1997) show that, in recurring auctions, bundle bidders who bid on multiple objects bid more aggressively than unit bidders who bid on a single object. Jeitschko and Wolfstetter (2001) have described the bidding behavior in first-price sealed-bid ascending recurring auctions. They show that previous winners may experience synergies in subsequent auctions. These auctions can also be viewed as a special case of affiliated auctions since bids may be correlated due to synergies and recurrence.

II.5. Empirical Literature

In this section, some asymmetric empirical studies are presented. The results of asymmetric private-value auctions and asymmetric common-value auctions are discussed. Some of the empirical results on road construction procurement auctions and recurring auctions are also considered.

Asymmetric Independent Private-Value Models

Considering asymmetric empirical independent private-value models, Meyer (1993) performed an experiment and found that market size is inversely related to the size of the entry fee, and that agents enter the auction until the average profitability equals or is less than the entry fee. Maskin and Riley (2000b) have provided examples to show that, with asymmetry, revenue equivalence no longer holds and that, under different assumptions about the nature of the heterogeneity, expected revenue in high-bid auctions might be higher or lower than in open auctions. Engelbrecht-Wiggans and Kahn (1998) have presented evidence of declining price patterns from data on cattle auctions. They have shown that prices decline over the course of the auction, with the steepest decline toward the end. These results are consistent with a simple model of sequential auctions of goods with independent private values.

Asymmetric Common-Value Models

Considering asymmetric empirical common-value models, Hendricks et al (1987), using data from federal auctions of drainage leases on the Outer Continental Shelf (OCS), examined asymmetries caused by differing levels of information, competition, and profits, and the validity of existing theoretical predictions of Wilson (1977), Weverbergh (1979), and Englebercht-Wiggans, Milgrom, and Weber (1983). They have shown that competition increases with an increase in the number of bidders, that profits were higher on tracts won by informed bidders and that uninformed bidders tend to face the winner's curse. Hendricks and Porter (1988), using OCS data, found that neighboring firms had better information about the value of an oil-lease than non-neighboring firms. Further, they showed that both types of firms bid strategically in accordance with the Bayesian-Nash equilibrium. One of their key findings was that neighbors and non-neighbors had different means but the same variances in their cost distributions.[15]

Kagel and Levin (1999) investigated common-value auctions with bidders having access to insider information. Each experimental session consisted of a series of auctions in which the highest bidder received a single unit of a commodity. They found that the presence of an insider or informed bidder does not preclude the winner's curse compared to symmetric common-value auctions. In contrast, the behavior of experienced bidders, who have largely overcome the winner's curse, fits the theoretical predictions of equilibrium bidding theory, namely: 1) average seller's revenue is larger with an informed bidder or insider than in symmetric information structure auctions; 2) insiders make greater profits, conditional on winning, than uninformed bidders or outsiders; and 3) insiders increase their bids in response to more rivals.

Many empirical studies have assumed the number of bidders exogenous to the model. Entry is typically endogenous and, for many auctions, the actual number of participants is neither known ex ante nor deterministic. Further, many bidders incur costs when submitting bids due to acquisition of private information and bid preparation. McAfee and Vincent (1992) addressed this problem in their study of US offshore oil auctions. They assumed an asymmetric information common-value model with endogenous entry and constructed a non-structural model that enabled them to calculate the optimal reservation price.

[15] Hendricks et al (1999) using OCS data show that the existence of winner's curse and that the bidders are aware of its presence and bids accordingly. In this study they assume a symmetric common value model.

Paarsch (1997) also recognized the importance of accounting for endogenous entry. He took great care to identify the set of potential bidders in a timber sale auction. He accounted for the cost of those who did not bid because they found the reservation price too high. Further, Bajari and Hortacsu (2000) studied the features of online bidding and selling behavior by using a data set consisting of e-Bay coin auctions. They also used a common-values model with endogenous entry. They found that bidders' expected profits decrease as the number of bidders increase and entry cost is a key feature in understanding observed bidding patterns.

Road Construction Procurement Auctions

When considering road construction procurement auctions, Porter and Zona (1993, 1999) examined bidding in auctions for state highway construction contracts to determine the occurrence of bid rigging. They proposed a multinomial logit model to detect the presence of such rigging on the basis of which they found that there was evidence of collusion and cartel activity.

In an earlier study, Feinstein et al (1985) looked at the cartel behavior of highway contractors in North Carolina. They assumed that costs were stochastic and projects awarded in adjacent periods were substitutes for one another. The empirical evidence suggested that cartels do, in fact, attempt to misinform purchasers in addition to raising the minimum bid on specific projects.

Thiel (1988), examining auctions of highway construction contracts by state governments, found no evidence of the winner's curse. He assumed that the state engineer's estimated cost of fulfilling the contract is an unbiased estimate of the true value. However, Levin and Smith (1991) showed that Thiel's equilibrium bidding strategies were mis-specified and that the results were not reliable.

Deltas (1996) examined highway construction contracts in the State of Connecticut. He applied a structural estimation procedure to show that the lognormal distribution is a better approximation to the distribution of contractor costs as compared to a uniform distribution or exponential distributions.

Jofre-Bonet and Pesendorfer (1999), using a similar two-stage approach as that of Elyakime et al (1994) and Guerre et al (2000), investigated bidding behavior in highway procurement contracts in California. In the first stage, they estimated the beliefs of bidders concerning the bids of other bidders. The estimate included bidder asymmetry, contract characteristics, and state variables. In the second stage, they inferred privately known costs using a structural relationship. Based on the model, they estimated cost parameters and examined equilibrium bid functions. They found that bidders that have large fractions of their capacity committed have, on average, a higher cost than bidders with little capacity committed. When all bidders are capacity constrained, the resulting low bid is higher than when all bidders are unconstrained.

Recurring Procurement Auctions

Empirical research on recurring procurement auctions with synergies is scarce. Gandal (1997)[16] and Ausubel et al (1997)[17] show that there are geographic synergies associated with winning multiple adjacent projects. Rusco and Walls (1999) show that, in repeated spatially correlated timber auctions, bidders bidding in multiple projects bid

[16] This study investigates the Israeli CATV licenses.
[17] This study investigates the existence of synergies in broadband personal communication service spectrum (PCS) auctions in United States.

more aggressively. Further, Porter and Zona (1999) and Bajari (2001),[18] have also shown that location plays a major role in a firm's bidding behavior.

II.6. Conclusion

This chapter has presented some of the crucial findings in the existing theoretical and empirical literature on auctions. Empirical studies have investigated asymmetries due to information, capacity constraints, collusion, and geographic advantages.

[18] This study investigates the bidding by highway construction firms for procurement contracts in California.

CHAPTER III

AN EMPIRICAL ANALYSIS OF ENTRANT AND INCUMBENT BIDDING IN ROAD CONSTRUCTION AUCTIONS

III.1. Introduction

This chapter compares the bidding patterns of entrant and incumbent firms in road construction auctions held by ODOT between January 1997 and August 2000. In any market, entrants or the threat of entry should act to increase competition. The benefits of competition can be even greater in procurement auctions where, in practice, there is a considerable history of collusion.[19] Larger participation can substantially reduce the returns of any bidding ring. However, entering firms may be at a significant disadvantage relative to incumbents in these auctions. Entrants may face higher uncertainty in the development of a bid as they lack bidding and production experience. They may also have access to less information than incumbent bidders regarding the pricing and cost of various bid components. Such asymmetries have not been studied empirically.

The theoretical literature on asymmetric auctions has explored aspects of bidding behavior in common- and private-value models. The earlier work of Milgrom and Weber (1982a) and Engelbrecht-Wiggans et al (1983) considers informational asymmetries in a common-value setting with emphasis on the value of information and the winner's curse. Recently, Marshall et al (1995), Lebrun (1999), and Maskin and Riley (2000a, 2000b) explore properties of bidding distributions focusing on differences in private costs that shape the form of the distribution function. Since there is little theoretical work on asymmetric auction models relative to their symmetric counterparts, some key results from this literature are presented. Then, concentrating on the behavior of entrants and incumbents in auctions, differences in the bidding distributions, through a model that introduces common- and private-cost components, are identified. The framework accommodates informational asymmetries due to a differential level of experience and efficiency and provides some explanation for the observed patterns.

In a common-value framework, Milgrom and Weber (1982b) show that the larger the informational gap that is known to exist among bidders, the more severe the problem of the winner's curse. Engelbrecht-Wiggans et al (1983) analyze a setting in which a bidder has private information about the common value of an object that is not available to the rest of the bidders. In a private-value framework, Lebrun (1999) and Maskin and Riley (2000a, 2000b) concentrate on asymmetries that could arise as a result of differences in private costs. These asymmetries can create advantages likely to justify stochastic dominance in the distribution of values. Empirical evidence supporting these theoretical results is presented. However, differences that are due to experience with emphasis on the behavior of entrants are emphasized. The distribution of cost estimates of an entrant, as a firm with no experience, exhibits a larger dispersion and is unlikely to preserve the property of stochastic dominance for all possible values. Nevertheless, if the property of stochastic dominance still holds for low values of the cost, the frequency of low bids will be larger for entrants than for incumbents.

The empirical literature on asymmetries in auctions has separately explored differences in information available to bidders and differences in private costs.

[19] See, for example, the work by Porter and Zona (1993) and Bajari (2000) for analyses of bid-rigging and collusive behavior in procurement auctions.

Hendricks and Porter (1988) examine the role of asymmetric information among bidders in Outer Continental Shelf (OCS) drainage lease auctions. They find that informed bidders (bidders that neighbor a particular tract) earn higher profits in drainage lease auctions and interpret their findings as being in concordance with predictions of models of common-value auctions with asymmetric information. A more recent paper by Jofre-Bonet and Pesendorfer (1999, 2000) examines asymmetries in bidding behavior for highway procurement contracts in California. This work focuses on asymmetries in costs due to differences in backlogs. They find that bidders that have large fractions of their capacity committed have, on average, higher cost than bidders with little committed capacity. When all bidders are capacity constrained, the resulting low bid is higher than that when all bidders are unconstrained. In both cases, asymmetries lead to differences in bidding behavior across firms and lead to differences in auction outcomes.

In this study, asymmetries between incumbent bidders and entrant bidders are examined. Entrant bidders can differ from incumbent bidders in a number of respects. Entrants may have less experience than incumbent bidders in production. They may be less certain of their own costs for completing a given project than incumbents, or they may have less information about the procurement auction process. Alternatively, incumbents facing entrants may be faced with a potential bidder they know little about and, hence, incumbent bidding may be influenced by the presence of entrants. This essay documents differences in the bidding patterns and the winning bids between entrants and incumbents. The results reveal that entrants generally bid more aggressively than incumbent bidders and win auctions with significantly lower bids than incumbents. Moreover, when entrants win auctions, they have a tendency to leave more money on the table than incumbents. That is, the difference between the winning bid and the second lowest bid is, on average, greater when an entrant wins an auction than when an incumbent does. Finally, our data provides an opportunity to test some of the theoretical claims by Maskin and Riley (2000b) and reveals that bidders who face tougher rivals (rivals with proven past wins) bid more aggressively and, generally, win with a lower bid.

The remainder of the chapter is organized as follows. Section III.2 describes the modeling framework. Section III.3 provides a description of the data, while Section III.4 reports the results. Section III.5 provides some summary comments.

III.2. Modeling Framework

Consider a first-price sealed bid auction in which two risk neutral bidders[20] compete for a government contract. The cost of the contract (c_i) to bidder i is drawn from a known distribution (F_i) with support $[c_L, c_H]$. F_i is twice continuously differentiable and has a density (f_i) that is strictly positive on the support. Each firm chooses a bid (b) to maximize its expected profit

$$\pi_i(b, c_i) = (b - c_i)(1 - F_j(b_j^{-1}(b)),$$

where $b_j^{-1}(b)$ is j's inverse bid function. LeBrun (1999) and Maskin and Riley (2000a, 2000b) have shown[21] that, when bidder types are distributed independently, in equilibrium the bid functions are increasing and differentiable so that, for each firm i, an inverse exists and is differentiable. Thereafter, in this study let $b_i^{-1}(b) = \phi_i(b)$.

[20] In this chapter, we differentiate between groups of bidders with emphasis on entrants and incumbents. That is why the simplifying assumption of two bidders (which one can think of as two groups of bidders) is appropriate.

[21] Their results are describing a framework in which the bidder with the highest value wins the auction. We are making here the appropriate changes in the objective function and the conclusions to fit the framework of construction contracts.

The equilibrium to this model can be characterized as the solution to a system of differential equations with boundary conditions. This solution is unique and constitutes a pair of inverse bid functions. In particular, for each i ($i \neq j$):

$$\frac{f_j(\phi_j(b))}{1-F_j(\phi_j(b))}\phi_j'(b) = \frac{1}{[b-\phi_i(b)]} \tag{III.1}$$

where every $\phi_i(b)$ is evaluated at b for all b in $[b_*, b^*]$. These differential equations should satisfy the following boundary conditions:

$$F_j(\phi_j(b_*)) = 0,$$
$$b^* = \phi_j(c_H) \ \forall \ j. \tag{III.2}$$

If the distribution of private costs of one bidder stochastically dominates the distribution of private costs of the other, then bidding carries the qualitative properties of the results in Maskin and Riley (2000b). Notice that a distribution (F_j *first order*) stochastically dominates another distribution (F_i) if and only if $F_i(c) \geq F_j(c)$ for all values of the cost (c). Stochastic dominance is likely in an environment in which the opportunity cost of completing a project is different for various contractors. This opportunity cost depends partially on the technology available and the level of managerial efficiency. Maskin and Riley show (in their Proposition 3.3) that, if the distribution of private costs of a "weak" bidder stochastically dominates the distribution of private costs of a "strong" bidder[22], the equilibrium bid distribution of a weak bidder stochastically dominates that of a strong bidder. Proposition 3.5 of the same paper establishes that: 1) a strong bidder will submit a bid that is further above his cost compared to a weak bidder, 2) if a weak bidder faces a strong bidder rather than another

[22] Evidence of strength can be provided by looking at the ratio of past wins relative to the number of bids submitted.

weak bidder, he will bid more aggressively (closer to his true valuation), and symmetrically, and 3) if a strong bidder faces a weak bidder rather than another strong bidder he will bid less aggressively[23]. In Section III.4, empirical evidence is provided that is consistent with some of these predictions, using two measures of strength. The one is a measure of toughness that captures the efficiency of opponents, and the other is a measure that captures a firm's own efficiency. The regression results presented in Table 3 indicate that bidders who face stronger opponents bid more aggressively, on average, as Maskin and Riley (2000b) suggest in Proposition 3.5. They also provide some evidence to support Proposition 3.3: more efficient firms bid more aggressively on average.

These results can be generalized to create a more realistic model in which the cost of the contract (c_i) to bidder i exhibits both private and common value characteristics. When bidders receive multiple signals, they must combine different pieces of information into a summary statistic. With a few exceptions, auction theory has restricted attention to cases were private information has one dimension. Consideration of multidimensional types poses substantial technical difficulties with the most important being the establishment of existence at some level of generality. At the core of this problem is the ability to order signals in multiple dimensions. One environment in which this study can provide a solution is the following: Suppose that bidder i makes an estimate of his private cost (t_i) and receives a signal (s_i) which is an unbiased estimate of the common cost (S). The estimates of the private cost and the signals of the common cost are independently distributed across bidders. Let $c_i=\alpha s_i+t_i+(1-\alpha)\Sigma_j\, s_j/(n-1)$ be the total estimated cost of a

[23] Proposition 3.3, in fact, also establishes that when an inexperienced bidder faces an experienced bidder rather than another inexperienced bidder he responds with a more aggressive bidding distribution in the sense of stochastic dominance, and symmetrically, when an experienced bidder faces an inexperienced bidder rather than another experienced bidder he responds with a less aggressive bid distribution.

contract to bidder i,[24] where α is a way to parameterize the degree of uncertainty that a bidder faces in the calculation of the common cost. The parameter α is common knowledge to all bidders. In a purely private-value model, $\alpha = 1$. In an affiliated environment, in which bidders symmetrically view the common component, $\alpha = 0$. In order to ensure monotonicity and existence within this framework, one must assume that the densities of the t_i's and the s_i's are log-concave.[25] Goeree and Offerman (1999) derived the equilibrium bidding functions in the symmetric case. The appendix extends this analysis to asymmetric auctions. This study derives a pair of inverse bid functions similar to (1), with the only difference being that F_i is now the distribution of the combined signal ($\alpha\, s_i + t_i$) that bidder i receives. The result that follows can thus be established in this more general framework.

III.3. Characterization of the Equilibrium Bid Distribution of Entrants and Incumbents

This section addresses the influence of the lack of bid-placing experience on the behavior of entrants (bidders with no prior bidding experience). The distribution of cost estimates for entrant firms is expected to exhibit a much greater dispersion, on average, relative to that of incumbents, reflecting an increased uncertainty caused by the lack of experience and greater variation in managerial efficiency. As a result, it may not satisfy stochastic dominance for every value of cost, and the characterization of relative bids by Maskin and Riley (2000b) may no longer apply. In such an environment, it is not possible to establish differences in bidding patterns that do not depend upon the parameters of the distributions of cost estimates. Nevertheless, the stochastic relation

[24] For more details on this modeling framework and a discussion of its advantages see Bikhchandani and Riley (1991), Alberts and Harstad (1991), Vincent (1995), Klemperer (1998), Bulow, Huang and Klemperer (1999), and Goeree and Offerman (1999).

among distributions for low values of the estimated cost could enable predictions of bidding patterns at the low end of the distribution. The following proposition shows that, if the distribution of cost estimates of entrants stochastically dominates that of incumbents, entrants will bid more aggressively relative to their cost estimates than incumbents in the neighborhood of $b_\bullet$ and vice versa. If the distribution of estimates of incumbents stochastically dominates that of entrants, incumbents will bid more aggressively relative to their cost estimates.

Proposition: If $f_E(\phi_I(b_\bullet)) < f_I(\phi_I(b_\bullet))$ then $\phi_E(b) > \phi_I(b)$ for any $b \in [b_\bullet, b_\bullet+\epsilon]$. Conversely, if $f_E(\phi_I(b_\bullet)) > f_I(\phi_I(b_\bullet))$ then $\phi_E(b) < \phi_I(b)$ for any $b \in [b_\bullet, b_\bullet+\epsilon]$.

Proof: This study will first prove that if $f_E(\phi_I(b_\bullet)) < f_I(\phi_I(b_\bullet))$ then $\phi_E(b) > \phi_I(b)$ for any $b \in [b_\bullet, b_\bullet+\epsilon]$. Since the lower bound of the distribution is the same for both bidders, $\phi_I(b_\bullet) = \phi_E(b_\bullet)$. Further, $f_E(\phi_I(b_\bullet)) < f_I(\phi_I(b_\bullet))$ implies that $F_E(x) < F_I(x)$ in the right neighborhood of $\phi_I(b_\bullet)$.

From the equilibrium condition:

$$\frac{f_E(\phi_E(b_\bullet))}{1-F_E(\phi_E(b_\bullet))}\phi_E'(b_\bullet) = \frac{1}{b_\bullet - \phi_I(b_\bullet)} = \frac{1}{b_\bullet - \phi_E(b_\bullet)} = \phi_I'(b_\bullet)\frac{f_I(\phi_I(b_\bullet))}{1-F_I(\phi_I(b_\bullet))}. \qquad \text{(III.3)}$$

It follows from (2) and (3) that $\phi_I'(b_\bullet) < \phi_E'(b_\bullet)$. Therefore, in the neighborhood of $b_\bullet$, $\phi_I(b) < \phi_E(b)$. The second part of the statement can be proved following similar arguments. *QED*

The greater uncertainty an entrant faces in practice, when he estimates the cost, implies that an incumbent's distribution of estimates stochastically dominates that of an entrant's estimates for low values. Taking into account the differences among the estimated distributions of costs in the two groups, an incumbent with a low estimate of

[25] Many commonly used densities such as the uniform, normal, chi-square and exponential densities satisfy this

the cost will bid more aggressively than an entrant. Strategic considerations of incumbents will induce more aggressive bidding relative to their estimate, to compensate for the anticipated behavior of entrants. However, aggressive bidding relative to one's cost estimate does not imply necessarily aggressive bidding relative to the engineering estimate. In fact, since $\phi_I(b_*) = \phi_E(b_*)$ and $f_E(\phi_I(b_*)) > f_I(\phi_I(b_*))$, it follows by continuity that, in the neighborhood of b_*, the distribution of bids of entrants stochastically dominates that of incumbents.[26] In other words, due to larger dispersion in the estimates, entrants will bid more aggressively relative to the engineering estimates. If $F_E(x)$ is much larger than $F_I(x)$ around c_L, the occurrence of low bids (for example in the lowest 10th or 25th percentile of all bids) is expected to be much greater for entrants than for incumbents and entrants will face more of the winner's curse.

More experienced bidders, on the other hand, are expected to be less uncertain about their costs and more efficient on average. There are two reasons why they should be more efficient. First, subcontractors tend to make different deals with different bidders and experience seems to be a natural instrument for differentiation. Second, the bidders that continue to bid in the long run are likely to be the most efficient, on average. However, since the variance of the distribution of estimated values as well as the level of efficiency are expected to differ among bidders with different levels of bidding experience, there is still more ambiguity as to the stochastic relation across distributions of the estimated costs for those bidders. Empirical observations on the behavior of firms with varied levels of experience conform to these expectations. The average bids are not monotonically decreasing in the level of experience.

assumption.

III.4. Data

The data used in our analysis comes from ODOT and contains information on all road construction projects offered for bid letting by the State of Oklahoma from January 1997 to August 2000. These projects include road construction and paving projects, traffic signal projects, bridge construction and maintenance projects, as well as smaller drainage and clearance type projects.[27] Projects are auctioned off on a monthly basis and the state uses a sealed-bid auction where the lowest bid is awarded the contract. The state may reject the lowest bid when it is 7% above the state's engineering cost estimate for the project.[28] For most projects, individual bidders must be pre-qualified. Pre-qualification involves the submission of certified financial statements to ODOT. The pre-qualification process determines the size of the projects a firm can bid on and is related to the level of working capital available to the firm and its past success rate in completing projects. Firms can be removed from the pre-qualification list if they fail to complete contracts successfully. Finally, bidders must include a payment of 5% of the value of the project on submission of the bid.[29]

The above auction data includes information on the identity of the firms that purchase plans for a project—the "plan-holders", the identity and the bids of all bidders for a project, and the winning bid (if the contract is awarded). Hence, this study has information on the set of firms considering making a bid, the bidders, and the winner for each project. Further, the state provides the location of each project, a description of the

[26] Maskin and Riley (2000b) have shown that this is true if the stochastic relation is extended to the entire support of types.

[27] Highway construction auctions have been examined in a number of papers including Thiel (1988), Porter and Zona (1993), Jofre-Bonet and Pesendorfer (1999) and Bajari (2000).

[28] There have been some exceptions to this rule mostly due to underestimation of the cost by the state.

project (e.g., bridge construction, asphalt paving, etc.), the details of the project (e.g., the length and depth of the paving surface, the type of asphalt or concrete product to utilize, the amount of excavation, etc.), the duration of the project (calendar days), and the engineering estimate of the project's total cost. Table 1 provides summary statistics on the number of auctions, the average number of plan-holders per auction, and the average number of bidders per auction. During the period of analysis, there were 1736 auctions with an average of 5.7 plan-holders and 3.3 bidders per auction. Of the 1736 auctions, 1411 were awarded contracts. A total of 284 different firms held plans while 218 firms bid on projects and 144 different firms won contracts.[30]

A specific definition of entry is used to distinguish between entering and incumbent firms. This study divides the sample of auctions into two periods—January 1997 to June 1998, and July 1998 to August 2000. The first period is used to identify incumbent bidders. Any firm that bids during the period January 1997 through June 1998 is considered an incumbent during the July 1998 to August 2000 period. A firm bidding for the first time in the July 1998 to August 2000 period is considered an entrant. If that firm bids again in the August 1998 to August 2000 period, it is classified as incumbent.[31] The third column of Table 1 reports auction statistics for the period July 1998 through August 2000. This sub-sample is comprised of 952 auctions. There were 5.7 plan-holders and about 3.2 bidders on average in each auction. Thus, the bidding statistics look quite similar in the sub-sample as compared to the overall period. Entrants make up

[29] In general, these requirements establish some barriers to entry for new firms. Firms must have sufficient liquidity to post a bond, they must provide audited financial accounts and they are limited to bidding on certain size projects based on their working capital.
[30] There are several firms in our data sets that purchase plans, bid and win frequently. The maximum number of bids we observe by one firm is 219 and the maximum number of wins by a firm is 60 wins.
[31] We verified the robustness of our results to the choice of entry threshold by dividing the time period in a different fashion. We defined as incumbent any firm that appeared in 1997 or 1998 and defined entrants in the 1999-2000 time period. The results that follow are consistent across both definitions.

a relatively small number of plan-holders and bidders. Of the 5427 plans purchased in that period, entrants (who eventually submitted 71 bids) purchased only 185. However, the number of auctions with entrants is somewhat higher: out of the 952 auctions under study, 140 contain entrants.

Figure 1 presents the bids (normalized by the project engineering cost estimates) of entrants versus incumbent bidders.[32] A low relative bid represents an aggressive bid in this figure. The mean relative bid across all auctions in the period July 1998 to August 2000 is 1.118. Figure 1 shows that entrants place more aggressive relative bids than incumbents. This is particularly true at the lower tail of the distribution. The picture suggests that greater variation in managerial efficiency and increased uncertainty caused by the lack of experience of entrants can increase the likelihood of low bids. While Figure 1 suggests that entrants place a larger number of low bids, this finding should be interpreted cautiously because there are, as yet, no controls for differences in project types, the numbers of competitors, or the characteristics of rivals faced by bidders. The next section presents some basic regression models that have been used to describe the differences between entrant and incumbent bidders more fully.

III.5. Empirical Analysis

This section presents differences in bidding between entrants and incumbents. As discussed previously, the distribution of entrants' bids may be considerably more dispersed than those of incumbents due to the higher level of uncertainty that entrants face. This may influence entrants, vis-à-vis incumbents, in two ways. First, greater uncertainty may result in entrants winning some auctions with very low bids (i.e., very aggressive bids). Second, greater uncertainty may result in some entrant winners leaving more money on the table. In both cases, entrants may incur greater losses because they have greater uncertainty regarding the costs of carrying out a specific project. Alternatively, it is not clear how average entrant bids will differ from incumbent bids. These issues are examined below with a simple reduced-form model of bidding in a procurement auction. The basic structure of the regression model is as follows

$$\begin{aligned} y_i &= \beta_0 + \sum_{j=1}^{6} \beta_j \mathrm{P}_{ji} + \beta_7 \log(engest_i) + \beta_8 \log(\#bidders_i) \\ &\quad + \beta_9 Entry_i + \beta_{10} WB_i + \beta_{11} IB_i + \beta_{12} ARWP_i + \varepsilon_i . \end{aligned} \tag{III.4}$$

Three dependent variables that summarize the bidding patterns in these auctions are studied: 1) log of the bid, 2) log of the winning bid, and 3) the money left on the table. Two different measures of the money left on the table are employed. In the first instance, the money left on the table variable is measured as the proportional difference between the lowest and the second lowest bid when there are multiple bidders. In the case of a single bidder, the money left on the table variable is constructed as the proportional difference between the winning bid and the reserve price. In the second case, this study constructs the money left on the table variable as the lesser of the difference between the lowest and second lowest bid or the lowest bid and the reserve price. The reserve price is constructed based on the state's reserve rule that sets the reserve at 7% above the engineering cost estimate.

The independent variables include controls for project characteristics (P_j's and log(engest)), the number of bidders (log(#bidders)), the characteristics of the bidders

[32] Figure 2 presents a kernel density distributions of relative bids for two groups of bidders. The bidders with the least experience (lowest quartile) are compared to the bidders with the most experience (upper quartile of experience).

(Entry and WB), and the characteristics of the rivals in each auction (IB and ARWP). The project characteristics include the state's estimate of the engineering cost (log(engest)) and a set of dummy variables for project types (P_j's). The engineering cost estimates are constructed by the state by pricing each feature outlined in the design and then deriving an overall cost estimate for the project. A set of six dummy variables are used to control for broad classes of project types—asphalt paving, clearance and bank protection, bridge work, grading and draining, concrete work, signals and lighting. The omitted group is miscellaneous work such as intersection modification, parking lots, and landscaping. While the engineering cost estimate should control for project-specific differences in cost, certain project classes have different pre-qualification standards. Hence, the pool of potential bidders may differ somewhat across project types.

With respect to information on the level of competitiveness in an auction, three variables are used to measure competition. First, as is standard in the auction literature, the study controls for the number of bidders (log(#bidders)). Second, past information on rivals' bidding success is used to summarize the competitiveness of the potential set of rivals (ARWP). The information in the plan-holder list helps identify the rivals for a particular auction. Recall that a bidder must be a plan-holder in order to participate in an auction and the plan-holder list is made available to all potential bidders prior to the auction. The measure of rivals' past average success in auctions is constructed as the average across rivals of the ratio of past wins to past number of plans held. This variable incorporates two aspects of past rival bidding behavior: the probability of a rival bidding given it is a plan-holder, and the probability of a rival winning an auction given that it bids. Third, a dummy variable (IB) is included in the regression when an entrant is present in the auction and, thus, the rival information on past winning and bidding information is incomplete. The dummy is set equal to one when a bidder faces an entrant in an auction.

With respect to bidders' own characteristics, two measures are included in the regressions. In order to distinguish entrants from incumbents, a dummy variable (1=entrant, 0=incumbent) is included. In addition to the entrant-incumbent variable, a variable is included that accounts for past success in auctions (WB): the ratio of the past number of wins to the past number of bids. This variable provides information on the previous bidding success of a firm and is included to control for differences in efficiencies across producers.

The data samples vary across the dependent variables. To examine the bids, all bidders' data for all auctions between July 1998 and August 2000 (where a contract was awarded) are included. When examining the winning bid and the money left on the table variable data from the winning bid record, as well as data at the auction level, are used. Contracts were awarded in 771 auctions. Table 2 provides summary statistics on the variables used in the regression analysis.

Table 3 presents the first set of regression results. The models are estimated using ordinary using least squares and report White-corrected standard errors to correct for heteroscedasticity. The first column reports results for the log of the bid variable. In this regression, the results indicate that entrants bid, on average, more aggressively than incumbents. This is not surprising given the bid distributions of entrants and incumbents presented in Figure 1. Bidders that have a history of higher than average past winnings tend to bid lower. The results on the prior-winning variable are mainly interpreted as picking out differences in efficiencies across bidders. As expected, the more competitive the set of rivals a firm faces, the more aggressively the firm bids. This is in agreement with the theoretical results presented by Maskin and Riley (2000b) in Section III.2. Finally, the engineering estimate has the expected impact on the bid while the number of bidders does not appear to affect the log of the bids.[33]

The second column in Table 3 reports the results for the winning bid regression. The results show that entrants win with much more aggressive bids as compared to incumbents. Again, a firm that faces rivals with strong previous winning records wins with a more aggressive bid. However, in the winning bid regression, the prior winning rate has no effect on the level of the winning bid. Hence, while firms with strong prior winning histories do bid lower, on average, relative to other firms (as is evident from the first column of Table 3), they do not win with disproportionately below average bids. This point is reiterated in the money left on the table results. The last two columns of Table 3 indicate that entrants' aggressive bidding results in higher than average money being left on the table for entrant bidders under either definition of the money left on the table variable. Alternatively, one's own past winning history and rivals' past winning histories do not have a statistically significant effect on the money left on the table.

The fact that entrants bid aggressively in the lower tail is more fully documented in Table 4. Table 4 presents information on bidding patterns of incumbents and entrants at the lower end of the distribution (lowest 25th and lowest 10th percentiles). The table indicates that entrants place a much larger proportion of their bids in the bottom 25%

[33] One issue is that the actual number of bidders is most likely endogenous. This point is raised in Hendricks, Porter and Boudreau (1987) and has been recently examined by Porter and Zona (1999) and by Bajari (2000). Later in this chapter, we report on the estimates of a model that uses the expected number of bidders calculated from past information on the number of plan holders and the probability of participation.

than do incumbents. The difference between the proportions of bids in the two groups is even more pronounced when you consider the lowest 10% of bids.

These simple observations can be formalized in the analysis of the quantile regression model (Koenker and Bassett, 1982) that follows. This model allows us to estimate differences in the distribution of bids between entrants and incumbents more accurately while taking into account other factors that contribute to the variability of bids. Estimation is restricted to five quantiles: 0.10, 0.25, 0.50, 0.75 and 0.90. The results of these estimations are presented in Table 5. The dependent variable in all regressions is the logarithm of bids. The analysis employs the same reduced form equation reported in Table 3 and emphasizes the difference in the bidding patterns of the two groups. The coefficient on the dummy variable on entry varies substantially in the quantiles. Entrants' bids are smaller than those of incumbents by a larger margin at the 0.10 quantile (40.55%) than at the 0.25 quantile (24.00%) or the 0.50 quantile (10.05%), holding everything else constant. The difference becomes smaller and statistically insignificant beyond the 0.50 quantile. These results are in agreement with the theoretical findings in Section III.3. The differences in bidding patterns could be consistent with an asymmetric model of auctions in which the distribution of an entrant's costs exhibits greater dispersion than that of an incumbent's.

When the logarithm of the winning bid is considered as the dependent variable, then the differences in the two groups become more pronounced (see Table 6). In particular, holding everything else constant, entrants' bids are smaller than those of incumbents by a margin of 72.31% at the 0.10 quantile, 35.15% at the 0.25 quantile, 20.26% at the 0.50 quantile, and 11.032% at the 0.75 quantile. Clearly, the quantile regressions indicate that entrants' bids are particularly aggressive at the lower tail of the bid distributions.

To check on the robustness of the main results, several alternative specifications have been estimated. First, a more general specification for bidder experience has been considered. Here, in addition to the entry dummy variable, a set of dummy variables has been considered to distinguish the level of bidder experience. Entrants' results are robust to this change in specification, but there is little pattern in the coefficients for more experienced bidders. Hence, the aggressive bidding pattern observed for entrants is not found for bidders with only modest experience (see Table 7).

Second, the period of analysis has been redefined: instead of July 1998 to October 2000, January 1999 to October 2000. This redefinition of the sample redefines the entrant group. Here, an entrant is defined as a new bidder that appears in the January 1999-August 2000 period. Under this new definition, two complete prior years (1997 & 1998) of bidding data are used to help identify incumbents and build up bidding histories. Given that both, the number of entrants and the number of auctions, are reduced under this criterion, it is not surprising that this study loses some efficiency as compared to the original results reported in Table 3. Overall, the results hold up reasonably well (see Table 8). The coefficients on the entry variable are quite similar to those reported in Table 3. However, the effect of entry in the winning bid and the money left on the table regressions is not statistically significant at the 5% level but is at the 10% level.

Third, the model using standard panel data techniques has been estimated. Rather than controlling for past winning history as the measure of bidder heterogeneity, a random-effects model controls for the unobserved heterogeneity of bidders. A random-effects model is employed in this situation to use the cross-firm variation between incumbents and entrants to identify the entry parameter. A fixed-effects model would use only within-firm variation to estimate the entry parameter. In addition, a fixed-effects model effectively reduces the number of entrant bids since a significant number of entering bidders submit only one bid during the period under study. The results are again consistent with the OLS results—entrants bid lower, win lower, and leave more money on the table as compared to incumbents (see Table 9).

Finally, the models using an expected number of bidders have been re-estimated (see Table 10). The expected number of bidders was constructed using historical information on individual bidder participation rates. For entrants that have no such history, the estimate of average participation across all auctions was used. The results for the entrant's own and rival characteristics are invariant to the use of expected versus actual number of bidders. The effect of the expected number of bidders, as compared to the actual number of bidders, is somewhat more muted across the regressions on the bids, the winning bid, and the money left on the table.[34]

III.6. Summary

This chapter examines the patterns of bidding by incumbent and entrant firms in road construction procurement auctions held by ODOT. It was found that entrants bid more aggressively, win with lower bids, and leave more money on the table than incumbent bidders. On a theoretical level, this study considered an asymmetric model of auctions, with emphasis on the characteristics of these groups, and produced testable

[34] We also re-estimate the models using the relative bid (bid to the engineering cost ratio) as the basis for the dependent variables (bids and winning bids). Entrants submit, on average, lower relative bids and lower relative winning bids. We also check the sensitivity of the results to the removal of outlier bids. We re-estimate the models using samples in which the very low bids and very high bids were omitted. The results show that entrants still submit

predictions: when the distribution of an entrant's costs exhibits greater dispersion than that of an incumbent's, the entrant with a low cost estimate will bid more aggressively (relative to the engineering estimate) than the incumbent.

Bidders who have a history of winning at auctions have a tendency to bid lower but do not win with overly aggressive bids and do not leave money on the table. It was also found that rival bidder characteristics affect bidding behavior: the tougher the average rival is in an auction, the lower the bid and the lower the winning bid. These results are consistent with the theoretical predictions of Maskin and Ridley (2000b) on bidding patterns in asymmetric auctions.

more aggressive bids, win with lower bids and leave more money on the table when extreme observations are deleted from the sample.

III.7. Appendix

Let $c_i = \alpha s_i + t_i + (1-\alpha)\Sigma_j s_j/(n-1)$. The density of the common cost component is $g(s)$ with support $[s_L, s_H]$. Similarly, a bidder's part of the cost that is purely private is drawn from a distribution $h_i(t)$ with support $[t_L, t_H]$ where $t_L \geq 0$. In order to ensure monotonicity and existence within this framework, it will be assumed that the densities $h_i(t)$ and $g(s)$ are log-concave. It follows from Lemma 1, in Goeree and Offerman (1999), that the distribution of $w_i = \alpha s_i + t_i$, F_{wi}, will also be log-concave and both $E(s|w_i \geq x)$ and $E(s|\, w_i = x)$ will be monotonic in x.

Goeree and Offerman (1999) solved for the equilibrium inverse bid functions in a symmetric auction environment. The equilibrium in this first-price asymmetric sealed bid auction is characterized with two bidders. Notice that the bid is a monotonic function of w_i. Taking this into account, consider a bidder's expected payoff from participation:

$$\pi_i(b) = [b - \alpha s_i - t_i - (1-\alpha)E[s_j \mid w \geq B_j^{-1}(b)]][1 - F_{w_j}(B_j^{-1}(b))].$$

Differentiating the expected payoff with respect to b and evaluating the expression at the optimal choice:

$$\begin{aligned}
\pi_i'(b) = &-\left[b - \alpha s_i - t_i - (1-\alpha)E[s_j \mid w \geq B_j^{-1}(b)]\right] f_{w_j}(B_j^{-1}(b)) B_j^{-1'}(b) + \\
&[1 - F_{w_j}(B_j^{-1}(b))]\Big[1 + (1-\alpha)E[s_j \mid w = B_j^{-1}(b)] \frac{f_{w_j}(B_j^{-1}(b))}{1 - F_{w_j}(B_j^{-1}(b))} B_j^{-1'}(b) \\
&- (1-\alpha)E[s_j \mid w \geq B_j^{-1}(b)] \frac{f_{w_j}(B_j^{-1}(b))}{1 - F_{w_j}(B_j^{-1}(b))} B_j^{-1'}(b)\Big] \\
&= \left[-b + \alpha s_i + t_i + (1-\alpha_i)E[s_j \mid w = B_j^{-1}(b)]\right] f_{w_j}(B_j^{-1}(b)) B_j^{-1'}(b) + 1 - F_{w_j}(B_j^{-1}(b)) = 0,
\end{aligned}$$

where $B_j^{-1}(b) = \alpha s_i + t_i$ is defined over $[\alpha s_L + t_L, \alpha s_H + t_H]$.

It follows that for each j (j≠i):

$$\frac{f_{w_j}(B_j^{-1}(b))}{1-F_{w_j}(B_j^{-1}(b))}B_j^{-1'}(b)=\frac{1}{[b-B_i^{-1}(b)]}.$$

where every $B_i^{-1}(b)$ is evaluated at b for all b in $[b_\bullet, b^*]$. These differential equations should satisfy the following boundary conditions:

$$F_j(B_j^{-1}(b_\bullet))=0,$$
$$b^*=B_j^{-1}(\alpha s_H+t_H)\ \forall\ j.$$

Figure-III.1: Entrants' and Incumbents' Bid Distributions

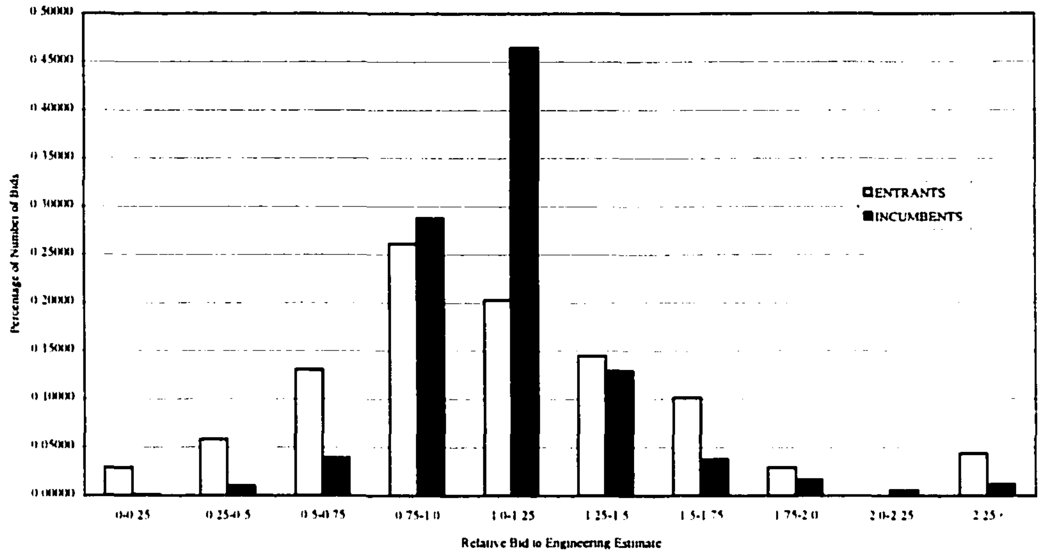

Figure-III.2: Experienced and Inexperienced Bidders' Bid Distributions

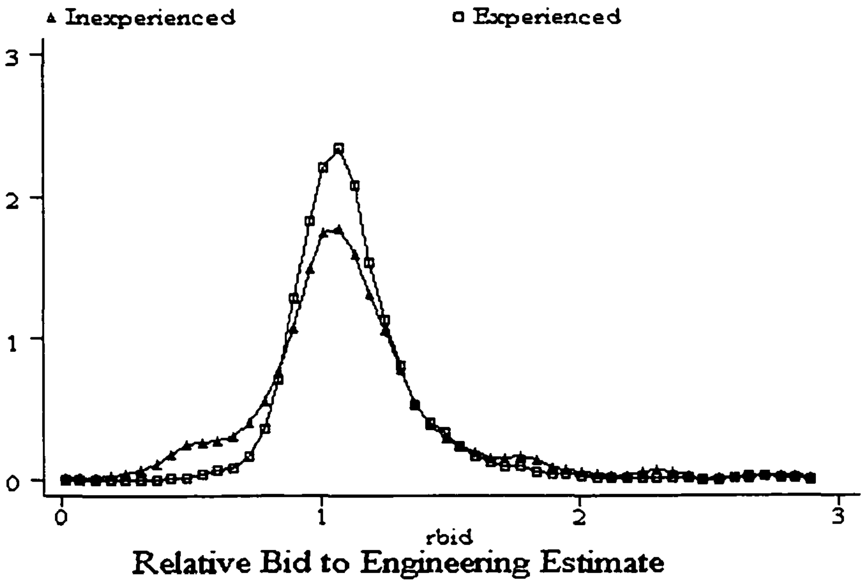

Table-III.1: Summary Statistics of Oklahoma Road Construction Auctions

Variable	Auction Statistics for Full Sample: 1997:1-2000:8	Auction Statistics for Second Sample: 1998:7-2000:8
Number of Auctions	1736	952
Number of Auctions w/ Winners	1411	771
Number of Firms	284	213
Number of Plans Purchased	9542	5247
Number of Bids	5279	2785
Average Number of Plan holders per Auction	5.708 (3.014)	5.686 (3.059)
Average Number of Bidders per Auction	3.323 (1.679)	3.183 (1.602)
Number of Plans Purchased by Entrants	--	185
Entrant Bidders	--	71
Entrant Winners	--	15

Note: Standard Deviations are in parentheses.

Table-III.2: Summary Statistics of Regression Variables

Variable	Mean (Standard Deviation)
Log of Bids	13.0742 (1.645)
Log of Winning Bids	12.8049 (1.652)
Money Left on the Table -1	0.0988 (0.107)
Money Left on the Table -2	0.0624 (0.087)
Log of Engineer's Estimate	13.0033 (1.656)
Standard Deviation of the Bids	0.1626 (0.225)
Log of Number of Bidders in an Auction	1.2783 (0.473)
Entrant Dummy Variable	0.0248 (0.155)
Dummy Variable for Incumbent Bidders that face Entrants	0.1537 (0.361)
Firm's Winning to Bidding Ratio	0.2608 (0.139)
Average Rivals Winning to Plan holder Ratio	0.1559 (0.0635)

Table-III.3: OLS Regression Results for Log of Bids, Log of Winning Bids, and Money Left on the Table

Independent Variable	*Dependent Variable*			
	Log of Bids	**Log of Winning Bids**	**Money Left on the Table**	
			(1)	**(2)**
Constant	0.7618*	0.1901	0.4607*	0.2009*
	(0.0868)	(0.1265)	(0.0506)	(0.0444)
Project-1	-0.0174	-0.0367	-0.0086	0.0009
	(0.0236)	(0.0409)	(0.0178)	(0.0134)
Project-2	-0.1291	-0.3253	0.0670	0.0803
	(0.0777)	(0.1753)	(0.0425)	(0.0437)
Project-3	-0.0320	-0.0376	-0.0115	0.0019
	(0.0229)	(0.0401)	(0.0165)	(0.0123)
Project-4	0.0228	-0.0157	0.0179	0.0160
	(0.0271)	(0.0448)	(0.0188)	(0.0147)
Project-5	0.2053*	0.1940	-0.0149	-0.0698*
	(0.0611)	(0.1028)	(0.0678)	(0.0223)
Project-6	-0.1539*	-0.0835*	-0.0586*	-0.0231
	(0.0296)	(0.0474)	(0.0182)	(0.0140)
Log of Engineer's Estimate	0.9588*	0.9952*	-0.0279*	-0.0124*
	(0.0061)	(0.0092)	(0.0034)	(0.0032)
Log of Number *of Bidders*	-0.0116	-0.0593*	-0.0206*	-0.0120
	(0.0110)	(0.0156)	(0.0074)	(0.0066)
Entry	-0.2152*	-0.4042*	0.1039*	0.1099*
	(0.0692)	(0.1664)	(0.0457)	(0.0410)
Firm's Winning to Bidding Ratio	-0.2816*	-0.0343	0.0367	0.0342
	(0.0458)	(0.0647)	(0.0283)	(0.0242)
Incumbent Bidders facing Entrants	-0.0180	-0.0386	0.0103	0.0064
	(0.0175)	(0.0332)	(0.0113)	(0.0096)
Average Rivals Winning to Plan holder Ratio	-0.2110*	-0.3764*	0.0759	0.1096
	(0.1038)	(0.1277)	(0.0712)	(0.0595)
Number of Obs.	2785	771	771	771
R^2	0.9734	0.9789	0.2043	0.1249

Note: White heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% significance.

Table-III.4: Summary Statistics of Bid Frequency

	Incumbents	*Entrants*
Total Number of Bids	2716	69
Number of Bids by the group in the bottom 25% of all bids	665	32
Number of Bids by the group in the bottom 10% of all bids	254	24
Proportion of bids by the group in the bottom 25% of all bids	24.48	46.38
Proportion of bids by the group in the bottom 10% of all bids	9.35	34.78

Table-III.5: Quantile Regression Results for Log of Bids

Variable	*Quantile*				
	0.1	*0.25*	*0.50*	*0.75*	*0.90*
Constant	-0.0934	0.2047*	0.5605*	1.0814*	1.6015*
	(0.1102)	(0.0221)	(0.0546)	(0.0730)	(0.1410)
Project-1	0.0101	0.0080	0.0015	-0.0199	-0.0963*
	(0.4056)	(0.0237)	(0.0206)	(0.0263)	(0.0435)
Project-2	-0.5867*	-0.2341*	-0.0754*	-0.0415	0.2118*
	(0.0561)	(0.0336)	(0.0295)	(0.0373)	(0.0616)
Project-3	-0.0012	0.0266	0.0072	-0.0204	-0.0824*
	(0.0373)	(0.0219)	(0.0193)	(0.0245)	(0.0412)
Project-4	0.0049	0.0143	0.0176	0.0248	-0.0110
	(0.0436)	(0.0250)	(0.0220)	(0.0286)	(0.0469)
Project-5	0.1512	0.1275*	0.1882*	0.2846*	0.2144*
	(0.0799)	(0.0496)	(0.0437)	(0.0550)	(0.0850)
Project-6	-0.1181*	-0.1213*	-0.1305*	-0.1437*	-0.1997*
	(0.0474)	(0.0274)	(0.0237)	(0.0302)	(0.0522)
Log of Engineer's Estimate	1.0029*	0.9875*	0.9710*	0.9441*	0.9169*
	(0.0077)	(0.0042)	(0.0037)	(0.0050)	(0.0095)
Log of Number of Bidders	-0.0100	-0.0053	-0.0143	-0.0178	-0.0069
	(0.0152)	(0.0094)	(0.0087)	(0.0115)	(0.0201)
Entry	-0.4055*	-0.2400*	-0.1005*	0.0297	-0.0186
	(0.0489)	(0.0303)	(0.0265)	(0.0335)	(0.0568)
Firm's Winning to Bidding Ratio	-0.1914*	-0.1823*	-0.1894*	-0.2632*	-0.3182*
	(0.0599)	(0.0346)	(0.0308)	(0.0421)	(0.0788)
Incumbent Bidders facing Entrants	-0.1480*	-0.0371*	0.0020	0.0271	0.0653*
	(0.0213)	(0.0127)	(0.0111)	(0.0141)	(0.0234)
Average Rivals Winning to Plan holder Ratio	-0.0943	-0.1672*	-0.2437*	-0.3235*	-0.2540
	(0.1396)	(0.0757)	(0.0690)	(0.0931)	(0.1754)
Number of Obs.	2785	2785	2785	2785	2785
R^2	0.8420	0.8568	0.8666	0.8733	0.8553

Note: Standard errors are in parentheses. * Denotes 95% significance.

Table-III.6: Quantile Regression Results for Log of Winning Bids

Variable	*Quantile*				
	0.1	*0.25*	*0.50*	*0.75*	*0.90*
Constant	-0.5210*	0.0104	0.1752*	0.4176*	0.8108*
	(0.2233)	(0.1260)	(0.0774)	(0.0880)	(0.1333)
Project-1	0.0017	0.0073	0.0140	0.0206	0.0522
	(0.0850)	(0.0484)	(0.0300)	(0.0327)	(0.0437)
Project-2	-0.5010*	-0.5513*	-0.3040*	-0.0623	-0.1185*
	(0.1097)	(0.0719)	(0.0463)	(0.0487)	(0.0606)
Project-3	-0.0206	0.0155	0.0222	0.0355	0.0602
	(0.0812)	(0.0458)	(0.0287)	(0.0314)	(0.0427)
Project-4	-0.0454	-0.0080	0.0087	0.0514*	0.1123*
	(0.0922)	(0.0529)	(0.0330)	(0.0359)	(0.0478)
Project-5	0.1329	0.1576	0.2120*	0.0904	0.1245*
	(0.0955)	(0.1024)	(0.0674)	(0.0704)	(0.0511)
Project-6	-0.0087	-0.0587	-0.0877*	-0.0417	0.0597
	(0.0923)	(0.0548)	(0.0340)	(0.0377)	(0.0506)
Log of Engineer's Estimate	1.0345*	1.0017*	0.9935*	0.9784*	0.9561*
	(0.0151)	(0.0088)	(0.0052)	(0.0060)	(0.0093)
Log of Number of Bidders	-0.0686*	-0.0408*	-0.0454*	-0.0493*	-0.0690*
	(0.0316)	(0.0185)	(0.0118)	(0.0131)	(0.0173)
Entry	-0.7231*	-0.3515*	-0.2026*	-0.1103*	-0.0316
	(0.0890)	(0.0661)	(0.0405)	(0.0428)	(0.0498)
Firm's Winning to Bidding Ratio	0.0210	-0.1299	-0.1004*	-0.0352	-0.0610
	(0.1119)	(0.0706)	(0.0445)	(0.0453)	(0.0467)
Incumbent Bidders facing Entrants	-0.1140*	-0.0415	-0.0221	-0.0081	0.0439
	(0.0486)	(0.0280)	(0.0172)	(0.0428)	(0.0245)
Average Rivals Winning to Plan holder Ratio	-0.5490*	-0.4063*	-0.2354*	-0.2438*	-0.4891*
	(0.2861)	(0.1542)	(0.0907)	(0.0930)	(0.1193)
Number of Obs.	771	771	771	771	771
R^2	0.8488	0.8714	0.8889	0.9036	0.8979

Note: Standard errors are in parentheses. * Denotes 95% significance.

Table-III.7: OLS Regression Results for Log of Bids, Log of Winning Bids, and Money Left on the Table: Alternative Experience Specification

Independent Variable	*Dependent Variable*			
	Log of Bids	**Log of Winning Bids**	**Money Left on the Table (1)**	**Money Left on the Table (2)**
Constant	0.7990*	0.2304	0.4627*	0.1988*
	(0.0873)	(0.1299)	(0.0509)	(0.0454)
Project-1	-0.0200	-0.0399	-0.0039	0.0032
	(0.0234)	(0.0411)	(0.0180)	(0.0135)
Project-2	-0.1334	-0.3238	0.0767	0.0834
	(0.0775)	(0.1777)	(0.0430)	(0.0449)
Project-3	-0.0386	-0.0443	-0.0081	0.0043
	(0.0230)	(0.0403)	(0.0170)	(0.0127)
Project-4	0.0219	-0.0245	0.0247	0.0205
	(0.0269)	(0.0455)	(0.0192)	(0.0150)
Project-5	0.2068*	0.2022	0.0051	-0.0606*
	(0.0608)	(0.1052)	(0.0666)	(0.0245)
Project-6	-0.1569*	-0.0965*	-0.0526*	-0.0187
	(0.0295)	(0.0471)	(0.0186)	(0.0143)
Log of Engineer's Estimate	0.9579*	0.9947*	-0.0287*	-0.0129*
	(0.0061)	(0.0095)	(0.0034)	(0.0033)
Log of Number of Bidders	-0.0114	-0.0566*	-0.0215*	-0.0130*
	(0.0111)	(0.0158)	(0.0073)	(0.0065)
Entry	-0.2383*	-0.4384*	0.1066*	0.1162*
	(0.0688)	(0.1645)	(0.0449)	(0.0404)
Experience Dummy-1	-0.0401	-0.0875	-0.0372*	-0.0108
	(0.0324)	(0.0475)	(0.0171)	(0.0131)
Experience Dummy-2	-0.0276	-0.0335	0.0131	0.0156
	(0.0197)	(0.0631)	(0.0118)	(0.0112)
Experience Dummy-3	-0.0239	-0.0552*	0.0186*	0.0163*
	(0.0126)	(0.0194)	(0.0091)	(0.0071)
Experience Dummy-4	-0.0389*	-0.0429*	0.0133	0.0115
	(0.0112)	(0.0179)	(0.0086)	(0.0073)
Firm's Winning to Bidding Ratio	-0.2808*	-0.0220	0.0248	0.0276
	(0.0450)	(0.0656)	(0.0269)	(0.0239)
Incumbent Bidders Facing Entrants	-0.0163	-0.0331	0.0114	0.0064
	(0.0174)	(0.0332)	(0.0113)	(0.0095)
Average Rivals Winning to Plan holder Ratio	-0.2058*	-0.3831*	0.0764	0.1093
	(0.1040)	(0.1257)	(0.0701)	(0.0596)
Number of Obs.	2785	771	771	771
R^2	0.9735	0.9791	0.2157	0.1322

Note: White heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% significance.

Table-III.8: OLS Regression Results for Log of Bids, Log of Winning Bids, and Money Left on the Table: Alternative Entry Specification

Independent Variable	*Dependent Variable*			
	Log of Bids	**Log of Winning Bids**	**Money Left on the Table**	
			(1)	**(2)**
Constant	0.6882*	0.1286	0.4480*	0.1874*
	(0.0909)	(0.1355)	(0.0548)	(0.0486)
Project-1	-0.0154	-0.0328	-0.0078	0.0055
	(0.0253)	(0.0458)	(0.0192)	(0.0147)
Project-2	-0.0654	-0.3743*	0.0612	0.0941
	(0.0764)	(0.1744)	(0.0493)	(0.0514)
Project-3	-0.0239	-0.0466	-0.0011	0.0124
	(0.0249)	(0.0457)	(0.0178)	(0.0134)
Project-4	0.0125	-0.0351	0.0195	0.0237
	(0.0285)	(0.0491)	(0.0205)	(0.0163)
Project-5	0.2010*	0.2573*	0.0064	-0.0690*
	(0.0722)	(0.1151)	(0.0800)	(0.0278)
Project-6	-0.1356*	-0.0685*	-0.0444*	-0.0154
	(0.0329)	(0.0544)	(0.0200)	(0.0155)
Log of Engineer's Estimate	0.9629*	1.0011*	-0.0278*	-0.0127*
	(0.0064)	(0.0096)	(0.0037)	(0.0036)
Log of Number of Bidders	-0.0074	-0.0558*	-0.0188*	-0.0100
	(0.0113)	(0.0173)	(0.0084)	(0.0074)
Entry	-0.1938*	-0.4037	0.0915*	0.1027
	(0.0796)	(0.2117)	(0.0567)	(0.0537)
Firm's Winning to Bidding Ratio	-0.2791*	-0.0815	0.0503	0.0446
	(0.0476)	(0.0677)	(0.0337)	(0.0289)
Incumbent Bidders who face Entrants	-0.0029	-0.0389	0.0154	0.0103
	(0.0188)	(0.0363)	(0.0132)	(0.0115)
Average Rivals Winning to Plan holder Ratio	-0.1431*	-0.4000*	0.0944	0.1467*
	(0.1075)	(0.1360)	(0.0793)	(0.0651)
Number of Obs.	2265	632	632	632
R^2	0.9751	0.9800	0.1984	0.1242

Note: White heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% significance.

Table-III.9: Random Effects Regression Results for Log of Bids, Log of Winning Bids, and Money Left on the Table

Independent Variable	*Dependent Variable*			
	Log of Bids	**Log of Winning Bids**	**Money Left on the Table**	
			(1)	**(2)**
Constant	0.8632*	0.2934*	0.4153*	0.1631*
	(0.0750)	(0.1156)	(0.0478)	(0.0410)
Project-1	-0.0075	0.0344	-0.0337	-0.0025
	(0.0264)	(0.0447)	(0.0186)	(0.0159)
Project-2	-0.0925*	-0.2906*	0.0669*	0.0662*
	(0.0414)	(0.0861)	(0.0340)	(0.0297)
Project-3	0.0037	-0.0267	-0.0231	-0.0009
	(0.0263)	(0.0441)	(0.0183)	(0.0157)
Project-4	0.0577*	0.0438	0.0113	0.0097
	(0.0277)	(0.0481)	(0.0201)	(0.0172)
Project-5	0.2019*	0.1037	-0.0334	-0.0523
	(0.0564)	(0.1072)	(0.0440)	(0.0378)
Project-6	-0.0328	-0.0241	-0.0488	-0.0295
	(0.0413)	(0.0628)	(0.0256)	(0.0221)
Log of Engineer's Estimate	0.9412*	0.9816*	-0.0226*	-0.0078*
	(0.0050)	(0.0079)	(0.0033)	(0.0028)
Log of Number of Bidders	-0.0136	-0.0585*	-0.0188*	-0.0122*
	(0.0108)	(0.0164)	(0.0069)	(0.0059)
Entry	-0.5586*	-0.3571*	0.1011*	0.1017*
	(0.0415)	(0.0819)	(0.0310)	(0.0275)
Incumbent Bidders who face Entrants	0.0013	-0.0011	-0.0017	-0.0043
	(0.0139)	(0.0239)	(0.0100)	(0.0086)
Average Rivals Winning to Plan holder Ratio	-0.1934*	-0.3834*	0.0510	0.1033*
	(0.0916)	(0.1361)	(0.0569)	(0.0486)
Number of Obs.	2785	771	771	771
R^2	0.9726	0.9785	0.1936	0.1137

Note: Standard errors are in parentheses. * Denotes 95% significance.

Table-III.10: OLS Regression Results for Log of Bids, Log of Winning Bids, and Money Left on the Table: With Expected Number of Bidders

Independent Variable	*Dependent Variable*			
	Log of Bids	**Log of Winning Bids**	**Money Left on the Table**	
			(1)	**(2)**
Constant	0.7532*	0.1460	0.4465*	0.1988*
	(0.0858)	(0.1280)	(0.0494)	(0.0454)
Project-1	-0.0130	-0.0368	-0.0068	0.0031
	(0.0239)	(0.0430)	(0.0182)	(0.0138)
Project-2	-0.1388	-0.3357	0.0062	0.0762
	(0.0772)	(0.1740)	(0.0432)	(0.0438)
Project-3	-0.0332	-0.0389	-0.0119	0.0016
	(0.0230)	(0.0410)	(0.0168)	(0.0121)
Project-4	0.0206	-0.0141	0.0181	0.0159
	(0.0271)	(0.0455)	(0.0191)	(0.0146)
Project-5	0.2047*	0.1893	-0.0163	-0.0704*
	(0.0615)	(0.1058)	(0.0685)	(0.0215)
Project-6	-0.1545*	-0.0874	-0.0601*	-0.0240
	(0.0297)	(0.0485)	(0.0186)	(0.0139)
Log of Engineer's Estimate	0.9568*	0.9953*	-0.0284*	-0.0130*
	(0.0062)	(0.0100)	(0.0034)	(0.0033)
Log of Number of Expected Bidders	0.0160	-0.0275	-0.0045	0.0007
	(0.0112)	(0.0191)	(0.0081)	(0.0067)
Entry	-0.2182*	-0.4151*	0.0992*	0.1066*
	(0.0693)	(0.1660)	(0.0463)	(0.0413)
Firm's Winning to Bidding Ratio	-0.2717*	-0.0137	0.0447	0.0395
	(0.0451)	(0.0657)	(0.0285)	(0.0240)
Incumbent Bidders Facing Entrants	-0.0237	-0.0422	0.0079	0.0042
	(0.0176)	(0.0337)	(0.0115)	(0.0098)
Average Rivals Winning to Plan holder Ratio	-0.2110*	-0.3514*	0.0793	0.1080
	(0.1056)	(0.1274)	(0.0725)	(0.0609)
Number of Obs.	2785	771	771	771
R^2	0.9734	0.9786	0.1960	0.1205

Note: White heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% significance.

CHAPTER IV

SEQUENTIAL BIDDING IN AUCTIONS OF CONSTRUCTION CONTRACTS

IV.1. Introduction

This essay investigates differences in bidding patterns between morning and afternoon auctions of construction contracts held by the ODOT in the period July 1998 to August 2000. The empirical literature on sequential auctions has mainly examined the direction of expected prices. This essay emphasizes differences in bidding behavior in later sessions conditional on the outcome (success or failure) of earlier auctions. This essay incorporates the number of bidders in these auctions, the characteristics of contracts, a measure of efficiency for each firm's rivals, and capital commitment that imposes budgetary restrictions. Evidence of strategic behavior has been found that is consistent with the predictions on asymmetric models of auctions. The asymmetries intensify in afternoon auctions due to the release of information in morning sessions.

The overwhelming majority of the theoretical work on sequential auctions assumes that bidders demand a single object. In auctions of construction contracts, however, there is no statistically significant difference in the probability of winners and losers of morning auctions submitting a bid. In this framework, the assumption of single unit demand would take away much of the asymmetry that characterizes bidding behavior in later rounds. Since the opportunity cost of completing a contract is different for each potential contractor and the differences become common knowledge through early bidding, asymmetries play an important role in this setting. In afternoon auctions, there is a significant adjustment in bidding behavior that is induced by the release of information on prices and bids in morning auctions. The evidence of bidding behavior in the afternoon auctions is consistent with some of the theoretical predictions in Maskin and Riley (2000b). For example, Proposition 3.3 predicts that, if a weak bidder faces a strong rather than another weak bidder, he responds with a more aggressive bid distribution. Further, this essay suggests that, on average, the more competitive the set of rivals a firm faces, the more aggressive are its bids. Even though the difference in the probability of submitting a bid is not statistically significant between winners and losers of early auctions, losers make a much larger adjustment in their afternoon bids relative to the winners. As shown in Maskin and Riley (2000b), identifying the nature of these asymmetries is important for the selection of the appropriate revenue-maximizing mechanism.

IV.2. Data

Bidding patterns for road construction projects are examined utilizing data from ODOT. The data contains information on all projects offered for bid letting by the State of Oklahoma between January 1997 and August 2000. These projects include road construction and paving, traffic signals, bridge construction and maintenance, as well as smaller drainage and clearance type projects. The state auctions off projects on a monthly basis and uses a sealed-bid auction format wherein the lowest bidder is awarded the contract.

To examine the process of sequential bidding, both morning and afternoon sessions are utilized. Bids must be received half an hour before each session. Hence, the outcomes from the morning session are known before the bids must be received for the afternoon session. In fact, there is a small window of time—3.5 hours—between the opening of the morning bids and the closing of the afternoon bids. This allows potential bidders to alter their bids or, possibly, their decision to participate in the afternoon session. Discussions with state officials have revealed that bids do arrive right up to the last possible moment.

The auction data that this study utilizes includes information on the identity of the firms that purchase plans for a project—"the plan holders," the identity and bids of all bidders for a project, and the winning bid (if the contract is awarded). Since, the data allow us to identify both firms holding plans and firms bidding, individual firms' bidding behavior across the morning and afternoon sessions are followed. In addition to information on the identity of potential bidders, the state also provides detailed information on the specific project: a description of the project (e.g., bridge construction, asphalt paving, etc.), the details of the project, the duration of the project (calendar days), the engineering estimate of the project's total cost, and the date and time of letting.

Throughout this analysis, the auction sample is divided into two time periods—January 1997 to June 1998, and July 1998 to August 2000. The first period is used to create historically based variables such as measures of rival efficiency and capacity commitment. The details of variable construction are discussed below. Only the bidding data of firms that submit multiple bids on a given auction day are utilized in order to use panel data techniques to control for unobserved bidder heterogeneity. In addition, to learn the effect of morning outcomes on afternoon bidding, firms submitting more than one bid are utilized. Table 1 provides data on both the overall sample and the sample restricted to multiple bidders. In the overall sample for July 1998 to August 2000, there were 952 auctions with 5247 plans purchased and 2785 bids submitted. This represents the activity of 213 individual firms. In our multiple-bid sample, 93 firms were represented and they submitted 1743 bids, purchasing 2473 plans.

IV.3. Empirical Analysis

The probability of participation in these auctions was analyzed first. Recall that both, the plan-holders and the bidders are known and, hence, the firms that actually submit a bid can be identified. The independent variables include controls for project characteristics, bidder characteristics, and rival characteristics in each auction. The project characteristics include the state's estimate of the engineering cost (log(engest)), and a set of dummy variables for project types (P_i's). The state constructs the engineering cost estimates by pricing each feature outlined in the design.[35]

With respect to bidders' own characteristics, a variable that describes capacity commitment (backlog) is included: for every contract won, the average monthly value is calculated. Each subsequent month, the average monthly value is subtracted from the initial size of the contract until the completion time of the project. Based on this calculation, the total remaining value of the projects that a firm has undertaken is determined at any given point in time. A firm that wins a contract at any point in time limits its free capacity to complete contracts in the future. Additional commitment of capital implies more budgetary restrictions since firms must include a payment of 5% of the value of the project upon submission of the bid. This is similar to the capacity measure used in Jofre-Bonet and Pesendorfer (2000). In addition to the capacity measure, dummy variables are included that indicate whether the firm won or lost in the

[35] The project dummies control for broad classes of project types -- asphalt projects, clearance and bank protection; bridge work, grading and draining, concrete work, signals and lighting projects. The omitted group is miscellaneous work such as intersection modification, parking lots, and landscaping.

morning. These are the variables that will pick up differences in the probability to submit bids in the afternoon based on morning results.

Past information on rivals' bidding success is used to summarize the competitiveness of the potential set of rivals (ARWP). The information provided in the plan-holder list allows us to identify the rivals for a particular auction. Note that a bidder must be a plan-holder in order to participate in an auction and the plan-holder list is made available to all potential bidders prior to the auction. The measure of rivals' past average success in auctions is constructed as the average across rivals of the ratio of past wins to the past number of plans held. This variable incorporates two aspects of past rival bidding behavior: the probability of a rival bidding given that it is a plan-holder, and the probability the rival wins an auction given that it bids.

The results of the probit analysis presented in column 1 of Table 2 reveals that there is no statistically significant difference between winners and losers in morning auctions in their probability to bid in the afternoon. This is contrary to an assumption, typically made in models of sequential auctions, that bidders have unitary demand. This assumption precludes the introduction of asymmetries that could complicate the analysis of bidding behavior. The analysis of bidding behavior in the afternoon auctions, conditional on the outcome of the morning auctions, will emphasize these asymmetries. These asymmetries lead to bidding patterns consistent with Maskin and Riley's (2000b) theoretical predictions.

Sequential bidding patterns in morning and afternoon sessions are examined with a simple reduced-form model of bidding in a procurement auction. The basic structure of the regression model is as follows

$$\log(b_{igt}) = \beta_{0i} + \sum_{j=1}^{6} \beta_j \mathrm{P}_{ji} + \beta_7 \log(engest_{igt}) + \beta_8 \log(\#bidders_{igt}) + \beta_9 winAM_{it}$$
$$+ \beta_{10} loseAM_{it} + \beta_{11} \log(backlog_{igt}) + \beta_{12} ARWP_{igt} + \varepsilon_{igt}.$$

Our dependent variable in the regression is the log of the bid. The independent variables include a set of dummy variables for project characteristics (P_i's), the log of engineering estimates, the number of bidders (log(#bidders)), controls for characteristics of the bidders (winAM, loseAM, and log(backlog)), and the characteristics of the rivals in each auction (ARWP).

Alternatively, this study will utilize a fixed-effects estimator that allows for bidder-time period effects. In this case, the error term is specified in the above equation as $\epsilon_{igt} = \bar{u}_{it} + \eta_{igt}$. The mean effect, captured here by $\bar{u}_{it}$, is a bidder-time-specific effect. Hence, different bidder effects are allowed for each auction date. This is important if bidder efficiency levels that are not captured by the backlog variable vary across time. When the fixed-effects model was estimated, the backlog variable was dropped. Accordingly, the hypothesis is that the dummy variables that indicate whether the firm won or lost in the morning will pick up differences in the aggressiveness of bids in the afternoon based on morning results.

Column 2 of Table 2 presents the OLS regression results and incorporates White-corrected standard errors to correct for heteroscedasticity. The results show that the more capacity a firm commits, the less aggressively it bids in an auction. The effect of a backlog on bids is small but consistent with Pitchik and Schotter's (1988) theory that attributes less aggressive bidding to budgetary restrictions. It is also consistent with the findings of Jofre-Bonet and Pesendorfer (2000). Looking at the afternoon bidding dummies, one can see that firms that win in the morning bid more aggressively in the afternoon. However, it is probably the case that our measure of backlog is not fully controlling for differences in firm efficiencies and that the negative coefficient on this variable reflects differences in overall efficiencies (winners vs. losers) as opposed to differences in the bidding behavior in the morning and in the afternoon. To correct for this potential, the model is estimated with firm-time period effects that should control for differences in unobserved heterogeneity across firms on a given auction day. In contrast to the OLS results that exploit cross-firm variation in bids, the fixed-effects results allow for a comparison of a given bidder's bidding behavior in the morning and afternoon. The results presented in Column 3 of Table 2 suggest that, on average, those firms that lost in morning sessions bid more aggressively in the afternoon, relative to their morning bid, than those firms that won at least one project. The winners of early auctions are typically the stronger bidders and, conditional on the outcome of early auctions, the weak bidders (i.e., the morning losers) adjust their strategies and bid more aggressively in afternoon auctions. In addition, the fixed effects results suggest that the more competitive the set of rivals a firm faces, the more aggressively the firm bids. These results are consistent with the prediction in Maskin and Riley's (2000b) Proposition 3.5: if a weak bidder faces a strong bidder rather than another weak bidder, it will bid more aggressively and vice versa.[36]

[36] Maskin and Riley (2000b) prove that in the high bid auction, the distribution of bids of the strong buyer stochastically dominates that of the weak buyer. In auctions of construction contracts, in which the lowest bidder is awarded the project, the inverse would hold. Notice that stochastic dominance in the distribution of bids implies that the mean value from one distribution will exceed the mean value from the other. In that sense, our results provide evidence supporting their theory.

Table- IV.1: Summary Statistics of Oklahoma Road Construction Auctions

Variable	Auction Statistics for Sample: 1998:7-2000:8	Auction Statistics for Multiple Bids Sample
Number of Auctions	952	744
Number of Firms	213	93
Number of Plans Purchased	5247	2473
Number of AM Plans Purchased	2851	1269
Number of PM Plans Purchased	2396	1204
Number of Bids (AM and PM)	2785	1743
Number of AM Bids	1511	898
Number of PM Bids	1274	845

Table-IV.2: Regression Results

Independent Variable	*Dependent Variable:* **Log of Bids**		
	Probit	*OLS*	*Fixed Effects*
Constant	1.9608*	0.5615*	0.9326*
	(0.3763)	(0.1146)	(0.0989)
Project-1	0.2262	-0.0128	0.0450
	(0.1492)	(0.0365)	(0.0404)
Project-2	0.0991	-0.0117	-0.1224*
	(0.2233)	(0.0959)	(0.0588)
Project-3	-0.0327	0.0172	0.1110*
	(0.1394)	(0.0361)	(0.0388)
Project-4	-0.0868	-0.0418	0.1314*
	(0.1516)	(0.0417)	(0.0423)
Project-5	-0.1491	0.2415*	0.2491*
	(0.3125)	(0.0824)	(0.0827)
Project-6	0.7783*	-0.0850*	0.0102
	(0.2031)	(0.0433)	(0.0622)
Log of Engineer's Estimate	-0.1513*	0.9629*	0.9327*
	(0.0254)	(0.0084)	(0.0068)
Log of Number of Bidders		-0.0076	-0.0035
		(0.0138)	(0.0143)
Firms that won in the morning	0.3273*	-0.0905*	-0.0115
	(0.0717)	(0.0169)	(0.0157)
Firms that lost in the morning	0.3364*	-0.0104	-0.0800*
	(0.0650)	(0.0104)	(0.0145)
Log of Firm's Backlog	0.0206*	0.0032*	
	(0.0043)	(0.0014)	
Average Rivals Winning to Plan holder Ratio	-1.5531*	-0.1263	-0.2856*
	(0.5301)	(0.1227)	(0.1296)
Number of Obs.	2274	1743	1743
R^2		0.9713	0.9694
Wald χ^2	203.23		

Note: White heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% significance.

CHAPTER V

SYNERGIES IN RECURRING PROCUREMENT AUCTIONS: AN EMPIRICAL INVESTIGATION

V.1. Introduction

This essay empirically investigates the impact of synergies and competitive advantages on bidder behavior in recurring auctions of road construction contracts held by ODOT from January 1997 to August 2000. In this study, synergies are defined as complementarities associated with winning a project(s) in a particular geographic area that are experienced by a previous winner with an ongoing project(s) in that area. Further, a firm's valuation of a project may depend upon competitive advantages associated with bidders' familiarity with local market resources, and inherent firm efficiencies. The first two advantages are crucially correlated to geographical space. Porter and Zona (1999), in their study of dairies bidding for contracts to supply milk, and Bajari (2001), in his study of highway construction firms bidding for procurement contracts, have also shown that location plays a major role in a firm's bidding behavior when collusion between firms is present.

When projects are irregularly dispersed and recorded as points in the landscape, it is more difficult to define a set of "influential" neighboring projects. Therefore, spatial relationships that reflect a decaying distance between points or locations identified by latitudes and longitudes are often assumed to be appropriate. Thus, when there is a correlation among projects due to location (spatial correlation), ignoring spatial interdependence of projects is like ignoring the sequential ordering of time-series studies.

Each year, federal and state agencies initiate large numbers of auctions that are spatially correlated.[37] An understanding of these spatial correlations could help state and federal governments sequence auctions of related projects more efficiently. This understanding is also beneficial to bidding firms, enabling them to take advantage of the synergies and economic advantages described above.

Recently, Krishna and Rosenthal (1995) and Branco (1997) have shown that, in recurring auctions, bundle bidders who bid on multiple objects bid more aggressively than unit bidders who bid on a single object. Jeitschko and Wolfstetter (2001) have described bidding behavior in first-price sealed-bid ascending recurring auctions and show that bidders who have previously won may experience the synergies described above in subsequent auctions.

Empirical research on synergies in auctions is scarce. Gandal (1997) shows that complementarities associated with winning multiple projects in a particular geographic area enhanced the values of neighboring CATV licenses in major metropolitan areas in Israel. Ausubel et al (1997)[38] show that there are geographic synergies associated with winning multiple adjacent licenses in spectrum license auctions in the United States. Rusco and Walls (1999) show that, in repeated spatially correlated timber auctions, bidders with complementarities associated with winning multiple projects bid more aggressively. Jofre-Bonet and Pesendorfer (2000) use data from repeated highway construction procurement auctions to show that the distance between firms and projects have a negative impact on the submission and value of bids. In addition, they have

[37] For example, cable television and telecommunications licenses, timber auctions, road-construction auctions. See Rusco and Walls (August 1999).

[38] This study investigates the existence of synergies in broadband personal communication service spectrum (PCS) ascending-bid auctions in United States.

shown that capacity unconstrained bidders (bidders with low backlogs) are more likely to submit a bid and to bid more aggressively than bidders with high capacity constraints.

In this study, I examine bidders' behavior in recurring auctions of road construction contracts held by ODOT between January 1997 and August 2000 to determine whether they have been affected by the synergies and competitive advantages (or no advantages) described above. This essay documents the participation patterns and differences in bidding patterns among firms to argue that they are caused by synergies that are spatially correlated and reports that, when a firm with potential synergies and competitive advantages participates in a recurring procurement auction, its probability of winning the auction, conditional upon bidding, increases. Further, this study finds that firms with potential synergies and competitive advantages bid more aggressively. Finally, the study supports Jofre-Bonet and Pesendorfer's (2000) claim that, when a firm's capacity constraint is low, it tends to bid more aggressively.

Section V.2 describes the modeling framework used in this study. Section V.3 outlines the equilibrium strategies utilized in this model. Section V.4 describes the data set; Section V.5 reports the results of the empirical analysis; and Section V.6 summarizes the main points of the essay.

V.2. Model

Jeitschko and Wolfstetter (2001) first developed the comparative model used in this study. They analyzed economic advantages in terms of economies of scale in first-price sealed-bid ascending auctions. This essay adapts their model to investigate first-price sealed-bid auctions of construction contracts and emphasizes synergies in which the lowest bidder is awarded the project.

Consider a sequence of two auctions in each of which a single project is auctioned to two bidders[39]. The winner of the first auction is hereafter referred to as the *incumbent* and the loser is the *contestant*. Prior to the first auction, each bidder privately observes his cost for the first project (C) but not the cost for the second project (C_H). A winner (the bidder with the lowest bid) is announced at the conclusion of the first auction, and then the bidders privately observe C_H, a random variable that depends upon the history (H) of a firm's winning or losing the first auction. The incumbent bidder has the potential to gain from synergies by winning the second project. In the second auction, the valuation of the incumbent bidder is C_I and that of the contestant bidder is C_C. C is drawn from a known distribution normalized to $\{0, c\}$, $c > 0$, with probability ρ, where $0 < \rho := \Pr\{C = c\} < 1$. The valuation of the second project is also drawn from $\{0, c\}$, $c > 0$, but C_H and C_C are stochastically independent. The probability of the event $C_H = c$, ($H \in \{I, C\}$) is not the same for incumbent and contestant bidders. Whereas the incumbent bidder with potential synergies gains from winning multiple projects in the same geographic location, the contestant bidder may not. Incumbent bidders have a higher probability of drawing a lower valuation for the project (σ) as compared to the contestant (i.e., $0 < \rho < \sigma < 1$) due to synergies and competitive advantages but, if they do not observe competitive advantages, their probability of incurring a lower valuation is $0 < \sigma < \rho < 1$. Hence, synergies and competitive advantages increase the expected value of a project for an incumbent.

Risk-neutral bidders maximize the sum of the payoffs from both auctions by placing real-valued bids. Thus, the study assumes that bidders do not discount their expected

[39] The study differentiates between groups of two bidders with emphasis on *incumbent* bidders and

payoffs for the second auction. This assumption is valid to this study's data set where bidders do not know about upcoming projects until the winners are notified about the results of the current auction. The payoff in the second auction is

$$U_H(C_H) := \Pr\{\text{winning the } 2^{nd} \text{ auction}\}\,(P_2 - C_H),\ \ H \in \{I, C\}, \tag{V.1}$$

where P_2 denotes the price received after the completion of the project, which is equal to the winning bid. As noted earlier, in a first-price sealed-bid auction, the incumbent will bid with probability σ and the contestant will bid with probability ρ when the incumbent has synergies and competitive advantages. The overall payoff, evaluated at the time of the first auction is

$$\begin{aligned} U(C) := {} & \Pr\{\text{winning the } 1^{st} \text{ auction}\}\,(P_I - C + E[U_I(C_I)]) \\ & + (1 - \Pr\{\text{ winning the } 1^{st} \text{ auction }\})\, E[U_C(C_C)], \end{aligned} \tag{V.2}$$

where P_I denotes the price received after the completion of the project, which is equal to the winning bid.

Let Δ denote the ex ante value of the synergy component. This is equal to the expected payoff differences between an incumbent and a contestant.

$$\Delta := E[U_I(C_I)] - E[U_C(C_C)], \tag{V.3}$$

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contestant bidders.

The overall payoff $U(C)$ can be identified as

$$U(C) := \Pr\{\text{ winning the } 1^{st} \text{ auction }\}\ (P_I - C + \Delta) + E[U_C(C_C)], \tag{V.4}$$

which is equal to the expected payoff of the contestant from the first auction and the realized synergy and profits gained by the probability of winning the first auction. In the first auction, ties are broken by the flip of a fair coin. In the second auction, the incumbent will bid aggressively if incurring synergies or competitive advantages. However, if the incumbent firm does not observe competitive advantages, it will bid less aggressively than contestants will. When the support of the distribution of types is discrete, rather than continuous, the players must play a mixed strategy in equilibrium.

This study applies the above model as follows: In a repeated procurement auction, the winner of a project will be viewed as an incumbent. When incumbents bid in related projects, they may observe potential synergies and, therefore, may bid more aggressively than contestants. However, incumbency is not permanent. A firm may lose its incumbency if it does not have any ongoing projects and will then bid as a contestant. This study investigates the effects of synergies on the bidding behavior of incumbents and contestants.

V.3. Equilibrium Strategies

In this section, we consider equilibrium strategies for bidders that may have potential synergies in the projects they are bidding for. Suppose both bidders draw cost $C = c - \Delta$ with probability ρ, and cost $C = c$ with probability $1-\rho$, randomizing according to the distribution strategy $F(s)$: $[s_L, s_H] \rightarrow [0, 1]$: and then $s_H = c$ and $s_L = c - \Delta\rho$. Now, consider first-price sealed-bid auctions with synergies. The incumbent has a higher probability of incurring a low valuation for the second project than the contestant. Hence, the unique equilibrium strategies of this auction are[40]:

Proposition 1 (Second Auction): In equilibrium, when $\sigma > \rho$ (with synergies), bidders with $C_H = c$ bid their value and bidders with $C_H = c - \Delta$ play mixed strategies $F_H : [c-\Delta\rho, c] \rightarrow [0, 1]$. Thus, the bid distributions can be expressed as follows:

$b_2(c) = c, \qquad H \in \{I, C\}$ (bidder with $C = c$) (V.5)

$F_C(b) = 1 - \dfrac{(1-\rho)(c-b)}{\rho(b-c+\Delta)}$ (contestant bidder with $C = c - \Delta$) (V.6)

$F_I(b) = 1 - \dfrac{\Delta(\sigma-\rho)-(1-\sigma)(b-c)}{\sigma(b-c+\Delta)}$ (incumbent bidder with $C = c - \Delta$). (V.7)

Bidder's equilibrium payoffs are:

$U_H(0) = 0$, $U_H(c) = c\,(\rho - 1)$, $H \in \{I, C\}$. (V.8)

The synergy component is calculated as follows. In the second auction, the bidder has a positive expected payoff only if he has cost $C_H = c - \Delta$. Therefore, after the first auction and before the second auction, the incumbent bidder's payoff is $E\,[U_I\,(C_I)] = \sigma\,(1-\rho)\Delta$, whereas the contestant bidder's payoff is $E\,[U_C\,(C_C)] = \rho\,(1-\rho)\Delta$. Hence, by definition (V.3),

$$\Delta_S := (\sigma - \rho)\,(1 - \rho)\Delta \qquad \text{(V.9)}$$

[40] See also Jeitschko and Wolfstetter (2001).

Note that a bidder takes into account the fact that, as a result of his winning the first auction, the contestant will recognize him as an incumbent bidder.

Now, consider the first auction. Proposition 2 summarizes the first auction as follows:

Proposition 2 (*First auction*): In equilibrium, when $\sigma > \rho$ (with synergies), bidders with $C_H = c$ bid according to the value of the synergy and bidders with $C_H = c - \Delta$ play mixed strategies $F_H : [c - \Delta_s, c] \rightarrow [0, 1]$. Thus, the bid distributions can be expressed as follows:

$$b(v) = c \tag{V.10}$$

$$F(b) = 1 - \frac{(1-\rho)(\Delta - 1)}{\rho(b - c + \Delta)}, \tag{V.11}$$

and both bidders continue in the second auction as in Proposition 1.

In case the incumbent does not observe competitive advantages ($0 < \sigma < \rho < 1$), the bidding patterns of incumbents and contestants in the second auction are nearly identical. The bidders' strategies and payoffs are as they are in Proposition 1, other than σ and ρ, with the contestant and incumbent bidders exchanging places. Therefore, bidders with $C_H = c$ bid their value and bidders with $C_H = c - \Delta$ play mixed strategies F_H : $[c - \Delta, c] \rightarrow [0, 1]$. Thus, the bid distributions can be expressed as follows:

$$F_I(b) = 1 - \frac{(1-\sigma)(c-b)}{\sigma(b - c + \Delta)} \qquad \text{(contestant bidder with } C = c - \Delta) \tag{V.6'}$$

$$F_{C'}(b) = 1 - \frac{\Delta(\rho - \sigma) - (1-\rho)(b-c)}{\rho(b-c+\Delta)} \qquad \text{(incumbent bidder with } C = c - \Delta\text{).} \qquad \text{(V.7')}$$

In sum, one can assume that, in the first auction, bidders with high costs will bid c and bidders with low costs will submit a bid drawn from the distribution presented in equation (11), which is lower than c. Thus, the low-value bidder will win the project since the analysis is for first-price sealed-bid construction contracts. In subsequent auctions, an incumbent (or contestant) with potential synergies or with competitive advantages (or no advantages), and with a low valuation of c - Δ, will submit a bid from the distribution presented by equation-V.7 (V.6') and win the project. Any bidder with a high valuation of c will not win the project. It is easy to establish that incumbents with synergies or with economic advantages bid more aggressively than contestants. From equations (V.6) and (V.7), one can establish that the cost distribution of a contestant stochastically dominates the distribution of an incumbent, $F_I(b) \geq F_C(b)$. This essay constructs synergy and competitive advantage variables to support the above theory, and empirical results supporting the above claims are presented in Section V.5.

V.4. Data

The data used in this analysis comprises information on all road construction projects auctioned by the ODOT from January 1997 to August 2000.[41] Projects are auctioned off once each month, in two sessions, in a first-price sealed-bid format. Major projects are auctioned off, like road construction and paving, traffic signaling, bridge

[41] Since I investigate synergies derived from divisional effects, statewide projects are excluded (3 auctions).

construction and maintenance, as well as minor projects like drainage and clearance.[42] The state reserves the right to reject any bid that is seven percent above the state's engineering cost estimate for the project, but there have been some exceptions to this rule mostly due to the underestimation of costs by the state. Generally, bidders must be pre-qualified to participate in these auctions. Pre-qualification involves bidders' submission of certified financial statements to ODOT and is related to the level of working capital available to the potential bidder as well as its history of successful completion of projects. The resultant evaluation is used to determine the size of projects a firm can bid on. Firms can be disqualified at any time if they fail to complete contracts successfully. Finally, bidders must make a down payment of five percent of the project's value when submitting a bid.[43]

The data examined in this study includes descriptions of "plan-holders" (firms that purchase project plans), all bids for the project, and the winning bid (if the contract is awarded). The state also provides the location of each project, a description (e.g., bridge construction, asphalt paving, etc.), relevant details (e.g., the length and depth of the paving surface, the type of material to be utilized, the amount of excavation, etc.), duration (calendar days), and the total engineering estimate. Table 1 provides summary statistics on the number of auctions, the average number of plan-holders per auction, and the average number of bidders per auction. During the period under study, there were 1734 auctions, with an average of 5.5 plan-holders and 3.3 bidders per auction. Contracts

[42] Highway construction auctions have been examined in a number of papers including Thiel (1988), Porter and Zona (1993), Jofre-Bonet and Pesendorfer (2000) and Bajari (2000). But they do not investigate the bidder behavior due to synergies.

[43] In general, these requirements establish some barriers for firms to extract synergies. Firms my have an ongoing project in an area but due to pre-qualification requirements firms may not be able to bid on upcoming projects even though they can realize synergies from it.

were awarded in 1409 of the 1734 auctions. A total of 284 different firms held project plans, 213 bid on projects, and 144 won contracts.[44]

ODOT has divided Oklahoma into eight divisions (Figure 1).[45] Most of the projects under study were located in Division 4 (278).[46] Most firms (49 out of 284) were also located in Division 4 and bid 2286 times, winning 612 projects. Table 2 shows the bid frequency by firm division and by project division. One can see that out-of-state firms (firm division = 0) bid all across Oklahoma. Their bid frequency on projects ranges from 6.8 percent (38 bids) in Division 2 to 20.7 percent (112 bids) in Division 8. Further, they account for 15.34 percent of all projects in Division 1. Table 2 reveals that firms in Oklahoma have strong regional preferences, with firms located in a certain division tending to bid on projects in their own division. For example, 32.49 percent of all the bids submitted by firms in Division 1 were submitted to projects in that division. Further, compared with other firm divisions, 28.29 percent of projects in Division 1 were submitted by firms in that division. This pattern can be observed for all project types.

V.5. Empirical Analysis

In this section, I model the differences in bidding due to synergies in spatially correlated auctions and utilize a simple reduced–form model of bidding in spatially correlated procurement auctions. Three dependent variables that summarize the participation and bidding patterns in these auctions are examined: 1) probability of bidding, 2) probability of winning conditional upon bidding, and 3) log of the bid. The independent variables that control for project characteristics are: 1) a set of dummy

[44] There are several firms in our data sets that purchase plans, bid and win frequently. The maximum number of bids we observe by one firm is 218 and the maximum number of wins by a firm is 59 wins.
[45] There are 77 counties in Oklahoma and ODOT has divided them into eight divisions.

variables for project types (P_j's), 2) the state's estimate of the engineering cost (log(engest)), and 3) the number of bidders (log(#bidders)). The project types include a set of six dummy variables: asphalt, clearance and bank protection, bridge work, grading and draining, concrete work, and signals and lighting. The omitted group is miscellaneous work such as intersection modification, parking lot construction, and landscaping. The engineering cost estimates are constructed by the state by pricing each feature outlined in the design and then deriving an overall cost estimate for the project. While the engineering cost estimate should control for project-specific differences in cost, certain project classes have different pre-qualification standards. Hence, the pool of potential bidders may differ somewhat across project types. With respect to information on the level of competitiveness in an auction, the study includes a variable to measure competition. As is standard in the auction literature, this study also controls for the number of bidders (log(#bidders)).

With respect to bidders' own characteristics, four measures are included in the regressions. The study categorizes incumbents and contestants into four different groups identified by three dummy variables: 1) incumbent bidders bidding in their own division[47] (dincumbent), 2) incumbent bidders bidding in different divisions[48] (ndincumbent), 3) contestant bidders bidding in their own division (dcontestant), and 4) the omitted group—contestant bidders bidding in different divisions (ndcontestant). In the period under study, incumbent bidders bidding in their own division make up about

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[46] It is worthwhile to mentioning that Oklahoma City, the largest city in State of Oklahoma is located in this division.

[47] In this case the firm's location and project location are in the same division. For example a firm in Division-4 that has won a project in Division-4 and is bidding in Division-4 in subsequent auctions.

[48] The different divisions are identified as divisions other than their own division where they have an on going project. For example a firm in Division-4 that has won a project in Division-2 and is bidding in Division-2 in subsequent auctions.

19.87 percent of plan-holders and 22.31 percent of bidders. Out of the 9526 plans purchased in that period, incumbent bidders bidding in their own division purchase 1893 plans and, eventually, submit 1165 bids. Out of the 1734 auctions under study, 778 contain incumbents bidding in their own division[49] who won 399 projects (Table 1).

Next, the study includes a variable that accounts for past success in auctions (wbratio). This variable is constructed as the ratio of the past number of wins to the past number of bids. It provides information on the previous success of a firm and is included to control for differences in firm efficiencies. In addition to the synergy variables, a backlog variable is constructed. For each firm, the average monthly value of every contract won is calculated. Each subsequent month, the average monthly value is subtracted from the remaining portion of the contract until the completion of the project. Thus, the total remaining value of the projects that a firm has undertaken can be calculated at any given point in time. Backlog[50] variable is used to control for firms' capacity constraints.

Theoretical predictions indicate that incumbents bid aggressively when they observe synergies. Therefore, the study expects the following empirical results. First, incumbents bidding in their own region will have a higher probability to bid, will have a higher probability to win conditional upon bidding, and will bid more aggressively compared to any other bidder since they gain from both synergies and competitive advantages associated with their familiarity with local market resources. Second, contestants will have a low probability to bid and to win conditional upon bidding, and

[49] Incumbents bidding in different divisions were present in 208 auctions, contestants bidding in their own division were present in 459 auctions, and contestants bidding in different actions were present in 1610 auctions.

will bid less aggressively regardless of whether they bid in their own division or not. Third, efficient firms will have a higher probability to bid and win and will bid aggressively and, therefore, the coefficient of the *wbratio* should indicate a negative sign. Finally, firms with low capacity constraints (high backlog) will bid less aggressively. Bidding behaviors are analyzed using probits, ordinary least squares (OLS), and standard panel data techniques.[51] Thus, the basic structure of the empirical model is as follows:

$$\begin{aligned} y_i = \beta_0 + \sum_{j=1}^{6} \beta_j \mathrm{P}_{ji} + \beta_7 \log(engest_i) + \beta_8 \log(\#bidders_i) + \beta_9 (dincumbent_i) \\ + \beta_{10}(ndincumbent_i) + \beta_{12}(dcontestant_i) + \beta_{13} \log(backlog_i) \\ + \beta_{14}(wbratio_i) + \varepsilon_{i\mu w} \end{aligned} \qquad \text{(V.12)}$$

As discussed earlier, interdependencies among projects and geographic areas may lead to spatial correlation among bids. If one observes spatial heterogeneity in a model, the estimation of that model with simple probits, OLS, and fixed effects will result in inefficient estimators. Therefore, this study will use spatial econometric techniques to analyze bidding behavior. There has been very little research on spatial models in auction markets[52] and this research affords new insights into procurement auction markets with spatial properties. Of the numerous spatial models available, [53] this study utilizes the Gibbs Sampling Bayesian heteroscedastic spatial probit method and the Gibbs

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[50] The study uses the log of the backlog. The log of backlog is calculated as follows: *lbacklog* = log(*backlog*+1).

[51] The study will use fixed effects model to analyze the within firm bidding behavior.

[52] Ausubel et al (1997) show that there are geographic synergies associated with winning multiple PCS licenses. Rusco and Walls (1999) have shown spatial correlation in timber market auctions. Further, Porter and Zona (1999), in their study of bidding by dairies for contracts to supply milk, and Bajari (2001), in his study of bidding by highway construction firms for procurement contracts, have also shown that location plays a major role in firm's bidding behavior.

[53] Methods proposed to estimate spatial models and applied studies are spatial probit error models (McMillen 1992), LeSage (2000), and LeSage and Smith (2000), generalized estimations of the probit (Pinske and Slade 1998), generalized method of moments by LaSage (1999a, 1999b), Kelejian and Prucha 1998, 1999), and Bell and Bockstael (2000), and simulated recursive sampling (Vijverberg 1997). For reviews see Anselin and Florax (1995).

Sampling Bayesian heteroscedastic spatial regression method introduced by LeSage (1999a, 1999b).[54]

There are numerous advantages to using the Gibbs Sampling Bayesian heteroscedastic spatial regression and probit methods (LeSage 1999a). First, this method, unlike others, allows for the assumption of non-constant variance for each region, resulting in efficient estimators. This can be easily explained by analyzing the structure of the error term. The random error vector, u, takes the following form: $u = \lambda Wu + \varepsilon$, where λ is a scalar parameter that indicates the magnitude of spatial correlation among projects and W is a known $n \times n$ spatial weight matrix generally constructed by using latitude and longitude coordinates, as in this essay. The random error vector, ε, is an $n \times l$ vector with a non-constant variance taking on different values for specific regions. Other methods, however, assume that there is a constant variance for all regions, meaning that there is no heterogeneity due to regions.

Second, unlike other methods, the Gibbs Sampling approach constructs complete conditional distributions for all the parameters in the model that converge in the limit to their true distributions of the parameters. This technique allows for constructing efficient estimators.

The third advantage is that in the Gibbs Sampling Bayesian heteroscedastic spatial probit methods, unlike in other methods, one does not have to specify a functional form for the random error term, ε. This would be impractical for large models when specifying the functional form and the variables involved in the models for variance of the error term. The basic idea of the Gibbs sampling is to create a large random sample

[54] See the appendix for a brief technical explanation.

of observations for the posterior density of parameters to be estimated, and then to approximate the shape of these probability densities.[55] LeSage (1999a p.87) explains the Gibbs sampling steps in detail.

First, the Lagrange Multiplier (LM) error test is used to test for spatial correlation. The null hypothesis of the LM test is that there is no spatial correlation in the models. The application of the LM test to the data set demonstrates that the model fits a *Spatial Error Model*, in which the error terms exhibit spatial dependence.[56] The observed LM values and corresponding probabilities are given in Table 4. This further justifies the existence of spatial correlations in this auction market. In this case, this essay utilizes the *Gibbs Sampling Bayesian Heteroscedastic Spatial Error Model* to analyze the data. See appendix (V.7.) for a brief description of the *Gibbs Sampling Bayesian Heteroscedastic Spatial Regression/Probit Models.*

Next, the study estimates probit models for bid submission. The first column in Table 5 reveals that incumbent bidders bidding in their own division are most likely to submit a bid. Further, incumbents bidding in different divisions and contestants bidding in their own division are also more likely to submit a bid compared to contestants bidding in different divisions. Firm efficiencies are captured by the past wins-to-bid ratio and this shows that efficient firms are more likely to submit bids. Therefore, the results are in accordance with the predictions of this study. Column 2 of Table 5 shows the Gibbs Sampling Bayesian heteroscedastic spatial probit results. The spatial probit results are also significant and consistent with the hypothesis. The most important point is that the λ

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[55] Kernel density functions can be used to approximate these distributions.

[56] There are three basic spatial models: 1) *General Spatial Model*, which includes both the spatial lagged term as well as a spatially correlated error structure, 2) *Mixed Autoregressive-regressive Model*, in which

parameter is significant. This indicates that projects are geographically correlated and, as the distance increases, the spatial correlation decreases. Both models show that bidders with synergies are more likely to bid than those with no competitive advantages.

The first column of Table 6 shows results for the probability of winning conditional upon bidding using a general probit model. The results indicate that incumbents bidding in their own division are more likely to win than any other bidder. Incumbents bidding in different divisions are also likely to win, but less than incumbents who are winning in their own divisions, compared to contestants winning conditional upon bidding in their own divisions and contestants winning conditional upon bidding in different divisions. There is no statistical difference between contestants winning conditional upon bidding in their own divisions compared to contestants winning conditional upon bidding in different divisions. As expected, efficient firms are more likely to win. In addition, capacity constrained bidders are less likely to win than capacity unconstrained bidders. Spatially adjusted probit results indicate that λ is insignificant. Both models show that bidders with synergies and competitive advantages are more likely to win conditional on bidding than those with no competitive advantages.

Table 7 presents the next set of regression results using an OLS model with White-corrected standard errors to correct for heteroscedasticity (column1) and Gibbs Sampling Bayesian heteroscedastic spatial error models (column 2). In OLS and spatially adjusted models, the results indicate that incumbents bidding in their own division or in different divisions bid more aggressively than any other bidder. This again supports the hypothesis that bidders who realize synergies will bid more aggressively. In

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the standard regression model is combined with a spatially lagged dependent variable, and 3) *Spatial Error Model*. LeSage (1999a) defines these spatial models in detail in Spatial Econometrics.

addition, Jofre-Bonet and Pesendorfer's (2000) claim—that capacity-constrained bidders are less likely to bid than capacity-unconstrained bidders—is supported.

Finally, the study uses a fixed-effects model to analyze the data. To observe within-firm effects, only firms with multiple bids have been used. In the fixed-effects models, the *wbratio* is excluded because the backlog variable is used to capture bidder efficiency due to capacity constraints over time. Further, a firm may bid as an incumbent in its own division as well as in a different division, simultaneously. In this case its *wbratio* will be the same. The incumbent and contestant dummies are expected to show differences in the aggressiveness of bids. Again, one should remember that incumbency is not permanent. The results indicate that, when a firm is an incumbent and bidding in its own division, it bids more aggressively than when it is an incumbent and bidding in a different division, or a contestant bidding in its own division or in a different division (Table 8). Finally, in all models, the results indicate that, when a firm is capacity constrained, it will bid less aggressively than when it has low capacity constraints. In the fixed-effects model, λ is insignificant, indicating that spatial dependence dissipates when looking at within-firm effects.

V.6. Summary

This paper examines the bidding behavior of firms with synergies in recurring spatially correlated road construction procurement auctions held by ODOT from January 1997 to August 2000. The study reveals that projects are spatially correlated and, as the distance increases, the correlation dissipates. The theoretical predictions indicate that incumbents with synergies will bid more aggressively than contestants. Firms with competitive advantages and inherent firm efficiencies will also bid more aggressively.

Incumbent bidders bidding in their own divisions with synergies and competitive advantages tend to have a high probability of winning conditional upon bidding than other bidders. Firm efficiencies increase the probability of bidding and winning, and also aggressiveness of bids. Further, the study shows that capacity constrained bidders bid less aggressively. Finally, the study shows that, when considering within-firm effects, the results indicate a similar pattern. That is, when a firm is an incumbent bidding in its own division, it tends to bid more aggressively than when it is a contestant.

V. 7. Appendix

A general version of the Gibbs Sampling Bayesian heteroscedastic spatial regression model with an informative prior can be written as (LeSage 1999a, p.86):

$$y = \rho Wy + X\beta + u$$

$$u = \lambda Wu + \varepsilon$$

$$\varepsilon \sim N(0, \sigma^2 V) \qquad \text{(V.13)}$$

$$V = diag(v_1, v_2, \ldots, v_n)$$

where y contains an $n \times 1$ vector of cross-sectional dependent variables. The matrix X represents an $n \times k$ matrix of explanatory variables such as explained earlier. The random error vector (u) is an $n \times 1$ vector with mean 0 and a non-spherical variance-covariance matrix $\sigma^2 (I - \lambda \mathrm{W})^{-1} \ (I - \lambda \mathrm{W}')^{-1}$. The random error vector (ε) is an $n \times l$ vector with an expected mean value of zero and a non-constant variance ($\sigma^2 V$) taking on different values for specific regions. Thus, spatial heterogeneity across ODOT divisions is assumed in this study. The magnitudes v_i, $i = 1, \ldots, n$ represent parameters to be estimated. A normal prior has been placed on the parameter β (mean $c = 0$ and variance $T = 1$), and an undetermined prior mean of μ and an undetermined prior variance d_0 are prior parameters for σ. The relative variance terms ($v_1, v_2, \ldots, v_n$) are assumed to be fixed but unknown parameters that need to be estimated in addition to n parameters.[57] The prior distribution of the v_i terms takes the form of an independent $\chi^2(r)/r$ distribution, where this χ^2 distribution is a single parameter distribution represented as r[58] and $r \sim \Gamma(m, k)$. W is a known $n \times n$ spatial weight matrix, usually containing first-order contiguity relations or functions of distance, and ρ and λ are scalar parameters to be estimated, where p and l are undetermined prior parameters for ρ and λ respectively. The parameter, λ, is a coefficient on the spatially correlated errors that shows the magnitude of spatial correlation among projects. Note that, when ρ is insignificant, the *General Spatial Model* collapses to a *Spatial Error Model* (SEM) and, when λ is insignificant, it collapses into a *Mixed Autoregressive Model* (SAR) (LeSage 1999a). In this study, latitude and longitude coordinates have been used to construct a contiguity matrix when estimating data. These latitude and longitude coordinates indicate each county seat. ODOT also uses county seats to calculate distance between counties. Since ODOT indicates the project location by county, these latitude and longitude coordinates are used to identify the project locations and to construct the W matrix, as indicated above.

One of the problems that Bayesian regressions face is in deriving a posterior distribution for parameters to be estimated. This problem can be overcome by using a Gibbs sampling procedure.[59] The basic idea of the Gibbs sampling procedure is to create a large random sample of observations from the posterior density of parameters to be

[57] LeSage (1999a) says that, estimating n parameters, $v_1, v_2, \ldots, v_n$, in addition to the $k+1$ parameters, β, and σ using n data observations is not a problem from a degrees of freedom perspective because, Bayesian methods rely on an informative prior for the v_i parameters.

[58] This additional parameter, r, allows us to estimate the additional n v_i parameters in the model. Note that as r becomes very large, the terms r/v_i will all approach unity, resulting in homoscedastic ($V = I_n$) error terms. Then this means that we start with a prior belief that the variance is constant over all regions (LeSage 1999a).

[59] This method is also called as the Markov Chain Monte Carlo procedure.

estimated and, then, to approximate the shape of these probability densities.[60] LeSage (1999a p.87) explains the Gibbs sampling steps in detail.

When ρ is insignificant, the *General Spatial Model* collapses to a *Spatial Error Model* (SEM). In this case, the *Gibbs Sampling Bayesian Heteroscedastic Spatial Error Model* will take the following form:

$$y = X\beta + u$$

$$u = \lambda W + \varepsilon \tag{V.14}$$

$$\varepsilon \sim N(0, \sigma^2 V)$$

$$V = diag(v_1, v_2, \ldots, v_n).$$

When considering probit models with heteroscedasticity, it is important to account for the heteroscedasticity because, if one assumes that errors are homoscedastic, the estimator will be inconsistent. LeSage (1999a, 2000) and LeSage and Smith (2000) introduce a Gibbs sampling Bayesian heteroscedastic spatial probit models that accounts for heteroscedasticity. LeSage (1999a) notes that evaluating likelihood functions for heteroscedastic spatial models is impractical.[61] Estimating with McMillen's (1992) approach also results in biased estimators. The Bayesian heteroscedastic spatial probit model overcomes these problems, and the basic idea of this model is as follows. Using the Gibbs sampling approach, one can construct a conditional distribution for the censored or latent observations conditional on all other parameters in the model. In the

[60] Kernel density functions can be used to approximate these distributions.
[61] The model contains a number of integrals that equal to the number of observations.

case of a probit model, this distribution is used to produce a random draw for all y_i in the model. This conditional distribution for the latent variables takes the form of a normal distribution centered on the predicted value truncated by 0 from the left for $y_i = 1$ and truncated by 0 from the right $y_i = 0$. This process ensures the predicted values to be between (0,1) interval. Then, LeSage (1999a, 2000) and LeSage and Smith (2000) note that, when one has a random normal sample for the unobserved latent variable, the model becomes a Bayesian heteroscedastic spatial regression model (as presented earlier) and all parameters and conditional distributions stay valid. Therefore, one can view this as a Bayesian heteroscedastic spatial error model with a binary dependent variable.

In this study, a latent but unobservable variable[62] is z, such that values of $z_i \leq 0$ produce observed variables, $y_i = 1$ and $z_i > 0$, resulting in $y_i = 0$. Therefore, we can formally sate that the conditional probability of z_i, given all other parameters, is:

$$f(z_i \mid \rho, \beta, \sigma) \sim \begin{cases} N(\tilde{y}_i, \sigma^2_{pi}), \text{ truncated at the left by 0 if } y_i = 1 \\ N(\tilde{y}_i, \sigma^2_{pi}), \text{ truncated at the right by 0 if } y_i = 0 \end{cases} \tag{V.15}$$

where the predicted value for z_i is denoted by $\tilde{y}_i$ which represents the ith row of $\tilde{y} = X\beta$ for the SEM. The variance of the prediction is $\sigma^2_{pi} = \sum_j \omega^2_{ij}$, where ω_{ij} denotes the ijth element of $(I_n - \rho W)^{-1}\varepsilon$.

[62] The latent variable can be defined as follows: firms do not observe their true cost for a project but knows their threshold cost, c^*, for each project. Therefore, we can set that when considering the probability of bidding, when a firm's cost is less than or equal to c^* then they will submit a bid, where $y = 1$. When considering the probability of winning conditional upon bidding, latent variable is set equal to the lowest cost.

Table-V.1: Summary Statistics of Oklahoma Road Construction Auctions

Variable	Auction Statistics
Number of Auctions	1734
Number of Auctions w/ Winners	1409
Number of Firms	284
Number of Plans Purchased	9526
Number of Bids	5221
Average Number of Plan holders per Auction	5.5305 (3.0578)
Average Number of Bidders per Auction	3.3026 (1.6843)
Number of Incumbent Plan Holders in their Own Division	1893
Number of Incumbent Plan Holders in Different Divisions	4516
Number of Contestant Plan Holders in their Own Division	939
Number of Contestant Plan Holders in Different Divisions	2178
Number of Bids by Incumbents who are Bidding in their Own Division	1165
Number of Bids by Incumbents who are Bidding in Different Divisions	2621
Number of Bids by Contestants who are Bidding in their Own Division	492
Number of Bids by Contestants who are Bidding in Different Divisions	943
Number of Incumbent Winners in their Own Division	399
Number of Incumbent Winners in Different Divisions	658
Number of Contestant Winners in their Own Division	135
Number of Contestant Winners in Different Divisions	217

Note: Standard Deviations are in parentheses.

Figure-V.1: ODOT Field Divisions

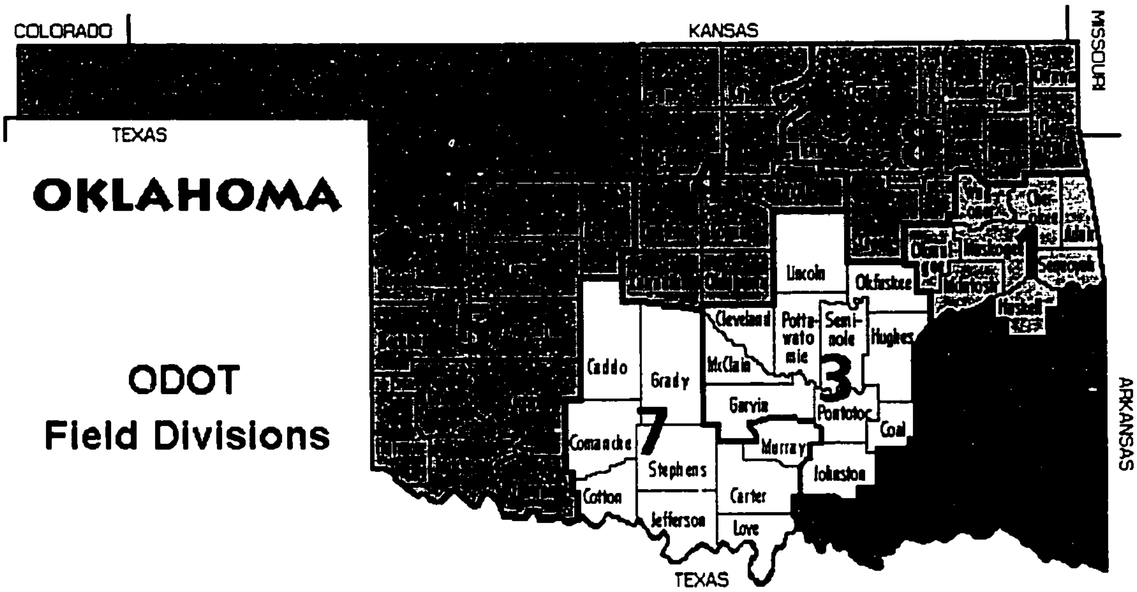

Table-V.2: Bid Frequencies by Firm Division and Project Division

Frequency Percent Row % Col. %	Projdiv-1	Projdiv-2	Projdiv-3	Projdiv-4	Projdiv-5	Projdiv-6	Projdiv-7	Projdiv-8	Total
Firmdiv-0	77 1.47 13.80 15.34	38 0.73 6.81 9.18	69 1.32 12.37 7.36	105 2.01 18.82 9.84	40 0.77 7.17 7.49	74 1.42 13.26 21.20	43 0.82 7.71 6.78	112 2.15 20.07 14.29	*558* *10.69*
Firmdiv-1	142 2.72 32.49 28.29	69 1.32 15.79 16.67	69 1.32 15.79 7.36	42 0.80 9.61 3.94	9 0.17 2.06 1.69	7 0.13 1.60 2.01	14 0.27 3.20 2.21	85 1.63 19.45 10.84	*437* *8.37*
Firmdiv-2	26 0.50 13.27 5.18	89 1.70 45.41 21.50	51 0.98 26.02 5.44	4 0.08 2.04 0.37	0 0.00 0.00 0.00	0 0.00 0.00 0.00	22 0.42 11.22 3.47	4 0.08 2.04 0.51	*196* *3.75*
Firmdiv-3	7 0.13 2.67 1.39	1 0.02 0.38 0.24	81 1.55 30.92 8.64	26 0.50 9.92 2.44	63 1.21 24.05 11.80	44 0.84 16.79 12.61	39 0.75 14.89 6.15	1 0.02 0.38 0.13	*262* *5.02*
Firmdiv-4	124 2.38 5.42 24.70	140 2.68 6.12 33.82	487 9.33 21.30 51.97	704 13.48 30.80 65.98	228 4.37 9.97 42.70	113 2.16 4.94 32.38	285 5.46 12.47 44.95	205 3.93 8.97 26.15	*2286* *43.78*
Firmdiv-5	3 0.06 1.16 0.60	2 0.04 0.77 0.48	25 0.48 9.65 2.67	30 0.57 11.58 2.81	101 1.93 39.00 18.91	56 1.07 21.62 16.05	35 0.67 13.51 5.52	7 0.13 2.70 0.89	*259* *4.96*
Firmdiv-6	0 0.00 0.00 0.00	1 0.02 3.13 0.24	0 0.00 0.00 0.00	0 0.00 0.00 0.00	3 0.06 9.38 0.56	28 0.54 87.50 8.02	0 0.00 0.00 0.00	0 0.00 0.00 0.00	*32* *0.61*
Firmdiv-7	9 0.17 2.60 1.79	19 0.36 5.49 5.49	53 1.02 15.32 5.66	35 0.67 10.12 3.28	65 1.24 18.79 12.17	13 0.25 3.76 3.72	147 2.82 42.49 23.19	5 0.10 1.45 0.64	*346* *6.63*
Firmdiv-8	114 2.18 13.49 22.71	55 1.05 6.51 13.29	102 1.95 12.07 10.89	121 2.32 14.32 11.34	25 0.48 2.96 4.68	14 0.27 1.66 4.01	49 0.94 5.80 7.73	365 6.99 43.20 46.56	*845* *16.18*
Total	*502* *9.62*	*414* *7.93*	*937* *17.95*	*1067* *20.44*	*534* *10.23*	*349* *6.68*	*634* *12.14*	*784* *15.02*	*5221* *100.00*

Table-V.3: Summary Statistics of Regression Variables

Variable	Mean (Standard Deviation)
Log of Bids	12.8824 (1.5899)
Log of Winning Bids	12.6465 (1.5981)
Log of Engineer's Estimate	13.0738 (1.6957)
Log of Number of Bidders in an Auction	1.2400 (0.473)
Probability of facing an incumbent who is bidding in his own division.	0.2231 (0.4164)
Probability of facing an incumbent who is bidding in a different division.	0.5020 (0.5000)
Probability of facing a contestant who is bidding in his own division.	0.0942 (0.2922)
Probability of facing a contestant who is bidding in a different division.	0.1806 (0.3847)
Log of Firm's Backlog	9.7314 (6.6558)
Firm's Winning to Bidding Ratio	0.2317 (0.1724)

Note: Standard Deviations are in parentheses.

Table-V.4: Spatial Dependence Test Statistics

Model	Test Statistics
Spatial Error Model	
LM value	7.237
Probability	0.0071
Mixed Autoregressive Model	
LM value	0.0148
Probability	0.9032

Table-V.5: Probit Results for Probability of Bidding

Variable	*Unadjusted for Spatial Correlation*	*Adjusted for Spatial Correlation*
Constant	1.1705*	1.3067*
	(0.1686)	(0.1877)
Project-1	0.1015	0.1137
	(0.0693)	(0.0736)
Project-2	-0.0750	-0.0583
	(0.0994)	(0.1106)
Project-3	-0.0244	0.0196
	(0.0669)	(0.0697)
Project-4	-0.2138*	-0.2316*
	(0.0749)	(0.0777)
Project-5	-0.0018	0.0127
	(0.1542)	(0.1671)
Project-6	0.4524*	0.4983*
	(0.0923)	(0.1035)
Log of Engineer's Estimate	-0.1013*	-0.1134*
	(0.0121)	(0.133)
Log of Firm's Backlog	-0.0082	-0.0082
	(0.0053)	(0.0060)
Firm's Winning to Bidding Ratio	0.3630*	0.4274*
	(0.0888)	(0.0964)
An Incumbent who is Bidding in his Own Division	0.5736*	0.6200*
	(0.0833)	(0.0946)
An Incumbent who is Bidding in a Different Division	0.5197*	0.5623*
	(0.0807)	(0.0895)
A Contestant who is Bidding in his Own Division	0.2090*	0.2341*
	(0.0516)	(0.0550)
λ		0.2864*
		(0.1412)
Num. of Obs.	8954	8954
LR χ^2	654.65	

Note: Standard Deviations are in parentheses. * Denotes 95% statistical significance.

Table-V.6: Probit Results for Probability of Winning

Variable	*Unadjusted for Spatial Correlation*	*Adjusted for Spatial Correlation*
Constant	-0.5384*	-0.5883
	(0.2342)	(0.2590)
Project-1	0.2158*	0.2445*
	(0.0926)	(0.1026)
Project-2	-0.1847	-0.2406
	(0.1380)	(0.1651)
Project-3	0.0054	0.0040
	(0.0904)	(0.1008)
Project-4	0.0613	0.0660
	(0.1064)	(0.1197)
Project-5	-0.0715	-0.1168
	(0.2123)	(0.2682)
Project-6	0.0218	0.0187
	(0.1105)	(0.1183)
Log of Engineer's Estimate	-0.0292	-0.0340*
	(0.0171)	(0.0197)
Log of Firm's Backlog	-0.0344*	-0.0378*
	(0.0064)	(0.0075)
Firm's Winning to Bidding Ratio	0.7547*	0.8482*
	(0.1216)	(0.1409)
An Incumbent who is Bidding in his Own Division	0.6636*	0.7392*
	(0.1030)	(0.1166)
An Incumbent who is Bidding in a Different Division	0.4300*	0.4782*
	(0.0995)	(0.1128)
A Contestant who is Bidding in his Own Division	0.0931	0.1083
	(0.0766)	(0.0875)
λ		0.2264
		(0.1325)
Num. of Obs.	5221	5221
LR χ^2	148.68	

Note: Standard Deviations are in parentheses. * Denotes 95% statistical significance.

Table-V.7: Regression Results for Log of Bids

Variable	*OLS*	*Adjusted for Spatial Correlation*
Constant	0.6370*	0.5583*
	(0.0636)	(0.0385)
Project-1	-0.0472*	-0.0276*
	(0.0180)	(0.0142)
Project-2	-0.0572	-0.0104
	(0.0466)	(0.0256)
Project-3	-0.0705*	-0.0416*
	(0.0184)	(0.0140)
Project-4	-0.0361	-0.0240
	(0.0203)	(0.157)
Project-5	0.1094*	0.1230*
	(0.0423)	(0.0381)
Project-6	-0.1808*	-0.1601*
	(0.0225)	(0.0175)
Log of Engineer's Estimate	0.9643*	0.9700*
	(0.0044)	(0.0027)
Log number of bidders	-0.0244*	-0.0302*
	(0.0078)	(0.0058)
Log of Firm's Backlog	0.0116*	0.0093*
	(0.0015)	(0.0011)
Firm's Winning to Bidding Ratio	-0.1565*	-0.1476*
	(0.0263)	(0.0189)
An Incumbent who is Bidding in his Own Division	-0.1266*	-0.1084*
	(0.0244)	(0.0171)
An Incumbent who is Bidding in a Different Division	-0.1116*	-0.0942*
	(0.0245)	(0.0169)
A Contestant who is Bidding in his Own Division	0.0002	-0.0074
	(0.0168)	(0.0113)
λ		0.2857*
		(0.0866)
Num. of Obs.	5221	5221
R^2	0.9731	0.9886

Note: Heteroscedasticity corrected standard errors are in parentheses. * Denotes 95% statistical significance.

Table-V.8: Fixed Effects Regression Results for Log of Bids

Variable	*Unadjusted for Spatial Correlation*	*Adjusted for Spatial Correlation*
Constant	0.8146*	-0.0005
	(0.0478)	(0.0027)
Project-1	-0.0468*	-0.0256*
	(0.0187)	(0.0149)
Project-2	-0.0154	-0.0230
	(0.0279)	(0.0258)
Project-3	-0.0146	-0.0084
	(0.0196)	(0.0160)
Project-4	0.0082	0.0114
	(0.0204)	(0.0156)
Project-5	0.1131*	0.1615*
	(0.0402)	(0.0366)
Project-6	-0.0441	-0.0344
	(0.0328)	(0.0269)
Log of Engineer's Estimate	0.9461*	0.9546*
	(0.0035)	(0.0029)
Log number of bidders	-0.0287*	-0.0279*
	(0.0079)	(0.0059)
Log of Firm's Backlog	0.0048*	0.0042*
	(0.0013)	(0.0100)
An Incumbent who is Bidding in his Own Division	-0.0694*	-0.0536*
	(0.0206)	(0.0154)
An Incumbent who is Bidding in a Different Division	-0.0424*	-0.0380*
	(0.0198)	(0.0151)
A Contestant who is Bidding in his Own Division	-0.0160	-0.0178
	(0.0157)	(0.0123)
λ		0.1917
		(0.0964)
Num. of Obs.	5161	5161
R^2	0.9725	0.9810

Note: Standard Deviations are in parentheses. * Denotes 95% statistical significance.

CHAPTER VI

CONCLUSION

VI.1. Introduction

Auction theory has increasingly come to be regarded as important for practical, empirical, and theoretical reasons. The ODOT awards its road construction contracts by procurement auctions. The objective of this study was to empirically investigate bidder behavior in procurement auctions due to asymmetries. Bidder asymmetry was defined and bidding behavior analyzed in three separate chapters. Road construction contract auctions held by ODOT from January 1997 to August 2000 provided the data for this empirical investigation.

The first essay, "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," examined the patterns of bidding by incumbent and entrant firms in road construction procurement auctions. The study found that entrant bidders bid more aggressively, win with lower bids, and leave more money on the table than incumbent bidders. On a theoretical level, the study considered an asymmetric model of auctions with emphasis on the characteristics of these groups, and produced testable predictions. In particular when the distribution of an entrant's costs exhibits greater dispersion than that of an incumbent's, the entrant with a low cost estimate will bid more aggressively relative to the engineering estimate than the incumbent. I found that bidders who have a history of past winning in auctions have a tendency to bid lower, but do not win with overly aggressive bids, and do not leave money on the table. The study also found that rival bidder characteristics affect bidding behavior. The tougher the average rival is in an auction, the lower the bid and the lower the winning bid.

The second essay, "Sequential Bidding in Road Construction Auctions," suggests that, on average, those firms that lost in morning sessions bid more aggressively in the afternoon, relative to their morning bid, than those firms that won at least one project. The winners of early auctions are typically stronger bidders and, conditional on the outcome of early auctions, the weak bidders (i.e., morning losers) adjust their strategies and bid more aggressively in afternoon auctions. In addition, fixed-effects results suggest that the more competitive the set of rivals a firm faces, the more aggressively the firm bids.

The final essay, "Synergies in Recurring Procurement Auctions: An Empirical Investigation," reveals that projects are spatially correlated. When bidders with synergies participate in procurement auctions, their probability of bidding and winning increases and they bid more aggressively. Finally, the study shows that a firm that is capacity unconstrained will bid more aggressively than one that is capacity constrained.

VI.2. Limitations

The limitations of the study arise from the data that forms the basis of this empirical investigation. With a limited data set, it was not possible to observe large numbers of entrants in the first essay. First, we have few entrants that bid multiple times. Since we have very few observations on entrant firms, we cannot use a fixed-effects model to examine within-firm effects. Examining data beyond August 2000 and observing more entrant bidders could overcome this problem.

Next, a fixed window was used to create histories. Some firms may enter and exit during that period or a firm may become inefficient and not bid or win as frequently as it used to. Updating the history throughout the sample was one attempt at overcoming this constraint, but using a rolling window could be a better measure. The ad hoc definition of entry used in this study is not theoretically backed. However, Dunne et al (1989) have used this kind of specification. In Chapters IV and V the backlog variable was used to measure capacity constraints. However, this variable actually shows the current workload rather than a firm's maximum capacity.

Further, bidders may have bid in auctions other than those of ODOT, which may have affected their capacity constraints. However, Jofre-Bonet and Pesendorfer (1999, 2000) have used a similar backlog variable to measure capacity constraints. Finally, in Chapter V, the spatial results are not significantly different from OLS results, but are a good robustness check for OLS results.

VI.3. Implications for Future Research

Future studies could investigate what factors influence a firm to submit a bid, the influence on bidding behavior when firms submit multiple bids simultaneously to gain from complementarities, and the influence on bidding behavior of minority set-aside programs. The above issues could also be investigated using ODOT data. These studies would be important contributions to the auction literature since there are not many empirical studies focusing on firms' decisions to enter an auction and on bidder behavior due to complementarities and minority set-aside programs. Such studies could provide new insights for auction theory that would be useful for governments and bidders.

VI.4. Conclusion

Overall, this study has shown that bidder asymmetry does affect the bidding behavior of firms. This information is important for policy-makers as well as for bidders. Policy-makers can encourage the participation of new entrants to increase competition and reduce the probability of collusion. They can achieve this by releasing more information about the auction process and characteristics of project locations. Further, they can arrange auctions in sequences that allow firms to gain from synergies that would lead to lower bids.

Firms also benefit from an understanding of the auction process and can gather the maximum information about projects before they submit bids. The study reveals that new entrants tend to leave more money on the table compared to experienced bidders. The sequence of auctions is also important for firms since they may gain from synergies. Therefore, one can say that understanding bidder behavior due to asymmetry is important for the auctioneer as well as for the bidder.

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