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Stochastic synergies in sequential auctions

Dakshina G. De Silva[a,*], Thomas D. Jeitschko[b], Georgia Kosmopoulou[c]

[a]*Department of Economics, Texas Tech University, Lubbock, TX 79409, United States*
[b]*Department of Economics, Michigan State University, East Lansing, MI 48824, United States*
[c]*Department of Economics, University of Oklahoma, Norman, OK 73019, United States*

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Abstract

We consider sequential construction contracts in which bidders may benefit from one auction to the next due to synergistic tasks across the projects auctioned. Theoretical considerations indicate that winners in the earlier auctions are more likely to participate in later auctions. Moreover, conditional on participation, past winners place lower bids, on average, and are so more likely to win in later auctions. We present evidence in support of these predictions using sequential construction auctions conducted by the Oklahoma Department of Transportation.

JEL classification: D44 (Auctions); H57 (Procurement)

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1. Introduction

Static auctions are fairly well-understood, both at a theoretical level as well as in regard to empirical implications. However, many auctions are imbedded in larger institutional settings, of which the effects on bidding are generally not yet as well-understood. Here, we present theoretical considerations and empirical evidence that is

* Corresponding author. Tel.: +1 806 742 2466x237; fax: +1 806 742 1137.
E-mail addresses: dakshina.de-silva@ttu.edu (D.G. De Silva), jeitschk@msu.edu (T.D. Jeitschko), georgiak@ou.edu (G. Kosmopoulou).

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consistent with these considerations concerning sequential construction contract bidding.

In multi-unit procurement auctions firms that win multiple contracts may gain from cost advantages that are present due to synergistic tasks. We investigate the impact of such synergies on bidding behavior in sequential auctions. Theory suggests that in such settings, a firm that wins a contract competes more aggressively for contracts being auctioned subsequently. We provide empirical evidence consistent with the theoretical hypothesis by examining data on sequential construction auctions conducted by the Oklahoma Department of Transportation.

Researchers have recently examined the importance of synergies in recurring auctions. McMillan (1994) and Cramton (1997) noted that in these auctions the two main concerns are bidders' extractions of complementarities between goods and the enhancement of efficiency in the distribution of goods. Krishna and Rosenthal (1996) and Branco (1997) show that in sequential second price auctions bidders who bid on multiple objects bid more aggressively than bidders who bid on a single object. Jeitschko and Wolfstetter (2002) examine the bidding behavior in sequential first-price auctions and find that bidders who win an item in the presence of synergies bid more aggressively and win other related items with a higher probability.

These results rely on the assumption that in the first auction bidders are as yet unaware of their values for the items in the subsequent auction. However, in many auctions, e.g., government procurement auctions, bidders know all projects that are up for auction in a sequential setting and they also know both their stand-alone values as well as their joint values for these items. We find that, due to positive synergies, winners of the first auction are more likely to participate in the second auction than losers of the first auction are. Furthermore, conditional on bidding in the second auction, winners of the first auction place lower bids in the second auction—thus, increasing their probability of being awarded the contract of the second auction. The uniqueness of our data set allows us to test and validate these theoretical predictions.

A number of recent empirical papers have emphasized spatial correlation in bids. Gandal (1997), using Israeli data, shows that winning multiple cable television licenses in neighboring geographic areas enhances the value of owning these licenses. Ausubel et al. (1997), who investigate the existence of cost advantages in broadband personal communication service spectrums (PCS) in ascending-bid auctions in the United States, find that there are geographic synergies associated with winning multiple adjacent spectrum licenses and that those synergies affect bidding.

Rusco and Walls (1999) analyze data from the timber industry, and De Silva (2005) considers Oklahoma road construction auctions. Both of these papers find that in recurring auctions there is spatial correlation of bids that induces aggressive bidding. Marshall et al. (2003) use the modeling framework of Krishna and Rosenthal (1996) to show that geographic synergies may account for a large percentage of costs in the distribution of school milk in the state of Georgia. Cantillon and Pesendorfer (2004) consider first price combinatorial auctions and investigate cost synergies in auctions of bus routes in London, suggesting that geographic synergies are accounted for when routes are offered at auction at the same time.

The most closely related paper to ours that does not focus on spatial correlation of bids is De Silva et al. (2002). Construction auctions held in two consecutive sessions (a morning and an afternoon session) on one single day every month are studied. The bidding behaviors in the late sessions are compared between those who win and those who lose in early sessions. The paper, thus, considers bidder-time effects using multiple bidders. Our interest is in the effect of synergies upon bidding.

Synergies create cost asymmetries among firms that compete for related projects. Supplying services on related contracts may create significant cost advantages: a firm can share resources on both projects effectively, it can avoid duplication of setup costs and it can acquire valuable expertise in the process. On the other hand, a firm that wins multiple contracts commits resources for the duration of each contract that may increase its cost on the margin. With that in mind, it is important to understand the bidding pattern within a firm when it has the potential to gain from winning two related projects and when it doesn't. We focus on differences in the bidding patterns for each firm when it wins in the morning, and when it either loses in the morning, or bids only in one session. Thus, we examine bidder-specific effects.

In Section 2, some theoretical background is given that is based on a brief sketch of cost synergies in sequential auctions that is found in Appendix A. This is used to formulate the relevant hypotheses. In Section 3, the data is described. Section 4 contains the results of the empirical analysis and in Section 5, the main findings of the study are summarized.

2. Theoretical hypotheses

Suppose two construction projects are auctioned in sequence, one in the morning and one in the afternoon. Each auction is a standard first price sealed bid procurement auction in which the lowest bidder is awarded the contract. After the first auction is completed, bidding for the second project commences. Thus, bidders can make their participation decision as well as their bids in the second auction contingent upon the outcome of the first auction.

A firm's cost to complete the second project depends on whether it wins the first contract. Despite the fact that a firm may increase its cost if it commits capital on a significant number of projects at a time, on average, there are scale economies or positive synergies when a firm undertakes both projects. This is primarily because a firm can avoid duplication of setup costs, it can share resources on both projects, and it can benefit from acquired expertise. Thus, in expectation, a firm's (marginal) cost for the second project is smaller, upon winning the first auction. These cost asymmetries created due to synergies suggest that bidding may be asymmetric in the second auction.

Maskin and Riley (2000) compare bidding patterns in a single auction with asymmetric bidders (in the sense of first order stochastic dominance in the distribution of their costs). Their Proposition 3.3, translated to our context, proves that the distribution of bids of the firm that has an expected cost advantage is stochastically dominated by the distribution of bids of the firm that doesn't. Thus, those who face synergies are expected to bid more aggressively than everyone else. It follows that, on average, those who face synergies place lower bids and are more likely to win. It also follows that if there is some threshold level of costs above which a bidder is not willing to prepare and submit a bid, the firm facing potential synergies is less likely than any other firm to have costs above that threshold. Hence, a firm that has won a related contract is more likely to bid in the second auction than other firms are.

A generalization of their results in a two stage game is extremely cumbersome, especially because only an implicit characterization of bids is possible even in their static framework. Nevertheless, as we sketch with an example described in the appendix, if the distribution of costs of winners is stochastically dominated by that of other bidders, and the distributions are uniform, we always have stochastic ranking of bids in the sense of first order stochastic dominance, whenever both bidders realize stochastic synergies. This is true even if one firm could possibly experience negative synergies from undertaking both projects at the same time as long as the negative synergies are not too strong.

3. Data

To examine the effect of potential synergies in sequential procurement construction auctions, we utilize data from the Oklahoma Department of Transportation (ODOT). The data comprise of information on all construction projects auctioned off by the State of Oklahoma from January 1997 to August 2000. Contracts are auctioned off every month and a sealed-bid auction format is used, wherein the lowest bidder is awarded the contract. The auctioned projects include traffic signals, bridge construction and maintenance, road construction and paving, as well as smaller, drainage- and clearance-type projects.

To examine the effect of potential synergies in sequential procurement construction auctions, we utilize a unique structure of the ODOT auction setting. In Oklahoma, projects are awarded both during morning and afternoon sessions each month. During each session a number of first price sealed bid auctions are held simultaneously and the lowest bidder in each auction is awarded the project. We treat the morning session as the first round and the evening session as the second round each month. Bids must be received half an hour before each session. Hence, the outcomes from the morning session are known before bids are placed for the afternoon session. In fact, there is a small time period–3.5 h–between the morning bid openings and the closing of the bids for the afternoon auctions. This allows potential bidders to alter their bids or even their decision to participate in the afternoon session. From discussions with state officials, we know that bids arrive up to the last possible moment.

We consider a two period bidding model, rather than a longer-term dynamic model, because there are a number of multiple bidders who win contracts only in a single month during the morning and afternoon sessions. For those bidders the number of observations are too few to make inferences about their behavior in a fully dynamic setting that spans several months. Other bidders win projects sparsely within the entire period of study.[1] A morning/

[1] The average number of months needed to complete a project is approximately 5 (145 days) with 50% of the projects completed in 4 months or less and 75% of the projects in 6 months or less. Out of the 117 different winners who have won contracts on different months throughout our sample period, 85 won projects in auctions held at least 4 months apart from each other, 77 won contracts in auctions held 5 months apart or more, and 66 won contracts at least 6 months apart. In other words, there are many months in which firms become inactive.

afternoon framework allows us to consider a single firm and ask how the firm behaves when it competes and wins or loses related projects back to back within the same month.

Despite the focus on morning and afternoon auctions, information from contracts auctioned off in past months is incorporated in the construction of the variables used. We did not, however, use any information about projects that are auctioned off in subsequent months, since the advertising period for a contract in Oklahoma is 28 days. Thus, firms are not aware of specific future contracts at the time they submit a bid in a given month.

The auction data that we utilize include information on the identity of the firms that purchase the plans for a project, i.e., the so-called 'plan holders', the identity and the 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, we follow individual firms' bidding behavior from the morning to the afternoon sessions. In addition to information on the identity of potential bidders, the state also provides detailed information on the specific project being auctioned. This includes a description of the project (e.g., bridge construction, asphalt paving, etc.), the details of the project location, how long the project will take (calendar days), the engineering estimate of the project's total cost, and the date and time of letting. Finally, we have information about firm location.

We discuss the details of variable construction below. We utilize the bidding data of firms participating in auctions held from January 1997 to December 1997 to create firm-specific histories. Then we use the data from January 1998 to August 2000 to analyze bidding patterns. Table 1 provides descriptive statistics about the data set. We only utilize the bidding data of firms that submit multiple bids. The reason is that we want to use panel data techniques to control for unobserved bidder heterogeneity in some of our empirical applications. In addition, we are interested in how morning outcomes affect afternoon bidding. Hence, the nature of the problem is one that focuses on firms that submit multiple bids.

Table 1
Summary statistics of Oklahoma road construction auctions

Variable	Auction statistics for full sample 1997:01–2000:08	Auction statistics for regression sample 1998:01–2000:08	AM auction statistics 1998:01–2000:08	PM auction statistics 1998:01–2000:08
# Auctions	1570	1152	610	542
# Firms	162	155	149	149
Plans purchased	11 882	6348	3360	2988
Bids placed	5038	3636	1924	1712
Wins	1371	1019	534	485
Avge. # plans	5.436	5.510	5.508	5.515
	(2.897)	(2.952)	(2.999)	(2.903)
Avge. # bids	3.209	3.156	3.154	3.157
	(1.663)	(1.568)	(1.586)	(1.549)
Relative bid	1.119	1.116	1.127	1.104
	(0.370)	(0.389)	(0.391)	(0.385)
Relative winning	0.970	0.967	0.973	0.960
bid	(0.218)	(0.228)	(0.213)	(0.244)
Avge. eng. est.	1163	1261	1275	1245
in '000s	(2543)	(2664)	(2646)	(2686)

Standard deviations are in parentheses.

In the full sample, there are 1570 auctions with 11882 plans purchased by 162 firms that submitted a total of 5038 bids. Out of these 1570 auctions only 1371 construction projects were awarded. In the regression sample, we observe that there are 1152 auctions with 155 different firms. For the 1019 awarded contracts there are 6348 plan holders who submitted a total of 3636 bids. In the morning regression sample, we observe that there are 149 different firms holding 3360 plans and submitting 1924 bids. Out of 610 morning auctions in the regression sample, only 534 result in contracts being awarded. Similarly, out of 542 evening auctions in the regression sample, only 485 projects are awarded. In these evening auctions, there are 149 firms that held 2988 plans and submitted 1712 bids.

In all samples we can see that the average number of plan holders is about 5.5 and the average number of bidders per auction is about 3.2. Hence, the two-bidder example in the appendix should be somewhat illustrative of actual bidding in the auctions. Finally, we observe that the average relative bid (i.e., Bid/Engineering Estimate) for the regression sample is 1.116 and the average relative winning bid (i.e., Winning Bid/Engineering Estimate) is 0.967. Thus, while average bids exceed the engineering estimate, winning bids usually come in below the estimate.

4. Empirical analysis

According to the theoretical considerations in Section 2, morning winners are more likely to bid in an afternoon auction compared to any other bidder. Furthermore, morning winners are more likely to submit lower bids in the sense of first order stochastic dominance and, consequently, are more likely to win due to their ability to realize potential synergies relative to other bidders.

The main focus in the empirical estimation is to investigate whether the conjectures of the theory are corroborated by the data. The basic structure of the regression model is as follows:

$$y_i = XB + Y\Gamma + Z\Lambda + \epsilon_i. \tag{1}$$

To examine the bidding patterns and the probability of bidding, we use six dependent variables: a bid dummy, a win dummy, the log of bids, the relative bids, the log of winning bids, and the relative winning bids.

The bid dummy is used to summarize bidder participation patterns, and the win dummy summarizes the probability of winning conditional on bidding. The log of bids and the relative bids are used to summarize bidding patters, while the log of winning bids and the relative winning bids summarize winning bid patterns.

The independent variables include three sets of controls— X controls for bidder characteristics, Y controls for rivals' characteristics, and Z controls for project characteristics.

With respect to bidders' own characteristics, we first identify the bidders with potential synergies using a dummy variable. These are the morning winners who have the ability to gain from synergies by winning in the evening session. Then, we identify in one group all other afternoon bidders, those who lost in the morning session and are bidding in the afternoon and those who bid only in the afternoon session. The omitted group of bidders is made up of all bidders who bid only in the morning.

In addition to the above variables, we include additional bidder-specific variables that control for capacity utilization and distance. The variable that controls for capacity utilization is the ratio of a firm's backlog divided by its maximum backlog over the entire period spanned by our data. This variable is similar to the one used by Porter and Zona (1993) in their study of auctions of highway construction contracts to examine evidence of cartel activity.

The firm's backlog is constructed as follows: For every contract won, we calculate the average monthly value. Each subsequent month, we subtract the average monthly value from the initial size of the contract until the completion time of the project. Based on this calculation, we determine the total remaining value of the projects that a firm has undertaken, at any given point in time. A contract backlog is constructed in each month by summing across the remaining value of all existing contracts for a firm. The value of a contract won in a particular month is added to the backlog starting a month after its awarding date to allow for sufficient amount of time until the beginning of the construction work. This adjustment reflects practice. As projects are completed, the backlog of a firm goes to zero unless new contracts are won. A firm that wins a contract today limits its free capacity to complete contracts in the future. Moreover, since firms must include a payment of five percent of the value of the project upon submission of a bid, an additional commitment of capital implies increased budgetary restrictions. By the very nature of our construction, the workload of a contract won in the morning does not enter immediately in the calculation of the capacity utilization when a decision is taken in the afternoon. As a result, our coefficient on the morning winners captures among other effects potential synergies arising from backlog considerations related to morning projects.

The other cost variable measures the distance between the bidder's location and the location of the project. Further, this variable is constructed in a way that allows us to capture the intensity of potential synergies. Our distance measure is constructed as the log of the distance between the firm's location and the 'county seat' of the project (log(distance + 1)). It is expected that as the distance between the bidder's location and the project increases, so will the cost of the project to the bidder.

In order to capture firm efficiencies, we create the variable *wbratio*. This variable is 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 systematic differences in efficiencies across contractors. We use data from January 1997 to December 1997 to create a history for this variable and then update it throughout the analysis. This firm efficiency variable is similar to that used by De Silva et al. (2002, 2003).

The rivals' characteristics (Y) include a measure of rivals' average past success in auctions, their minimum log of distance between project locations and the minimum log of backlog.[2] These latter two rival variables are similar to those used by Bajari and Ye (2003) and De Silva et al. (2003). The measure of rivals' past success is constructed as the average across rivals of the ratio of the past number of wins to the past number of plans

[2] Notice that for rivals we estimate the backlog and not a measure of capacity utilization, since the latter requires detailed knowledge of maximum commitment of capital for a long period of time. This detailed information is unlikely to be available to rivals and therefore it is unlikely to be a consideration to them when formulating their bids.

Table 2
Summary statistics of regression variables

Variable	Mean (std. error)
Log of bids	12.971 (1.641)
Relative bids	1.116 (0.389)
Log of winning bids	12.720 (1.643)
Relative winning bids	0.967 (0.228)
Probability of observing a bidder with potential synergies	0.129 (0.335)
Probability of observing a bidder with no potential synergies	0.342 (0.474)
Firm's capacity utilized	275 (0.431)
Log of distance to project	4.146 (1.601)
Firm's winning-to-bidding ratio	0.252 (0.149)
Rivals' average winning-to-plan holder ratio	0.153 (0.060)
Log of Rival's min. dist. to project	2.890 (1.771)
Log of Rival's min. backlog	2.853 (5.431)
Log of engineer's estimate	13.208 (1.732)
Log number of bidders	1.192 (0.522)

held. This variable is designed to capture some of the heterogeneity across firms that could be due to efficiency considerations and it is similar to the one used by De Silva et al. (2002, 2003).

With respect to project characteristics (Z), we include the state's estimate of the engineering cost (log(engest)), and a set of dummy variables for project types. The project dummies control for broad classes of project types—asphalt, 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. The engineering cost estimates are constructed by the state by pricing each feature outlined in the design and then deriving an overall engineering cost estimate for the project. We have also included the number of bidders (log(#bidders)), in the project characteristics. Table 2 provides descriptive statistics of the regression variables.

First we test for asymmetries among bidders using the technique advocated by Pesendorfer (2000). Pesendorfer studies collusion in Florida and Texas milk markets. He identifies two bidder groups: cartel bidders and non-cartel bidders. Using a Chow test he concludes that there are asymmetries among the two groups. Similarly, we identify two

Table 3
Probit regression results for probability of bidding and winning

Independent variables	Dependent variable			
	Bid submission	Bid submission (clustered by firms)	Wining conditional on bidding	Winning conditional on bidding (clustered by firms)
Bidders with potential synergies	0.173* (0.052)	0.173* (0.067)	0.240* (0.064)	0.240* (0.077)
Bidders with no potential synergies	−0.062 (0.035)	−0.062 (0.037)	−0.102* (0.051)	−0.102* (0.055)
Firm's capacity utilized	0.046 (0.039)	0.046 (0.066)	−0.138* (0.057)	−0.138* (0.066)
Log of firm's distance to project	−0.045* (0.011)	−0.045 (0.024)	−0.068* (0.016)	−0.068* (0.021)
Firm's winning-to-bidding ratio	0.576* (0.113)	0.576* (0.258)	0.878* (0.160)	0.878* (0.189)
Rival's average winning-to-plan holder ratio	−1.183* (0.317)	−1.183 (0.434)	−1.115 (0.404)	−1.115 (0.583)
Log of Rival's min. distance to project	0.052* (0.010)	0.052* (0.015)	0.054* (0.015)	0.054* (0.072)
Log of Rival's min. backlog	0.007* (0.003)	0.007 (0.004)	0.016* (0.004)	0.016* (0.006)
Log of engineer's estimate	−0.106* (0.015)	−0.106* (0.022)	0.039 (0.020)	0.039 (0.029)
Number of observations	6348	6348	3636	3636
LR χ^2	−4097.838	−4097.838	−2077.834	−2077.834

All regressions include six project class dummy variables; an asterisk (*) denotes significance at the 95% level; standard deviations are in parentheses.

bidder groups, namely those with potential synergies and all other bidders and a Chow test confirms that there are asymmetries between these groups.[3]

Table 3 presents the results of the probit analysis. The first column of Table 3 shows the plan holders' probability of submitting bids. It reveals that bidders with potential synergies, specifically, bidders who won in the morning session, are more likely to participate in the evening compared to other bidders; thus, supporting theory. The coefficient of the log of distance indicates that as the distance between the project and firm location increases, bidders are less likely to participate. The coefficient of

[3] Specifically, as a first step, we estimate the coefficients using bids by all bidders. As a second step, we estimate the coefficient using bidders with potential synergies and all other bidders separately. Then we conduct a Chow test for equality of coefficients. Under the null hypothesis, the estimates from the two sub-samples are identical to those from the full sample. The F-statistic calculated from our data is equal to 4.046 with (15, 3606) degrees of freedom, which allows us to reject the null hypothesis.

past winning-to-bidding ratio indicates that firm efficiencies matter and efficient firms are more likely to participate compared to inefficient firms. With respect to rivals' average past winning to plan holder ratio, the results indicate that the presence of more efficient rivals discourages participation. As rivals' minimum distance and backlog increase, bidders' participation increases. Furthermore, bidders are less likely to participate as project size increases.

We also examine the probability of participation using probits with clustering by individual firms. This technique allows us to examine the probability of bidding and the probability of winning conditional upon bidding for individual firms. This is similar to the approach taken by Jofre-Bonet and Pesendorfer (2003). The results in the second column of Table 3 indicate that a firm is more likely to bid and win if it has the potential to gain from synergies than if it does not. The third and the fourth columns of Table 3 report the probability of winning conditional upon bidding. Note that the probit results presented in the fourth column are clustered by firms. The results in the third and fourth columns clearly indicate that bidders with potential synergies are more likely to win an auction compared to other bidders. This evidence supports the theory that morning winners with the potential to gain from synergies have a higher probability of participating and winning in the evening session.

Table 4
OLS regression results for log of bids, log of winning bids, and relative winning bids

Independent variable	Log of bids	Relative bids	Log of winning bids	Relative winning bids
Bidders with potential synergies	−0.069*	−0.073*	−0.042*	−0.040*
	(0.013)	(0.015)	(0.021)	(0.017)
Bidders with no potential synergies	−0.003	−0.000	0.013	0.007
	(0.010)	(0.015)	(0.016)	(0.017)
Firm's capacity utilized	0.029*	0.018	−0.001	0.001
	(0.013)	(0.012)	(0.031)	(0.021)
Log of firm's distance to project	−0.005	−0.005	−0.005	−0.003
	(0.003)	(0.005)	(0.005)	(0.005)
Firm's winning-to-bidding ratio	−0.182*	−0.249*	0.055	0.031
	(0.039)	(0.052)	(0.062)	(0.054)
Rival's average winning-to-plan holder ratio	−0.159*	0.092	−0.349*	−0.301*
	(0.087)	(0.146)	(0.110)	(0.108)
Log of Rival's min. distance to project	−0.000	0.002	0.001	−0.000
	(0.003)	(0.004)	(0.005)	(0.005)
Log of Rival's min. backlog	0.001	−0.000	0.003*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Log numbers of bidders	−0.015	−0.036*	−0.074*	−0.077*
	(0.010)	(0.018)	(0.014)	(0.016)
Log of Engineer's Estimate	0.972*		1.013*	
	(0.006)		(0.009)	
Number of observations	3636	3636	1019	1019
Adj-R^2	0.973	0.044	0.978	0.046

All regressions include six project class dummy variables; an asterisk (*) denotes significance at the 95% level; standard deviations are in parentheses.

Table 5
Fixed effect and Heckman regression results for log of bids and relative bids

Independent variable	Fixed effects (with bidder fixed effects)		Heckman	
	Log of bids	Relative bids	Log of bids	Relative bids
Bidders with potential synergies	−0.054*	−0.058*	−0.070*	−0.070*
	(0.012)	(0.018)	(0.013)	(0.019)
Bidders with no potential synergies	−0.015	−0.018	−0.002	−0.001
	(0.009)	(0.013)	(0.010)	(0.014)
Firm's capacity utilized	0.017	0.013	0.028*	0.018
	(0.013)	(0.018)	(0.011)	(0.015)
Log of firm's distance to project	0.008*	0.000	−0.004	−0.005
	(0.004)	(0.005)	(0.003)	(0.004)
Firm's Winning-to-Bidding Ratio			−0.187*	−0.238*
			(0.033)	(0.047)
Rival's average winning-to-plan holder ratio	−0.169*	0.082	−0.151	0.087
	(0.083)	(0.116)	(0.081)	(0.111)
Log of Rival's min. distance to project	0.002	0.007	−0.001	0.003
	(0.002)	(0.004)	(0.003)	(0.004)
Log of Rival's min. backlog	0.000	−0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Log Numbers of Bidders	−0.021*	−0.031*	−0.021	−0.027*
	(0.010)	(0.014)	(0.013)	(0.019)
Log of engineer's estimate	0.948*		0.973*	
	(0.004)		(0.004)	
Mills ratio			−0.016	0.027
			(0.023)	(0.032)
Number of Observations	3636	3636	6348	6348
Adj-R^2	0.978	0.194		
Censored observations			2712	2712
Uncensored Observations			3636	3636
Wald χ^2			102360.620	789.760

All regressions include six project class dummy variables; the Heckman runs include 37 'large firm' dummies to identify the top 25% bidding firms and a variable 'minor' identifying the minority set-aside percentage for each project; an asterisk (*) denotes significance at the 95% level; standard deviations are in parentheses.

The first two columns of Table 4 report the OLS regression results for log of bids and relative bids. The OLS results indicate that bidders with potential synergies bid more aggressively–on average about seven percent less–compared to any other bidder. These results are in line with the theoretical considerations as well. The results also indicate that capacity-constrained bidders bid less aggressively while efficient firms bid more aggressively on average. The distance to the project does not influence either the log of bids or the relative bids. Furthermore, the rivals' average winning to plan holder ratio indicate that when a firm faces a more competitive set of rivals, it bids more aggressively. This result is consistent with the prediction in Maskin and Riley (2000) on the relative bidding behavior of asymmetric firms, which suggests that when a weak firm faces a strong firm rather than another weak bidder, the former will bid more aggressively and vice versa. On the other hand, the rivals' minimum distances to the project or their backlogs do not influence the bidding

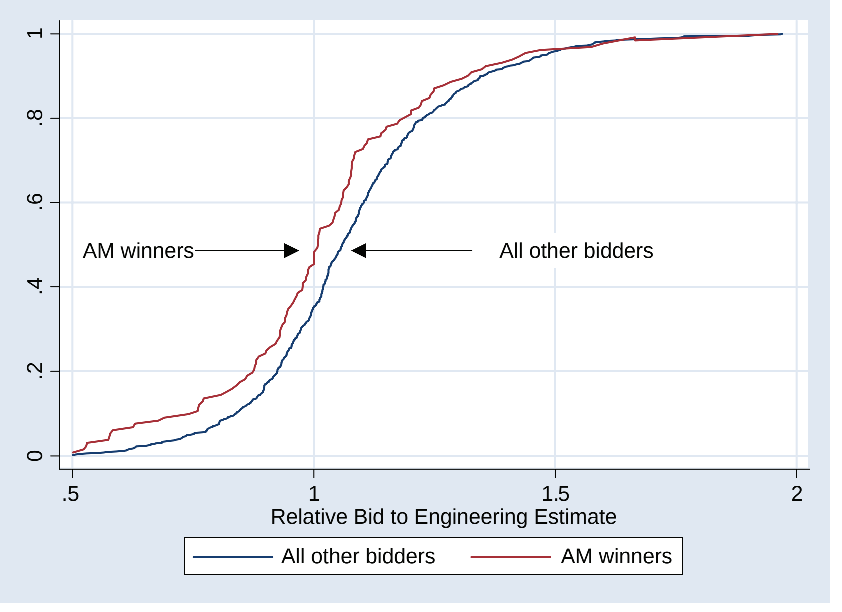

Fig. 1. Cumulative distribution functions of am winners and all other bidders.

patterns. In general, as the number of bidders increases, bidding behavior becomes more aggressive.

The last two columns of Table 4 report the results for log of winning bid and relative winning bid regressions. The results indicate that morning winners tend to win in the afternoon, with bids about four percent lower than any other bidder. We observe that a firm's past winning-to-bidding history has no effect on the winning bid. As in De Silva et al. (2003) the results indicate that efficient firms tend to bid aggressively compared to inefficient firms, but they do not win with excessively low bids. As in the bid regressions, distance to the project does not influence either the log of the winning bid or the winning relative bid. Again the coefficient of the rivals' average winning to plan holder ratio strongly indicate that when a firm faces a more competitive set of rivals, then that firm wins with more aggressive bids. Once more, the rivals' minimum distances to the project or their backlogs have no significant effect here either, which means they do not influence the winning patterns. One reason for those variables to be insignificant is that they measure the distance of the closest rival to the project and the minimum backlog of all rivals, and while these variables vary across bidders in an auction, their variation is small.[4]

In the analysis so far we tried to capture project, firm and rival characteristics that may affect bidding behavior. We used information from the bidders' number of bids and wins or volume of activity to create measures of past performance. Still, if there is nevertheless unobserved bidder heterogeneity across firms it is likely to bias the estimates. We try to

[4] Thus, in any auction the minimum distance of a rival to the project will be the same for all bidders other than the one that is located closer to the project.

Table 6
Quantile regression results for relative bids

Independent variable	Quantile				
	0.15	0.25	0.50	0.75	0.85
Bidders with potential synergies	−0.048*	−0.052*	−0.051*	−0.049*	−0.050*
	(0.014)	(0.012)	(0.009)	(0.016)	(0.018)
Bidders with no potential synergies	−0.028*	−0.020*	−0.005	0.015	0.020
	(0.010)	(0.009)	(0.010)	(0.012)	(0.018)
Firm's capacity utilized	0.025	0.017	0.025*	0.024	−0.005
	(0.013)	(0.011)	(0.008)	(0.013)	(0.018)
Log of firm's distance to project	−0.008*	−0.005	0.000	0.002	0.004
	(0.004)	(0.003)	(0.002)	(0.004)	(0.006)
Firm's winning-to-bidding ratio	−0.101*	−0.122*	−0.150*	−0.219*	−0.310*
	(0.034)	(0.029)	(0.023)	(0.041)	(0.064)
Rival's average winning-to-plan holder ratio	−0.217*	−0.097	−0.157*	−0.062	0.007
	(0.081)	(0.070)	(0.058)	(0.102)	(0.156)
Log of Rival's min. distance to project	0.001	−0.004	0.000	0.001	−0.005
	(0.003)	(0.003)	(0.002)	(0.004)	(0.005)
Log of Rival's min. backlog	0.003*	0.002*	0.000	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Log number of bidders	−0.006	−0.012	−0.027*	−0.038*	−0.036
	(0.009)	(0.009)	(0.008)	(0.013)	(0.020)
Number of observations	3636	3636	3636	3636	3636
R^2	0.036	0.029	0.028	0.040	0.057

All regressions include six project class dummy variables; an asterisk (*) denotes significance at the 95% level; standard deviations are in parentheses.

control for unobserved bidder heterogeneity in several ways. First, we introduce firm fixed effects. The first and the second columns in Table 5 report these results. We utilize a fixed-effects estimator to investigate bidder-specific effects. Recall that the 'morning winner' identity is not permanent. Therefore, the same bidder can be a 'morning winner' in one month and a 'morning loser' or an 'am-only' or a 'pm-only' bidder the next. Hence, to capture the effect of synergies upon bidding, it is important to understand the bidding pattern within a firm when it has the potential to gain from winning two related projects and when it doesn't.

In the fixed-effects models, the past winning-to-bidding ratio, *wbratio*, is excluded because the backlog variable is used to capture bidder efficiency due to capacity constraints over time. As in OLS models, rivals' minimum distances to the project or backlog do not influence the bidding patterns either.[5] Further, when the number of bidders in an auction increases, a firm tends to bid more aggressively. Finally, the results in the

[5] Once more this is true because within an auction the set of rivals each bidder faces differs slightly. For example, when constructing the minimum log of backlog of the group, all bidders but one will have the same minimum backlog of rivals.

first and second columns of Table 5 indicate that when a firm is identified as a firm with potential to gain from synergies, in other words is a 'morning winner,' it bids aggressively. Again, the data are strongly consistent with our theoretical hypotheses. A joint statistical test of all the variables indicates that we cannot reject the null hypothesis (at the 5% level) that these variables do not matter. All regression models are estimated with a constant and project dummies.

Second, we identify the 37 firms that make up the largest 25% of firms. We also identify minority set-aside projects for which bids of unqualified bidders will not be observed.[6] Estimating the model with a Heckman procedure, including the 37 dummies for large firms and a minority set-aside variable, we find that the coefficients do not change significantly. Thus, excluding other unobserved firm heterogeneity does not seem to bias the estimates. These results are presented in the last two columns of Table 5.

The theoretical considerations have implications concerning average bidding behavior that we tested via the OLS and fixed effects results. In another vein, Fig. 1 presents the cumulative distribution functions of relative bids for morning winners and all other bidders separately using our data set. This figure shows that the probability that a morning winner will submit a lower relative bid is higher. Indeed, the entire distribution of relative bids of morning winners appears to the left of that of the rest of the bidders, indicating first order stochastic dominance in the distribution of relative bids. While Fig. 1 suggests that bidders with potential synergies (AM winners) bid more aggressively compared to bidders with no synergies (all other bidders), we need to be cautious in interpreting it. There are yet no controls for bidder, project, and rivals characteristics. We thus present tests that are used to describe the differences between bidders with potential synergies and bidders with no synergies.

There are testable implications about the form of the bidding distributions. In particular, as we expect that the distribution of bids by bidders who face synergies will be stochastically dominated by the distribution of bids by those who do not face synergies, we can also examine bids other than average bids. Thus, to investigate the properties of the bid distributions, we use the quantile regression technique introduced by Koenker and Bassett (1982).

The quantile regression technique allows us to estimate differences in the distribution of bids between bidders who face potential synergies (AM winners bidding in the PM) and all other bidders, while controlling for other factors that contribute to the variability of bids. We restrict the estimation to five quantiles: 0.15, 0.25, 0.50, 0.75 and 0.85. The results of these estimations are presented in Table 6. The dependent variable in all regressions is the relative bid.

The bids of morning winners are smaller compared to other bidders at every quantile, holding everything else constant. This is clearly seen by the magnitude of the coefficient–which is about 5%–and it is statistically significant at every quantile. These results are in agreement with the theoretical hypotheses. The differences in bidding patterns between bidders with potential to gain from synergies and others is consistent

[6] Certain federal projects auctioned off by ODOT require that a given portion of the contract be completed by a minority owned agency. Therefore, contractors frequently subcontract certain parts of the contract to qualified minority owned firms.

with an asymmetric model of auctions in which the distribution of morning winners' costs is stochastically dominated by that of the rest of the bidders. Further, these findings validate Fig. 1 which shows that bidders with potential synergies bid more aggressively.

5. Conclusion

We consider sequential construction contracts in which bidders may benefit from one auction to the next due to synergistic tasks across the projects that are auctioned off. Theoretical considerations indicate that winners in the former auctions may experience synergies and are then more likely to participate in latter auctions. Due to synergies, latter auctions have asymmetric distributions of valuations across winners and non-winners of the earlier auctions. As a result, the theory suggests that conditional on participation in the latter auction, previous winners' bids are stochastically dominated by those of other bidders in a first order sense. Hence, previous winners–who benefit from synergies–are more likely to win in latter auctions.

We present strong evidence in support of these predictions using sequential construction auctions conducted by the Oklahoma Department of Transportation. In particular, we examine bidding patterns of individual firms across auctions conducted on the same day, and discern clear differences conditional upon potential synergies between the auctions, by accounting for bidder fixed effects. Winners of early auctions are more likely to participate in later auctions. The general distribution of bids placed by past winners is dominated by those placed by other bidders in the sense of first order stochastic dominance. Hence, previous winners are more likely to win later auctions.

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Appendix A

In this appendix we sketch a model of stochastic synergies that has motivated our investigation and that yields insights that are in line with the empirical analysis and findings.

A.1. General set-up

There are two bidders, $i=1$, 2, who vie to acquire the right to undertake one or two construction projects that are auctioned in sequence. Bidders' costs for the first project, c^i, are the realization of independent draws from a distribution $F(c^i)$.

The winner of the first auction has costs for the second project distributed according to $F_W(c_W^i)$; similarly, the costs of the loser are distributed according to $F_L(c_L^i)$. We assume that the draws of c^i; c_W^i and c_L^i are independent of each other and independent across bidders.

We define stochastic synergies by letting $F_W(x) \geq F_L(x)$, $\forall x$. That is, the ex ante distribution of the cost of completing the second project is greater whenever one wins the first auction when compared to one having lost the first auction, in the sense of first-order-stochastic-dominance. Thus, letting z^i: $c_L^i - c_W^i$ denote bidder i's cost-advantage when winning, stochastic synergies imply that $Ez^i > 0$, and allow for $z^i < 0$.

Bidders observe all three of their own cost realizations, c^i, c_L^i, c_W^i, before placing a bid in the first auction. After the first auction all bids are revealed and the winner is determined as the bidder with the lowest bid. Thereafter, bidders update beliefs about their rival's type, decide whether to enter the second auction, and conditioned on entering the second auction determine their bid for the second project. The second auction is resolved the same way as the first auction.

In determining the bid in the first auction, bidders account for the potential profit obtained from executing the first construction project. However, they also account for how this bid affects their second auction expected payoff. There are two ways that first auction bids affect second auction expected payoffs. First, a first auction bid affects the probability of winning the first auction, and this determines whether or not a bidder realizes potential synergies for the second project. The second channel through which the first auction bid affects the second auction payoff is the updating of beliefs that takes place after the first auction bids are revealed. Specifically, bidders update their beliefs about their rival's cost for the second project once the first auction bids are revealed, and the expected payoffs for the second auction are functions of the resulting continuation equilibrium.

A.2. Second auction equilibrium example

Since our interest is in the bidding in the second auction, assume that costs for the first project are the same, i.e., $c^1 = c^2 = \bar{c}$; and let the prior distributions of costs for the second project, F_W and F_L, be uniform distributions on the respective supports of $[a_W, b_W]$ and $[a_L, b_L]$, where $0 < a_W \leq a_L < b_W \leq b_L$, with at least one of the weak inequalities being strict. Moreover, let $b_W - a_W > b_L - a_L \Leftrightarrow a_L - a_W > b_L - b_W$.[7]

In the first auction bidders not only compete for the rights to the first project, but they also compete for the expected value of their stochastic synergies. Consequently, first auction bidding is a function of the bidders' respective cost-advantages, defined as $z^i = c_L^i - c_W^i$. The functional form the underlies first auction bidding depends on the expectation of the second period equilibrium. However, since we are only interested in the second auction, it is only relevant that the first period bidding function be monotone in order to draw inferences about bidders' cost advantages, once the bids of the first auction are revealed.

[7] This final assumption is made without loss of generality, it serves to eliminate the discussion of the mirror-image case distinction when doing Bayesian updating.

Table 7
Second auction scenarios

First auction inference	Second auction distributions	
	$\tilde{a}_{\mathrm{W}} \leq \tilde{a}_{\mathrm{L}}$	$\tilde{b}_{\mathrm{W}} \leq \tilde{b}_{\mathrm{L}}$
$z^{\mathrm{L}} \leq z^{\mathrm{W}} \leq b_{\mathrm{L}} - b_{\mathrm{W}}$	whenever $z^{\mathrm{W}} \geq 0$	whenever $z^{\mathrm{L}} \geq 0$
$z^{\mathrm{L}} \leq b_{\mathrm{L}} - b_{\mathrm{W}} \leq z^{\mathrm{W}} \leq a_{\mathrm{L}} - a_{\mathrm{W}}$	✓	whenever $z^{\mathrm{L}} \geq b_{\mathrm{L}} - b_{\mathrm{W}} - z^{\mathrm{W}}$
$z^{\mathrm{L}} \leq b_{\mathrm{L}} - b_{\mathrm{W}} < a_{\mathrm{L}} - a_{\mathrm{W}} \leq z^{\mathrm{W}}$	✓	whenever $z^{\mathrm{L}} \geq b_{\mathrm{L}} - b_{\mathrm{W}} - z^{\mathrm{W}}$
$b_{\mathrm{L}} - b_{\mathrm{W}} \leq z^{\mathrm{L}} \leq z^{\mathrm{W}} \leq a_{\mathrm{L}} - a_{\mathrm{W}}$	✓	✓
$b_{\mathrm{L}} - b_{\mathrm{W}} \leq z^{\mathrm{L}} \leq a_{\mathrm{L}} - a_{\mathrm{W}} \leq z^{\mathrm{W}}$	✓	✓
$a_{\mathrm{L}} - a_{\mathrm{W}} \leq z^{\mathrm{L}} \leq z^{\mathrm{W}}$	✓	✓

Given that the revelation of the first auction bids allows inferences on bidders' respective cost-advantages, distributional assumptions governing the second auction equilibrium are updated from the prior distributions. Thus, letting $z^{\mathrm{W}} = c_{\mathrm{L}} - c_{\mathrm{W}}$ denote the stochastic cost advantage of the winner of the first auction, the posterior distribution of the costs for the second project for the bidder that won the first project[8] is again given by a uniform distribution. Specifically, letting the support of this distribution be given by $[\tilde{a}_{\mathrm{W}}, \tilde{b}_{\mathrm{W}}]$, then,

$$c_{\mathrm{W}}|z^{\mathrm{W}} \sim U\left[\tilde{a}_{\mathrm{W}}, \tilde{b}_{\mathrm{W}}\right] = \begin{cases} U[a_{\mathrm{L}} - z^{\mathrm{W}}, b_{\mathrm{W}}] & \text{if } z^{\mathrm{W}} \in [a_{\mathrm{L}} - b_{\mathrm{W}}, b_{\mathrm{L}} - b_{\mathrm{W}}], \\ U[a_{\mathrm{L}} - z^{\mathrm{W}}, b_{\mathrm{L}} - z^{\mathrm{W}}] & \text{if } z^{\mathrm{W}} \in [b_{\mathrm{L}} - b_{\mathrm{W}}, a_{\mathrm{L}} - a_{\mathrm{W}}], \\ U[a_{\mathrm{W}}, b_{\mathrm{L}} - z^{\mathrm{W}}] & \text{if } z^{\mathrm{W}} \in [a_{\mathrm{L}} - a_{\mathrm{W}}, b_{\mathrm{L}} - a_{\mathrm{W}}]. \end{cases}$$

Analogously,

$$c_{\mathrm{L}}|z^{\mathrm{L}} \sim U\left[\tilde{a}_{\mathrm{L}}, \tilde{b}_{\mathrm{L}}\right] = \begin{cases} U[a_{\mathrm{L}}, z^{\mathrm{L}} + b_{\mathrm{W}}] & \text{if } z^{\mathrm{L}} \in [a_{\mathrm{L}} - b_{\mathrm{W}}, b_{\mathrm{L}} - b_{\mathrm{W}}], \\ U[a_{\mathrm{L}}, b_{\mathrm{L}}] & \text{if } z^{\mathrm{L}} \in [b_{\mathrm{L}} - b_{\mathrm{W}}, a_{\mathrm{L}} - a_{\mathrm{W}}], \\ U[z^{\mathrm{L}} + a_{\mathrm{W}}, b_{\mathrm{L}}] & \text{if } z^{\mathrm{L}} \in [a_{\mathrm{L}} - a_{\mathrm{W}}, b_{\mathrm{L}} - a_{\mathrm{W}}], \end{cases}$$

with $z^{\mathrm{L}} \leq z^{\mathrm{W}}$ under monotone bidding in the first auction.

Notice the intuitive property that,

$$\left(\frac{\mathrm{d}}{\mathrm{d}z^{\mathrm{W}}}\right) E\left[c_{\mathrm{W}}|z^{\mathrm{W}}\right] < 0, \text{ and } \left(\frac{\mathrm{d}}{\mathrm{d}z^{\mathrm{L}}}\right) E\left[c_{\mathrm{L}}|z^{\mathrm{L}}\right] > 0,$$

so that the expectation of the costs for the second project of the winner of the first auction is decreasing in his cost advantage, whereas the expectation of the loser's costs for the second project are increasing in his cost advantage.

Given the updated (posterior) beliefs on second period costs, the possible distributional scenarios in the second auction are presented in Table 7, where we ascertain the instances in which $\tilde{a}_{\mathrm{W}} \leq \tilde{a}_{\mathrm{L}} < \tilde{b}_{\mathrm{W}} \leq \tilde{b}_{\mathrm{L}}$, i.e., in which the second auction distributions exhibit a ranking by first-order stochastic dominance in favor of the bidder who wins the first auction.

The relevance of these scenarios can be assessed by looking at the relative likelihood of their occurrence. Thus, let G denote the initial distribution of a bidder's cost advantage z,

[8] Of course, the winner of the first auction knows his own costs for the second project, c_{W}, but equilibrium bidding in the second auction is a function of the loser's (updated) beliefs about the winner's costs, and both bidders therefore account for updated beliefs.

and let G^{W} and G^{L} denote the distributions of z^{W} and z^{L}. Then, given our initial distributive assumptions, $G(z)$ is distributed uniformly on $[a_{\mathrm{L}}-b_{\mathrm{W}},\ b_{\mathrm{L}}-a_{\mathrm{W}}]:=[a_z,\ b_z]$ and, with monotone bidding in the first auction, one obtains

$$G^{\mathrm{W}}(x)=[G(x)]^2=\left(\frac{x-a_z}{b_z-a_z}\right)^2, G^{\mathrm{L}}(x)=[1-G(x)]G(x)+G(x)$$
$$=\frac{(x-a_z)(2b_z-x-a_z)}{(b_z-a_z)^2},$$

which allows one to obtain the likelihood that the second auction is asymmetric in the sense given in our initial hypotheses.

However, even without specific calculations, Table 7 reveals that we always have a stochastic ranking of bidder types in favor of the winner of the first auction in the sense of first-order stochastic dominance, whenever both bidders have realized stochastic synergies so that their costs for the second project is lower when they win the first project. Moreover, this is true even if only one bidder has realized synergies, provided that the rival did not simultaneously experience strong negative-synergies (did not have a much lower cost for the second project due to losing the first project). Moreover, if posterior distributions are truncated at the upper end, i.e., if participation only takes place for some (cost-) value that is not too large, then all second period auctions follow the postulated pattern provided at least one bidder has the potential to realize synergies.

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