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Editor:

Prof. Dr. Hans-Theo Normann
Düsseldorf Institute for Competition Economics (DICE)
Phone: +49(0) 211-81-15125, e-mail: normann@dice.hhu.de

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The Impact of Timing on Bidding Behavior in Procurement Auctions of Contracts with Private Costs*

Dakshina G. De Silva† Georgia Kosmopoulou‡ Beatrice Pagel§

Ronald Peeters¶

June 2012

Abstract

We provide a comparison of bidding behavior between multi-round and single-round auctions considering bid lettings for asphalt construction contracts that are known to have primarily private costs. Using a reduced-form difference-in-difference approach as well as the nonparametric estimation technique that was proposed by Racine and Li (2004) we find that bidding is more aggressive in a sequential multi-round setting than in a simultaneous single-round format. We explore potential causes for the bidding difference across formats that are related to synergies and the level of bidder participation.

JEL Classification D44 · H57
Keywords Multi-unit auctions, Procurement auctions

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†Department of Economics, Lancaster University, Lancaster, LA2 9QZ, UK: Tel: 44-1524-594023. Email: d.desilva@lancaster.ac.uk.

‡Corresponding author: Department of Economics, University of Oklahoma, 203 Hester Hall, 729 Elm Av, Norman, OK 73019. Tel: 1-405-325-3083; Email: georgiak@ou.edu.

§Düsseldorf Institute for Competition Economics (DICE), Universitätsstr. 1, 40225 Düsseldorf, Germany. Tel: 49-211-8110251. Email: pagel@dice.hhu.de.

¶Department of Economics, Maastricht University, P.O. Box 616, 6200 MD Maastricht, The Netherlands. Tel: 31-43-3883730. Email: r.peeters@maastrichtuniversity.nl.

1 Introduction

In an effort to reduce operational costs, the Oklahoma Department of Transportation (ODOT) decided in March of 2002 to change the design of their monthly procurement auctions for road construction contracts. ODOT used to auction contracts in two separate sessions on a single day, with roughly half of the contracts being auctioned simultaneously in the morning (AM) and the remaining contracts in the afternoon (PM). All submitted bids in AM auctions were publicly revealed before PM bidding. Since March 2002, all projects are auctioned simultaneously in one single session.

Theoretical and empirical investigation of bidding and participation behavior (Milgrom and Weber (1982), Goeree and Offerman (2003), and De Silva et al. (2008)) has shown that bidding behavior is markedly different across project types. As such, it becomes more urgent that policy recommendations are tailored to general characteristics of projects.

In this study, we examine empirically the impact of the change in auction format on participation and bidding behavior focusing on asphalt projects that are known to have primarily private costs (Bajari and Ye (2003), Porter and Zona (1993)). Throughout the entire period investigated, the Texas Department of Transportation (TxDOT) auctioned all its contracts in two lettings every month. We use the road construction auction data from Texas as a control group against which we compare eventual changes in Oklahoma. We selected a tight time window around the implementation of this policy: from March 2000 to August 2003. During this period of analysis, asphalt projects absorbed 58.7% of the road construction budgets of Oklahoma and Texas (or $5.88 billion dollars) while participating firms submitted about 6,000 bids.

We find a significant impact on bidding behavior: Bidding has become less competitive. The shift to a single-round auction has caused an increase in the procurement costs for asphalt projects. We attribute this effect primarily to the low level of synergies in projects that are auctioned across sessions. However, our results suggest that the design change has not induced a change in auction participation. There is no statistically significant change in bid submission probability or in the number of actual bidders per project.

Section 2 gives a short but comprehensive review of the literature that compares simultaneous and sequential private value auctions. Section 3 offers a detailed description of the data set, followed by the empirical analysis in Section 4. A discussion and concluding remarks are in Section 5.

2 Literature Review

In a recent related study, De Silva et al. (2007) examined the timing effects of a switch from a sequential to a simultaneous format and found no statistically significant difference in bidding behavior that could be attributed to the change. Notably, this empirical analysis was conducted on an aggregation of decisions over a large variety of project categories – ranging from projects with a predominant private cost component to projects with primarily common costs. As suggested by the literature, bidding can differ substantially by project type.

Construction firms often compete for multiple projects at a time and may realize economies of scope, depending on the location and project similarities. Even though a fraction of costs may be common to all firms and informational effects may play a role in the bidding process, asphalt paving projects have primarily private costs. One source of uncertainty that is common to all bidders is related to future trends in the price of oil, which influences the average price of asphalt. This uncertainty is typically not resolved until the project is completed. Observing morning bids can inform bidders about price expectations but mostly affirm the potential for some synergies.

The comparison of bidding behavior and revenue between multi-round and single-round auctions within the independent private value (IPV) setting is limited in the theoretical literature. Krishna and Rosenthal (1996) consider an IPV framework and focus on synergistic effects. Their analysis applies to circumstances where some bidders have an additive value (synergy) from winning two units of an object and some bidders are single unit buyers. They find that a sequential auction generates higher (lower) revenue than the simultaneous one when synergistic effects are small (large). In Albano et al. (2001) simultaneous auctions outperform sequential auctions if there are many competitors trying to take advantage of synergies.[1]

Feng and Chatterjee (2010) explore within an IPV framework the question of whether an auctioneer can benefit by dividing a stock of items into two identical lots and auctioning the lots sequentially (in two periods), rather than selling them all in one session. Considering impatient bidders with a unitary demand, they showed that it may not always be better to sell all of the items in one period. Which auction format performs better is largely determined by the relationship between the number of items that are sold and the number of bidders that are competing. The sequential auction format produces higher revenue when competition intensity is low. When buyers are impatient, a sequential sale can be more profitable for the seller as it stimulates competition among forward-looking bidders.

Milgrom and Weber's (2000) work in an affiliated values model suggests that sequential auctions can generate more revenues than simultaneous auctions, due to "informational effects." These informational effects can be more persistent in common cost settings (Hausch (1986)).

Our analysis takes into account all of these factors that are relevant to the auction outcome and are standard in road construction and examines their significance in the selection of an auction format.

3 Data

We use data from the Oklahoma Department of Transportation (ODOT) and the Texas Department of Transportation (TxDOT) on auctions that took place between January 1997 and August 2003.[2] In order to reduce the cost and time required to auction their projects, ODOT decided in March 2002 to start offering all contracts simultaneously instead of the previous format of sequentially splitting the auctions into two sessions that were held on the same day (AM and PM auctions).

This unique natural experiment allows us to evaluate the impact of the change in format on bidder participation and bidding behavior in ODOT road construction auctions compared

[1]Krishna and Rosenthal (1996) used a parameterized example with two bidders – one global (experiencing synergies from undertaking multiple projects) and one local (interested in one item) – and provide a numerical solution. They noted that: "A general comparison of the revenues from the simultaneous auction [and] the sequential auction ... appears to be rather difficult, even with a single global bidder." Albano et al. (2001) extend the parameterized example of Krishna and Rosenthal (1996) by using two global bidders.

[2]The data were gathered from bid reports that were provided by ODOT and TxDOT.

to a control group. Our control group consists of auctions that were held by TxDOT in which a uniform policy of holding two sessions within a month was in effect throughout our period of analysis.

In both states, the auction process is similar: All bidders learn the location and the detailed project description, the estimated number of days to complete the project, the engineer's cost estimate, and the list of contractors who purchased plans (plan holders) at least four weeks before an auction letting. The auctions are held using the low-price sealed-bid auction format. The bidding is open after the plan for a project is posted, and bidders can adjust bids until 15 minutes before bid letting. At the conclusion of each session, the bids submitted by each bidder are revealed and the winner is announced.[3] In particular, before the policy change all submitted bids in morning auctions were publicly revealed before the afternoon letting.

We are interested in examining the participation and bidding behavior of bidders who bid before and after March 2002. We focus on auctions of asphalt projects that typically have a strong private cost component. In our empirical analysis, we utilize data from March 2000 until August 2003.[4] Data from January 1997 to March 2000 are used to create variables on bidder history, the potential to gain from synergies, potential rivals' strength and capacity commitment.

Table 1 presents summary statistics for asphalt projects in Oklahoma and Texas.[5] For both states, the number of plan holders and number of bidders per auction have increased after March 2002. There are 60% more plan holders and bidders per auction in Texas across both periods. The average relative bids (bids relative to the engineer's cost estimate) and winning bids are comparable between states in the period before the format change, but there is an increase in Oklahoma relative to Texas since March 2002. In Oklahoma the average relative bid and relative winning bids have increased by about 2-3%, while in Texas they have decreased by about 2-3%.

4 Empirical model and results

We adopt two approaches for measuring the differential impact of the two auction formats on procurement costs: First, we use a panel-data difference-in-differences approach. This approach provides flexibility in estimation and allows controls for format, bidder heterogeneity including potential synergies from existing workload, auction characteristics, rival characteristics, and business conditions. It is a straightforward way to model the format change and allow for a wide range of robustness checks. Our second approach is to use the nonparametric regression technique that was proposed by Racine and Li (2004) to provide the predicted

[3]In case there is no specific starting date mentioned in the plan of the project, the project will start within 30 days of the bid letting date.

[4]Prior to March 2000 the policy on the release of information related to the engineering cost estimate was different in Texas and Oklahoma. Our data analysis window spans from March 2000 until August 2003 thus avoiding complications that could arise from multiple contemporary policy considerations.

[5]Projects from different counties were auctioned in each session. In addition, different projects from a single county could be auctioned in different sessions within a given month (before the design change in OK and for the whole sample period in TX). Hence, there is no county-bias in our data. Table 11 in the Appendix provides information on the average, minimum and maximum number of auctions held for the auction sessions in the different states throughout the periods before and after the design change.

Table 1: Summary statistics for asphalt projects that were auctioned by ODOT and TxDOT between March 2000 and August 2003.

	Oklahoma		Texas	
Variable	Before March 2002	Since March 2002	Before March 2002	Since March 2002
Number of awarded projects	173	130	744	433
Number of plan holders	826	689	4754	3258
Number of bids submitted	487	429	3211	2048
Average number of plan holders per project	3.988 (1.864)	4.469 (2.113)	6.340 (2.989)	7.499 (3.274)
Average number of bidders per project	2.636 (1.334)	2.962 (1.241)	4.266 (1.993)	4.704 (2.217)
Average relative value of bids	1.043 (.206)	1.064 (.184)	1.046 (.194)	1.019 (.219)
Average relative value of winning bids	.949 (.137)	.982 (.144)	.951 (.153)	.925 (.193)

Standard deviations are in parentheses.

distributions of bids in Oklahoma before and after the format change and compare them to Texas.[6]

4.1 Reduced-form estimation

In order to understand better the patterns of bidding in auctions held by ODOT, we present a set of reduced-form regressions that show how participation and bidding varies across the two periods and states. As mentioned earlier, in Texas, there was no change in the bid letting process for the entire sample period. In Oklahoma, there was a distinct change in the format as described above. We model this change by classifying our auctions into two distinct time periods: before March 2002 (before the format change) and since March 2002. We then estimate a difference-in-differences (DID) model that allows for differential effects across the two periods.

Our basic econometric specification is:

$$y_{iast} = \alpha_0 + \beta_1 D_s + \beta_2 A_t + \beta_3 (D_s \times A_t) + x'_{iast}\gamma + \epsilon_{iast}, \tag{1}$$

where the unit of observation is firm i holding a plan and possibly submitting a bid in auction a in state s in time period t. Since we are interested in examining bidder participation and bidding behavior, we use the number of plan holders, number of bidders, relative bid, and relative winning bid as our main dependent variables. The independent variables can be classified into five main groups: format controls, auction characteristics, bidder characteristics, rival characteristics, and business environment characteristics. In this specification, the βs measure the change in bidding that occurs between Texas and Oklahoma across the two periods of analysis.

The variable D_s takes the value of 1 if the bid was observed in Oklahoma. A_t takes the value of 1 for bids observed after the format change. The coefficient on D_s, β_1, measures the

[6]Racine and Li (2004) allow for nonparametric estimation with continuous and categorical variables using the kernel method of density estimation rather than the conventional frequency estimation process that is used to handle categorical variables. This smoothing method has been shown to have significant efficiency gains over the conventional nonparametric and semiparametric approaches for finite samples.

average difference in bidding between auctions held in Oklahoma and Texas. The coefficient β_2 captures the average difference in bidding before and after the format change. The coefficient β_3 measures the change in bidding in Oklahoma auctions compared to Texas auctions in the period after the format change.

Our main interest is on β_3, expressed in this DID model by:

$$\begin{aligned}&(\, E[\, y \,|\, x,\, D_s\!=\!1,\, A_t\!=\!1\,] - E[\, y \,|\, x,\, D_s\!=\!0,\, A_t\!=\!1\,]\,)\\ &\qquad - (\, E[\, y \,|\, x,\, D_s\!=\!1,\, A_t\!=\!0\,] - E[\, y \,|\, x,\, D_s\!=\!0,\, A_t\!=\!0\,]\,),\end{aligned} \tag{2}$$

where the first two terms represent the difference between the expected value of bids in Oklahoma and Texas after the format change and the last two terms isolate the expected difference in bids across the two states before the format change. Since ODOT's goal was to reduce the operational cost, not to increase the construction costs to the public, we are interested in examining the sign of β_3 and its statistical significance.

All of the variables that are used in our analysis are described in Table 9 in the Appendix. There are three auction-level variables: the number of plan holders, the number of bidders, and the log of number of days to complete the project. The first two variables control for differences in competition across auctions.

In all of the models, we include variables on bidder characteristics, so as to capture cost heterogeneity across bidders. They are measures on capacity utilization rate and the firm's distance to a project. As a bidder's capacity utilization rises or as a firm's distance to a project increases, we expect lower participation and higher bid values. Further, we include a dummy variable that indicates if a firm is bidding in a division where there is an ongoing project, to control for any geographical synergies with the bidding firm's existing projects. We also include bidder's log of past number of wins (from March 2000 to the date of the auction) to capture firm experience.

Additionally, we include the dummy variables 'bidders with potential synergies' and 'bidders with no potential synergies' in order to capture winners and losers of AM sessions prior to the policy change. As contracts were auctioned in two bid lettings before March 2002, synergies arising from projects won in AM auctions may influence bidding behavior in PM sessions. Naturally, these variables are only used during sequential bidding sessions.

We control for rivals' characteristics using three variables: First, we construct the average winning percentage of all rival plan holders in an auction. This variable controls for rivals' toughness. We expect firms to bid more aggressively when they face a set of tough rivals. Then, as in Bajari and Ye (2003), we include the smallest distance to the project among the rivals and the smallest backlog among the rivals. These variables are also used to control for rival cost heterogeneity.[7]

Note that every firm that intends to bid in an auction must purchase a plan for a project. This list of plan holders is available to all firms prior to the bid letting, which gives contractors the possibility to identify their rivals for a given project. Thus, the plan holder list describes the potential competition in an auction.

We use three variables that control for the business environment: (1) the monthly variation in the amount of projects that are being let, (2) the monthly state-level unemployment rate, and (3) the monthly average of the relative number of building permits. The first variable measures the real volume of projects that are auctioned in each state in each month. The

[7] See also Jofre-Bonet and Pesendorfer (2003) and De Silva et al. (2008).

aggregate real volume of projects auctioned in a month in a state will vary due to seasonal factors and budgetary conditions. Finally, we use 32 project division dummy variables to control for project location heterogeneity. Table 9 and Table 10 in the Appendix provide a detailed definition for each of the variables that are used in the study and the summary statistics.

4.1.1 Difference-in-differences results

Table 2 presents the probit regression results on the probabilities of bidding and of winning conditional on bidding.[8]

The key parameter of interest is β_3, which measures the difference between Oklahoma and Texas auctions in the period since March 2002. We see no difference in entry decisions in Oklahoma across the periods compared to Texas. As bid preparation entails an elaborate process, there is no difference in the information that is available to the bidders at the time that a decision on entry is made across formats. In the sequential format, bidders learn who has won the morning auctions. With the new information at hand, one may expect a revision in bid size, but no change in the likelihood of participation.[9]

When considering other controls we see that geographic synergies matter for entry and winning. If a firm has an ongoing project in the same location, then the probability of entering and of winning increases. When a firm's distance to the location of a project increases, the probability of entering and of winning decreases. As the closest rival's distance to the project location increases, the bidders are more likely to enter and to win.

Columns (1) and (2) of Table 3 present the results for the regressions on bidding behavior relative to the engineer's cost estimate. Our main result indicates that the change in the 'timing' of lettings has adversely affected relative bids.[10] We estimate our models using the number of bidders in one specification (first column) and the number of plan holders in the other (second column). Both the number of bidders and the number of plan holders have a negative effect on the bid level. We also estimated the models with firm fixed effects to control for bidder heterogeneity. Naturally, we included only bidders that have submitted multiple bids. The results are reported in Columns (1) and (2) of Table 4 and show consistency.

When considering other variables, bidders that have ongoing projects in the same division bid more aggressively while capacity-constrained bidders bid less aggressively. As the distance to the project location increases, bidders tend to bid less aggressively. The estimate on the rivals' past winning to plan holder ratio indicates that when bidders face tough rivals they tend to bid more aggressively. As in De Silva et al. (2005), we also observe that bidders

[8]Since firms are observed repeatedly, the observations may not be independent. In this case standard errors can be underestimated. Therefore, we report standard errors that are clustered by firms as suggested by Moulton (1990).

[9]Moreover, De Silva et al. (2002) found no statistically significant difference in the probability of bidding in the afternoon session among those who won and those who lost in the morning sessions in Oklahoma before the change in auction design.

[10]The estimated coefficients related to the variables "Bidders with potential synergies" and "Bidders with no potential synergies" suggest that ex post knowledge of the winning outcome in a sequential setting has a competitive effect on bids. These variables, however, do not capture possible changes in bidding behavior in response to the anticipation of the possibility to appropriate synergies. The sequential setting provides an opportunity to receive information on the outcome of the morning sessions that is critical to resolve some of the uncertainty of anticipation. β_3 is capturing this information difference effects across formats.

Table 2: Probit regression results.

Variable	Probability of bidding (1)	Probability of winning conditional on bidding (2)
Oklahoma bids (β_1)	-.227	-.054
	(.117)	(.074)
Bids after March 2002 (β_2)	-.009	-.050
	(.043)	(.045)
Oklahoma bids after March 2002 (β_3)	.073	-.018
	(.055)	(.057)
Log of engineering's cost estimate	.006	.005
	(.011)	(.008)
Number of plan holders	-.030**	-.036**
	(.005)	(.005)
Oklahoma number of plan holders after March 2002	.011**	.005
	(.005)	(.007)
Number of plan holders after March 2002	-.024	-.000
	(.015)	(.017)
Log number of days to complete the project	-.011	-.004
	(.015)	(.012)
Firm bidding in a division where there is an ongoing project	.123**	.048**
	(.016)	(.014)
Bidder's capacity utilized	.034	-.029
	(.028)	(.022)
Log number of past wins	.032**	.004
	(.005)	(.005)
Bidder's distance to the project location	-.018**	-.030**
	(.006)	(.005)
Average rival's winning-to-plan-holder ratio	-.178	-.473**
	(.136)	(.110)
Closest rival's distance to the project location	.016**	.024**
	(.004)	(.004)
Rivals' smallest backlog	.001	.001
	(.001)	(.001)
Seasonally unadjusted unemployment rate	-.011	.001
	(.013)	(.012)
Three-month average of relative real value of engineer's estimates	-.080**	.019
	(.026)	(.029)
Three-month average of relative number of building permits	-.298**	.139
	(.115)	(.113)
Project division effects (32)	Yes	Yes
Number of Observations	9430	6175
Pseudo R^2	.062	.059
Wald χ^2	581.18	485.79

** denotes statistical significance at the 5% level.
* denotes statistical significance at the 10% level.
Robust clustered standard errors using firm level clusters are in parentheses.
All regressions include a constant term and 11 monthly dummy variables.

with potential synergies bid more aggressively. This effect seems to be relatively small, not exceeding 2.9%.

If potential synergies from undertaking multiple projects are low or limited the sequential auction format can produce more competitive bids according to Krishna and Rosenthal (1996). Measuring the intensity of synergies for projects that were offered within a month is not easy in practice. We have identified, however, projects that were offered in the same division, conjecturing that proximity can reduce moving costs and create the opportunity to share resources more effectively across projects. The larger the number of asphalt projects that

Table 3: Regression results for relative bids and relative winning bids.

	Relative bids		Relative winning bids	
Variable	(1)	(2)	(3)	(4)
Oklahoma bids (β_1)	.056	.057	.016	.008
	(.060)	(.061)	(.096)	(.101)
Bids after March 2002 (β_2)	-.074***	-.080***	-.057**	-.066**
	(.013)	(.013)	(.020)	(.021)
Oklahoma bids after March 2002 (β_3)	.053**	.057**	.076**	.079**
	(.015)	(.015)	(.021)	(.021)
Number of bidders	-.010**		-.021**	
	(.001)		(.002)	
Number of plan holders		-.004**		-.009**
		(.001)		(.002)
Log number of days to complete the project	.000	.000	.019**	.018**
	(.004)	(.004)	(.007)	(.007)
Firm bidding in a division where there is an ongoing project	-.025**	-.023**	-.006	-.004
	(.006)	(.006)	(.009)	(.009)
Bidders with potential synergies	-.029**	-.028**	-.024*	-.022
	(.010)	(.010)	(.014)	(.015)
Bidders with no potential synergies	.006	.006	.002	.003
	(.008)	(.008)	(.012)	(.013)
Bidder's capacity utilized	.019**	.018**	.037*	.039*
	(.009)	(.009)	(.019)	(.020)
Log number of past wins	-.001	-.001	-.002	-.002
	(.002)	(.002)	(.004)	(.004)
Bidder's distance to the project location	.001	.001	.005	-.005
	(.002)	(.002)	(.003)	(.003)
Average rivals winning-to-plan-holder ratio	-.221**	-.221**	-.254**	-.267**
	(.050)	(.051)	(.080)	(.083)
Closest rival's distance to the project location	-.012**	-.011**	-.008**	-.007**
	(.002)	(.002)	(.003)	(.003)
Rivals' smallest backlog	.000	.000	.000	.000
	(.000)	(.000)	(.001)	(.001)
Seasonally unadjusted unemployment rate	-.000	.002	.001	.003
	(.006)	(.006)	(.008)	(.008)
Three-month average of relative real value of engineer's estimates	.051**	.055**	.040**	.051**
	(.012)	(.012)	(.017)	(.018)
Three-month average of relative number of building permits	.220**	.235**	.126	.162**
	(.054)	(.054)	(.079)	(.081)
Project division effects (32)	Yes	Yes	Yes	Yes
Number of Observations	6175	6175	1480	1480
Adjusted R^2	.061	.056	.109	.079

*** denotes statistical significance at the 1% level.
** denotes statistical significance at the 5% level.
* denotes statistical significance at the 10% level.
Robust clustered standard errors using firm level clusters are in parentheses.
All regressions include a constant term and 11 monthly dummy variables.

were offered in the same division the larger would be the potential of significant synergies.

In our sample, of the 247 bids that were submitted in afternoon sessions in Oklahoma before the format change, only 50 bids (20.24%) were submitted by bidders who bid for projects in the same division in the morning. Of the 85 contracts that were awarded in afternoon sessions, only 9 morning winners (10.58%) had the ability to extract synergies by winning projects in the same division. In that sense, we have not identified significant direct effects across projects. Inclusion of these variables in regression analysis produced limited

Table 4: Regression results for relative bids and relative winning bids with firm effects.

	Relative bids		Relative winning bids	
Variable	(1)	(2)	(3)	(4)
Oklahoma bids (β_1)	.019	.022		
	(.075)	(.076)		
Bids after March 2002 (β_2)	-.060**	-.067**	-.031	-.039
	(.015)	(.015)	(.024)	(.025)
Oklahoma bids after March 2002 (β_3)	.056**	.060**	.070**	.074**
	(.019)	(.018)	(.028)	(.029)
Number of bidders	-.013**		-.006**	
	(.002)		(.002)	
Number of plan holders		-.007**		-.002
		(.001)		(.001)
Firm bidding in a division where there is an ongoing project	-.018** (.006)	-.016** (.006)	-.004 (.010)	-.003 (.010)
Bidders with potential synergies	-.019**	-.018**	-.014	-.015
	(.009)	(.009)	(.016)	(.016)
Bidders with no potential synergies	.001	.002	-.002	-.003
	(.008)	(.008)	(.013)	(.014)
Log number of past wins	-.001	-.001	-.004	-.006
	(.003)	(.003)	(.004)	(.004)
Bidder controls	Yes	Yes	Yes	Yes
Rival controls	Yes	Yes	Yes	Yes
Market characteristics	Yes	Yes	Yes	Yes
Project division effects (32)	Yes	Yes	Yes	Yes
Number of Observations	6108	6108	1427	1427
Adjusted R^2	.060	.197	.394	.368

** denotes statistical significance at the 5% level.
Robust clustered standard errors using firm level clusters are in parentheses.

effects.[11] These results provide one more piece of evidence that the level of synergies is small.

Another competing explanation of the increase in bids since March 2002 could be provided in the work by Feng and Chatterjee (2010) who relied on low participation per auction and bidder impatience. Columns (1) and (2) of Table 5 consider the relative bids in auctions that were held in Texas and Oklahoma when the number of bidders and potential participants per auction increases. The results suggest that bids become more competitive in simultaneous auctions as the number of bidders or plan holders increase.[12] This factor captures only a small fraction of the difference in bidding.

Columns (3) and (4) of Table 3 report the results of the regressions on the winning bids relative to the engineering cost estimate. The main qualitative finding is that winning bids have increased after the change in format. Less aggressive bidding behavior and unchanged participation have led to a significant increase in winning bids and thus construction costs to the public. Once more, we estimated the model with firm fixed effects to control for unobservable bidder heterogeneity in Columns (3) and (4) of Table 4. This time we included only bidders that won multiple projects. The results confirm the adverse effect of the design change and limited synergy effects across sessions.

[11]We isolated bidding behavior in Oklahoma road construction auctions involving asphalt work and identified, within the simultaneous and sequential settings, synergies that could be realized by bidding for multiple contracts in the same division within the same month. We differentiated between multiple bids in AM sessions, multiple bids in PM sessions, multiple bids across sessions and multiple bids in the simultaneous setting since March 2002. We did not find a significant difference in bidding. These results are available upon request.

[12]The assumption we are making here is that bidders can be somewhat impatient.

Table 5: Regression results for relative bids and relative winning bids.

	Relative bids		Relative winning bids	
Variable	(1)	(2)	(3)	(4)
Oklahoma bids (β_1)	.070	.065	.025	.013
	(.060)	(.061)	(.096)	(.101)
Bids after March 2002 (β_2)	-.029*	-.036*	-.058**	-.062*
	(.017)	(.020)	(.027)	(.036)
Oklahoma bids after March 2002 (β_3)	.081**	.078***	.159**	.131**
	(.030)	(.025)	(.043)	(.038)
Number of bidders	-.006**		-.020**	
	(.002)		(.003)	
Number of bidders after March 2002	-.008***		.000	
	(.002)		(.004)	
Oklahoma number of bidders after March 2002	-.013*		-.028**	
	(.007)		(.011)	
Number of plan holders		-.002		-.009**
		(.001)		(.002)
Number of plan holders after March 2002		-.005**		-.000
		(.002)		(.003)
Oklahoma number plan holders after March 2002		-.008**		-.012**
		(.004)		(.006)
Firm bidding in a division where there is an ongoing project	Yes	Yes	Yes	Yes
Bidders with potential synergies	No	No	No	No
Bidders with no potential synergies	No	No	No	No
Log number of past wins	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes
Rival controls	Yes	Yes	Yes	Yes
Market characteristics	Yes	Yes	Yes	Yes
Project division effects (32)	Yes	Yes	Yes	Yes
Number of Observations	6175	6175	1480	1480
Adjusted R^2	.060	.197	.113	.081

*** denotes statistical significance at the 1% level.
** denotes statistical significance at the 5% level.
* denotes statistical significance at the 10% level.
Robust clustered standard errors using firm level clusters are in parentheses.

Columns (3) and (4) of Table 5 consider the relative winning bids in auctions held in Texas and Oklahoma when the number of bidders and potential participants per auction increases. As Proposition 1 of Feng and Chatterjee (2010) suggests, the sequential auction format produces lower procurement costs when the level of competition, that is either captured by the number of bidders or by the number of plan holders, is low.

Next, we show that the less aggressive bidding behavior in Oklahoma after the format change is not due to a truncation of the distribution of bids at the lower end but due to effects that are persistent at every level. To do so, we use the quantile regression technique introduced by Koenker and Bassett (1982) and restrict estimation to three quantiles (0.25, 0.50, and 0.75) and estimate the relative bid and winning bid models.[13]

The results are presented in Tables 6 and 7. Our main finding is that after the policy change Oklahoma bidders bid and win consistently higher across the distribution. We then test the difference across the three quantiles from the two models in Columns (1) and (2) in

[13]These models are similar to the ones we used in OLS regressions presented in Table 3. In addition, we produced estimates that include fixed effects, and our conclusions remain robust. These results are available from the authors upon request.

both Tables 6 and 7.

Table 6: Quantile regression results for relative bids.

	Relative bids					
	(1)			(2)		
Variable / Quantile	.25	.50	.75	.25	.50	.75
Oklahoma Bids (β_1)	.010	.021	.099	.023	-.011	.034
	(.131)	(.059)	(.101)	(.125)	(.064)	(.098)
Bids after March 2002	-.044**	-.056**	-.058**	-.051**	-.059**	-.057**
(β_2)	(.014)	(.013)	(.017)	(.017)	(.014)	(.021)
Oklahoma Bids after	.061**	.048**	.033	.069**	.047**	.039
March 2002 (β_3)	(.019)	(.019)	(.022)	(.017)	(.019)	(.028)
Number of bidders	Yes	Yes	Yes			
Number of plan holders				Yes	Yes	Yes
Number of Observations	6175	6175	6175	6175	6175	6175
Pseudo R^2	.033	.031	.038	.032	.029	.033

** denotes statistical significance at the 5% level.
* denotes statistical significance at the 10% level.
All regressions are similar to runs in Table 3.

Hypothesis test results for H_1: $\beta_3^{.25} = \beta_3^{.50} = \beta_3^{.75}$
1) With number of bidders: $F(2, 6115) = .830$
2) With number of plan holders: $F(2, 6115) = .394$

Table 7: Quantile regression results for relative winning bids.

	Relative winning bids					
	(1)			(2)		
Variable / Quantile	.25	.50	.75	.25	.50	.75
Oklahoma Bids (β_1)	-.076	-.092	-.083	-.066	-.086	-.043
	(.069)	(.070)	(.064)	(.071)	(.068)	(.065)
Bids after March 2002	-.030	-.036	-.057**	-.027	-.036	-.052*
(β_2)	(.025)	(.024)	(.026)	(.024)	(.026)	(.028)
Oklahoma Bids after	.070**	.062**	.064**	.066**	.063**	.048*
March 2002 (β_3)	(.027)	(.025)	(.029)	(.028)	(.022)	(.027)
Number of bidders	Yes	Yes	Yes			
Number of plan holders				Yes	Yes	Yes
Number of Observations	1480	1480	1480	1480	1480	1480
Pseudo R^2	.074	.068	.080	.064	.053	.061

** denotes statistical significance at the 5% level.
All regressions are similar to runs in Table 3.

Hypothesis test results for H_1: $\beta_3^{.25} = \beta_3^{.50} = \beta_3^{.75}$
1) With number of bidders: $F(2, 1420) = .955$
2) With number of plan holders: $F(2, 1420) = .850$

Our results from Table 6 indicate that there is no statistically significant difference in the estimate of β_3 across the quantiles, but all coefficients and their significance levels within each model signify a large and persistent change in bidding behavior after the format change was implemented. The results are qualitatively similar in Table 7.

4.1.2 Robustness analysis

Next, we estimate a number of alternative specifications in order to examine the robustness of our results. While we have employed clustered standard errors throughout the paper to address the problems of within group correlation that was raised by Moulton (1990), Bertrand et al. (2004) raise the point that clustered standard errors are biased downward in panel data if serial correlation is present.

The approach that Bertrand et al. (2004) recommend is to collapse the data to pre- and post-format change and estimate the parameters. Therefore, we aggregate the relative bids pre- and post-March 2002 data by firm. Note that, in this case we require each firm to be bidding in both periods in order to estimate the models with firm fixed effects.[14] The first two columns of Table 8 present these results. The results are consistent with the model reported in Table 3 in terms of sign and statistical significance.[15]

Table 8: Robustness table for relative bids.

	Relative bids					
	Pre-format change (averaged by period)		Time trend analysis		Instrumented with number of plan holders	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Oklahoma bids (β_1)	.254	.272			.059	-.064
	(.250)	(.254)			(.061)	(.055)
Bids after March 2002 (β_2)	-.085	-.094			-.075**	-.058**
	(.073)	(.071)			(.013)	(.014)
Oklahoma bids after March 2002 (β_3)	.101*	.104**			.056**	.055**
	(.052)	(.050)			(.015)	(.019)
Time			.002	.003**		
			(.001)	(.001)		
Time × Oklahoma bids			.001	.001		
			(.002)	(.002)		
Number of bidders	Yes		Yes			
Number of plan holders		Yes		Yes		
Synergy variables	Yes	Yes	Yes	Yes	Yes	Yes
Bidder controls	Yes	Yes	Yes	Yes	Yes	Yes
Rival controls	Yes	Yes	Yes	Yes	Yes	Yes
Market characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Project division effects (32)	No	No	Yes	Yes	Yes	Yes
First stage instrument						
Number of plan holders					.526**	.511**
					(.006)	(.007)
Firm effects	Yes	Yes	Yes	Yes	No	Yes
Number of Observations	430	430	3650	3650	6175	6108
Adjusted R^2	.444	441	.202	.199		
Hausman test (p-value)					.162	.399

** denotes statistical significance at the 5% level.
* denotes statistical significance at the 10% level.
Robust clustered standard errors using firm level clusters are in parentheses.

Another issue is whether the format dummy variable is just picking up an increasing trend in Oklahoma relative bids over time. To test this possibility we estimate the relative bid model using only data from the period before the format change and include time variables to measure the trends in relative bids in both states over this period. These models include an overall trend term and the trend term interacted with Oklahoma auctions to test for differences in trend between both states. Columns (3) and (4) of Table 8 contain the results. The estimated trend terms show no statistically significant difference between Oklahoma and

[14]A joint statistical test of the firm effects indicates that we cannot reject the null hypothesis (at the 5% level) that firm effects do not matter.

[15]We do not include county effects since the number of observations is very low.

Texas. Hence, Oklahoma's relative bids were not trending upward prior to the format change relative to Texas.

Finally, we allow for endogeneity in the number of bidders and re-estimate the model using instrumental variable techniques. We instrument the number of bidders with the number of plan holders.[16, 17] The estimates are presented in the last two columns of Table 8. One can see that there is little difference between these results and the OLS results of Table 3 or the fixed effects results of Table 4.

4.2 Nonparametric estimation

In this section we estimate the log bids for Oklahoma and Texas before and after the change in auction format separately using a nonparametric regression technique that was proposed by Racine and Li (2004). This estimation technique allows the data to provide a modeling framework for the relationship among variables applying a kernel method of density estimation to discrete variables that admit no natural ordering such as the project divisions used here. This method was shown to have higher predictive power than other conventional approaches in the presence of categorical variables.

Consider the following empirical model

$$b_{iat} = g(X_{iat}) + \mu_{iat}, \tag{3}$$

where $g(\cdot)$ has an unknown functional form and X_{iat} represents a set of continuous and discrete regressors. We define $X_{iat} = (X^d_{iat}, X^c_{iat})$ with X^c_{iat} representing the subset of continuous variables and X^d_{iat} the discrete variables.[18] In our case, the continuous variables are the log number of plan holders, log number of days to complete the project, log of engineer's cost estimate, bidder's capacity utilized, bidder's distance to the project location, average rivals' winning-to-plan-holder ratio, closest rival's distance to the project location, rivals' smallest backlog, seasonally unadjusted unemployment rate, three-month average of relative real value of engineer's estimates, three-month average of relative number of building permits, and log number of past wins.

We treat the monthly dummy variables and project divisions as unordered discrete variables. In addition, we use a dummy variable for firms that bid in a division where the firm has an ongoing project. This variable is commonly introduced across the two states and time periods.[19]

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[16]See also Haile et al. (2006) for the use of the number of plan holders as an instrument for number of bidders in procurement auctions.

[17]The issue of endogenous entry and participation in auctions has received considerable attention in the theoretical literature (see Samuelson (1985), Levin and Smith (1994), Deltas and Jeitschko (2007), Marmer et al. (2007) and Palfrey and Pevnitskaya (2008) among others). In the pure private value case, Li and Zheng (2009) developed and tested an entry and bidding model with important implications. They found that procurement cost may rise in the presence of endogenous entry because of the fact that a positive "entry effect" may outweigh the negative "competition effect." Clearly, the impact of increased potential competition on bidding behavior depends on the characteristics of the project that is auctioned. Despite the rich literature on endogenous entry, a theoretical or empirical study that compares participation behavior or bidding behavior in multi-round auctions with that of single-round auctions is still non-existent.

[18]Optimal smoothing parameters for $g(\cdot)$ were chosen using the 'leave-one-out cross-validation' mechanism when estimating the fitted values. Bandwidths were chosen using Silverman's rule of thumb and using triweight kernels when estimating results.

[19]We tested for joint significance of the monthly dummy variables and the division dummy variables for all relevant regressions and find that all of these variables are significant.

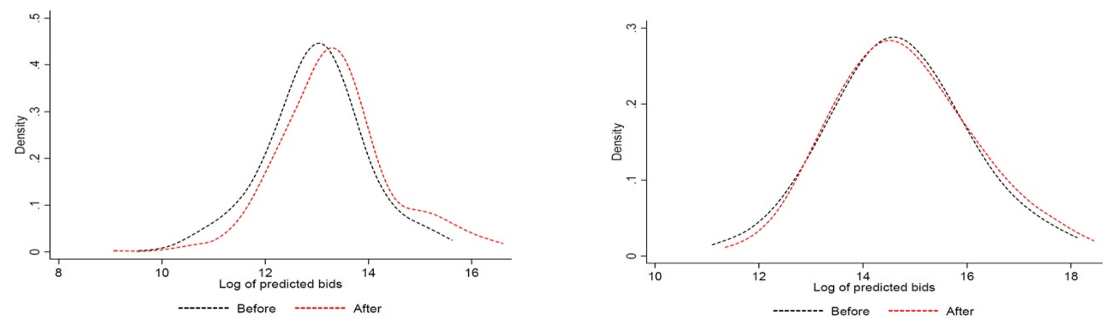

Figure 1: Predicted log of the bids from auctions held in Oklahoma (left panel) and Texas (right panel) using nonparametric estimation.

Figure 1 shows the predicted values of bids from Oklahoma and Texas distinguishing between the two time periods. The figure suggests that after the format change the predicted bids in Oklahoma are less aggressive than before. The bid distribution after the format change first-order stochastically dominates the bid distribution before the format change. When we examine the bid distributions from Texas, no such pattern appears, which provides consistent supporting evidence for our earlier findings. In fact, a Kolmogorov-Smirnov test for the equality of distribution functions that was performed led to rejection of the null hypothesis of equality of distributions for Oklahoma across the periods but not for Texas.[20, 21]

5 Conclusion

Considering the set of asphalt projects offered for bid letting by the Oklahoma Department of Transportation, we have shown that auctioning all projects simultaneously has led to a statistically significant increase in bid values relative to the previous bid letting scheme where half of the contracts were offered simultaneously in an AM session and half in a PM session. We attribute this effect primarily to the low level of synergies in projects that are auctioned across sessions, which can lead to higher bids and higher procurement costs (see Krishna and Rosenthal (1996)). If potential synergies from undertaking multiple projects are low or limited, the sequential auction format (the standard in Oklahoma before March 2002) can produce lower relative bids. Our evidence provides support for this theory. The information that is provided in a sequential setting is a driver of aggressive bidding behavior. At the same time, the uncertainty that is inherent in a simultaneous setting, coupled with the low

[20] When estimating predicted values for Texas using Racine and Li (2004), we use 500 randomly selected auctions instead of all 1,177 auctions. With these predicted values we have drawn the right panel of Figure 1. Converge time for these 500 auctions using the Racine and Li (2004) method was about 4 hours. The relative bids for the period before and after policy change in the sample are 1.062 (.187) and 1.003 (.182) and are statistically not different from the Texas full sample in Table 1. In the sample there were 1287 bids before and 833 bids after the policy change.

[21] We also used the methodology by Haile et al. (2006) to uncover "homogenized bids" before and after the format change, addressing endogeneity issues as well. Haile et al. (2006) control for auction specific variation to create a set of bids as if they were from a sample of auctions of identical projects. We used these bids to test if there are any remaining systematic differences in bidding behavior before and after the format change. The results are available from the authors upon request.

probability of anticipated synergies, reduces bidding aggressiveness in our data.

Another competing explanation of the increase in bid values post March 2002 could be provided in the work by Feng and Chatterjee (2010), who relied on low participation per auction and bidder impatience. Table 5 considers the relative bids in auctions held in Texas and Oklahoma when the number of bidders and potential participants per auction increases. The results suggest that bids become more competitive in simultaneous auctions as the number of bidders or plan holders increase; or, as the theory suggests, the sequential auction format produces higher revenue when the level of competition is low.[22] This factor captures only a small fraction of the difference in bidding and is not the driving force of our results.

[22]The assumption we are making here is that bidders can be somewhat impatient.

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Appendix: Variable description and summary statistics

Table 9: Variable description.

Variable	Definition
Oklahoma bids	Dummy variable that identifies the bids submitted for Oklahoma auctions.
Bids after March 2002	Dummy variable that identifies bids that were submitted after March 2002.
Oklahoma bids after March 2002	Dummy variable that identifies Oklahoma bids submitted after March 2002.
Log of bids	Log value of bids.
Engineer's cost estimate (ECE)	The value of the pavement work bid items as estimated by the state engineer.
Relative bid	The value of the concrete work bid items relative to the ECE.
Relative winning bid	Winning bid divided by the ECE.
Number of bidders	The number of bidders in an auction.
Number of plan holders	Number of plan holders in an auction.
Bidder's capacity utilized	The utilization rate is the current project backlog of a firm divided by the maximum backlog of that firm during the sample period. For firms that have never won a contract, the utilization rate is set to zero. Data from the year 1997 are used to construct a set of initial starting values for the capacity utilization variable. The 1997 data are not used in the empirical models. The backlog variable is constructed as follows: For each project awarded, both the value of the contract and the length of the contract in days are given. We assume that a project is completed in a uniform fashion over the length of the contract. A contract backlog is constructed in each month by summing across the remaining value of all existing contracts in Texas and/or Oklahoma for a firm. So for both Texas and Oklahoma firms, the backlog includes all awarded projects in the states. As projects are completed, the backlog of a firm goes to zero unless new contracts are won.
Log number of days to complete the project	Log number of days to complete the project.
Bidder's distance to the project location	The logarithm of the distance to a project is constructed as the distance between the county in which the project is located and the distance to the county of the firm's location [log(distance+1)]. The county location is measured by the longitude and latitude at the centroid of the 'county seat'.
Firm bidding in a division where there is an ongoing project	This dummy variable identifies bidders when they are bidding on projects where they have an ongoing project in the same county.
Log number of past wins	Bidder specific number of past wins calculated from the beginning of the regression sample (March 2000) to the date of the auction.
Bidders with potential synergies	This dummy variable identifies a morning session winning bidder that is bidding in the afternoon session on given month.
Bidders with no potential synergies	This dummy variable identifies a morning session losing bidder that is bidding in the afternoon session on given month.

Variable	Definition
Average rivals' winning-to-plan-holder ratio	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's bidding given that is is a plan holder, and the probability that the rival wins an auction given that it bids. These probabilities are updated monthly using the complete set of bidding data in Texas and Oklahoma. The probabilities are initialized using data from 1997.
Closest rival's distance to the project location	This variable measures the distance (log of miles) between the project location and the closest rival.
Rivals' smallest backlog	This variable contains the smallest backlog among the rival firms in an auction [log(backlog+1)]. See the capacity utilization discussion above for a detailed explanation of how the backlog variable is constructed.
Large firm dummy variables	This is a dummy variable that identifies the firm size by the number of past wins. For asphalt projects the large firm dummy variable takes the value 1 when a firm has won at least 34 projects.
Seasonally unadjusted unemployment rate	The monthly state-level unemployment rate in Oklahoma and Texas from the US Bureau of Labor Statistics.
Three-month average of relative real value of engineer's estimates	This variable measures the three-month moving average of the real volume of all projects for Oklahoma and Texas. The real volume of projects is constructed by adding the ECE across projects up for bid in a month for Oklahoma and Texas, respectively, and deflating the current value by the PPI. Then we divide it by the average of the real volume for each state to calculate the relative real volume.
Three-month average of relative number of building permits	This variable measures the three-month moving average of the relative number of building permits for Oklahoma and Texas. The data come from the US Bureau of Economic Analysis.
Monthly dummy variables	Monthly dummy variables are set of 11 variables that control for the months of the year. The omitted month is January.
Project division dummy variables	ODOT has divided the state of OK into eight divisions. Similarly TxDOT has divided TX into 25 divisions. The project location dummy variables identify the 32 divisions. OK division 1 is the omitted division.

Table 10: Summary statistics for regression variables.

Variable	Mean (Stdev)	Minimum	Maximum
Oklahoma bids (dummy)	.159 (.366)	0	1
Bids since March 2002 (dummy)	.414 (.493)	0	1
Oklahoma bids since March 2002 (dummy)	.072 (.259)	0	1
Engineer's cost estimate (in US$)	4,590,325 (8,626,752)	6,245	1.02e+08
Relative bid	1.038 (.203)	.184	3.684
Relative winning bid	.946 (.164)	.184	3.347
Number of bidders	4.800 (2.387)	1	15
Number of plan holders	7.678 (3.561)	1	26
Bidder's capacity utilized	.297 (.306)	0	1
Number of days to complete the project	191.601 (243.062)	1	2,209
Bidder's distance to the project (in miles) location	61.848 (92.791)	0.368	649.687
Firm bidding in a division where there is an ongoing project	.393 (.488)	0	1
Number of past wins	33.883 (62.832)	0	704
Bidders with potential synergies	.056 (.230)	0	1
Bidders with no potential synergies	.153 (.360)	0	1
Average rivals' winning-to-plan-holder ratio	.160 (.060)	0	1
Closest rival's distance to the project location (in miles)	14.664 (21.261)	0.368	443.134
Rivals' smallest backlog	2.780 (5.668)	0	27.383
Seasonally unadjusted unemployment rate	5.268 (1.227)	2.800	7.700
Three-month average of relative real value of engineer's estimates	1.110 (.338)	.386	2.423
Three-month average of relative number of building permits	1.027 (.126)	.549	1.344

Table 11: Summary statistics of the number of auctions per session.

Time period & Location		Mean (Stdev)	Minimum	Maximum
Before March 2002				
	OK AM	10.421 (4.782)	1	17
	OK PM	9.726 (4.058)	1	15
	TX AM	18.951 (7.531)	4	32
	TX PM	19.595 (7.412)	5	34
After March 2002				
	OK	24.213 (15.021)	1	46
	TX AM	15.538 (7.042)	8	29
	TX PM	16.696 (7.726)	3	33

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Heinrich-Heine-University of Düsseldorf

**Düsseldorf Institute for
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Universitätsstraße 1 _ 40225 Düsseldorf
www.dice.hhu.de

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