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18 October 2010

Online at <https://mpra.ub.uni-muenchen.de/27355/>
MPRA Paper No. 27355, posted 10 Dec 2010 22:43 UTC

The impact of timing on bidding behavior in procurement auctions of contracts with private costs*

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October 18, 2010

Abstract

We provide a comparison of bidding behavior between multi-round and single-round auctions considering bid lettings for asphalt construction contracts. Using a reduced-form difference-in-difference approach as well as the nonparametric estimation technique 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 related to synergies and level of bidder participation.

JEL Classification: D44, H57.

Keywords: Multi-unit auctions, Procurement auctions.

*The authors would like to thank Fernando Antonio Postali, Artyom Shneyerov and conference participants at the 2010 International Industrial Organization Conference in Vancouver for helpful comments and suggestions.

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1 Introduction

In an effort to reduce operational costs, the Oklahoma Department of Transportation (ODOT) decided to change the design of their monthly procurement auctions for road construction contracts in March of 2002. Until that date, ODOT auctioned off the contracts in two separate sessions on a single day, with roughly one half of the contracts being auctioned off 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 off simultaneously in one single session. We examine empirically the impact of the change in auction format on participation and bidding behavior focusing on asphalt projects.

In a recent related study, De Silva et al. (2007) examined timing effects of a switch from a sequential to a simultaneous format to find 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 theoretical and empirical investigation of bidding and participation decisions in Milgrom and Weber (1982), Goeree and Offerman (2003) and De Silva et al. (2008) behavior is markedly different across project types. As such, it becomes more urgent that policy recommendations are tailored to general characteristics of projects. Potential economies of scope and informational differences between a multi-round and a single-round format are bound to have a differential effect on bidding behavior across project categories.

In this study, we focus on asphalt paving projects that have primarily private costs (Bajari and Ye (2003), De Silva et al. (2008), Porter and Zona (1993)). We use about 6,000 bids submitted by construction firms in Oklahoma and Texas over the period from March 2000 to August 2003 to analyze bidding strategies. Throughout the entire period investigated, the Texas Department of Transportation (TxDOT) auctioned all its contracts in two lettings every single month. We use the road construction auction data from Texas as a control group against which to mirror eventual changes in Oklahoma. Our results suggest that the design change has not induced a change in auction participation. There is no significant change in the number of plan holders (the firms that express interest by buying a plan to examine the details of a project description), their bid submission probability, and the number of actual bidders per project. We do, however, find a significant impact on bidding behavior; bidding has become less competitive. All in all, the shift to a single-round auction has caused an

increase in the procurement costs for asphalt projects.

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) on the other hand simultaneous auctions outperform sequential auctions if there are many competitors trying to take advantage of synergies.¹ Feng and Chatterjee (2005) 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 off 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 items in one period. Which auction format performs better is largely determined by the relationship between the number of items sold and the number of bidders competing. The sequential auction format produces higher revenues 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)).

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. These projects absorbed 58.7% of the road construction budgets of Oklahoma and Texas (or \$5.88 billion dollars) during the period of analysis but attracted a relatively low number of potential bidders (3 to 4) per auction. Our analysis takes into account all these factors that are relevant to the auction outcome and standard in road construction and examines their significance in the selection of an auction format.

¹Krishna 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, the sequential auction, and the combinatorial 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.

Section 2 offers a detailed description of the data set that is followed by the empirical analysis in Section 3. A discussion and concluding remarks are included in Section 4.

2 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 As mentioned earlier, ODOT decided in March of 2002 to start offering all contracts simultaneously instead of holding two sessions on a single day. This unique natural experiment allowed us to evaluate the impact of the change in format on bidder participation and bidding behavior in ODOT road construction auctions compared to a control group. Our control group consists of auctions 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. At the conclusion of each session, the bids submitted by each bidder are revealed and the winner is announced. Table 8 in Appendix A provides a detailed definition for each of the variables used in the study.

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 are typically having a strong private cost component. We utilize data from March 2000 until August 2003 in the empirical analysis.³ Data from January 1997 to March 2000 are used to create variables on bidder history, potential to gain from synergies, potential rivals' strength and capacity commitment.

Table 1 presents summary statistics for asphalt projects in Oklahoma and Texas. For both states, the number of plan holders and number of bidders per auction have increased after March 2002. However, data indicate that there are more asphalt projects in Texas than in Oklahoma. Also there are about 60% more plan holders and bidders per auction in Texas asphalt projects. When considering the average relative bids (the bid relative to the engineer's cost estimate) and winning bids for asphalt projects, we notice an increase in those bids at

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

³Prior 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.

the mean level in Oklahoma relative to Texas. In the next section, we analyze empirically the participation patterns and bidding behavior.

Variable	Oklahoma		Texas	
	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.

Table 1: Summary statistics of asphalt projects auctioned in Oklahoma and Texas.

3 Empirical model and results

In this section, we present two approaches on how to measure 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 allowing 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 allowing for a wide range of robustness checks. Our second approach is to use the nonparametric regression technique proposed by Racine and Li (2004) to provide the predicted distributions of bids in Oklahoma before and after the format change and compare them to Texas. Racine and Li (2004) allows for nonparametric estimation with continuous and categorical variables using the kernel method of density estimation rather than the conventional frequency estimation process used to handle categorical variables.⁴

⁴This smoothing method has been shown to have significant efficiency gains over the conventional nonparametric and semiparametric approaches for finite samples.

3.1 Reduced-form estimation

In order to understand better the patterns of bidding in auctions held by the Oklahoma Department of Transportation, we present a set of reduced-form regressions that show how participation and bidding varies across the two periods. In addition, to capture better the effect of the format change we compare bidding behavior in Oklahoma and Texas. In Texas, there was no change in the timing of the bid letting 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 after 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:

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

where the unit of observation is firm i bidding 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 β s 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 average difference in bidding between Oklahoma and Texas auctions. 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:

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

where the first two terms ($E[y|x, D_s=1, A_t=1] - E[y|x, D_s=0, A_t=1]$) represent the difference between the expected value of bids in Oklahoma and Texas after the format change. The last two terms ($E[y|x, D_s=1, A_t=0] - E[y|x, D_s=0, A_t=0]$) 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 to examine if β_3 turns out to be non-positive and if it is statistically significant.

All variables used in our analysis are described in Table 8 in Appendix A. There are three auction-level variables: the number of plan holders, the potential number of rivals, and the log of number of days to complete the project. The first two variables control for differences in competition across auctions.

In all models we include variables on bidder characteristics to capture cost heterogeneity across bidders. They are measures on capacity utilization rate and 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 level of bidding. Further, we include a dummy variable indicating if a firm is bidding in a division where there is an ongoing project, to control for any geographical synergies with existing projects defining a firm's workload.

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 rivals' minimum distance to the project and the minimum backlog of the rivals. These variables are also used to control for rival cost heterogeneity.⁵

Finally, we use three variables that control for the business environment: (1) the monthly variation in the amount of projects being let, (2) the monthly unemployment rate, and (3) the monthly building permits. The first variable measures the real volume of projects auctioned off in each state in each month. The aggregate real volume of projects auctioned off in a month in a state will vary due to seasonal factors and budgetary conditions.

3.1.1 Difference-in-differences results

Table 2 presents the entry and winning probabilities conditional upon entry. Results from both tables indicate that generally the participation of bidders and winning probabilities have not changed after the format change. The key parameter of interest is β_3 that measures the difference in entry between Oklahoma and Texas auctions in the period after March 2002. We see no difference in entry decisions in Oklahoma across the periods compared to Texas. Results also indicate that there is an inverse relationship between the entry and winning probabilities and the number of rivals.⁶

⁵See also Jofre-Bonet and Pesendorfer (2003) and De Silva et al. (2008).

⁶Since 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).

Variable	Probability of bidding (1)	Probability of winning conditional on bidding (2)
Oklahoma Bids (β_1)	-.107** (.046)	.034 (.040)
Bids after March 2002 (β_2)	-.015 (.043)	-.048 (.044)
Oklahoma Bids after March 2002 (β_3)	.076 (.056)	-.012 (.057)
Log of Engineering Estimate	.012 (.010)	.004 (.008)
Number of rivals (plan holders)	-.028** (.005)	-.038** (.005)
Oklahoma number of rivals after March 2002	-.022 (.014)	-.002 (.011)
Number of rivals after March 2002	.012** (.005)	.005 (.007)
Log number of days to complete the project	-.018 (.014)	.002 (.011)
Firm bidding on a division where there is an ongoing project	.142** (.017)	.052** (.014)
Bidders capacity utilized	.062** (.028)	-.026 (.021)
Bidders distance to the project location	-.017** (.007)	-.025** (.005)
Average rivals winning to plan holder ratio	-.238* (.143)	-.427** (.118)
Closest rival's distance to the project location	.014** (.004)	.023** (.004)
Rivals minimum backlog	.001 (.001)	.001 (.001)
Seasonally unadjusted unemployment rate	-.006 (.013)	.001 (.012)
Three month average of relative real value of engineer's estimates	-.079** (.027)	.020 (.027)
Three month average of relative number of building permits	-.299** (.114)	.135 (.113)
Number of Observations	9430	6175
Wald χ^2	381.77	316.99

** 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.

Table 2: Probit regression results.

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 to enter

and win increases. When a firm faces a rival with a significant record of success in the past or when a firm's distance to the location of a project increases, the probability of entry and winning decreases. However, as the closest rival's distance to the project location increases the bidders are more likely to enter and win.

Table 3 presents the results for relative bid regressions. Our main result indicates that the change the 'timing' of lettings has adversely affected the relative bids for projects with

Variable	Relative bids	
	(1)	(2)
Oklahoma Bids (β_1)	-.007 (.012)	-.001 (.012)
Bids after March 2002 (β_2)	-.066** (.012)	-.071** (.012)
Oklahoma Bids after March 2002 (β_3)	.057** (.015)	.060** (.015)
Number of bidders	-.009** (.001)	
Number of plan holders		-.004** (.001)
Log number of days to complete the project	.001 (.004)	.001 (.004)
Firm bidding on a division where there is an ongoing project	-.029** (.005)	-.027** (.005)
Bidders capacity utilized	.016 (.009)	.015 (.009)
Bidders distance to the project location	.003 (.002)	.002 (.002)
Average rivals winning to plan holder ratio	-.274** (.049)	-.268** (.050)
Closest rival's distance to the project location	-.009** (.002)	-.009** (.002)
Rivals minimum backlog	.000 (.000)	.000 (.000)
Seasonally unadjusted unemployment rate	-.005 (.006)	-.003 (.006)
Three month average of relative real value of engineer's estimates	.048** (.012)	.052** (.012)
Three month average of relative number of building permits	.227** (.054)	.241** (.054)
Number of Observations	6175	6175
Adjusted R^2	.037	.032

** 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.

Table 3: Regression results.

large independent private cost components. We estimate our models using the number of bidders in one specification and the number of plan holders in the other. Columns (1) and (2) of Table 3 provide these estimates. In private value auctions (asphalt projects) both the number of bidders and 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 Table 9 (Appendix B) and show consistency.

When considering other variables, bidders who have ongoing projects in the same division bid more aggressively while capacity constrained bidders bid less aggressively. As the distance to the project location increase 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.

Table 4 reports the winning bid regression results. The main qualitative finding is that winning bids for asphalt projects 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 Table 10. This time we included only bidders that won multiple projects. The results confirm the adverse effect of the design change.

Variable	Relative winning bids	
	(1)	(2)
Oklahoma Bids (β_1)	-.023 (.015)	-.013 (.016)
Bids after March 2002 (β_2)	-.047** (.020)	-.055** (.020)
Oklahoma Bids after March 2002 (β_3)	.078** (.021)	.081** (.021)
Number of bidders	Yes	No
Number of plan holders	No	Yes
Firm bidding on a division where there is an ongoing project	Yes	Yes
Number of Observations	1480	1480
Adjusted R^2	.092	.063

** denotes statistical significance at the 5% level.

Robust clustered standard errors using firm level clusters are in parentheses.

All regressions are similar to runs in Table 3.

Table 4: Regression results.

The OLS and fixed effects results above indicate that on average bidders bid less aggressively in Oklahoma after the format change compared to Texas. In our analysis of bids, we have considered differences in expected values. We will now show that the level of bids is consistently higher in Oklahoma than in Texas after the format change not only in expectation but across the bidding distributions. We can thus provide evidence that the less aggressive bidding behavior 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. In order to investigate this issue, we use the quantile regression technique introduced by Koenker and Bassett (1982). We restrict estimation to three quantiles: 0.25, 0.50, and 0.75 and estimate the relative bid and winning bid models.⁷ The results are presented in Tables 5 and 6. Our main finding is that after policy change Oklahoma bidders bid less aggressively by 4.7% and win with 6.1% higher bids. We then test the difference across the three quantiles from the two models in Columns (1) and (2) in both Tables 5 and 6. Our results from Table 5 indicate that there is no statistically significant difference in the estimate of β_3 across the quantiles, but all coefficients are statistically significant within each model signifying a large and persistent difference in the bidding behavior across the two states after the format change was implemented. The

Variable / Quantile	Relative bids					
	(1)			(2)		
	.25	.50	.75	.25	.50	.75
Oklahoma Bids (β_1)	-.016 (.013)	.005 (.012)	.23 (.020)	-.015 (.015)	.008 (.016)	.034* (.018)
Bids after March 2002 (β_2)	-.028** (.012)	-.040** (.012)	-.053** (.015)	-.028** (.015)	-.045** (.013)	-.067** (.017)
Oklahoma Bids after March 2002 (β_3)	.067** (.015)	.047** (.015)	.043** (.021)	.063** (.017)	.047** (.018)	.058** (.021)
Number of bidders	Yes	Yes	Yes	No	No	No
Number of plan holders	No	No	No	Yes	Yes	Yes
Number of Observations	6175	6175	6175	6175	6175	6175
Pseudo R^2	.033	.031	.038	.033	.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: $F(2, 6125) = 1.02$

2) With number of plan holders: $F(2, 6125) = .66$

Table 5: Quantile regression results with large firm effects.

⁷These models are similar to the ones we used in OLS regressions. In addition, we include large firm dummies as in De Silva et al. (2008).

Variable /	Quantile	Relative winning bids					
		(1)			(2)		
		.25	.50	.75	.25	.50	.75
Oklahoma Bids (β_1)		-0.38 (.033)	-.008 (.019)	-.011 (.026)	-.023 (.030)	.003 (.024)	.008 (.029)
Bids after March 2002 (β_2)		-.013 (.027)	-.021 (.021)	-.030 (.026)	-.025 (.024)	-.026 (.025)	-.034 (.029)
Oklahoma Bids after March 2002 (β_3)		.070** (.032)	.062** (.027)	.030 (.035)	.084** (.028)	.061** (.028)	.026 (.034)
Number of bidders		Yes	Yes	Yes	No	No	No
Number of plan holders		No	No	No	Yes	Yes	Yes
Number of Observations		1480	1480	1480	1480	1480	1480
Pseudo R^2		.072	.067	.080	.063	.053	.061

** denotes statistical significance at the 5% level.

All regressions are similar to runs in Table 4.

Hypothesis test results for $H_1: \beta_3^{.25} = \beta_3^{.50} = \beta_3^{.75}$

- 1) With number of bidders: $F(2, 1430) = .54$
- 2) With number of plan holders: $F(2, 1430) = 1566$

Table 6: Quantile regression results with large firm effects.

results are qualitatively similar in Table 6 showing statistically significant difference in the winning bids at the median level and the .25 quantile.

3.1.2 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 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 down to pre and post format change and estimate parameters. Therefore, we aggregate the 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 effects. The first two columns of Table 7 present these results. The results are consistent with the model reported in Table 3 for asphalt work in terms of sign and statistical significance.

Another issue is whether the format dummy 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

Variable	Pre-relative bids – Averaged by period		Time trend analysis		Instrumented with number of plan holders	
	(1)	(2)	(3)	(4)	(5)	(6)
Oklahoma Bids (β_1)	.251 (.248)	.276 (.254)	-.002 (.116)	.017 (.117)	-.006 (.012)	.034 (.053)
Bids after March 2002 (β_2)	-.072 (.073)	-.081 (.071)			-.067** (.012)	-.051 (.014)
Oklahoma Bids after March 2002 (β_3)	.091* (.050)	.093* (.049)			.058** (.015)	.055** (.018)
Time			.002* (.001)	.003** (.001)		
Time \times Oklahoma Bids			.001 (.002)	.001 (.002)		
Number of bidders	Yes	No	Yes	No		
Number of plan holders	No	Yes	No	Yes		
Firm effects	Yes	Yes	Yes	Yes	No	Yes
<i>First stage instrument</i>						
Number of plan holders					.539** (.006)	.513** (.008)
Number of Observations	430	430	3650	3650	6175	6108
Adjusted R^2	.441	.438	.178	.174	.037	.182
Hausman test (p -value)					.240	.367

** 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.

Table 7: Robustness checks.

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 7 contain the results. The estimated trend terms show no statistically significant difference between Oklahoma and 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.^{8,9} The estimates are presented in the last two columns of Table 7. One can see

⁸See also Haile et al. (2006) for the use of the number of plan holders as an instrument for number of bidders in procurement auctions.

⁹The 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 (2010) 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 auctioned off. Despite the rich literature on endogenous entry, a theoretical or empirical study that compares participation behavior or bidding behavior

that there is little difference between these results and the OLS results of Table 3 or the fixed effects results of Table 9.

3.2 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 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

$$b_i = g(X_i) + \mu_i, \tag{3}$$

where $g(\cdot)$ has an unknown functional form and X_i represents a set of continuous and discrete regressors. We define $X_i = (X_i^d, X_i^c)$ with X_i^c representing the subset of continuous variables and X_i^d the discrete variables.¹⁰ In our case, the continuous variables are the log number of plan holders, log number of days to complete the project, log of engineering cost estimate, bidders capacity utilized, bidders distance to the project location, average rivals winning to plan holder ratio, closest rival's distance to the project location, rivals minimum backlog, seasonally unadjusted unemployment rate, three month average of relative real value of engineer's estimates and three month average of relative number of building permits. We treat monthly dummies and project divisions as unordered discrete variables. In addition, we use a dummy variable for firms bidding in a division where there is an ongoing project. This variable is commonly introduced across the two states and time periods.

Figures 1 and 2 show the predicted values of bids from Oklahoma and Texas distinguishing between the two time periods. These figures suggest 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 considering the bid distributions from Texas, no such pattern appears providing consistent supporting evidence to our earlier findings. In fact, a Kolmogorov-Smirnov test for the

in multi-round auctions with that of single-round auctions is still non-existent.

¹⁰Optimal 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.

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.^{11, 12}

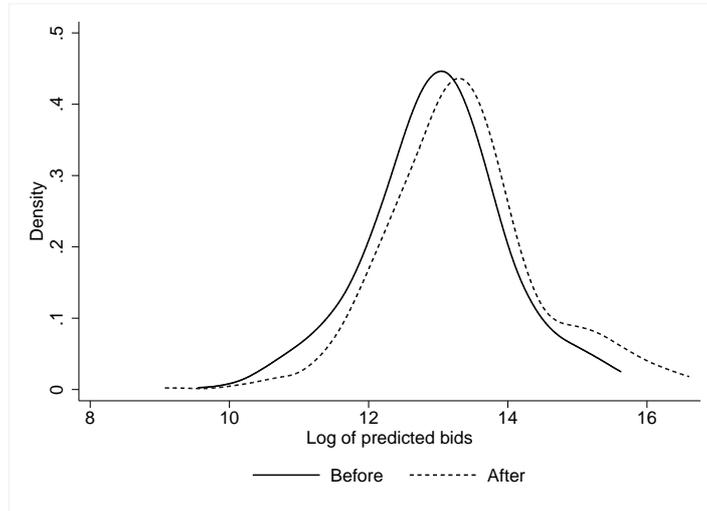


Figure 1: Predicted log of bids using nonparametric estimation.

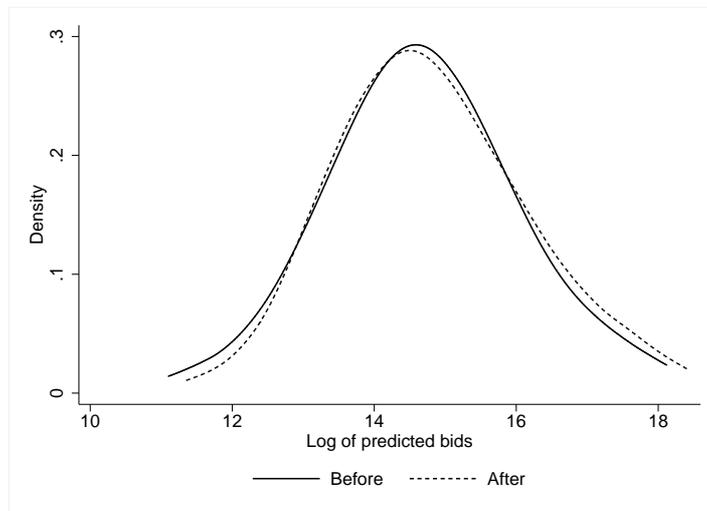


Figure 2: Predicted log of bids using nonparametric estimation.

¹¹When estimating predicted values for TX using Racine and Li (2004), we use 500 randomly selected auctions instead of all 1,177 auctions. With these predicted values we have drawn Figure 2. Converge time for these 500 auctions using 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 statistically not different from the TX full sample in Table 1. In the sample there were 1287 bids before and 833 bids after policy change.

¹²We 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 by the authors upon request.

4 Discussion

Considering the set of asphalt projects offered for bid letting by the Oklahoma Department of Transportation, we have shown that auctioning off all projects simultaneously has led to a statistically significant increase in bids 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. Such patterns in an affiliated values framework could be attributed to informational effects. Those effects are likely to be secondary here as asphalt contracts have primarily private costs. Another explanation for the increased procurement costs can be found in the work by Krishna and Rosenthal (1996). If potential synergies from undertaking multiple projects are low or limited the sequential auction format can produce more competitive bids. Measuring the intensity of synergies for projects offered within a month is not easy in practice. We have identified, however, projects 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 offered in the same division the larger the potential of significant synergies. In our sample, of the 247 bids submitted in afternoon sessions in Oklahoma before the format change only 50 bids (20.24%) are submitted by bidders who bid for projects in the same division in the morning. Of the 85 contracts 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.¹³

Yet another explanation of the increase in bids post March 2002 could be provided in the work by Feng and Chatterjee (2005) relying on low participation per auction and bidder impatience. Table 11 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.¹⁴ This factor is capturing only a small fraction of the difference in bidding.

¹³We also 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 post March 2002. We didn't find significant differences across formats.

¹⁴The assumption we are making here is that bidders can be somewhat impatient.

References

- [1] Albano G, F Germano and S Lovo (2001). A comparison of standard multi-unit auction with synergies. *Economics Letters* 71 (1): 55-60.
- [2] Bajari P and L Ye (2003). Deciding between competition and collusion. *Review of Economics and Statistics* 85 (4): 971-989.
- [3] Bertrand M, E Duflo and S Mullainathan (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics* 119 (1): 249-275.
- [4] Deltas G and T Jeitschko (2007). Auction hosting site pricing and market equilibrium with endogenous bidder and seller participation. *International Journal of Industrial Organization* 25 (6): 1190-1212.
- [5] De Silva DG, A Kankanamge and G Kosmopoulou (2007). A change in timing of auctions with synergies and its impact on bidding behavior. *Economics Letters* 95 (1): 60-65.
- [6] De Silva DG, T Dunne, A Kankanamge and G Kosmopoulou (2008). The impact of public information on bidding in highway procurement auctions. *European Economic Review* 52 (1): 150-181.
- [7] Feng J and K Chatterjee (2005). Simultaneous vs. sequential sales, intensity of competition, and uncertainty. Working paper, University of Florida and Penn State University.
- [8] Goeree J and T Offerman (2003). Competitive bidding in auctions with private and common values. *Economic Journal* 113 (489): 598-613.
- [9] Haile P, H Hong and M Shum (2006). Nonparametric tests for common values in first-price sealed-bid auctions. Working paper.
- [10] Hausch D (1986). Multi-objects auctions: Sequential vs. simultaneous sales. *Management Science* 32 (12): 1599-1610.
- [11] Jofre-Bonet M and M Pesendorfer (2003). Estimation of a dynamic auction game. *Econometrica* 71 (5): 1443-1489.
- [12] Koenker R and G Bassett Jr (1982). Robust tests for heteroscedasticity based on regression quantiles, *Econometrica* 50 (1): 43-61.

- [13] Krishna V and R Rosenthal (1996). Simultaneous auctions with synergies. *Games and Economic Behavior* 17 (1): 1-31.
- [14] Levin D and J Smith (1994). Equilibrium in auctions with entry. *American Economic Review* 84 (3): 585-599.
- [15] Li T and X Zheng (2009). Entry and competition effects in first-price auctions: Theory and evidence from procurement auctions. *Review of Economic Studies* 76 (4): 1397-1429.
- [16] Marmer V, A Shneyerov and P Xu (2007). What model for entry in first-price auctions? A nonparametric approach. Working paper, University of British Columbia and Concordia University.
- [17] Milgrom P and R Weber (1982). A theory of auctions and competitive bidding. *Econometrica* 50 (5): 1089-1122.
- [18] Milgrom P and R Weber (2000). A theory of auctions and competitive bidding, II. In: P Klemperer (ed.) *The Economic Theory of Auctions Vol. 1* (Cambridge, UK: Edward Elgar): pp. 179-194.
- [19] Moulton B (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics* 72 (2): 334-338.
- [20] Palfrey T and S Pevnitskaya (2008). Endogenous entry equilibrium in first price private value auctions: An experimental study. *Journal of Economic Behavior and Organization* 66 (3-4): 731-747.
- [21] Porter R and J Zona (1993). Detection of bid rigging in procurement auctions. *Journal of Political Economy* 101 (3): 518-538.
- [22] Racine J and Q Li (2004). Nonparametric estimation of regression functions with both categorical and continuous data. *Journal of Econometrics* 119 (1): 99-130.
- [23] Samuelson W (1985). Competitive bidding with entry costs. *Economics Letters* 17 (1-2): 53-57.

A Variable description

Variable	Definition
Oklahoma Bids	Dummy to identify the bids submitted for Oklahoma auctions.
Bids after March 2002	Bids submitted after March 2002.
Oklahoma Bids after March 2002	Dummy to identify Oklahoma bids submitted after March 2002.
Log of bids	Log value of bids.
Engineers cost estimate (ECE)	The value of the pavement work bid items relative to the ECE.
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.
Bidders 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 value for the capacity utilization variable. The 1997 data is 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.
Bidders distance to the project location	The logarithm of the distance to a project is constructed as the distance between the county the project is located in and the distance to the county of the firm's location $[\log(\text{distance}+1)]$. The county location is measured by the longitude and latitude at the centroid of the 'county seat.'
Firm bidding on 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.
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.
Multiple bids in the same division in AM auctions	This dummy variable identifies a firm submitting multiple bids in the morning session on given month in the same division.
Multiple bids in the same division in PM auctions	This dummy variable identifies a firm submitting multiple bids in the afternoon session on given month in the same division.

Variable	Definition
Multiple bids in the same division in AM and PM auctions	This dummy variable identifies a firm submitting multiple bids (at least one bid in the morning and afternoon session) on given month in the same division before policy change.
Multiple bids in the same division after March 2002	This dummy variable identifies a firm submitting multiple bids on given month in the same division after policy change.
Average rivals winning to plan holder ratio	The measure of rivals' past average success (ARWP) 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. It incorporates both the probability of a rival bidding given they are a plan holder and the probability the rival wins an auction given that they bid. 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 minimum backlog	This variable contains the minimum the backlog of the rival firms in an auction $[\log(\text{backlog}+1)]$. See the capacity utilization discussion above for a detailed explanation of how the backlog variable is constructed.
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 dummies	Monthly dummies are set of 12 variables that control for the months of the year. The omitted month is January.
Project location dummies	ODOT has divided the state of OK into eight divisions. Similarly TxDOT has divided TX into 25 divisions. The project location dummies identify the 33 divisions from which we draw data for our analysis. OK division 1 is the omitted group in the Poisson regressions.

Table 8: Variable description.

B Fixed effects and explanatory regressions

Variable	Relative bids	
	(1)	(2)
Oklahoma Bids (β_1)	.035 (.053)	.042 (.053)
Bids after March 2002 (β_2)	-.053** (.014)	-.059** (.015)
Oklahoma Bids after March 2002 (β_3)	.057** (.018)	.061** (.018)
Number of bidders	-.013** (.002)	
Number of plan holders		-.007** (.002)
Firm bidding on a division where there is an ongoing project	Yes	Yes
Number of Observations	6108	6108
Adjusted R^2	.182	.177

** denotes statistical significance at the 5% level.

Robust clustered standard errors using firm level clusters are in parentheses.

All regressions are similar to runs in Table 3.

Table 9: Regression results with firm effects.

Variable	Relative winning bids	
	(1)	(2)
Oklahoma Bids (β_1)	-.037 (.082)	-.027 (.079)
Bids after March 2002 (β_2)	-.018 (.023)	-.025 (.024)
Oklahoma Bids after March 2002 (β_3)	.066** (.028)	.071** (.029)
Number of bidders	-.022*** (.003)	
Number of plan holders		-.011** (.002)
Firm bidding on a division where there is an ongoing project	Yes	Yes
Number of Observations	1427	1427
Adjusted R^2	.381	.355

*** denotes statistical significance at the 1% level.

** denotes statistical significance at the 5% level.

Robust clustered standard errors using firm level clusters are in parentheses.

All regressions are similar to runs in Table 4.

Table 10: Regression results with firm effects.

Variable	Relative bids			
	(1)	(2)	(3)	(4)
Oklahoma Bids (β_1)	.010 (.013)	.015 (.013)	.010 (.013)	.015 (.013)
Bids after March 2002 (β_2)	-.037** (.018)	-.044** (.021)	-.037** (.018)	-.044** (.021)
Oklahoma Bids after March 2002 (β_3)	.096*** (.031)	.087*** (.024)	.096*** (.029)	.087*** (.024)
Number of bidders	-.006** (.002)		-.006** (.002)	
Number of bidders after March 2002	-.008*** (.002)		-.008*** (.002)	
Oklahoma number of bidders after March 2002	-.015** (.007)		-.015** (.007)	
Number of plan holders		-.002 (.001)		-.002 (.001)
Number of plan holders after March 2002		-.004*** (.002)		-.004*** (.002)
Oklahoma number plan holders after March 2002		-.008** (.003)		-.008** (.003)
Firm bidding on a division where there is an ongoing project	Yes	Yes	Yes	Yes
Bidders with potential synergies	No	No	Yes	Yes
Bidders with no potential synergies	No	No	Yes	Yes
Number of Observations	6175	6175	6175	6175
Adjusted R^2	.043	.038	.043	.037

*** denotes statistical significance at the 1% level.

** denotes statistical significance at the 5% level.

Robust clustered standard errors using firm level clusters are in parentheses.

Table 11: Regression results.