How to Achieve Efficiency in Public Procurement Auctions*

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Abstract

This paper empirically investigates the optimal number of bidders to achieve the lowest procurement prices in public procurement auctions. We use a unique data set provided by the Public Procurement Authority of Turkey that covers ***all*** government procurement auctions for the years 2004-2010, 472560 auctions. We conclude that there is an optimal number of bidders and this number vary for different types of products. These results indicate that auctioneers should promote competition in public procurement. The optimal number of bidders can be used by the authorities as focal points to analyze whether competitive efficiency is achieved in the public procurement auctions.

Keywords: Public Procurement Auctions; Governance; Competition

JEL Classifications: C31, D44, H57

*We are grateful to the Public Procurement Authority of Turkey (PPA) for providing us the data used in this paper. The data set is open to public and the PPA of Turkey should be contacted for the complete data set.

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1 Introduction

In the wake of the recent crisis many countries face problems caused by budget deficits. To be able to lower their budget deficits these governments should conduct their expenditures at the lowest possible prices. To achieve this objective many countries use auctions to administer government procurements. Turkey is one of the countries where government procurement (now on GP) is conducted mainly using first-price auction methodology.

In this study, we make use of a unique data set provided by the Public Procurement Authority (PPA) of Turkey which comprises detailed information about all GP auctions for the years 2004-2010, 472560 first-price auctions. Using this data set, we empirically investigate the the optimal competitive environment for lowest procurement costs. First, we analyze the effect of number of bidders on the procurement price (winning bid). Then we examine the main research question of the paper and investigate the optimal number of bidders for different types of products which renders lowest procurement costs.

The effects of increasing the number of participants on procurement auctions have been extensively investigated in the literature. These studies show that the effect of an increase in the number of participants on the cost of procurement might be positive or negative. For example, Hong and Shum (2002) find that median procurement costs rise as competition intensifies. They argue that this results stems from the "winner's curse". In the common-value setting, the competition effect tapers off when the number of bidders is large. Similarly, Fan and Wolfstetter (2008) theoretically show that the equilibrium price increases in the number of bidders. They argue that a profit maximizing procurer should restrict the number of bidders to two.

On the other hand, the independent private value paradigm (IPVP) indicates that the equilibrium bid function may be monotonic in number of bidders.

Iimi (2006) investigates the competition effect in the Japanese Official Development Assistance (ODA) projects. He reports that winning bid decreases as the number of bidders increases. Estache and Iimi (2008) considers how sectoral differences affect the competition effect in government procurement auctions by examining procurement data from ODA projects in three main infrastructure sectors: roads, electricity, and water and sanitation. They conclude that seven bidders are required to take full advantage of competition in the roads and water sectors, whereas the optimal number of bidders is three for the power sector. In a closely related paper, Onur et al. (2012) analyze the Turkish GP auctions for the 2004-2006 period, 90089 auctions. Using a limited data set they show that the number of bidders significantly and negatively affects the procurement price. This study differs from Onur et al. (2012) in two major ways. First, we examine the optimal number of bidders for each product type which has not been analyzed in Onur et al. (2012). Second, we use a much extended data set which contains five times more auctions than Onur et al. (2012). Extending the data set is essential because many government institutions started to use auctions more actively in the recent years. This can be seen by the increase in number of auctions after 2006. The data set used in this paper covers most of the GP activity in Turkey.

Very few studies in the literature investigate procurement auctions especially for developing economies. The main reason of the lack of empirical studies is nonexistent or restricted access to comprehensive procurement auction data. The PPA of Turkey collects detailed information about all Turkish GP auctions. The data collection is required by the Turkish Public Procurement Laws 4734 and 4735. Hence, the PPA provides a data set which can be used for empirical analysis of GP auctions.

The PPA data set contains 472560 first-price GP auctions for the years

2004 to 2010.[1] Using this unique data set, we first analyze the determinants of number of bidders. Then, we focus on the effect of competitive environment on the procurement costs by examining the effect of various explanatory variables on the difference between the contract price and the estimated cost of auctions. Finally, we analyze the optimal number of bidders for different product types. We take into account the endogeneity of the number of bidders while conducting these analysis.

We have two major results. First, we show that the number of bidders significantly and negatively affects the procurement price. Thus, existence of a more competitive environment significantly decreases government procurement costs in Turkey. Second, the optimal number of bidders to take the full advantage of competition differs among auctions for different types of products. At least nine bidders are needed for services; six bidders are required for the goods and construction auctions to be able to achieve the lowest procurement price possible. The findings of our study are in line with the standard theoretical predictions of the IPVP auction models and confirm some of the key empirical findings of previous studies like Iimi (2006).

The rest of the paper is organized as follows: Section 2 describes the data. Section 3 presents the empirical methodology and results. Section 4 concludes and summarizes some policy implications of the results.

2 Data

2.1 Data Description

The PPA data set used in this study contains data about all GP auctions

[1] The original data set contains 748772 procurements conducted using the following methods: first-price auction, negotiation, direct purchase, and constrained participation first-price auction. Among 751611 procurements 472560 procurements are done using first-price auctions.

from 2004 to 2010[2]. The employ the following variables:

1. Winning bid (WINBID): The PPA data set contains the winning bids (lowest bid) for each of the public procurement auctions run during the 2004-2010 period[3]. The PPA law requires collection of only the value of the winning bid and number of bidders. Thus, we do not have losing bids in the data set.

2. Estimated cost (ESTIMATE): Experts estimate the cost of the procurement before the auction announcements are made. The PPA controls the accuracy of these estimates.

3. Number of bidders (N): The number of valid bids submitted by the bidders. A bidder can only submit one bid for each procurement auction thus the number of bids is equal to the number of bidders for a given auction.

4. Dummy variables for public institutions that conduct the procurement (INST): There are 29 different institutions that conduct procurement auctions. We use institution dummies to control for institutional differences.

5. Dummy variables for the auctioned good types (AUCTYPE): The PPA separates auctions into 3 different categories with respect to type of procurement; construction, service and goods.

We add new variables that are necessary for our analysis in addition to the PPA data set. Firstly, we construct a dummy variable named ABOVE THRESHOLD. The PPA determines a threshold value for various types of procurement

[2]The data period is limited by the availability of detailed data provided by the PPA.

[3]One can think of the changes in prices of the procured items due to inflation. As explained in Section 3, we use the log difference of the winning bid and the estimated cost. Since both the winning bid and the estimation price are in that year's prices, the log difference becomes unit free; hence the inflation effect is eliminated.

auctions according to the rules specified by the legislation and announced to the public. The auction rules vary depending on the estimated cost (ESTIMATE) for a specific auction being above or below the threshold value. After collecting the published threshold values, we create ABOVE THRESHOLD dummy variable which is equal to 1 if the ESTIMATE is above the threshold value, and 0 otherwise. When the estimated cost is above the threshold value (ABOVE THRESHOLD=1), the institutions have the option to offer price advantages to domestic bidders whereas if the estimate is below the threshold value, then no price advantage can be offered.

We define another variable by identifying all the Turkish cities in which auctions took place. We then group the auctions into regional dummies depending on which stimulus region the city is located in. The Turkish Government provides financial support to investors that invest in less developed regions. The Ministry of Development identifies 6 stimulus regions according to the economic development of those regions. The first region is the most developed and the sixth region is the least developed region. Firms which invest in region 1 is not eligible for any financial support whereas firms invest in region 6 can get tax refunds, financial support for employment and can be eligible for rent-free land. These regional variables are important since some regions could attract more/less participants due to their geographical location and their economic development. Following Onur et al. (2012), we classify the cities in which the auctions took place as a BIG CITY if the population is greater than or equal to one million. Finally, we construct the EDUCATION variable which represents the percentage of the population in each city who are at least high school graduates.[4]

[4]The data is from the Turkish Statistical Institute.

2.2 Analysis of the data set:

We examine 472560 auctions in the econometric analysis. Table I presents the summary statistics of these auctions. The average winning bid is lower than the average estimated cost which shows existence of competitive effect and efficiency in Turkish procurement auctions. Therefore, we construct a new variable which is the natural logarithm of the lowest bid minus the natural logarithm of the estimated cost. This new variable allows us to observe the auction prices in accordance with the estimated cost and thus offers us an opportunity to compare the winning bids with respect to their closeness to the estimated cost. This variable is used as the dependent variable.

Table I shows that the mean of the dependent variable is -0.216 which indicates that on average the winning bid is lower than the estimated cost. The mean of number of bidders is 3.28 with a minimum of 1 and a maximum of 543 participants which is an auction for transportation of elementary school students. When we observe the THRESHOLD variable we see that only 6 percent of the auctions have an estimated cost that is higher than the threshold value. [5]

(TABLE I ABOUT HERE)

Regarding the types of procurement auctions listed, we see that goods auctions take the majority with 42.05 percent of all auctions, followed by auctions for services with 34.6 percent and finally procurement auctions for construction comprising 23.33 percent. All the other variables we have in our data set are categorical variables which represent 29 different institutions and the dummy variables for the six economic stimulus regions of Turkey. All these categorical

[5] This suggests existence of very few auctions in which a domestic price advantage can be offered but at the same time a high number of auctions in which the contracting entity retains the right to exclude foreign participation.

variables are used as control variables.

3 Empirical Specification:

In order to examine the research questions raised in the introduction section we conduct the following analysis. First, we run two sets of regressions in order to separately investigate the effects of our explanatory variables on the bidders' decision to enter an auction and how the auction prices are determined. Following Bajari and Hortacsu (2003), we use a negative binomial regression model to analyze bidders' entry decision and how auction specifications affect the number of participants. Then we conduct the auction price determination regression to analyze the determinants of auction prices and the effect of number of bidders on auction prices. We take into account the possible endogeneity. Endogeneity problem might affect the empirical results since unobserved variables correlated both with the number of bidders and with the auction price might exist. We implement the GMM methodology to control for endogenous regressors. Finally, we search for the optimal number of bidders for each product type by comparing the mean of dependent variables for different number of bidders. Estimation procedures and the results are discussed in detail in the following sections.

3.1 Entry Decision of Bidders

The determinants of entry for bidders in Turkish procurement auctions are examined using a count data model as in Bajari and Hortacsu (2003) and Li and Perrigne (2003). We regress the number of bidders in an auction on various covariates. The results are presented in Table II.

(TABLE II ABOUT HERE)

We find that the estimated cost (ESTIMATE) has a positive and significant effect on the number of bidders (N); which points out that procurement auctions with higher value attract more bidders. All of the Stimulus Region dummy variables are significant. Regions 2 and 3 have negative coefficients whereas the coefficients of regions 4, 5 and 6 are positive. These results indicate that the stimulus packages are effective in attracting additional bidders into less developed regions. Compared to the most developed region, Region 1, significantly more bidders submit bids in the least developed region, Region 6. The coefficient of Region 6 is ten times higher than the other positive coefficients. Additionally, the auction type (AUCTYPE) has a significant effect on the number of auction participants. Namely, a construction auction has 0.56 higher units in terms of the difference in the logs of the expected number of participants compared to a procurement auction for services, while holding everything else constant. The coefficient is only 0.05 for goods auctions. When the estimate for the auction is above the government determined threshold value (THRESHOLD=1), then the difference in the logs of expected number of bidders is 0.14 unit lower. The results of Table II also provides us insight about possible valid instruments of number of observations variable by identifying variables closely related with number of bidders.

3.2 Determinants of Auction Prices:

In this section we analyze the factors that affect the contract prices in procurement auctions. We estimate the following regression specification:

$$
\begin{aligned}
ln(\frac{wb_{it}}{ecost_{it}}) \quad = \quad & \beta_0 + \beta_1 N_{it} + \sum_{j=1}^{5} \beta_{j+1} Stimulus\,Region_{it}^{(j+1)} + \sum_{k=1}^{2} \beta_{k+6} AUCTYPE_{it}^{k} \\
& + \sum_{z=1}^{28} \beta_{z+8} Institution_{it}^{z} + \sum_{n=1}^{7} \beta_{z+36} year_{it}^{n} + \varepsilon_{it}
\end{aligned}
$$

wb_{it}= winning bid of auction i at time t

$ecost_{it}$ = estimated cost of auction i at time t.

The dependent variable is the log difference of the winning bid and the estimated cost of the auction, $ln(\frac{wb_{it}}{ecost_{it}})$. The selection of the dependent variable is motivated by the following reasons. First of all, the data set include auctions of different types of goods and services thus the data set contains different auctions with varying procurement prices. The dependent variable provides a common measure for different types of auctions. De Silva et al. (2005) and De Silva et al. (2007) employ the same dependent variable which they define as the bid divided by the engineering cost estimate. They name this variable as "relative bids". The ratio of winning bids to the estimated costs provides us an index common for all auctions. Finally, using $ln(\frac{wb_{it}}{ecost_{it}})$ eliminates the effect of inflation on the winning bid.

To sum up, we construct a robust index by using the log difference of the winning bid and the estimated cost as the dependent variable. High values of $ln(\frac{wb_{it}}{ecost_{it}})$ mean that the contract price of the procured auction is considerably higher than the estimated cost, whereas a lower index value would indicate that the auction is more efficient; the auction achieves a price that is closer to the cost of the procured goods or services. We focus on the "Number of bidders" (N) and its effect on the auction prices since this variable gauges the competition effect in Turkish procurement auctions. The remaining variables are used as control variables.

We take into account the possible endogeneity of the variables while conducting the regression analysis. We treat the number of bidders (N) as endogenous. The intuition is that some firms may self-select into tendering process. Even after controlling for various auction types, institutions and sectors, there may be heterogeneity in the projects which might not be captured. Therefore we use the EDUCATION and the BIGCITY variables as instruments in our GMM regression. We select these variables since they are closely related with number of bidders as shown in table II and they are strictly exogenous. We utilize both of these instruments since econometric theory suggests that this would lead to a more efficient estimator than using only one. Statistical analysis conclude that these variables are valid instruments.

(TABLE III ABOUT HERE)

In Table III, we regress the normalized winning bid on auction specific variables from Table I including number of bidders. First column presents the results of an exogenous OLS regression. The second column displays the endogeneity-corrected results of GMM instrumental variable regression. In both of these specifications, we find that an increase in the number of bidders significantly lowers the difference between procurement prices and the estimated cost. The presence of an extra bidder results in an around 3.3% decrease in procurement price relative to the estimated cost. Another interesting result is the significant and negative coefficient of Stimulus Region 6 dummy variable. The procurement prices in Region 6 are 1.3% lower than the estimated cost compared to the most developed region, Region 1.

Additionally, we test the validity of our instrumental variables. The overidentified model allows us to calculate the Hansen J statistic. The test statistic has a p-value of 0.38. Thus, we do not reject the null hypothesis that all instruments are valid. To sum up, the additional statistical analysis conclude that EDUCATION and BIGCITY are valid and strong instruments.

3.3 Different Auction Types

GP is conducted for three different types: goods, services and construction. The technical specifications of these types might be significantly different. Thus, we analyze how the coefficients of interest behave for various types. Table IV displays the summary statistics for three product types and table V presents the GMM regression results for different types of procurement. Table V concludes that competition effect is present for all types. The coefficient is largest for goods auctions indicating that an increase in number of bidders result in much higher procurement price reduction for the goods sector.

(TABLE IV ABOUT HERE)

(TABLE V ABOUT HERE)

3.4 Optimal Number of Bidders

In the previous sections we presented that the Turkish Government can significantly lower procurement costs by increasing number of bidders. This raises a practical policy related question: What is the optimal number of bidders to achieve the lowest possible procurement price? Estache and Iimi (2008) implement the methodology proposed by Rezende (2005) to answer a similar question about official development assistance infrastructure procurement auctions. They create a dummy variable for each number of bidders and use each dummy variable as explanatory variables where the procurement price is the dependent variable.

As presented in Rezende (2005) to be able to implement that methodology the orthogonality condition should be satisfied. In other words, the variable of interest, number of bidders, should be exogenous. We can not implement the OLS methodology of Rezende (2005) because of the endogeneity of number of bidders. The basic idea behind that methodology is to measure the conditional mean of the dependent variables (Difference in our case) at each level of number of bidders. If the coefficient of the specific bidder number dummy variable is significant and negative that indicates that the conditional mean of the dependent variable is lower compared to the case that bidder number is equal to 1. The optimal number of bidders is found by analyzing when the coefficient becomes insignificant. An insignificant coefficient denotes that reaching that number of bidders does not have an affect on the dependent variable.

The same methodological argument can be carried out without using OLS. The means of the dependent variable at two different number of bidders, for example when N = 6 and N = 7 can be calculated. Then, a hypothesis test about whether the means at two different number of bidder levels are equal or not can be conducted. If the test concludes that the two means are equal then this result indicates that increasing number of bidders from 6 to 7 does not have an effect on the dependent variable. To deal with the endogeneity of number of bidders we refrain from using the regression methodology and implement hypothesis tests to compare procurement price means of auctions with different number of bidders.

Table VI displays the means at each level of number of bidders for services, goods and construction auctions. The coefficients between parentheses under each coefficient present the test statistic of the null hypotheses that the mean at that level of number of bidders, N, and at the level of N-1 are equal. If the hypothesis is rejected and mean at N is lower than the mean at N-1 that demonstrates that increasing number of bidders from N to N-1 significantly decreases the dependent variable, procurement price.

(TABLE VI ABOUT HERE.)

The first column of table VI exhibit the auctions that services are procured. The test statistic is significant when N is equal to nine at 5% significance level and the mean of DIFFERENCE variable is equal to -0.41 compared to -0.2 when N = 2 and -0.344 when N = 8. After N = 9 the test statistic is always insignificant. This indicates when number of bidders is larger than nine an increase in number of bidders does not significantly decrease the procurement price. Hence, we conclude that the optimal level of number of bidders for services procurement auctions is nine. For goods procurement auctions, the test statistic is significant when N is equal to six at 1% significance level and the mean of DIFFERENCE variable is equal to -0.426 compared to -0.232 when N = 2 and -0.393 when N = 5. After N = 6 the test statistic is always insignificant. The optimal number of bidders is the same for construction auctions. The test statistic is significant till N = 6. The test statistic is significant when N is equal to six at 1% significance level and the mean of DIFFERENCE variable is equal to -0.342 compared to -0.137 when N = 2 and -0.297 when N = 5.

4 Conclusion and Policy Implications

In this study, we investigate the competitive environment and its effects on procurement prices for all Turkish GP auctions for the years 2004 to 2010. We utilize a unique and extensive data set collected by the PPA. We first study the effect of auction characteristics on the number of participants and show that especially AUCTYPE, Stimulus Region and THRESHOLD variables have notable effects on the number of bidders while keeping in mind that higher-valued auctions also attract more participants. Next, we investigate the effect of our explanatory variables on the difference between contract price and the estimated cost of auctions while controlling for endogeneity of one of our main variables, number of bidders (N). We conclude that the number of bidders significantly and negatively affects the difference between the procurement price and the estimated cost, suggesting that competitive environment considerably improves efficiency of government procurement auctions in Turkey. Our empirical analysis indicate that at least nine bidders are needed for services, six for the goods and construction sectors to be able to achieve the lowest procurement prices.

From a practical point of view, our findings might have important policy implications. Governments can device policies to increase the number of bidders which may lead to considerable savings due to the decreases in the winning bids. Our empirical results show that increasing the number of bidders by one participant would on average lead to around %3.3 lower prices compared to the estimated costs. Also, the optimal number of bidders found out in this study can be used by the authorities as focal points to analyze whether competitive efficiency is achieved in the public procurement auctions.

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Table I

Summary Statistics of the Variables

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Winning Bid (WINBID)	472560	1865439	6.59e+08	1	3.85e+11
Estimated Cost (ESTIMATE)	472560	2200063	7.65e+08	3	3.95e+11
Dependent Variable[1]	472560	-.216	.48	-14.598	13.658
Number of Bidders (N)	472560	3.28	3.65	1	543
THRESHOLD[2]	472560	5000235	8185583	398685	2.36e+07
AUCTYPE: Services	163565 (34.6%) among 472561 auctions				
AUCTYPE: Goods	198732 (42.05%) among 472561 auctions				
AUCTYPE: Construction	110264 (23.33%) among 472561 auctions				
INST	There are 28 different main institutions that conduct the procurement auctions.				
Stimulus Region	Dummy variables representing six stimulus regions of Turkey identified by the Ministry of Development. The first region is the most developed.				
YEAR1-7	Dummy variables for each year between 2004-2010.				

Notes: Only the first price auctions are analysed in the regressions. The table presents the summary statistics of first price auctions.

[1] Dependent Variable = log(winning bid) - log(estimated cost)
[2] 30,114 auctions are above treshold.

Table II

Determinants of Auction Entry: Bidder Entry-Negative Binomial Regression

Variable	Estimate
ln(ESTIMATE)	0.21
	(182.51)**
Stimulus Region 2	-0.01
	(2.64)**
Stimulus Region 3	-0.05
	(9.06)**
Stimulus Region 4	0.03
	(6.16)**
Stimulus Region 5	0.03
	(5.89)**
Stimulus Region 6	0.29
	(48.35)**
AUCTYPE: Goods	0.05
	(14.24)**
AUCTYPE: Construction	0.56
	(148.77)**
ABOVE THRESHOLD	-0.14
	(21.43)**
EDUCATION	0.28
	(18.37)**
BIGCITY	0.06
	(15.41)**
Constant	-1.45
	(69.44)**
Number of observations	472560

Note: The dependent variable is the number of bidders. Robust z statistics are displayed in parentheses. ** indicates significance at 1% level, * indicates significance at 5% level. Institution and year dummy variables were also included as regressors.

Table III

Determinants of Auction Prices

Variable	OLS	GMM
Number of Bidders (N)	-0.027	-0.033
	(14.68)**	(11.92)**
Stimulus Region 2	0.026	0.021
	(11.09)**	(7.66)**
Stimulus Region 3	0.023	0.017
	(8.82)**	(5.09)**
Stimulus Region 4	0.006	0.000
	(2.10)*	(0.10)
Stimulus Region 5	0.023	0.018
	(8.19)**	(5.36)**
Stimulus Region 6	-0.013	-0.013
	(4.30)**	(4.31)**
AUCTYPE: Goods	-0.09	-0.089
	(55.97)**	(55.89)**
AUCTYPE: Construction	-0.035	-0.016
	(5.91)**	(1.81)
Constant	-0.1	-0.080
	(14.97)**	(8.48)**
Number of observations	472560	472560
R-squared	0.05	-----
Instrumental Variables		EDUCATION
		BIGCITY
Overidentification test of all instruments Ho: Instruments are valid		
Hansen J statistic		0.79
		(p = 0.38)

Note: The dependent variable is the natural logarithm of the lowest bid minus the natural logarithm of the estimated cost. Institution and year dummy variables are not presented. Robust z statistics in parentheses. ** indicates significance at 1% level, * indicates significance at 5% level.

Table IV

Variable	Services				Goods				Construction			
	Mean	**St. Dev**	**Min**	**Max**	**Mean**	**St. Dev**	**Min**	**Max**	**Mean**	**St. Dev**	**Min**	**Max**
Lowest Bid (WINBID)	2155875	5.92e+08	2	2.34e+11	2169660	8.63e+08	1	3.85e+11	886301.6	8299282	10	8.40e+08
Estimated Cost (ESTIMATE)	2669194	8.57e+08	3	3.47e+11	2316365	8.86e+08	3	3.95e+11	1294542	1.22e+07	6	1.31e+09
Dependent Variable	-0.146	0.417	-13.228	13.658	-0.244	0.564	-14.6	11.394	-0.27	0.382	-13.873	13.253
No of Bidders (N)	2.451	2.991	1	543	2.62	2.383	1	446	5.691	5.1	1	125
Number of Observations	163565				198732				110264			

Auction Type: Services, Goods, Construction

Table V

Determinants of Auction Prices

GMM Analysis

Variable	Auction Type		
	Services	Goods	Construction
Number of Bidders (N)	-0.036	-0.047	-0.033
	(8.64)**	(3.69)**	(17.83)**
Stimulus Region 2	0.044	0.026	-0.033
	(7.32)**	(6.68)**	(9.39)**
Stimulus Region 3	0.025	0.032	-0.039
	(3.51)**	(5.89)**	(10.50)**
Stimulus Region 4	0.028	-0.008	-0.042
	(4.25)**	(1.22)	(11.30)**
Stimulus Region 5	0.043	0.011	-0.024
	(6.65)**	(1.87)	(5.13)**
Stimulus Region 6	0.000	-0.015	-0.014
	(0.01)	(2.09)*	(2.87)**
Constant	-0.066	-0.149	-0.091
	(4.61)**	(4.37)**	(5.03)**
Number of observations	163565	198731	110264

Note: The dependent variable is the natural logarithm of the lowest bid minus the natural logarithm of the estimated cost. Institution and year dummy variables are not presented. EDUCATION and BIGCITY are used as instrumental variables. Robust z statistics in parentheses. ** indicates significance at 1% level, * indicates significance at 5% level.

Table VI

Means of Dependent Variable According to Number Bidders

Number of Bidders (N)	Auction Type					
	Services		Goods		Construction	
	Number of Observations	Mean	Number of Observations	Mean	Number of Observations	Mean
1	90294	-0.055	71091	-0.13	15113	-0.093
2	26203	-0.2 (20.74)**	50242	-0.232 (17.47)**	14936	-0.137 (3.82)**
3	15656	-0.218 (1.71)	32591	-0.291 (8.24)**	15280	-0.192 (4.74)**
4	9354	-0.264 (3.56)**	18242	-0.349 (6.22)**	12520	-0.244 (4.35)**
5	6143	-0.299 (2.13)*	10634	-0.393 (3.6)**	10111	-0.297 (3.93)**
6	4193	-0.327 (1.39)	6190	-0.426 (2.11)*	8258	-0.342 (3.04)**
7	3041	-0.339 (0.52)	3716	-0.438 (0.56)	6539	-0.362 (1.23)
8	2292	-0.344 (0.18)	2140	-0.462 (0.88)	5309	-0.396 (1.8)
9	1605	-0.41 (1.96)*	1389	-0.437 (0.73)	4326	-0.406 (0.53)
10	1190	-0.392 (0.43)	801	-0.506 (1.56)	3485	-0.414 (0.34)
11	917	-0.389 (0.07)	499	-0.565 (1.03)	2846	-0.437 (0.92)
12	623	-0.439 (0.98)	318	-0.54 (0.35)	2230	-0.44 (0.08)
13	490	-0.452 (0.21)	228	-0.654 (1.32)	1800	-0.465 (0.82)
14	374	-0.422 (0.82)	166	-0.739 (0.83)	1419	-0.469 (0.11)
15	277	-0.522 (0.82)	115	-0.587 (1.26)	1120	-0.483 (0.35)
16	277	-0.522 (0.01)	80	-0.848 (1.8)	930	-0.487 (0.09)
17	209	-0.522 (0.32)	54	-0.711 (0.79)	734	-.49 (0.05)
18	172	-0.536 (0.16)	27	-0.478 (1.00)	534	-0.49 (0.11)
19	116	-0.55 (0.01)	40	-0.875 (1.61)	502	-0.489 (0.08)
20	89	-0.642 (0.58)	29	-0.161 (1.19)	362	-0.556 (0.98)

t-statistics of diff = mean(1) - mean(2) Ho: diff = 0 between parentheses. ** indicates significance at 1% level, * indicates significance at 5% level.