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Abstract

In government procurement auctions of construction contracts, entrants are typically less informed and bid more aggressively than incumbent firms. This bidding behavior makes them more susceptible to losses affecting their prospect of survival. In April of 2000, the Oklahoma Department of Transportation started releasing the internal cost estimates to complete highway construction projects. Using newly developed quantile regression approaches, this paper examines the impact of the policy change on aggressive entrants. First, we find that the information release eliminates the bidding differential between entrants and incumbents attributed to informational asymmetries. Second, we argue that the policy change affects the prospects of survival of entrants in the market. We find that those who used to exit the market relatively soon are now staying 37 percent longer, while at the median level bidding duration increased by roughly 68 percent. The policy has the potential to encourage entry in government procurement auctions and thus increase competition.

1 Introduction

Models of imperfect competition make varying predictions about the effects of entry in a market. Contestable market theory predicts that the threat of entry alone can restrain market power. Other theoretical work shows that barriers to entry can limit the effect of potential competitors on a market, and only actual entry can have significant competitive effects. The qualitative predictions on the prevalence and consequences of entry depend on the market structure and characteristics. In some industries for instance, entrants may be at a considerable disadvantage relative to incumbents due to

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asymmetric information. In the road construction industry in particular, entering firms bidding in procurement auctions typically face higher uncertainty in developing bids. This uncertainty originates in the lack of relevant information and production or bidding experience. Incumbents are typically better informed on the cost and pricing of various bid components. As a result, entrant firms bid more aggressively and win with significantly lower bids compared to incumbents (see De Silva, Dunne and Kosmopoulou (2003)). The uncertainty is affecting the prospect of survival in these markets and their effectiveness in enhancing competition and deterring other firms from entering in collusive agreements.

We consider construction auctions in the state of Oklahoma for a period encompassing an information policy change, designed to eliminate informational asymmetries. In April of 2000, the Oklahoma Department of Transportation started releasing the internal cost estimates to complete highway construction projects. Our data provide an opportunity to examine entrant and incumbent bidding behavior, and to some extent, their survival patterns. The information release policy was shown to induce more aggressive bidding behavior by all firms reducing the cost of procurement (De Silva, Dunne, Kankanamge and Kosmopoulou (2007)). It could, however, have a heterogeneous effect on bidders, affecting the degree of competition in the market. Is this aggressive bidding behavior discouraging or encouraging entrant firms? In the long run, is the information release favoring a few established firms thus facilitating collusion? Our analysis shows that the asymmetry between entrant and incumbent bidding behavior became less pronounced after the state decided to release its own engineering cost estimate for each project. We find that entrants submitted relatively more aggressive bids before the policy change, fully adjusting their bidding behavior after. This additional information can help entrants with initially low estimates of the cost, to modify their bidding behavior and avoid undertaking contracts at a loss. As a result, the aggressive entrants who adjust their bids upwards will most likely prolong their presence in these auctions. Indeed, firms who used to exit the market relatively soon are now staying 37 percent longer while, at the median level, bidding duration increased by 68 percent.

The theoretical literature has explored some aspects of bidding behavior in asymmetric auctions (see Lebrun (1998 and 1999), Maskin and Riley (2000b) and Pesendorfer (2000)). They focused on settings likely to justify stochastic dominance among the distributions of values. This would be relevant for contractors, if the opportunity cost of completing projects differed among firms, and some had systematically higher costs than others. De Silva, Dunne and Kosmopoulou (2003) considered asymmetric bidding when stochastic dominance persists for low costs but not throughout the range of values. They provided empirical evidence of bidding asymmetries between entrants and incumbents in construction auctions consistent with the theory. Their paper does not examine any informational or survival effects. The data set extends until August of 2000 where the information policy is for the most period unchanged. We are not aware of any empirical literature that examines the prospects of survival based on issues of informational asymmetries between entrants and incumbents. When considering firm survival in markets, the literature largely deals with differences in the structure and characteristics of firms (see for example, Dunne, Roberts and Samuelson (1988), Baldwin and Gorecki (1991), and Dunne, Kliemk and Roberts (2003)). Nevertheless, those informational asymmetries can be critical for the composition of the pool of bidders and the level of competition in this market. For the entire period of our analysis, construction contracts in Oklahoma had an estimated cost of 2.8 billion dollars. The US federal and state governments paid 70 billion dollars in 2003 on road construction contracts.[1] Given the amount of government spending allocated to these projects, it is evident that decisions on the level of information released can have a significant impact on the budget.

The paper is organized as follows: Section 2 discusses the theoretical model, and section 3 presents the data. Section 4 provides empirical results on relative bidding behavior of entrants and incumbents and the survival of entrants. Section 5 offers concluding remarks.

2 Model

We consider first price auctions of construction contracts and focus on differences in the behavior of entrants and incumbents. Our framework accommodates asymmetries due to a differential level of experience and efficiency, and provides some explanation for the observed patterns. We first describe

[1] This figure was reported by the American Association of State Highway and Transportation Officials at the annual meetings of the Transportation Research Board in January of 2005. See http://www.transportation.org.

existing results using an affiliated values model. This model is most suitable for construction work since it involves typically some cost components that are known to a specific firm and relate directly to its efficiency and others that are more uncertain and common to all firms (these could be future input prices in general or the cost of excavation and demolition in specific projects). Then, we provide a characterization of bidding distributions in the neighborhood of low costs based on characteristics of the cost distributions that are unique to this setting.

Consider a first price sealed bid auction in which two risk neutral bidders compete for a government contract.[2] The cost of the contract c_i to bidder i exhibits both private and common value characteristics. For simplicity, we assume that $c_i = t_i + \lambda s_i + (1-\lambda)\sum_j s_j/(n-1)$ for $i \neq j$, where t_i is an estimate of his private cost and s_i, is a signal which is an estimate of the common cost S. The parameter λ represents the degree of uncertainty a bidder faces in the calculation of the common cost. In a purely private value model λ=1. In an affiliated value environment, in which bidders view symmetrically the common component, λ=0. The parameter λ is common knowledge to all bidders. The privately observed component of the cost, $t_i + \lambda s_i$, is drawn from a known distribution F_i with support $[t_L + \lambda s_L,\ t_H + \lambda s_H]$. The distribution function F_i is twice continuously differentiable, and has a density f_i that is strictly positive on the support. Consideration of multidimensional types at some level of generality may pose the problems of monotonicity and existence. Within our framework, we can overcome this problem by making the assumption that the densities of the $t_i's$ and the $s_i's$ are logconcave.[3] When the bidders' costs are private and are distributed independently, LeBrun (1999) and Maskin and Riley (2000a,b) have shown[4] in general that in equilibrium the bid functions are increasing and differentiable so that, for each firm i, an inverse exists and is differentiable. De Silva, Dunne and Kosmopoulou (2003) have provided the same equilibrium solution in the case of affiliated values considered here. We let $b_i^{-1}(b) = \phi_i(b)$ be i's inverse bid function. Each firm chooses a bid b

[2] In this paper, we emphasize differences between entrants and incumbents at a group level. Based on this distinction, we make the simplifying assumption of two bidders with different characteristics. In fact, Lebrun (1998) shows that, the characterization results he generates assuming two bidders with asymmetric private value distributions generalize to the case of n bidders with no more than two different probability distributions.

[3] Many commonly used densities such as the uniform, normal, chi-square and exponential densities satisfy this assumption (see Goeree and Offerman (2003)).

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

to maximize its expected profit

$$\pi_i(b, c_i) = (b - c_i)\left(1 - F_j\left(\phi_j(b)\right)\right).$$

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

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

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

$$F_j\left(\phi_j(b_*)\right) = 0, b^* = \phi_j\left(t_H + \lambda s_H\right) \quad \forall\ j. \tag{2}$$

If the distribution of the privately observed component of the cost of one bidder stochastically dominates the cost distribution of the other, the results in Maskin and Riley (2000b) continue to hold. Notice that, a distribution F_j *first order* stochastically dominates another distribution F_i if and only if $F_i(x) \geq F_j(x)$ for all x. This can happen, if the opportunity cost of completing a project differs systematically among contractors. If the cost distribution of a "weak" bidder stochastically dominates the cost distribution of a "strong" bidder, Maskin and Riley showed that the equilibrium bid distribution should also exhibit stochastic dominance. The same paper establishes that if a weak bidder faces a strong bidder rather than another weak he will bid more aggressively, and vice versa. When considering the cost of road construction for entrants and incumbents, the stochastic dominance relation no longer holds throughout the range of values.

2.1 Characterization of the equilibrium bid differential for low estimates of the cost

In this section, we concentrate on differences in the distribution of costs between entrants and incumbents in the period before and after the information release. In general, entrants are bidders with no prior bidding experience. The distribution of estimated costs for those firms is likely to have a higher mean and to exhibit a much greater dispersion on average relative to that of incumbents. These dissimilarities can be attributed to real and perceived cost differences reflecting larger variation in managerial efficiency and lack of relevant knowledge and experience.[5] As a result, the entrants' distribution of cost estimates may not stochastically dominate that of incumbents' for every value of costs, and the characterization of relative bids of the previous section may no longer apply. In fact, due to uncertainty, the stochastic relation is likely to be reversed for low values of the estimated cost distribution. In such an environment, it is not possible to establish a general pattern of bidding differences consistent across the distribution. Nevertheless, the stochastic relation among distributions for low values of the estimated cost has allowed De Silva, Dunne and Kosmopoulou (2003) to predict relative bidding patterns. They have shown in their proposition that, if the cost estimates exhibit a stochastic dominance relation at the lower end of the distribution the results by Maskin and Riley (2000b) will continue to hold in the neighborhood of b_*. Fibich, Gavious and Sela (2002) established similar conclusions for ascending auctions in the private values framework. We also place emphasis on studying estimates at the lower end of the distribution because those bidders are more likely to win contracts and face excessive losses.

Construction activity exhibits some degree of common cost uncertainty embedded in the performance of tasks. This uncertainty makes bidders reluctant to bid aggressively to avoid the winner's curse. The release of information on the engineer's cost estimate is expected to affect the estimated distribution of costs and change their bidding behavior (see Milgrom and Weber (1982), Goeree and Offerman (2003), and De Silva, Dunne, Kankanamge and Kosmopoulou (2007)). This information will have a larger impact on entrants who have less experience to begin with. Entrants have a priori more uncertainty about the cost estimates whose distribution is expected to be more dispersed. As a result, we expect that the distribution of perceived costs of incumbents will stochastically dominate that of entrants for low values of the cost. We will show here that, as the information is released, and the stochastic dominance relation becomes weaker at the lower end of the distribution of cost estimates

[5] The real cost differences are differences in the private construction cost (having to do with volume or network externalities) and differences in managerial efficiency that are unrelated to informational effects.

(due to reduced differences at the level of uncertainty across the two groups), the difference in the bidding between entrants and incumbents will be lessened. No matter what the relationship is for high values of the cost, if the estimate provided by the state eliminated informational asymmetries, it could help the most aggressive bidders (experienced or not) formulate a uniform strategy to avoid the potential for an excessive loss. This information strategy can help the entering firms that are least informed and most at risk of failure to survive longer in this market.

Let $f_{E_B}(\cdot)$ and $f_{I_B}(\cdot)$ be the densities of the entrants' and incumbents' distributions of estimated costs for the period before the information release. Let $f_{E_A}(\cdot)$ and $f_{I_A}(\cdot)$ be the corresponding densities for the period after the information release. We expect that, $f_{E_i}\left(\phi_{E_i}(b_*)\right) > f_{I_i}\left(\phi_{I_i}(b_*)\right)$ for $i = B, A$. Furthermore, we expect that $f_{E_B}\left(\phi_{E_B}(b_*)\right) - f_{I_B}\left(\phi_{I_B}(b_*)\right) > f_{E_A}\left(\phi_{E_A}(b_*)\right) - f_{I_A}\left(\phi_{I_A}(b_*)\right) > 0$ reflecting smaller informational asymmetries and reduced variability in perceived costs after the information release. Based on these assumptions, we will show here that as the stochastic dominance effect weakens at the level of costs due to the information release, the bids of entrants are expected to be closer to those of incumbents in the period after the policy change.

Proposition 1 *If* $f_{E_i}\left(\phi_{E_i}(b_*)\right) > f_{I_i}\left(\phi_{I_i}(b_*)\right)$ *for* $i = B, A$ *and* $f_{E_B}\left(\phi_{E_B}(b_*)\right) - f_{I_B}\left(\phi_{I_B}(b_*)\right) > f_{E_A}\left(\phi_{E_A}(b_*)\right) - f\ _{I_A}\left(\phi_{I_A}(b_*)\right) > 0$, *then* $\phi_{I_B}(b) - \phi_{E_B}(b) > \phi_{I_A}(b) - \phi_{E_A}(b)$ *for any* $b \in [b_*,\ b_* + \varepsilon]$. *In words, in the neighborhood of* b_* *the bidding differential between the two groups of bidders will be smaller after the information release.*

Proof. Following De Silva, Dunne and Kosmopoulou (2003), we can show first that if $f_{I_i}\left(\phi_{I_i}(b_*)\right) < f_{E_i}\left(\phi_{E_i}(b_*)\right)$ then $\phi_{I_i}(b) > \phi_{E_i}(b)$ for any $b \in [b_*,\ b_* + \varepsilon]$ and $i = B, A$. Since the lower bound of the distribution is the same for both bidders, $\phi_{E_i}(b_*) = \phi_{I_i}(b_*)$. Furthermore, $f_{I_i}\left(\phi_{I_i}(b_*)\right) < f_{E_i}\left(\phi_{E_i}(b_*)\right)$ implies that $F_{I_i}(x) < F_{E_i}(x)$ in the right neighborhood of $\phi_{I_i}(b_*)$.

From the equilibrium condition, we have:

$$\frac{f_{E_i}\left(\phi_{E_i}(b_*)\right)}{1 - F_{E_i}\left(\phi_{E_i}(b_*)\right)}\phi'_{E_i}(b_*) = \frac{1}{b_* - \phi_{I_i}(b_*)} = \frac{1}{b_* - \phi_{E_i}(b_*)} = \phi'_{I_i}(b_*)\frac{f_{I_i}\left(\phi_{I_i}(b_*)\right)}{1 - F_{I_i}\left(\phi_{I_i}(b_*)\right)}. \tag{3}$$

It follows from (2) and (3) that $\phi'_{E_i}(b_*) < \phi'_{I_i}(b_*)$. Therefore, for those bids observed in the neighborhood of b_*, the associated cost of incumbents will be higher than that of entrants (i.e., $\phi_{E_i}(b) <$

$\phi_{I_i}(b))$. In words, incumbents facing poorly informed entrants that are willing to bid low are going to submit more competitive bids. Now consider the possibility that $f_{E_B}\left(\phi_{E_B}(b_*)\right) - f_{I_B}(\phi_{I_B}(b_*) > f_{E_A}\left(\phi_{E_A}(b_*)\right) - f_{I_A}\left(\phi_{I_A}(b_*)\right) > 0$. In the neighborhood of $\phi(b_*)$, it should be the case that $F_{E_B}(x) - F_{I_B}(x) > F_{E_A}(x) - F_{I_A}(x)$. Considering these differences in the densities and distribution functions in equation (3), we get that $\phi_{I_B}(b) - \phi_{E_B}(b) > \phi_{I_A}(b) - \phi_{E_A}(b)$ for any $b \in [b_*, b_* + \varepsilon]$. In words, as the stochastic dominance effect weakens, the difference between the bids of entrants and incumbent becomes smaller in the period after the policy change. ■

3 Data

The data used in this paper comprises of information on all road construction projects auctioned by the Oklahoma Department of Transportation (ODOT) from January 1997 to August 2003.[6] These include asphalt projects, traffic signal projects, bridge projects, as well as, smaller drainage and clearance type projects. Each month the Department of Transportation advertises these projects 3 weeks before the actual bid letting date. The auctions take place using a sealed-bid format where the low bid is awarded the contract.[7] Firms must be pre-qualified to bid on most of these projects and pre-qualification involves the submission of certified financial statements to the state department of transportation. This pre-qualification process determines the size of the projects a firm can bid on. Further, this pre-qualification is related to the level of working capital available to the firm and their past success rate in completing projects. Firms are removed from the pre-qualification list and become 'black listed' if they fail to complete contracts successfully.

The ODOT auction data include information on the identity of the firms that purchase the plans for a project – "the plan holders", the identity and the bids of all bidders for a project, and the winning bid if the contract is awarded. Therefore, we have information on potential bidders, the actual bidders and the winner for each project auctioned off. Furthermore, for each project we can observe the location

[6] We have excluded state wide projects since we cannot calculate the distance between a specific project location and firm location.

[7] The ODOT will reject the low bid when it is 7% above the engineering cost estimate for the project. A large number of projects have been awarded above this threshold suggesting a non-binding reserve price rule.

of the project, a description of the project (e.g., bridge construction, asphalt paving, etc), the details of the project (e.g, the length and depth of the paving surface, the type of asphalt or concrete product to utilize, the amount of excavation, etc), the days to complete the project (calendar days), and the engineering cost estimate of the project.

The engineering cost estimate is constructed for each available project by the Department of Transportation. This estimate was not released by the state authorities before April 2000 and is fully disclosed to potential bidders since then. The ensuing information policy change involves the release of more than the state's overall estimate of the project cost. The state now reveals its estimate for each component of the project by releasing a set of individual cost estimates for each quantity of material used and each important task involved. As a result, this policy change provides detailed information that can reduce substantially the uncertainty related to common components of the cost. For example, in one case, the state can reveal the cost of excavation which depends on soil conditions, and in another, the cost of a specific bridge repair which depends on the extent of the damage.

Table 1 provides summary statistics for the period of analysis. First, we divide the data into two time periods. The period between January 1997 and June 1998 is used to identify incumbents and entrants, and the period between July 1998 and August 2003 is used for data analysis. Any firm that has submitted a bid during the first period will be considered an incumbent in the period of analysis starting in July of 1998. When a firm submits its first bid after July 1998, we consider it as an entrant. If the same firm bids again, all subsequent bids are classified as bids of an incumbent. Our definition of entry is the same as in De Silva, Dunne and Kosmopoulou (2003). This definition allows us to explore the effect of the new policy when the asymmetries in information are most pronounced. The entering firms at this stage are more at risk of failure and easily discouraged from participation. According to our data, the estimated probability that they will bid only once from our sample is roughly 40%. We divide the data analysis window running from July 1998 to August 2003 in two parts: the period before the policy change (July 1998 to March 2000) and the period after the policy change (April 2000 to August 2003). In this second period ODOT started releasing to bidders, for each project, a detailed account of its engineering cost estimate on all components of the cost.[8]

Table 1 reports on auction statistics for the full sample period and separately for the periods before and after the policy change. In the entire period of analysis, there were 2174 projects auctioned off and 1741 of them were awarded. There were approximately twice as many auctions after the information release policy as before, consistent with the relative length of the two periods. The overall number of auctions with an entrant was 314, 99 of which were held until March 2000 and 215 after. On average, there were 6.2 plan holders and 3.5 bidders in each auction. There were 322 incumbent firms and 109 entrant firms at these auctions. The number of entrants in the period after the policy change almost doubled from 37 to 72. The number of bids submitted by an entrant increased from 42 to 84 between the two periods while the number of subsequent bids submitted went up from 64 to 511. When considering the competitive effects of an entrant's presence in the market, we see that before the policy change only 17 out of 34 (45.95%) entrant firms submit a bid for a second time. In the period after the policy change, we observe 49 entrants out of 72 (68.06%) bidding for a second time. In a later section, we will explore, through a measure of participation, the effect of the new policy on entrants' survival in the market.

Figure 1 considers the non-parametric kernel density estimator introduced by Rosenblatt and Parzen in the 60s. We obtain a Gaussian kernel estimate $\hat{f}_h(y)$ of a density f on a random sample of relative bids $\{y_1, y_2, ...y_n\}$, where h is a bandwidth that tends to zero as the number of observations n tends to infinity. We used most of the bandwidth choices considered in the literature (see, e.g., Silverman (1986), Scott (1992), Sheather and Jones (1991)), and we observed that the shape of the density remains the same. Therefore, we estimate density functions in Figure 1 considering Silverman's "rule of thumb". The figure shows that both groups of bidders place on average lower, more aggressive bids, after the policy change than before, something well established in the theoretical literature. Comparing across the groups, for low values of the relative bids the probability mass under the entrants' distribu-

[8] At the end of section 4.1, we consider an alternative definition of entry and examine bidding patterns. We classify all bids of a firm entering after July 1998 as bids of an entrant. Placing all bids of an entering firm submitted between July 1998 and August 2003 in the same pool, assumes away some of the uncertainty that is associated with entry as there are significant learning effects taking place along the path. As a result, this analysis is expected to show a diminished differential impact of information between entrants and incumbents. It may also understate the beneficial effect that information has on entrants when they are most at risk of failure.

Variable	Full Sample Period (06:98-08:03)	Before the Policy Change (06:98-03:00)	After the Policy Change (04:00-08:03)
Total number of projects	2174	723	1424
Number of awarded projects	1741	576	1165
Average number of plan holders per project	6.201 (3.416)	5.905 (3.124)	6.452 (3.585)
Average number of bidders per project	3.518 (1.691)	3.359 (1.630)	3.633 (1.732)
Number of bids submitted by incumbents	6616	2122	4494
Number of wins by incumbents	1710	563	1147
Incumbents' relative bid	1.070 (.389)	1.137 (.427)	1.038 (.365)
Incumbents' relative winning bid	.932 (.231)	.978 (.232)	.909 (.228)
Number of incumbent firms	322	146	176
Entrant plan holders	423	125	298
Number of auctions with entrants	314	99	215
Number of bids submitted by entrants	126	42	84
Number of wins by entrants	31	13	18
Entrants' relative bid	1.168 (0.938)	1.047 (0.404)	1.229 (1.111)
Entrants' relative winning bid	.827 (.302)	.787 (.319)	.856 (.296)
Number of entrant firms	109	37	72
Number of entrant firms who bid at least for a second time	66	17	49
Number of entrant held plans at least for a second time	61	20	68
Number of bids submitted by entrants at least for a second time	575	64	511
Number of wins by entrants at least for a second time	111	12	99
Entrants' relative bid after initial bid	1.082 (.520)	1.240 (.828)	1.062 (.464)
Entrants' relative winning bid after initial winning bid	.853 (.244)	.862 (.259)	.852 (.243)

Table 1: Summary Statistics. Standard Deviations are in parenthesis.

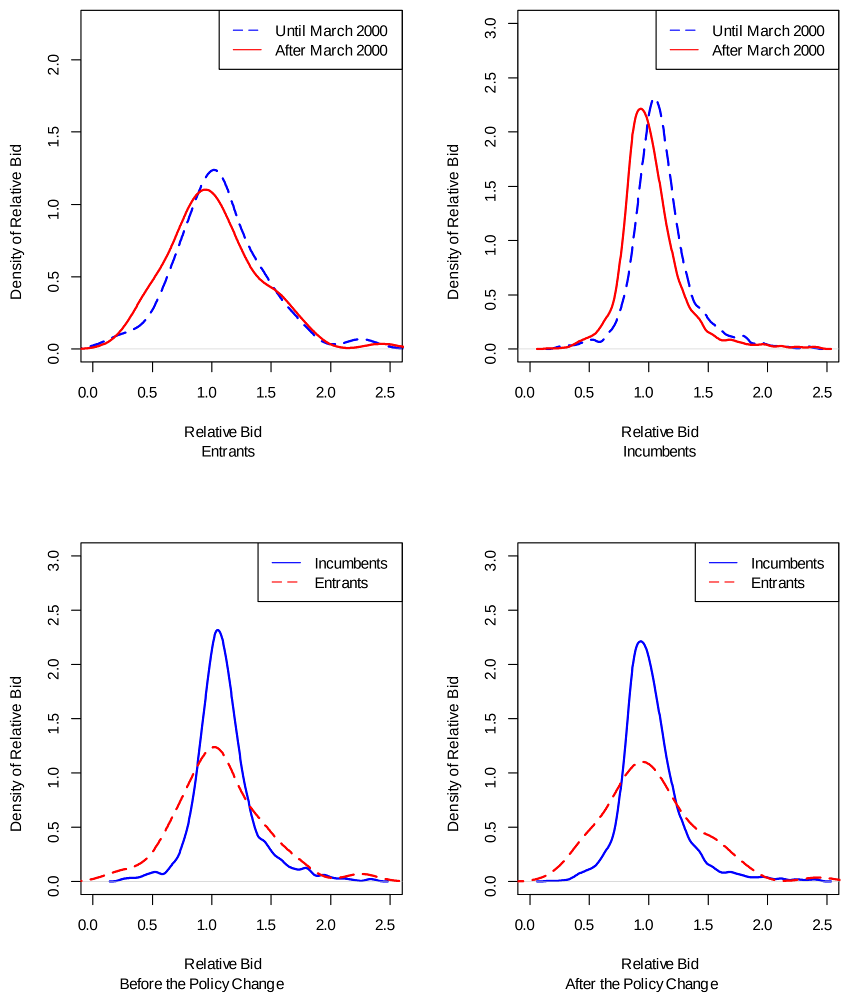

Figure 1: Kernel Density Estimates for Relative Bids. The figure considers bidders' relative bids before the policy change (July 1998 to March 2000) and after the policy change (April 2000 to August 2003).

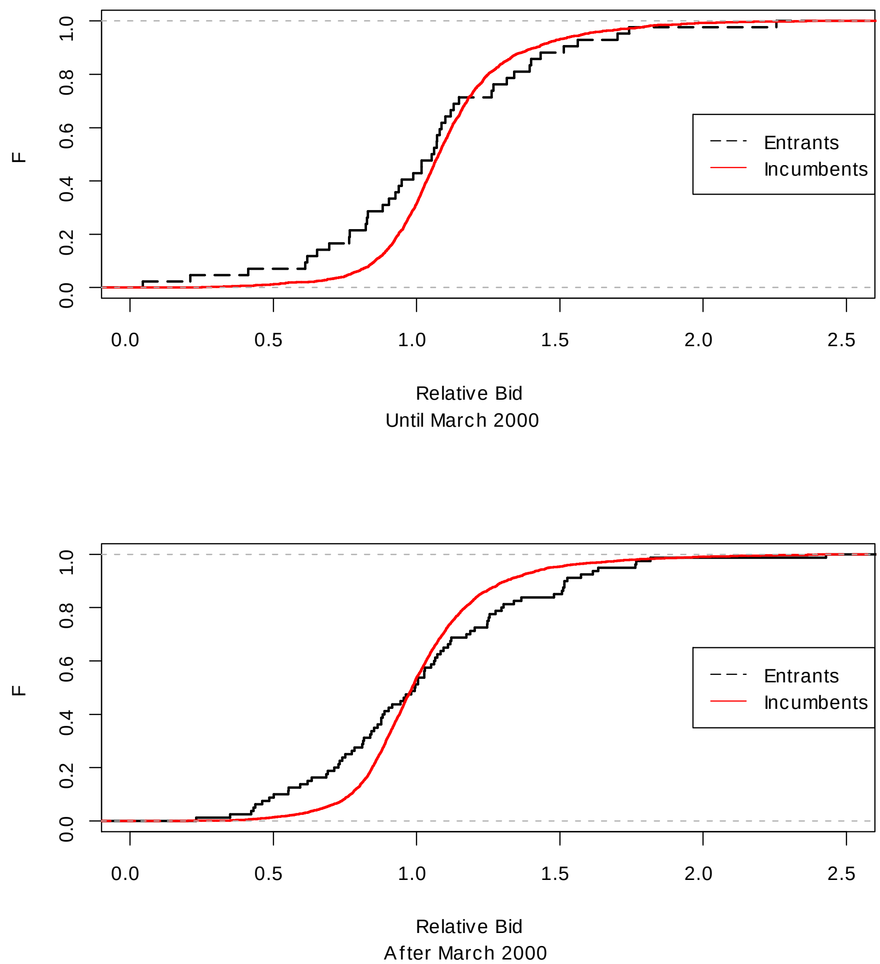

Figure 2: Cumulative Distribution Functions for Entrants and Incumbents before the policy change (July 1998 to March 2000), and after the policy change (April 2000 to August 2003).

tion is larger. The figure also suggests that entrants' bid variance is larger and leads to a distribution that does not stochastically dominate that of incumbents for all range of relative bids. This pattern is consistent with the fact that, entrants face more uncertainty about the cost of the project and greater variation in construction cost and managerial efficiency. In that case, the entrants' cost distribution does not stochastically dominate that of incumbents for all range of values.

Figure 2 presents the cumulative distribution functions for relative bids for each period separately. The upper panel shows that the probability of submitting a relatively low bid until March 2000 is higher for entrants than for incumbents. The crossing of the cumulative distribution functions makes more obvious the fact that the relation of stochastic dominance does not hold for the entire range of values. A similar pattern can be seen after the policy change, which is depicted in the lower panel of Figure 2. The two distributions now cross at a lower level of relative bid and they are closer together for all values of relative bid less than 1 indicating that, as proposition 1 suggests, entrants and incumbents will bid more similarly after the information release at the low end of the distribution. Even though these estimates support the theory, we must still be cautious in drawing final conclusions. There are yet no controls for differences in bidder, rival, business environment, or project type characteristics. Our next section is designed to overcome this issue.

4 Empirical Results

This section presents some basic regression models that will be used to document more precisely the differences between entrant and incumbent bidding patterns before and after the policy change. We analyze three dimensions of the information release policy. First, we investigate the effect of the policy on bidding behavior of entrants and incumbents. Then, we consider differences in participation patterns. Finally, we study policy effects on entrants' bidding times and their survival.

4.1 Changes in Bidding Behavior of Entrants and Incumbents

In this section, we estimate a panel data model focusing on the effect of the information release policy on bidding behavior[9]. Our basic econometric specification is given below as

$$y_{iat} = \beta_1 E_{it} + \beta_2 A_t + \beta_3 (E_{it} \times A_t) + \mathbf{z}'_{iat}\delta + d_t + \alpha_i + u_{iat} \tag{4}$$

where the unit of observation is a bid submitted by bidder i, in auction a, in month t. The relative bid y_{iat} is the main dependent variable used throughout the analysis, but we also use the logarithm of bid in alternative specifications. The relative bid is measured as the bid divided by the engineering cost estimate. The variables E_{it} and A_t are indicator variables for entrants and years after the policy change, initiated in April of 2000. The coefficient on E_{it}, β_1, measures the difference in bidding between entrants and incumbents. The coefficient β_2 captures the difference in bids after the ODOT policy change. Lastly, the coefficient β_3 measures the difference in bidding behavior between entrants and incumbents after the ODOT policy change. Our main interest is on the coefficient β_3. Based on the theory, we expect the coefficient β_1 to be negative indicating that overall entrants bid more aggressively than incumbents (see De Silva, Dunne and Kosmopoulou (2003)). We also expect a positive difference between entrants' and incumbents' bids after the policy change (i.e., $\beta_3 > 0$), at least for low values of the bidding distribution, since the release of information reduces informational asymmetries. As a result, entrants and incumbents should be bidding more similarly after the policy change than before. This positive coefficient on β_3 is partially countering the impact that large asymmetries between the two groups had on their bids.

In order to interpret the coefficient β_3 as reflecting the change in bidding due to the ODOT policy change, it is important that we control for any additional factors that could impact differentially entrants and incumbents and could bias the coefficient estimates. This is a set of controls

[9] A number of recent papers in the empirical auction literature have estimated structural models (e.g., Campo, Perrigne and Vuong (2003) in an affiliated private value environment) or both structural and reduced form models (e.g., Marion (2007)) considering asymmetries in the independent private value framework). Unfortunately, given the nature of our problem (incorporating costs with a private and common value component in an asymmetric framework and more importantly trying to isolate the impact of reduced common cost uncertainty) the structural approach is, to our knowledge, intractable. The reduced form approach, however, offers the possibility of investigating the differences at the lower end of their bidding distribution where entrants are typically having the problem of placing a relatively large number of bids with adverse consequences to their survival. It provides flexibility in the estimation allowing us to isolate informational effects while controlling for bidder heterogeneity, auction and rival characteristics.

$\mathbf{z} = [\mathbf{z}_1', \mathbf{z}_2', \mathbf{z}_3', \mathbf{z}_4']'$ for additional bidder, rival and auction characteristics, as well as business condition variables. The model also includes monthly dummy variables d_t's, and firm specific effects α_i's. The firm effects measure differences in managerial efficiency and network externalities affecting private costs that are constant over time and across auctions. The variable u_{iat} is the error term, assumed to be the sum of an auction specific effect μ_a and a disturbance ϵ_{iat}, in some of the specifications presented below.

The independent variables $\mathbf{z}$ can be classified into four main groups (Table 2). The first group represents additional bidder characteristics ($\mathbf{z}_1$'s). We include two dummy variables to control for potential differences in bidding behavior when bidders face at least one rival firm that is an entrant in an auction. The dummy variable "Bidders facing entrants" controls for the difference in bidding when facing entrants. The dummy variable "Bidder facing entrants after March 2000" controls for the difference in bidding behavior that occurs when a bidder faces an entrant after the ODOT policy change. We also include three continuous variables to control for bidder's capacity utilization rate, the bidder's distance to a project from its base location, and past winning to bidding ratio[10]. As the capacity utilization rises or the distance to a project location increases, we expect a bidder to submit less aggressive bids. The variable, "Firm's past winning to bidding ratio", accounts for past success in auctions. This variable is constructed as the ratio of the past number of wins to the past number of bids. It provides information on the previous success of a firm and is included to control for differences in efficiency across bidders.

In the second group, we consider rivals characteristics ($\mathbf{z}_2$'s), using three variables. First, we utilize past information on rivals' bidding success and construct the variable, "Rival's average past 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 past number of plans held. Note that, a bidder must be a plan holder in order to participate in an auction and that the plan holder list is made available to all potential bidders prior to the auction. This variable is a measure of rival toughness. Then, we

[10] Alternatively, we used past number of bids and past winning to bidding ratio in the same equation. The results were similar to the ones presented below.

Variable		Mean	Std. Dev.
Bid dummy		0.536	0.499
Winning bid dummy		0.138	0.345
Relative bid		1.072	0.406
Relative winning bid		0.930	0.233
Log of bids		13.303	1.620
Log of winning bids		12.744	1.641
Entrants	entrants	0.034	0.180
Bids after March 2000	after	0.679	0.467
Entrants' bids after March 2000	entrants after	0.024	0.152
Bidders facing entrants	bidders	0.165	0.371
Bidders facing entrants after March 2000	bidders after	0.115	0.319
Expected number of rivals	erivals	3.617	1.928
Expected number of bidders	ebidders	4.168	1.899
Log of engineering estimate		13.261	1.744
Capacity utilized	capacity	0.231	0.278
Distance to the project location	distance	4.283	1.591
Firm's past winning to bidding ratio	wbratio	0.249	0.145
Rival's average winning to plan holder ratio	wpratio	0.149	0.058
Closest rival's distance to the project location	rivdist	2.967	1.780
Rivals minimum backlog	minback	2.357	5.073
Seasonally unadjusted unemployment rate	unem	4.051	0.903
Three month average of the real volume of projects	volume	1.080	0.386
Three month average of the number of building permits	permits	1.008	0.173
Large firm dummy	large	0.240	0.427
Asphalt paving projects	asphalt	0.162	0.368
Drainage and erosion control projects	drainage	0.013	0.114
Bridge work projects	bridge	0.415	0.493
Grading and Draining projects	grading	0.260	0.438
Concrete projects	concrete	0.029	0.168
Traffic signal projects	traffic	0.078	0.267
Miscellaneous projects	misc	0.043	0.204

Table 2: Descriptive Statistics for the Regression Variables. The second column offers the names of the variables as used in Figures 4 and 5.

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 and are similar to variables used by Bajari and Ye (2003).[11]

In the third group, we incorporate auction characteristics ($\mathbf{z}_3$'s), using the expected number of bidders and project type dummy variables. The auction participants know only the number and identity of plan holders when they submit their bids. Bajari and Ye (2003) and Krasnokutskaya (2004) argued that this is a small market and participants are well informed about each others' potential to bid. As a result, they can predict from the plan holder list more or less accurately the number of bidders at the auction. The variable "expected number of bidders" is a measure of this prediction and is used to control for differences in competition across auctions. It is calculated using past information for the firms in the plan holder list. First, we take the past bidding to plan holder ratio for each firm, which is the probability of participation. Then for an auction at time t, we sum across these participation probabilities for all plan holders in an auction.[12] This variable construction is similar to the ones used by Hendricks, Pinkse, and Porter (2003).[13] We also use project type dummies to control for the fact that we observe differences in bidding across project categories. All projects are grouped into seven main categories based on the description of the project. They are asphalt paving projects, clearance and bank protection projects, bridge projects, grading and drainage projects, concrete work, traffic signals and lighting projects, and miscellaneous projects. The dummy on miscellaneous projects is the omitted group in the regressions.

The final set of variables represents market factors ($\mathbf{z}_4$'s) that change over time. Three variables are included to control for the business environment: (1) the variation in the amount of projects being

[11] See also Jofre-Bonet and Pesendorfer (2003), De Silva, Dunne and Kosmopoulou (2003), and De Silva, Jeitschko and Kosmopoulou (2005).

[12] In an alternative formulation, we used number of plan holders instead of expected number of bidders as a robustness check. We estimated all the variants of the models observing that the change in variable does not alter the findings. We found that entrants made an adjustment in their bidding behavior after the policy change as the theory predicts.

[13] When estimating probit models we use expected number of rivals. This is constructed based on the number of rival planholders.

Independent Variable	Bid Regression			
	OLS		Fixed Effects	
	Relative Bid	Log of Bid	Relative Bid	Log of Bid
	(1)	(2)	(3)	(4)
Entrants (β_1)	-.188**	-.239**	-.020	-.103
	(.068)	(.096)	(.064)	(.084)
Bids after March 2000 (β_2)	-.130**	-.114**	-.116**	-.098**
	(.016)	(.014)	(.019)	(.015)
Entrants' bids after March 2000 (β_3)	.299**	.216*	.074	.132
	(.139)	(.115)	(.081)	(.104)
Bidders facing entrants (β_4)	.037	-.021	.012	-.023
	(.039)	(.024)	(.044)	(.032)
Bidders facing entrants after	.104*	.110**	.102*	.104**
March 2000 (β_5)	(.058)	(.038)	(.058)	(.040)
Number of Observations	6742	6742	6742	6742
Adj.R^2	.059	.973	.038	.955

Table 3: Least Squares Results for Relative Bids and Log of Bids. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level. Robust standard errors are in parentheses. In the log regression equations, we are using log of engineering estimate and log of expected number of bidders as independent variables.

let,[14] (2) the monthly unemployment rate,[15] and (3) the three month moving average of building permits.[16] The first variable measures the real volume of projects auctioned off in each state. The aggregate real volume of projects auctioned off in a month will vary due to budgetary conditions and seasonal factors. This may affect bidding behavior if firms bid more or less aggressively as the relative real volume of projects being auctioned off changes. With respect to the state unemployment rate and the state building permits, we expect that as they change over time, firms' non-state construction activity may fluctuate and may affect bidding on ODOT projects.

Table 3 presents OLS and fixed effects results considering both relative bids and logarithm of bids as dependent variables. These models were estimated using the covariates described above, but we simply present the results on the effects of interest. Considering the possibility that the standard errors may be underestimated (Moulton 1990), we report cluster robust standard error where clustering is

[14]This variable measures the three month moving average of the real volume of all projects for Oklahoma. The real volume of projects is constructed by adding the engineering cost estimates across projects up for bid in a month for Oklahoma 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.

[15]The monthly state-level unemployment rate for Oklahoma was collected from the US Bureau of Labor Statistics.

[16]The data set was obtained from the US Bureau of Economic Analysis.

on firms in the OLS regressions, and on auctions in the fixed effects regressions. The results of the first two columns suggest that entrants bid on average more aggressively than incumbents, but adjusted their bids upwards after the policy change. The last two columns report results when firm effects are introduced to account for unobserved differences in managerial efficiency and overall private costs. On average, entrants bid more aggressively than incumbents, but now the estimated effects are insignificant. This may suggest that existing informational asymmetries between the two groups of bidders do not play a fundamental role in explaining *average* differences in bidding behavior. This is plausible since we believe that the information provided by the state (or the lack of it) impacts the variability of bids but not their mean level.

With regard to the other variables in the model, the expected number of bidders has a significant negative effect in the relative bid specifications. Increased competition results in lower procurement costs for the state. The only other variable that consistently matters is the unemployment rate. As unemployment rises, bidders are competing more intensely for projects.[17]

The conditional mean model estimated above is limited if the focus is rather on bidding patterns between entrants and incumbents in the lower tail of the conditional distribution of relative bids. One can investigate this issue considering a simple quantile regression model of the form,

$$Q_{Y_{iat}}(\tau|\mathbf{x}_{iat}) = \mathbf{x}'_{iat}\boldsymbol{\gamma}(\tau)$$

where $Q(\cdot|\cdot)$ is the τ-th conditional quantile function, $\boldsymbol{\gamma}(\tau) = (\beta_1(\tau), \beta_2(\tau), \beta_3(\tau), \boldsymbol{\delta}(\tau)')'$ is the vector of parameters, and $\mathbf{x}_{iat} = [E_{it} \;\; A_t \;\; E_{it} \times A_t \;\; \mathbf{z}'_{iat}]'$ is the vector of independent variables. Koenker and Bassett (1978) suggest to estimate the quantile model via optimization, finding

$$\hat{\boldsymbol{\gamma}}(\tau) = \arg\min \sum_i \sum_a \sum_t \rho_\tau(y_{iat} - \mathbf{x}'_{iat}\boldsymbol{\gamma}(\tau))$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the quantile regression "check function"[18]. We restrict the estimation to five quantiles $\tau = \{0.1, 0.25, 0.5, 0.75, 0.9\}$.

[17] There is a more extensive discussion of most of these variable and their effects on bidding behavior in general in De Silva, Dunne and Kosmopoulou (2003) and De Silva, Dunne, Kankanamge and Kosmopoulou (2007). We focus here on the effects of the information policy change across the two groups of bidders.

[18] There are several methods for doing inference in quantile regression (see, e.g., Koenker 2005). The alternatives include rank-based methods, resampling approaches, and estimation of the asymptotic covariance matrix. We consider the latter approach, which is implemented in most of the statistical softwares.

Variable	Quantile				
	.10	.25	.50	.75	.90
	Dependent Variable = Relative Bids				
Entrants (β_1)	-.244**	-.130**	-.103**	-.025	-.069
	(.046)	(.037)	(.037)	(.053)	(.098)
Bids after March 2000 (β_2)	-.100**	-.095**	-.095**	-.108**	-.151**
	(.012)	(.009)	(.010)	(.014)	(.027)
Entrants' bids after March 2000	.181**	.047	.093**	.114*	.307**
(β_3)	(.056)	(.044)	(.045)	(.064)	(.116)
Bidders facing entrants (β_4)	-.095**	-.018	.011	.019	.033
	(.018)	(.015)	(.015)	(.021)	(.038)
Bidders facing entrants after	.140**	.050**	.076**	.153**	.279**
March 2000 (β_5)	(.022)	(.018)	(.017)	(.025)	(.045)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.000	0.026	0.011	0.212	0.066
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.027	0.031	0.002	0.002
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.058	0.001	0.702	0.021	0.001
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.001	0.002	0.000	0.000	0.000
	Dependent Variables = Log of Bids				
Entrants (β_1)	-.315**	-.157**	-.115**	-.057	-.060
	(.069)	(.039)	(.034)	(.044)	(.063)
Bids after March 2000 (β_2)	-.120**	-.099**	-.093**	-.088**	-.100**
	(.017)	(.010)	(.009)	(.012)	(.017)
Entrants' bids after March 2000	.256**	.072	.100**	.141**	.197**
(β_3)	(.083)	(.046)	(.041)	(.053)	(.075)
Bidders facing entrants (β_4)	-.126**	-.011	.007	.021	.056**
	(.027)	(.015)	(.013)	(.017)	(.024)
Bidders facing entrants after	.182**	.049**	.065**	.085**	.102**
March 2000 (β_5)	(.033)	(.018)	(.016)	(.021)	(.029)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.000	0.003	0.002	0.032	0.005
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.063	0.039	0.074	0.362
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.231	0.002	0.547	0.009	0.003
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.005	0.001	0.000	0.000	0.000

Table 4: Quantile Regression Results for Relative Bids and Log of Bids. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level. Note that in log runs, we are using log of engineering estimate and log of expected number of bidders as independent variables.

The results of Table 4 indicate that entrants submit more aggressive bids than incumbents in the lower tail of the conditional distribution of relative bids. Furthermore, the differences in the bidding behavior between these groups of bidders becomes smaller after the policy change at the .10, .25, and .50 quantiles, holding everything else constant. The table also shows that the difference between β_1 and β_3 is statistically significant at the .10 and .25 quantiles. These results are in agreement with the theoretical findings in section 2. We see that (a) entrants bid more aggressively than incumbents, and (b) the difference in bidding behavior of these two groups tends to be smaller after the policy change.

Consider for a moment the possibility that the distribution of costs of an entrant stochastically dominated the distribution of an incumbent. Proposition 3.5 of Maskin and Riley (2000b) in the context of the presented work establishes that: (1) if an entrant bidder faces an incumbent rather than another entrant, he bids more aggressively; and symmetrically, (2) if an incumbent bidder faces an entrant bidder rather than another incumbent, he bids less aggressively. Here we can compare how bidders behave if they face an entrant in an auction versus incumbents alone. The coefficient of the variable "bidder facing entrants" should be positive indicating that the presence of weak bidders (entrants) induces less aggressive behavior on average. Now, since we believe that the relation of stochastic dominance does not hold throughout the distribution in general, when there is common and private cost uncertainty, we do not necessarily expect statistically significant evidence of such a relationship until March 2000. After March 2000, however, one expects that the major difference in the distribution of costs will be due to private cost differences and not common cost differences since most of the uncertainty should disappear. In that case, a clearer pattern of stochastic dominance may arise. In other words, it is more likely to observe any such effect after the policy change than before. The empirical findings seems to be in agreement with these theoretical implications. For instance, Table 4 shows a positive and significant coefficient on the variable "bidder facing entrants" after March 2000 at any quantile of the conditional distribution of the responses.

As discussed above, the observed differences between entrants and incumbents bidding behavior can be attributed to perceived and real cost differentiations. The previous model, however, confounds the effect of uncertainty embedded in the performance of tasks with the structure of private costs on bidding behavior. To get around this problem, we now consider a quantile regression model with bidders' fixed effects,

$$Q_{Y_{iat}}(\tau|\mathbf{x}_{iat}, \alpha_i) = \mathbf{x}'_{iat}\boldsymbol{\gamma}(\tau) + \alpha_i.$$

This model can be estimated using a newly developed method for estimation that considers estimating simultaneously J quantiles, solving,

$$\{\hat{\boldsymbol{\gamma}}(\tau), \hat{\alpha}_i\} = \arg\min \sum_j \sum_i \sum_a \sum_t \omega_j \rho_{\tau_j}(y_{iat} - \mathbf{x}'_{iat}\boldsymbol{\gamma}(\tau_j) - \alpha_i),$$

by interior point methods (Koenker 2004). While the covariate's effect is to shift the location, scale, and possibly the shape of the conditional distribution of the response, the effect α_i represents an individual location shift that is independent of the quantiles τ_j's. The weight ω_j controls the influence of the jth quantile on the estimation of the individual effects. We restrict attention to constant weights equal to $1/J$ over the quantiles $\{0.1, 0.25, 0.5, 0.75, 0.9\}$.[19]

We find that entrants bid more aggressively than incumbents as before, but now we see that the differences in bidding behavior are insignificant beyond the 0.1 quantile. Moreover, entrants seem to adjust their bidding after the policy change by submitting relatively higher bids. (At the 0.1 quantile, the sum between β_1 and β_3 is statistically insignificant). The upper part of Table 5 shows that, after introducing individual fixed effects that are likely to control for differences in private costs, entrants (a) bid more aggressively than incumbents in the lower tail of the conditional bid distribution, and (b) make a full adjustment by bidding less aggressively after the policy change.

Figure 3 presents estimates of the intercept and the main covariate's effects as a function of the quantile τ of the conditional distribution of relative bids. While the first six plots show quantile regression estimates, the remaining plots depict fixed effects quantile regression results. In each graph, the continuous dotted line shows the estimates, and the shaded region represents a .95 (pointwise)

[19]We explored the possibility of using two schemes for inference. First, we estimate the asymptotic covariance matrix derived in Koenker (2004, p. 79), considering Powell's (1991) kernel method to estimate the nuisance parameter $f(\xi(\tau))$. We also considered a resampling method that accommodates to forms of heterocedasticity replacing pairs $\{\mathbf{y}_i, \mathbf{x}_i\}$ over cross-sectional units i. We observed that both methods produce similar results, but the estimation of the asymptotic covariance matrix is computationally attractive to resampling methods for multilevel responses.

Variable	Quantile				
	.10	.25	.50	.75	.90
	Dependent Variable = Relative Bids				
Entrants (β_1)	-.201*	-.011	-.010	-.050	-.072
	(.119)	(.067)	(.050)	(.056)	(.066)
Bids after March 2000 (β_2)	-.103**	-.089**	-.093**	-.099**	-.124**
	(.010)	(.008)	(.008)	(.010)	(.014)
Entrants' bids after March 2000	.246**	.047	-.036	-.065	.171**
(β_3)	(.118)	(.074)	(.062)	(.065)	(.078)
Bidders facing entrants (β_4)	-.151**	-.016	.007	.053*	-.083*
	(.035)	(.020)	(.017)	(.026)	(.038)
Bidders facing entrants after	.167**	.046	.063	.099	.226
March 2000 (β_5)	(.038)	(.023)	(.021)	(.034)	(.063)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.057	0.665	0.809	0.895	0.072
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.132	0.123	0.412	0.117
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.129	0.307	0.243	0.001	0.037
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.226	0.012	0.000	0.000	0.000
	Dependent Variables = Log of Bids				
Entrants (β_1)	-.289*	-.117	-.002	-.034	-.101**
	(.173)	(.132)	(.053)	(.055)	(.050)
Bids after March 2000 (β_2)	-.115**	-.097**	-.089**	-.087**	-.096**
	(.011)	(.009)	(.007)	(.009)	(.010)
Entrants' bids after March 2000	.332*	.149	-.040	-.014	-.002
(β_3)	(.172)	(.136)	(.066)	(.065)	(.057)
Bidders facing entrants (β_4)	-.175**	-.020	-.008	-.024	-.092*
	(.051)	(.019)	(.017)	(.020)	(.028)
Bidders facing entrants after	.188**	.052**	.070**	.091**	.076*
March 2000 (β_5)	(.053)	(.023)	(.021)	(.027)	(.037)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.070	0.316	0.734	0.837	0.311
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.072	0.032	0.126	0.791
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.186	0.367	0.321	0.151	0.001
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.418	0.015	0.000	0.000	0.000

Table 5: Fixed Effects Quantile Regression for Relative Bids and Log of Bids. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level. Note that in log runs, we are using log of engineering estimate and log of expected number of bidders as independent variables.

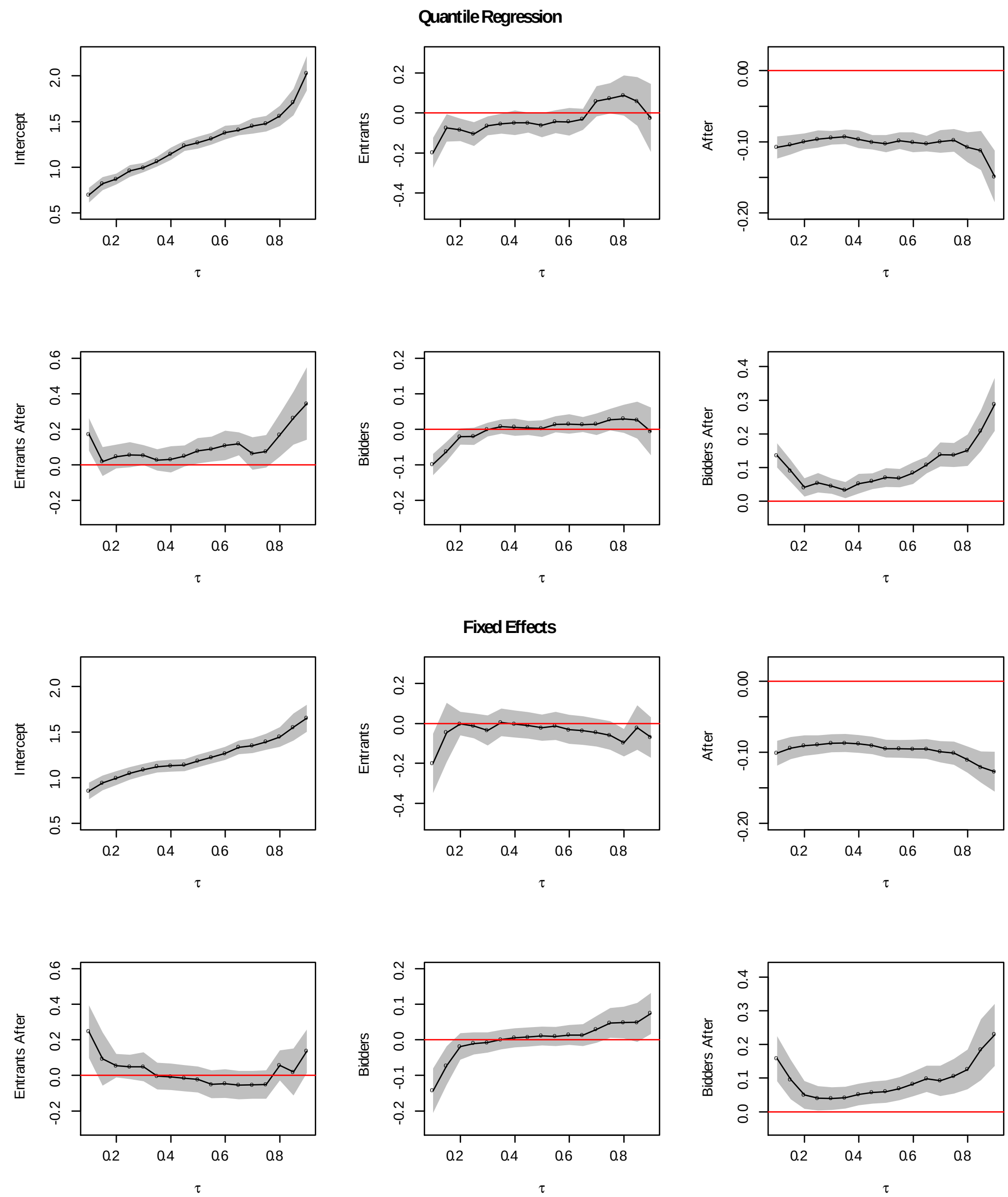

Figure 3: Quantile Regression and Fixed Effects Quantile Regression Results. We report the estimates of the effects of interest. The continuous dotted lines show the estimates, and the shaded region represents a .95 (pointwise) confidence interval.

confidence interval for the point estimates. For instance, the second graph on the top row shows estimates of the differential effect in bidding between entrants and incumbents, $\hat{\beta}_1$. While the estimate is negative and significant at the 0.1 quantile, it is close to zero and insignificant at the 0.9 quantile. The advantage of Figure 3 is that it allows us to carefully examine the difference between the distributions of bids at any quantile τ. In light of the theory, we would expect to see a positive estimate $\hat{\beta}_3$ in the lower tail. We observe that the estimates related to the bidding differential effects after the policy change are positive and significant at the 0.1 quantile, suggesting that entrants made a relative adjustment in their bidding behavior of about 20 percent after the policy change. The results are in agreement with the theory, hence introducing firm effects do not drastically alter the main empirical finding. Notice also that, the graphs on "entrants" and "entrants after" appear to be mirror images of one another particularly in the fixed effects model signifying that when the informational asymmetries disappear bidders adjust their strategies accordingly to eliminate relevant differences in their behavior.

Next, we investigate empirically the question of whether the policy change had an effect on the number of participants. We estimated a Poisson model for the number of bidders and number of plan holders, considering the policy variables, auction characteristics, and business condition variables. We found that entrants were weakly attracted by the policy change, since the coefficient on the variable identifying entrants after the policy change was not statistically significant.[20]

Although entrants do not seem to enter the market at a different rate in the period after the policy change, one might think that they would self-select into small projects. The ODOT data, however, does not provide such evidence. Even though the median engineering estimate on projects they bid is slightly lower than the median for the entire sample of projects, the average level is slightly above the sample average. Nevertheless, it is possible that entrants' behavior may take into account additional auction characteristics, some of them unobserved by the econometrician. We investigate this potential issue introducing auction specific effects μ_a's in the previous conditional quantile function. Ideally, we would like to estimate a linear quantile function $Q_{Y_{iat}}(\tau|\mathbf{x}_{iat}, \alpha_i, \mu_a)$ conditional on policy variables and independent variables $\mathbf{x}_{iat}$, firm effects α_i's, and auction effects μ_a's, but some of the policy

[20]These results are available by the authors upon request.

Variable	10 percent		15 percent		20 percent	
	Before	After	Before	After	Before	After
Entrants	.187**	.147**	.212**	.141**	.103**	.094**
	(.100)	(.068)	(.096)	(.065)	(.064)	(.053)
Bidders facing entrants	.035	-.080**	.040	-.035*	.028**	-.030*
	(.031)	(.024)	(0.25)	(.019)	(.014)	(.016)
Expected numbers of	.002	.030**	-.003	.015**	-.003	.004
bidders	(.006)	(.006)	(.005)	(.005)	(.002)	(.003)
Capacity utilized	-.078*	-.013	-.042	-.028	-.013	-.038*
	(.046)	(.042)	(.038)	(.031)	(.015)	(.021)
Distance to the project	.003	-.002	-.001	.005	.001	.004
location	(.007)	(.007)	(.006)	(.007)	(.003)	(.006)
Firm's past winning to	.237**	.360**	.151**	.273**	.038	.170**
bidding ratio	(.087)	(.080)	(.058)	(.062)	(.027)	(.047)
Rival's average winning	.377*	.092	.264*	.010	.116*	.049
to plan holder ratio	(.196)	(.139)	(.125)	(.121)	(.067)	(.088)
Closest rival's distance	.002	-.003	.004	-.002	.002	-.004
to the project location	(.004)	(.005)	(.004)	(.004)	(.002)	(.003)
Rivals minimum backlog	-.001	.001	-.001	-.001	-.002**	-.003**
	(.002)	(.002)	(.001)	(.001)	(.001)	(.001)
Seasonally unadjusted	-.030*	.090**	-.016	.055**	-.013**	.023**
unemployment rate	(.018)	(.017)	(.013)	(.013)	(.007)	(.009)
Three month average of	.269**	-.013	.138	-.004	.061	.005
the real volume of projects	(.132)	(.034)	(.098)	(.026)	(.057)	(.018)
Three month average of	.919**	-.367**	.914**	-.167*	.404**	-.049
the number of building permits	(.397)	(.122)	(.309)	(.090)	(.219)	(.058)
Number of Observations	1582	5142	1582	5142	1582	5142
Adj. R^2	.103	.054	.132	.054	.187	.065

Table 6: Probability of bidding below engineering cost before and after March 2000. ** Denotes statistical significance at 5 percent level and * denotes statistical significance at 10 percent level. Robust standard errors are in parentheses.

variables cannot be identified. There is no within auction variation before and after the policy change to identify the policy effects of interest. Alternatively, we estimated the conditional quantile function by letting the smallest estimates of auction specific effects $\hat{\mu}_a \to 0$ (Lamarche 2006). Although this estimation procedure could potentially generate small biases, it gave us the opportunity of controlling for auction specific unobserved effects while estimating the policy variables' effects on the conditional distribution of relative bids y_{iat}. In this model, the auction effects, μ_a's, should control for differences in efficiency at the average level for all firms participating in an auction. The results are similar to the ones described in Table 4, so we omit the presentation to avoid repetition in our discussion. The findings again suggest that entrants bid more aggressively than incumbents, and bid less aggressively after the policy change.[21]

Finally, another way to look at the bidding differences between the two groups is to estimate the conditional probability of bidding 10, 15, and 20 percent below the engineering cost estimate. According to the predictions of the theory, we expect to find the estimate of the parameter β_1, describing the difference in bidding between entrants and incumbents, to be (a) positive and significant before the policy change, and (b) smaller and possibly close to zero after the policy change. The results in Table 6 suggest that although entrants have a higher probability of bidding below the engineering cost than incumbents, the probability differences tends to be smaller after the information release.

The definition of entry, that has been used so far, allowed us to investigate the behavior of entering firms when the uncertainty is most pronounced and the likelihood of failure is larger. As those firms continue bidding and start undertaking projects, the difference in the amount of information possessed by surviving entrants and incumbents, and the bidding differential attributed to this informational disparity should become smaller. This prediction can be simply investigated by estimating firms' bidding patterns while considering as entrants' bids to be all their bids submitted within the period of analysis. Once more, the results of Table 7 suggest that (a) entrants bid more aggressively than incumbents in the lower tail of the conditional distribution of relative bids, and (b) the bidding differential is smaller

[21] In a different line of work, Krasnokutskaya (2004) considers private value procurement auctions with an auction specific common cost component that is known to all bidders and unknown to the researcher. The effort is concentrating in the identification of the unobserved auction heterogeneity. Unlike our paper, in her work any heterogeneous group of bidders has the same information about the common costs.

Variable	Quantile				
	.10	.25	.50	.75	.90
	Method = Quantile Regression				
Entrants (β_1)	-.126**	-.066**	-.042*	-.027	-.055
	(.033)	(.023)	(.022)	(.037)	(.052)
Bids after March 2000 (β_2)	-.099**	-.093**	-.096**	-.104**	-.145**
	(.013)	(.009)	(.009)	(.016)	(.023)
Entrants' bids after March 2000	.095**	.051**	-.028	-.036	-.031
(β_3)	(.036)	(.025)	(.024)	(.040)	(.056)
Bidders facing entrants (β_4)	-.104**	-.015	.011	.053	.022*
	(.021)	(.014)	(.014)	(.023)	(.033)
Bidders facing entrants after	.151**	.049	.075	.153**	.282**
March 2000 (β_5)	(.025)	(.017)	(.016)	(.027)	(.039)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.001	0.012	0.125	0.399	0.410
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.031	0.026	0.004	0.000
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.031	0.133	0.157	0.628	0.034
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.001	0.001	0.000	0.000	0.000
	Method = Fixed Effects Quantile Regression				
Entrants (β_1)	-.060	-.014	.049	.067	.091**
	(.038)	(.037)	(.045)	(.043)	(.041)
Bids after March 2000 (β_2)	-.103**	-.090**	-.092**	-.095**	-.114**
	(.010)	(.008)	(.008)	(.010)	(.014)
Entrants' bids after March 2000	.073*	.022	-.045	-.083	-.108
(β_3)	(.043)	(.039)	(.048)	(.048)	(.047)
Bidders facing entrants (β_4)	-.151**	-.014	.010	.038	.084**
	(.036)	(.020)	(.017)	(.025)	(.038)
Bidders facing entrants after	.172**	.045**	.060**	.124**	.228**
March 2000 (β_5)	(.038)	(.023)	(.021)	(.033)	(.063)
Number of Observations	6742	6742	6742	6742	6742
P-value from testing $H_0 : \beta_1 = \beta_3$	0.095	0.634	0.309	0.087	0.021
P-value from testing $H_0 : \beta_4 = \beta_5$	0.000	0.148	0.167	0.114	0.115
P-value from testing $H_0 : \beta_1 + \beta_3 = 0$	0.411	0.578	0.792	0.410	0.310
P-value from testing $H_0 : \beta_4 + \beta_5 = 0$	0.137	0.013	0.000	0.000	0.000

Table 7: Quantile Regression Results for Relative Bids. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level. The table shows results based on entrants defined as firms that submit a bid after July 1998.

after the policy change. As expected, the coefficient estimates are notably reduced relative to the ones presented in Tables 4 and 5.

4.2 Changes in Participation and Winning Patterns of Bidders

In this section, we examine the rate of participation of both entrants and incumbents before and after the information release, and consider changes in the probability of winning across the two groups. Table 8 presents the first set of regression results describing those patterns. Both models of this table are estimated with a set of monthly dummy variables along with the controls for bidder, rival, auction characteristics and business conditions introduced in the previous sections. The standard errors reported are cluster-robust standard errors where the clustering is on firms. The first two columns of Table 8 report on the probability of bidding. The last two columns report on the probability of winning conditional upon bidding. The results indicate that entrants bid less frequently than incumbents do, but conditional on bidding, only entrants that are identified by their first bid win with higher probability. Entrants' participation and winning patterns on average did not show a statistically significant change after the information release; adjustments made by both groups left their chances to bid and win unaffected.

When considering other variables, the ones that appear to have the most consistent impact are the expected number of rivals, rivals' distance to the project, bidders' own distance to the project, and past winning to bidding ratio. As the expected number of rivals or a firm's own distance to the project location increases, a bidder become less inclined to participate and has a low probability of winning. Further, as a rivals' distance to project location increases a bidder's probability of submitting a bid and winning increases. On the other hand, if the firm has a higher past winning to bidding ratio, in other words if it is more efficient, then it has a higher probability of participation and probability to win conditional upon bidding. The variables that measure business conditions show no significant impact on either participation or winning patterns.

Variable	Probability of			
	Bidding		Winning	
	(1)	(2)	(1)	(2)
Entrants (β_1)	-.156**	-.185**	.227**	.038
	(.059)	(.045)	(.082)	(.047)
Bids after March 2000 (β_2)	.000	.015	.008	.009
	(.022)	(.021)	(.022)	(.022)
Entrants' bids after March 2000 (β_3)	-.071	-.031	-.075	-.045
	(.070)	(.054)	(.067)	(.050)
Bidders facing entrants (β_4)	-.018	-.019	-.024	-.031
	(.028)	(.027)	(.027)	(.027)
Bidders facing entrants after March 2000 (β_5)	-.059	-.040	.035	.037
	(.036)	(.037)	(.038)	(.038)
Expected number of rivals	-.022**	-.021**	-.033**	-.032**
	(.005)	(.005)	(.005)	(.005)
Capacity utilized	.027	.001	-.056**	-.061**
	(.039)	(.038)	(.025)	(.025)
Distance to the project location	-.019**	-.016**	-.021**	-.021**
	(.003)	(.008)	(.005)	(.005)
Firm's past winning to bidding ratio	.247**	.203**	.476**	.441**
	(.102)	(.092)	(.052)	(.055)
Rival's average past winning to plan holder ratio	.066	.127	-.189	-.192
	(.181)	(.172)	(.150)	(.150)
Closest rival's distance to the project location	.021**	.020**	.008*	.008*
	(.005)	(.005)	(.005)	(.005)
Rivals minimum backlog	-.002*	-.002*	.001	.001
	(.001)	(.001)	(.001)	(.001)
Seasonally unadjusted unemployment rate	-.002	.005	-.013	-.013
	(.008)	(.012)	(.010)	(.011)
Three month average of the real volume of projects	-.022	-.019	.005	.005
	(.018)	(.021)	(.024)	(.024)
Three month average of the number of building permits	-.083	-.124	.062	.065
	(.061)	(.087)	(.072)	(.079)
Number of Observations	12579	12579	6742	6742
Wald χ^2	255.29	305.87	310.11	292.50

Table 8: Bidder Participation and Winning Patters considering alternative entry definitions. While in column (1) entrants are identified considering only their first bid, in column (2) entrants are firms submitting bids after July 1998. ** Denotes statistical significance at 5 percent level and * denotes statistical significance at 10 percent level. Robust standard errors are in parentheses.

4.3 Survival of Entrants

We focus now on entrants considering two periods: before (B) and after (A) the information release. We will first provide a theoretical foundation for survival analysis and then present our empirical findings. Our notion of survival in this market is associated with the number of months a firm continues bidding in the procurement auctions.

We index the time period by $t = \{B, A\}$. The information release decreases the common cost uncertainty and therefore decreases the variance of the perceived distribution of costs. Consider for simplicity the case where the true cost is the same in both periods. In that case, when we compare entrants' distributions across periods, we expect that the distribution of perceived cost after the information release will stochastically dominate the distribution of costs before the information release at the lower tail. With that in mind, we will consider properties of the hazard rate across periods and relate their implications on expected profits to the survival of entrants.

It is well known that if the distribution of costs exhibits stochastic dominance the hazard rate exhibits a stochastic dominance relation as well. We can easily establish that this is also true if the stochastic dominance relation is only confined at the lower tail of the distribution. That is, if $f_{E_B}\left(\phi_{E_B}(b)\right) > f_{E_A}\left(\phi_{E_A}(b)\right)$ for any $b \in [b_*, b_* + \epsilon]$, and consequently $F_{E_A}(x) < F_{E_B}(x)$ in the right neighborhood of $\phi_E(b_*)$, then,

$$\frac{f_{E_B}\left(\phi_{E_B}(b)\right)}{1 - F_{E_B}\left(\phi_{E_B}(b)\right)} > \frac{f_{E_A}\left(\phi_{E_A}(b)\right)}{1 - F_{E_A}\left(\phi_{E_A}(b)\right)}.$$

The hazard rate represents the probability that the bid will be in the right neighborhood of b_* given that it is as high as b. The interpretation of this hazard rate inequality is the following: Fix a target level of cost that can produce a bid b. Any realization of the cost greater than that, leads to at least as high a bid. The probability of bidding at least as high as b then is $1 - F_{E_t}(\phi_{E_t}(b))$. The provision of information increases the likelihood of higher bids in $[b_*, b_* + \epsilon]$, and the hazard rate above represents the rate of such an increase. Since the actual cost is the same across periods and all that changes is the available information and the distribution of perceived costs, we can see that entrants are now

Time	Survival Function Estimates	
	Before the Policy Change	After the Policy Change
1 Month	.433	.641
	(.091)	(.054)
2 Months	.300	.573
	(.084)	(.058)
3 Months	.267	.533
	(.081)	(.061)
5 Months	.200	.456
	(.073)	(.066)
15 Months	.125	.424
	(.062)	(.069)

Table 9: Kaplan-Meier Estimates for the Bidding Times Probability by periods: July 1998 to March 2000 (second column) and April 2000 to August 2003 (third column). Standard Errors are in parenthesis.

bidding higher at the low tail of the distribution. With that in mind consider an entrant's profit as,

$$\pi_{E_t} = (b_t - c_E)\,(1 - F_I(\phi_I\,(b_t))\,.$$

If the bid is higher in the period after the information release, the profit margin will increase but the probability to win a contract may increase or decrease depending on the behavior of incumbents. Incumbents receive the same information as the entrants making adjustments in anticipation of the entrant's strategies. If, as we observe in the data, the probability of a win does not change across the two periods then entrants who adjust their bids upwards will have a higher profit margin and will make a higher profit on average on any project they win. Therefore, they will survive for longer periods of time.

This last argument suggest the possibility that the information release will affect the length of bidding activity of entrants. The idea is that an entrant's probability of surviving t periods of time should be higher after the policy change. Therefore they should continue bidding in Oklahoma for a longer period of time.[22] A simple first empirical test could consider estimating the probability that entrants bids t months before and after the policy change, which is presented in Table 9. Standard non-parametric Kaplan-Meier survival function estimates suggests that the number of months within which a firm is submitting bids decline more rapidly in the period until March 2000 than in the period

[22] We consider the number of months an entrant submits a bid as a measure of bidding time in the Oklahoma market. We do not differentiate between instances in which one or two bids were submitted by a bidder.

after March 2000. For instance, while the probability of bidding for 3 months is 27 percent before the information release, it rises up to 53 percent after March 2000.

We need to draw attention to two important issues associated with this analysis using ODOT data. First, the number of observations is drastically reduced as the sample now only includes entrants.[23] Consequently, the quantile regression analysis presented below will be restricted to $\tau = \{0.25, 0.4, 0.5, 0.6, 0.75\}$. Second, when we examine the survival of firms, we consider a firm exiting the Oklahoma market if it did not submit any bid for a period extending beyond 12 months. If by the end of the sample period the firm (a) did not submit a bid, and (b) its last bid was submitted within a year, the observation is treated as censored. This twelve month cutoff is based on the fact that roughly 90 percent of the projects are completed within a year. Consequently, most of the firms will have very limited backlog after a year and a higher incentive to bid. In our entire sample period and considering all firms, it takes on average 2.4 months between submissions of bids by a bidder, while in 90% of cases the time distance between the placement of two bids is at most 5 months, and in 95% of the cases it is at most 8 months. We created a window that is 4 months larger than the estimate of the 95th percentile to be as confident as possible about our prediction of exit. In general, however, it is not possible to know with certainty if a firm is out of the market or still competing in it, when there is no bid submitted for an extended period.

Keeping in mind the issues, we estimate the impact of the release of the engineering costs on the bidding times distribution. We consider a quantile regression model,

$$Q_{h(T)}(\tau|\mathbf{x}) = \mathbf{x}'\boldsymbol{\gamma}(\tau),$$

where $h(\cdot)$ is a monotone function, and T denotes number of months a firm continues bidding in the Oklahoma auction market. Koenker and Geling (2001) noted that a logarithmic transformation gives a quantile regression approach for the accelerated failure time model, which can be written as

[23] We omit the survival analysis for incumbents here. This is because it poses different considerations than that for entrants. Note that, incumbents have been defined as the firms that submitted a bid before July 1998. Those firms, if they continue bidding after March 2000, will be established firms and their survival in the market may be highly correlated with their stage of maturity and experience, not necessarily with the release of information.

$h(T) = \mathbf{x}'\boldsymbol{\gamma} + u$ with $h(\cdot) = \log(\cdot)$.[24] In the quantile regression model, we have that

$$Q_{h(T)}(\tau|\mathbf{x}) = h(Q_T(\tau|\mathbf{x})),$$

therefore for the log transformation, we should consider a model for bidding times distribution as, $Q_T(\tau|\mathbf{x}) = \exp\{\mathbf{x}'\boldsymbol{\gamma}(\tau)\}$. It is natural to extend this analysis to the case of time-varying regressors, but one needs to be careful because the classical proportional hazard model cannot be simply transformed into an accelerated failure time model (Fitzenberger and Wilke 2006). With this caveat in mind, we propose to estimate first a longitudinal model, $Q_{\log(T_{it})}(\tau|\mathbf{x}_{it})$. For the estimation and inference of this model we consider the quantile regression method presented above.

Table 10 presents results on the effect of the information release policy on the log of bidding survival time distribution, obtained from a model that includes the covariates presented in Table 2 and monthly dummy variables. Note that, the coefficients β_1 and β_3 in our previous specifications are not identified because we consider a sample of entrants, but it is possible to estimate β_2 at any quantile τ. The coefficient $\beta_2(\tau)$ measures the horizontal distance between the conditional distribution of the log of bidding times before and after the policy change. If the information release has an effect on the survival probabilities, and consequently on the length of bidding time, we expect to find positive estimates at the lower quantiles.

We find estimates of β_2 ranging from 0.59 to 0.88 at the center of the conditional distribution, which suggest that the median bidding time duration increased at least $\exp\{0.59\} \approx 1.80$, or roughly 80 percent after the information release. The effect at the 0.25 quantile is also positive and significant, suggesting a 28 percent increase after the information release among entrants who stop bidding relatively soon. These important findings suggest that entrants continue bidding in the market for a longer period of time after the policy change.

Table 11 presents additional results, obtained this time from a model that not only includes the covariates and monthly dummy variables from Table 10, but also large firm and project effects to

[24] The accelerated failure time (AFT) model represents a general class of survival models including the Exponential and Gamma parametric models as particular cases (see, e.g., Lancaster 1990). The log version of the accelerated failure time model includes as a particular case the Cox (1972) model with Weibull baseline hazard.

Variable	Quantile				
	.25	.40	.50	.60	.75
After March 2000	.246**	.589**	.670**	.882**	1.011**
	(.124)	(.225)	(.343)	(.304)	(.158)
Bidders facing entrants	1.228**	1.511**	1.412**	1.305**	.996**
	(.191)	(.442)	(.673)	(.613)	(.326)
Bidders facing entrants after March 2000	-.713**	-1.098**	-1.094	-1.031	-.708**
	(.209)	(.469)	(.716)	(.653)	(.350)
Expected number of bidders	.015	-.016	-.042	.042	.009
	(.019)	(.037)	(.061)	(.057)	(.029)
Capacity utilized	1.170**	.640**	.519	.506	.500**
	(.120)	(.236)	(.378)	(.330)	(.168)
Distance to the project location	-.121**	-.217**	-.235**	-.238**	-.223**
	(.020)	(.040)	(.064)	(.058)	(.029)
Firm's past winning to bidding ratio	.593**	1.138**	1.191**	.789**	.217
	(.206)	(.339)	(.478)	(.382)	(.171)
Rival's average winning to plan holder ratio	.458	-.760	-1.921	-2.081*	-1.305*
	(.341)	(.742)	(1.307)	(1.181)	(.788)
Closest rival's distance to the project location	.023	.097**	.132**	.135**	.147**
	(.020)	(.038)	(.060)	(.054)	(.030)
Rivals minimum backlog	.005	.022**	.015	.010	.009
	(.008)	(.015)	(.025)	(.022)	(.013)
Seasonally unadjusted unemployment rate	.197**	.316**	.275	.277*	.211**
	(.062)	(.118)	(.183)	(.162)	(.085)
Three month average of the real volume of projects	.123	-.028	.233	.367	.347**
	(.121)	(.234)	(.3730)	(.333)	(.164)
Three month average of the number of building permits	-1.051**	-.960	-.485	-.090	.410
	(.457)	(.870)	(1.348)	(1.202)	(.638)
Number of Observations	397	397	397	397	397

Table 10: Quantile regression results for log of bidding times. The model includes monthly dummy variables. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level.

Variable	Quantile				
	.25	.40	.50	.60	.75
After March 2000	.318*	.403	.519*	.616**	.694**
	(.191)	(.267)	(.279)	(.181)	(.081)
Bidders facing entrants	1.319**	.912*	.831	.884**	.784**
	(.316)	(.511)	(.553)	(.335)	(.170)
Bidders facing entrants after	-.650*	-.394	-.361	-.433	-.431**
March 2000	(.351)	(.550)	(.596)	(.362)	(.182)
Expected number of bidders	.004	.024	.003	-.038	.007
	(.032)	.048	(.051)	(.033)	(.156)
Capacity utilized	1.072**	.750**	.734**	.679**	.504**
	(.202)	(.292)	(.313)	(.190)	(.081)
Distance to the project location	-.148**	-.206**	-.215**	-.187**	-.201**
	(.034)	(.050)	(.053)	(.032)	(.014)
Firm's past winning to bidding	-.002	.329	.454	.570**	.433**
ratio	(.321)	(.420)	(.401)	(.229)	(.095)
Rival's average winning to plan	-.083	-.350	-.792	-.813	-.616**
holder ratio	(.586)	(.962)	(1.100)	(.764)	(.274)
Closest rival's distance to the	.026	.042	.053	.039	.069**
project location	(.035)	(.051)	(.052)	(.033)	(.015)
Rivals minimum backlog	-.007	.018	.011	-.003	.004
	(.013)	(020)	(.021)	(.013)	(.006)
Seasonally unadjusted	.258**	.340**	.331**	.297**	.306**
unemployment rate	(.100)	.146	(.149)	(.097)	(.041)
Three month average of the real	-.065	.167	.146	.093	.221**
volume of projects	(.206)	(.289)	(.307)	(.200)	(.087)
Three month average of the	-1.382*	-.966	-.955	-.295	-.300
number of building permits	(.718)	(1.044)	(1.100)	(.705)	(.326)
Number of Observations	397	397	397	397	397

Table 11: Quantile regression results for log of bidding times. The model includes monthly dummy variables, as well as large firms' fixed effects and projects' type dummies. ** Denotes statistical significance at the 5 percent level and * denotes statistical significance at the 10 percent level.

control for unobserved heterogeneity[25]. We find that now the estimates range from 0.40 to 0.61 at the center of the log of bidding times distribution. At the median, entrants' length of bidding time duration in the Oklahoma market seems to increase by $(\exp\{0.52\}-1) \approx .68$ percent after March 2000. The effect in the lower tail is positive and significant, suggesting that the release of the engineering cost information increased the length of bidding time by 37 percent.

The previous analysis does not incorporate the fact that entrants may plan to submit bids t periods ahead. We try to address this issue by estimating a model for the number of times an entrant bids in the Oklahoma procurement auctions, conditional on the covariates $\mathbf{x}$.[26] The results are presented in Figure 4. The continuous dotted line shows the estimates, and the shaded region in each panel represents .95 percent (pointwise) confidence interval. We observe now that the difference between the distributions of the response before and after the policy change tends to disappear beyond the 0.30 quantile. In the lower tail, however, the effect of the release of information is positive and significant, suggesting that the length of bidding in the market increased roughly 60 percent after March 2000. Moreover, while the vast majority of the control variables seem to have no effect on the distribution of the log of the maximum bidding time duration, as bidder's capacity utilization increases and bidder's distance to a project decreases, the bidding length tends to be higher, improving the prospects for survival.

The previous quantile regression model does not address explicitly the potential issue of censored observations. Note that, entrants submit bids at different points in time, and by the end of the sample period, they have censored spells. Portnoy (2003) proposes a censored quantile regression approach assuming that the duration times and the censoring times are independent, conditional on the covariates. We use this approach as a robustness check, exploring the possibility that random censoring is affecting our previous conclusions. We estimate a model for the number of bids submitted

[25] We also estimated the models using number of plan holders instead of expected number of bidders. The evidence is consistent with the finding that entrants continue bidding in the market for a longer period of time after the policy change.

[26] In this case, we essentially let the quantile regression mimic the time varying effect of the covariates. Our setting can be interpreted as a particular case of a model with time-varying coefficients, $\log(T_i(t)) = \mathbf{x}'_{it}\boldsymbol{\beta}_t + u_i(t)$, where T_i denotes bidding time at duration t. While this model includes coefficient changing over time, the quantile regression coefficient $\boldsymbol{\beta}(\boldsymbol{\tau})$'s changes as a function of the quantile (Fitzenberger and Wilke 2006).

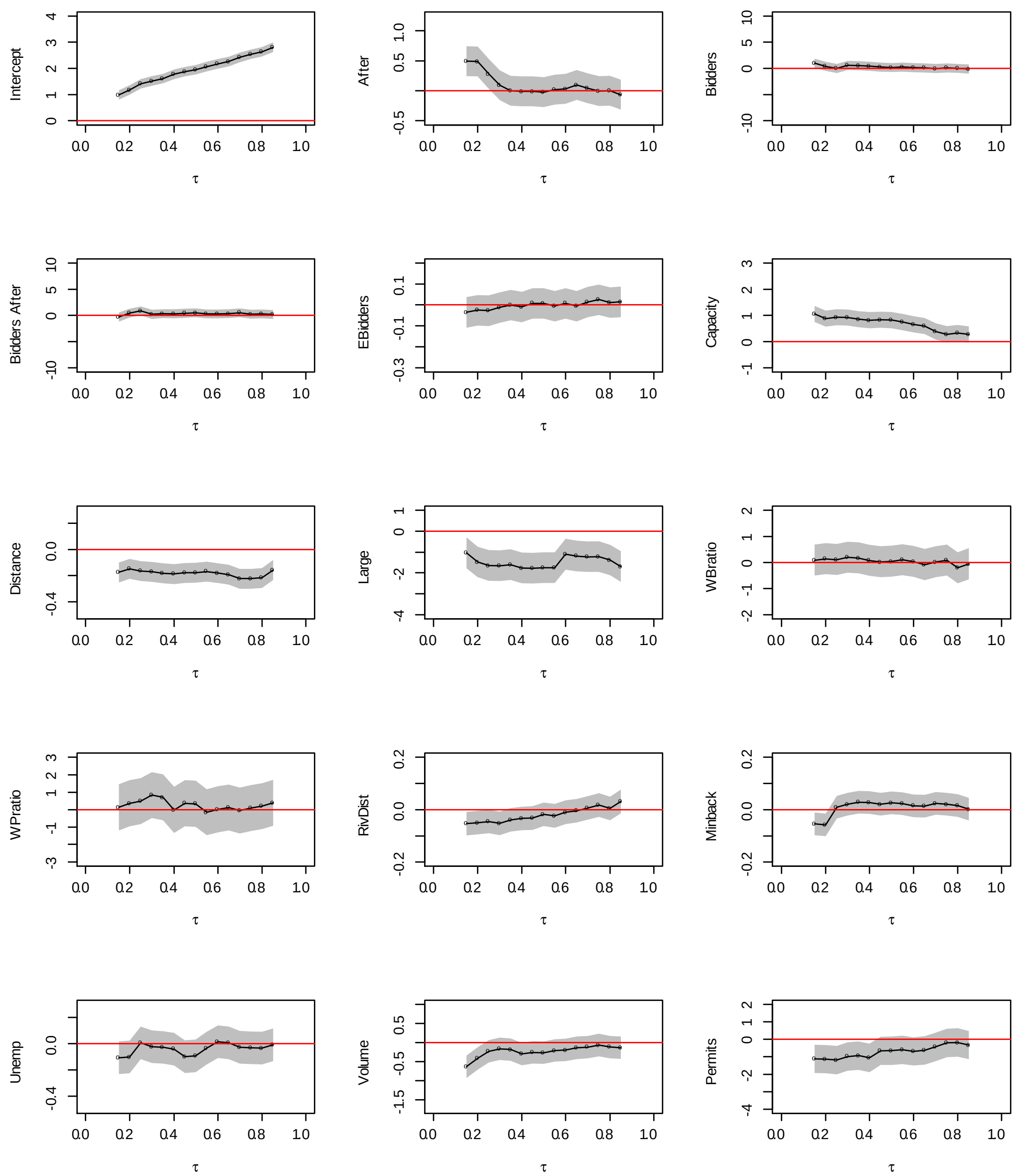

Figure 4: Bidding Times Distribution. The models include project type dummies based on the description of the model. We report the estimates of the effects of interest. The continuous dotted lines show the estimates, and the shaded region represents a .95 (pointwise) confidence interval.

by an entrant conditional on mean values of the covariates.[27] We find that the results are similar in nature to the ones described in Figure 4. For instance, the shape of the censored quantile regression point estimates for the effect after the policy change is similar to the one described in the previous figure, presenting an estimate equal to 0.52 in the lower tail. Summing up, we find that among all the variants of the model and methods we have considered, the median entrants' bidding times increased after March 2000. The findings also suggest that among entrants that exit the procurement auctions relatively soon, the release of information increased their bidding duration at least 28 percent.

5 Conclusions

In April 2000, the Oklahoma Department of Transportation started releasing the state's internal estimate of the costs to complete highway construction auctions. This paper examines the effect of this policy change on bidding and participation differences across two groups of bidders: entrants and incumbents. In light of our findings, we then examine the implications of the observed changes on the duration of the entrants' presence in the procurement auctions.

We find that overall, the release of the engineering cost estimate prior to bidding reduces informational asymmetries and as a result entrants and incumbents bid more alike. When we introduce fixed effects to control for differences in private costs, we find that entrants (a) submit relatively more aggressive low bids before the policy change and (b) adjust fully their bidding behavior after the policy change to "correct" for their earlier lack of information. Entrants adjust their bidding behavior roughly 20 percent more than the incumbents after the policy change. These results are similar when we change the specification of the dependent variable, and we control for auction and project unobserved heterogeneity.

As far as participation is concerned, the results indicate that entrants bid less frequently overall than incumbents do, but win with a higher probability, conditional on bidding. This behavior is unaffected by the policy change.

[27] Portnoy (2003) considers a model with time invariant covariates, recognizing that one disadvantage of the approach appears when the independent variables change over time. The approach remains to be developed, but a simple solution could be to replace the time varying covariate by its average value during the spell.

The fact that entrants behave more like the experienced incumbents after the information release, without lowering their probability of a win, suggests the possibility that their profit margin increases (or their losses are reduced) after the policy change, affecting their prospects for survival in this market. We consider the entrants' survival by measuring the number of months entrants submitted bids, and examine any potential change in their behavior induced by the release of information on the engineering cost estimate. Simple nonparametric estimates suggest that the probability that an entrant will continue bidding declines more rapidly over time in the period before the information release than in the period after. While controlling for observed heterogeneity, we find that at the median level, their length of presence in the Oklahoma procurement auctions increased by 68 percent. Furthermore, entrants that used to exit relatively soon continue bidding 37 percent more after the policy change.

References

Bajari, P., and L. Ye (2003): "Deciding Between Competition and Collusion," *Review of Economics and Statistics*, 85(4), 971–89.

Baldwin, J., and P. Gorecki (1991): "Firm Entry and Exit in the Canadian Manufacturing Sector, 1970-1982," *The Canadian Journal of Economics*, 24(2), 300–323.

Campo, S., I. Perrigne, and Q. Vuong (2003): "Asymmetry in First-Price Auctions with Affiliated Private Values," *Journal of Applied Econometrics*, 18(2), 179–207.

Cox, D. R. (1972): "Regression models and life tables," *Journals of the Royal Statistical Society*, 34, 187–200.

De Silva, D. G., T. Dunne, A. Kankanamge, and G. Kosmopoulou (2005): "The Impact of Public Information on Bidding in Highway Procurement Auctions," Available at SSRN: http://ssrn.com/abstract=851644.

De Silva, D. G., T. Dunne, and G. Kosmopoulou (2003): "An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions," *Journal of Industrial Economics*, 51(3), 295–316.

De Silva, D. G., T. D. Jeitschko, and G. Kosmopoulou (2005): "Stochastic Synergies in Sequential Auctions," *International Journal of Industrial Organization*, 23(3-4), 183–201.

Dunne, T., S. D. Klimek, and M. J. Roberts (2005): "Exit from regional manufacturing markets: The role of entrant experience," *International Journal of Industrial Organization*, 23(5-6), 399–421.

Dunne, T., M. J. Roberts, and L. Samuelson (1988): "Patterns of Firm Entry and Exit in U.S. Manufacturing Industries," *RAND Journal of Economics*, 19(4), 495–515.

Fitzenberger, B., and R. Wilke (2006): "Using Quantile Regression for Duration Analysis," *Allgemeines Statistisches Archive*, 90(1), 105–120.

Goeree, J. K., and T. Offerman (2003): "Competitive Bidding in Auctions with Private and Common Values," *Economic Journal*, 113(489), 598–613.

Hendricks, K., J. Pinkse, and R. H. Porter (2003): "Empirical Implications of Equilibrium Bidding in First-Price, Symmetric, Common Value Auctions," *Review of Economic Studies*, 70(1), 115–45.

Jofre-Bonet, M., and M. Pesendorfer (2003): "Estimation of a Dynamic Auction Game," *Econometrica*, 71(5), 1443–89.

Koenker, R. (2004): "Quantile Regression for Longitudinal Data," *Journal of Multivariate Analysis*, 91, 74–89.

——— (2005): *Quantile Regression*. Cambridge University Press.

Koenker, R., and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46(1), 33–50.

Koenker, R., and O. Geling (2001): "Reappraising medfly longevity: A quantile regression approach," *Journal of the American Statistical Association*, 96, 458–468.

Krasnokutskaya, E. (2004): "Identification and Estimation in Highway Procurement Auctions Under Unobserved Auction Heterogeneity," working paper, Department of Economics, University of Pennsylvania.

Lamarche, C. (2006): "Quantile Regression for Panel Data," Ph.D. Dissertation, University of Illinois at Urbana-Champaign.

Lancaster, T. (1990): *The Econometric Analysis of Transition Data*. Cambridge University Press.

Lebrun, B. (1998): "Comparative Statics in First Price Auctions," *Games and Economic Behavior*, 25(1), 7–110.

——— (1999): "First price auctions in the asymmetric N bidder case," *International Economic Review*, 40, 125–142.

Marion, J. (2007): "Are bid preferences benign? The effect of small business subsidies in highway procurement auctions," *Journal of Public Economics*, 91, 1591–1624.

Maskin, E., and J. Riley (2000a): "Equilibrium in Sealed High Bid Auctions," *Review of Economic Studies*, 67(3), 439–454.

——— (2000b): "Asymmetric Auctions," *Review of Economic Studies*, 67(3), 413–438.

Milgrom, P. R., and J. W. Robert (1982): "A Theory of Auctions and Competitive Bidding," *Econometrica*, 50(5), 1089–1122.

Moulton, B. R. (1990): "An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units," *Review of Economics and Statistics*, 72(2), 334–38.

Pesendorfer, M. (2000): "A Study of Collusion in First-Price Auctions," *Review of Economic Studies*, 67(3), 381–411.

Portnoy, S. (2003): "Censored Regression Quantiles," *Journal of The American Statistical Association*, 98, 1001–1010.

Powell, J. L. (1991): "Estimation of Monotonic Regression Models under Quantile Restrictions," in *Nonparametric and Semiparametric Methods in Econometrics*, ed. by W. Barnett, J. Powell, and G. Tauchen. Cambridge University Press, Cambridge.

Scott, D. W. (1992): *Multivariate Density Estimation: Theory, Practice and Visualization*. Wiley and Sons, New York.

Sheather, S. J., and M. C. Jones (1991): "A reliable data-based bandwidth selection method for kernel density estimation," *Journal of the Royal Statistical Society, Series B*, 53, 683–690.

Silverman, B. W. (1986): *Density Estimation for Statistics and Data Analysis*. Chapman & Hall, London.