Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior*

Georgia Kosmopoulou† University of Oklahoma

Xueqi Zhou‡ Langston University

September 12, 2012

Abstract

The fluctuations in fuel prices over the past decade led a number of government agencies to introduce price adjustment clauses in procurement contracting. Those clauses were primarily designed to reduce contractors' uncertainty without considering the impact of such initiatives on bidding and the budget. We analyze a newly constructed, detailed panel of observations on bids for construction contracts and compare bidding behavior across periods and projects, and across items within projects. Estimates from a difference-in-differences approach, indicate that bidding becomes more aggressive and less dispersed after the implementation of this policy. The difference is more pronounced when we consider itemized bids than overall project bids. Alternative techniques of regression discontinuity and nonparametric estimation are applied and yield consistent results.

JEL Classification: D81, H57, L38
Keywords: Procurement auctions, decision making under uncertainty.

I. INTRODUCTION

The prices of crude oil and its by-products have been on the rise for a considerable part of this past decade. In the middle of 2008 fuel prices increased to a level that was nearly triple that of 2006. The persistent high volatility in crude oil prices creates new challenges for industries that use oil-based inputs and rely on the public procurement process for most of their business activities. One such example is the road construction industry. Unpredictable crude oil prices are a significant concern for contractors when projecting costs to propose bids.

In an effort to reduce the risk faced by contractors, the US Federal Highway Administration (FHWA) and several state Departments of Transportation (DOTs) have recently been directing price adjustment clauses to selected construction materials. For applicable items, if prices fluctuate beyond a predetermined range, some DOTs guarantee an adjustment in payments to or from firms depending on the direction of the price change. The presence of price adjustment clauses mitigates the extent of common risk firms are faced with. Opponents of such a policy argue that adjustments based on a price indexing system give a state agency the additional role of an insurer, raising construction and operational costs. Is this policy providing primarily protection and support to less productive firms?

Despite the increasing popularity of those clauses and the debate on the resulting benefits, there has been little systematic study on how incentives and bidding behavior of firms are affected by

*We are grateful to Dakshina G. De Silva, Danny Gierhart, Joakim G. Laguros and the staff at the at the Oklahoma Department of Transportation for providing useful information. We also thank Carlos Lamarche for generously sharing his programs on panel quantiles, and Xin Huang and Gregory Burge for helpful comments.

†Corresponding author: Georgia Kosmopoulou, 318 Hester Hall, 729 Elm Ave, Norman, OK 73019, U.S.A. Tel:1-405-325-3083, Email: georgiak@ou.edu.

‡School of Business, Langston University, Langston, OK 73050, U.S.A. Tel:1-405-466-2958. Email: xzhou@langston.edu.

the presence of price adjustment policies. Our paper seeks to fill this gap in the empirical literature by evaluating the price adjustment clauses that were applied to selected fuel-based construction materials (bituminous) by the Oklahoma Department of Transportation (ODOT) since June 2006. We use a newly constructed data set on construction auctions taking place between 2003 and 2009. We also present a model that highlights the effects of the reduction in cost uncertainty upon bidding, in an effort to discern the effect of this policy on firm behavior and budget outlays.

This recent policy change provides an appropriate object for empirical study for a number of reasons. First, Oklahoma is among the early states to institute price adjustments, generating a sufficiently large window for policy analysis and impact assessment. Second, to this date the special provisions on asphalt and related materials are the only price adjustments ever implemented by ODOT, which frees us from the complication of multiple contemporary policy changes. Third, detailed project level information is available allowing us to control for individual heterogeneity that may not have been possible otherwise. The data set is enriched by our access to itemized bids for each auction.[1] This important feature of our data allows us to assess the effect of adjustment clauses on targeted tasks closely.

A number of states have price indexing programs in place not only for asphalt items but also for items directly related to diesel fuel use.[2] Early in 2009, ODOT drafted a clause for diesel fuel items, but has yet to put it into use. We collected information on itemized bids for all applicable asphalt and fuel materials that either have been or will be subject to price adjustments, enabling an immediate comparison of bids on the pair of closely tied inputs. According to State officials, between August 2006 and June 2009, ODOT granted a net payment to firms equal to 5.05% of the contracted values on asphalt items eligible for adjustment. We estimate that, winning bids on asphalt items relative to other items were 11.7% lower in the same period. After the price adjustment policy was enacted, firms bid on average 12.7% lower on eligible items relative to ineligible items, and 14.5% lower on eligible items relative to fuel related items. Our evidence also suggests that there is no significant correlation between firm productivity and policy eligibility. The policy does not seem to favor less productive firms.

The interest in the price adjustment policy extends even beyond industries whose daily operation is impacted significantly by uncertainty in oil prices. The recent federal health reform legislation in the US, as well as Medicare Part D, which was enacted in 2003 through the Medicare Prescription Drug, Improvement and Modernization Act, included similar provisions. In this case, the US federal government is setting up ”risk corridors” that would limit to some extent the profits and losses of private health insurers if their costs were outside a specific range. The goal is to influence bids for health insurance premiums in the new exchanges and reduce the soaring medical insurance costs. Another example is in defense contracting. First price auctions with economic price adjustments (FPEPA) are used in 13.6% of the Air Force engine contracts studied in Crocker and Reynolds [1993] as well as 4% of the active major defense acquisition aircraft contracts awarded between January 1997 and December 2011.[3]

The paper is organized as follows. Section II provides background information on the price adjustment policy, and a review of existing literature. Section III discusses the theoretical model framing our statistical analysis. Section IV presents the data. Section V provides empirical results and section VI offers concluding remarks.

[1]ODOT collects bidding amounts for each project from a standardized item sheet. This sheet includes an exhaustive list of items used in a project along with individual quantities specified and a benchmark cost estimated by engineers. Contractors are submitting itemized bids, and their final bid becomes the weighted sum of unit prices and associated quantities.

[2]As of September 2009, 40 states applied some form of price adjustment for bituminous material and 39 for diesel fuel. Diesel fuel is a product from crude oil distillation, as is hot mixed asphalt. Their prices have exhibited similar fluctuations and trends in the past few years.

[3]The data is available through the Federal Procurement Database System at: https://www.fpds.gov/fpdsng_cms/.

II. BACKGROUND

II(i). *ODOT Price Adjustment for Asphalt Binder*

By increasing demand from primary contractors, ODOT amended its standard specification to include special provision 109.12 on price adjustment for asphalt binder, effective on its June 2006 letting. A monthly index based on "Asphalt Weekly Monitor" by Poten & Partners is available online at www.okladot.state.ok.us. For all projects with applicable items,[4] when the index in period $t+1$ ($\overline{c}_{t+1}$) increases by more than 3% from its base value ($\overline{c}_t$), a lump-sum payment is automatically triggered from the department of transportation to the contractor, with the amount contingent on the quantity of eligible items and the extent of price deviation. The direction of payment is reversed if the current cost of asphalt binder is lower than the base value by 3%. The reimbursement amount per unit of eligible item, for example if there is an increase in the index by 3% or more, is $\overline{c}_{t+1} - 1.03\overline{c}_t$.

As of September 2009, 40 states apply price adjustment for asphalt in their contracts of public construction and two, Minnesota and Arizona, are in the process of adopting one. The clauses may not be uniform in terms of trigger value, choice of index, or identification of applicable items, but their purpose is common, namely to relieve construction firms from excessive uncertainty of input prices. Few states have had such clauses in place for more than a decade. Most states, such as Colorado, Illinois, and Michigan, implemented the new policy in a recent wave.[5]

II(ii). *Related Literature*

At first glance, by shifting risk from contractors to the government agency, the price indexing system benefits private firms while increasing the direct cost of procurement.[6] However, early theoretical work by Holt [1979] has shown that when firms are risk averse a government procurement agency can reduce costs by accepting a greater share of risks. Hong and Shum [2002] used an affiliated value model with risk neutral bidders to measure the effects of winner's curse on equilibrium bidding. Goeree and Offerman [2003] showed that bidders bid more aggressively when provided with information that reduces common uncertainty, even if they are risk neutral.[7] The bidders' reaction to policies that reduce uncertainty can benefit government agencies as buyers.

The auction literature has been studying the effectiveness of mechanisms used to procure construction contracts and the impact of new policies. Based on state auctioned contracts offered between 1997 and 2003 in Oklahoma and Texas, De Silva *et al.* [2008] assessed how the release of information on internal cost estimates affects bidding. Bidding preference toward certain groups, such as domestic suppliers or small disadvantaged businesses, has been the focus of a number of studies (Naegelen and Mougeot [1998], Marion [2007], De Silva *et al.* [2010]). Thomas and Wilson [2002] and Bajari *et al.* [2009] investigated optimal allocation mechanisms by comparing competitive bidding with negotiation to show that auction competition is generally favored from an efficiency point of view, but negotiation facilitates communication and may be preferable in highly complex situations. Bajari *et al.* [2006] found that even in standard procurement contract-

[4]A list of those items can be found at http://www.okladot.state.ok.us/c_manuals/specprov2009/pdfs/xspn109-7.pdf.

[5]Medicare Part D has similar provisions. According to the Appendix on risk corridor policy by the Congressional Budget Office: "The system would work in the following way. At the end of the calendar year, the Department of Health Services (HHS) would compare each plan's expected and actual benefit/costs (excluding federal reinsurance payments and administrative costs). Drug plans incurring benefit costs that exceeded their expected levels by a sufficient degree would then be partially compensated by additional federal payments, while benefit costs that fell far enough below their expectations would generally have to reimburse Medicare at the same rate."

[6]See the American Association of State Highway & Transportation Officials (AASHTO) subcommittee's survey. One perceivable direct return to the government is the savings when prices drop.

[7]The policy limits private information rents.

ing, anticipated changes to initial plans after awarding contracts can cause firms to bid higher due to adaptation costs.

Our paper is among the first empirical attempts to evaluate the impact of price adjustment clauses, designed to reduce firm uncertainty, on government procurement auctions of construction contracts. Eckert & Eger [2004] approached the question by consulting state engineers and government employees who participated in similar programs in Georgia's neighboring states (Alabama, Florida, etc.), and based their conclusion that there are no considerable benefits on a simple comparison of basic statistics and interviewees' experiences. Their research was done prior to the recent sharp rise of energy prices and didn't apply estimation techniques to analyze bids.[8] Section III provides theoretical predictions for the effects of this policy focusing on two characteristics of the economic environment impacting road construction in recent years: price uncertainty and increasing price trends.

III. A MODELING FRAMEWORK

We consider a simple theoretical model of auction competition to formalize the impact of price adjustment clauses on the bidding outcome. A number, n, of bidders compete for a government contract in a low price sealed bid auction held at time t. The project will be completed at time $t+1$.

Bidders are risk neutral. The cost of the contract to bidder i consists of two components: The private cost, $c_{it} \in [c_{itL}, c_{itH}]$, known by bidder i at time t, and a common cost component $c_{mt+1} \in [\underline{c}_{mt+1}, \overline{c}_{mt+1}]$. Both costs are drawn from twice continuously differentiable distributions with strictly positive densities on their supports. Each contractor receives a private information signal x_{it} of the common cost component with $x_{it} = c_{mt+1} + \eta_{it+1}$. Only the distribution of η_{it+1} is known at t, with $E(\eta_{it+1}) = 0$. As such, x_{it} constitutes an unbiased estimate of the value of c_{mt+1}.[9] In the context of our empirical study, due to uncertainty in the price of crude oil, the actual cost of asphalt mixture[10] to firm i in period $t+1$ when the contract is fulfilled may differ from c_{it} and that difference is determined by market forces. We assume that the densities f_c and f_x are logconcave.[11]

The bidder who bids b_{it} and is awarded the contract receives ex post a utility of $u(b_{it}, c_{it}, c_{mt+1}) = b_{it} - c_{it} - c_{mt+1}$. The unique symmetric equilibrium bidding strategy for bidder i in the first price auction held at t is:

$$B(s_{it}) = E(y_{1t} | y_{1t} \geq s_{it}) - E(\eta_{it+1} | s_t \geq s_{it}) \tag{1}$$

where $s_{it} = c_{it} + x_{it}$ is i's privately observed component of the cost at the time of bidding, and y_{1t} denotes the infimum of the remaining $n-1$ estimates of s_t.

Let $\overline{c}_{t+1}$ and $\overline{c}_t$ be cost indices at the time of construction completion and letting respectively. $\overline{c}_{t+1}$ is a random variable with a known distribution ex ante. One can think of this cost index realization in the following way: A firm receives a quote, an estimate, from a supplier at time t on the price of asphalt at $t+1$. This estimate reflects the cost if the asphalt mixture had been delivered at t. The price index at t is the average of the quotes received at t. The index at $t+1$ includes, apart from the average cost estimate, the impact of exogenous economic shocks on the price of asphalt at $t+1$ (c_{mt+1}), to be known only at $t+1$. In other words, $c_{mt+1} = \overline{c}_{t+1} - \overline{c}_t$.

[8] They base their analysis on aggregate cost measures and consider average quotes on asphalt concrete.

[9] More intuitively from the perspective of the bidder, we can write $c_{mt+1} = x_{it} - \eta_{it+1}$.

[10] Asphalt is a by-product of crude oil.

[11] The assumption of logconcavity is discussed extensively in Goeree and Offerman [2003]. It guarantees that a lower privately observed cost implies, on average a lower overall cost.

The price adjustment clause provides additional compensation to contractors for fluctuations in item prices related to asphalt work.[12] With the indexing policy in place, the realized cost payment due to market fluctuations is:

$$c^*_{mt+1} = \begin{cases} \overline{c}_{t+1} - \overline{c}_t & | \quad -1 \leq \frac{\overline{c}_{t+1}-\overline{c}_t}{\lambda \overline{c}_t} \leq 1 \\ \lambda \overline{c}_t & | \quad \frac{\overline{c}_{t+1}-\overline{c}_t}{\lambda \overline{c}_t} > 1 \\ -\lambda \overline{c}_t & | \quad \frac{\overline{c}_{t+1}-\overline{c}_t}{\lambda \overline{c}_t} < -1 \end{cases},$$

where λ is the proportion of price adjustment specified by the policy. One can bound the value of λ between 0 and 1 by assuming that $\overline{c}_{Ht+1} < 2\overline{c}_{Lt}$ and $\overline{c}_{Lt+1} > 0$ ($\lambda = 0.03$ in the case of Oklahoma asphalt binder adjustment).

The bidding strategy then with the adjustment clause in place becomes:

$$B(s_{it}|\lambda) = E(y_{1t}|y_{1t} \geq s_{it}, \lambda) - E(\eta_{it+1}|s_t \geq s_{it}) \tag{2}$$

[Place Figure 1 about here.]

The likelihood of cost overruns increased substantially in the past ten years, i.e., $E(c_{mt+1}) \geq 0$ increasing the likelihood of adjustments. The plot showing the price trend of asphalt in the past two decades suggests an unambiguous upward pressure (see Figure 1).[13] Assuming rational expectations $B(s_{it}|\lambda) \leq B(s_{it})$. The effect of adjustment clauses on the variance of bids can be evaluated by considering the derivative of the variance with respect to the threshold parameter: $\frac{\partial V[B(s_{it}|\lambda)]}{\partial \lambda}$. We show in the Appendix that, $\frac{\partial V[B(s_{it}|\lambda)]}{\partial \lambda}$ increases as λ becomes larger, implying that bids would become more dispersed when the uninsured corridor is broadened.[14] We also find that, by examining the index month to month, it has been almost twice more likely for asphalt prices to rise or remain at the same level than to drop.[15] When there is expectation of price fluctuations leading to higher costs, the distribution of c^*_{mt+1} tends to be less dispersed but also more skewed towards low adjusted costs. As a result, we expect: (1) more aggressive bidding; (2) a disproportionate decrease of high bids after the policy is enacted. The smaller the uncertain component is in the total cost, the smaller the effect of the policy on bidding behavior.[16]

IV. DATA DESCRIPTION AND QUALITATIVE ANALYSIS

The panel generated for this study was based on data collected from the ODOT online sources and includes all public construction projects auctioned off monthly between September 2003 and September 2009.

[12] For projects with applicable bituminous mix, adjustments to eligible payments are made on a moving basis, with current asphalt index taken as the date on the purchase invoice of the contractor.

[13] The data provided in Figure 1 are from the Arizona Department of Transportation due to lack of information from ODOT for the entire period of analysis. The indices across states are highly correlated. For the period where both indices are available, their correlation coefficient exceeds 0.9.

[14] We can think of the situation without any ex-post transfers as equivalent to one with an unrealistically high λ being set. Therefore, implementing the indexing policy is equivalent to lowering the value of threshold.

[15] The nuclear accident in Japan prompted the need for testing the safety of a number of nuclear reactors around the world (New York Times, 3/25/2011). The closure of some nuclear facilities (Washington Post 3/17/2011) is creating expectations of an increase in demand for petroleum products in the future (Associated Press 4/11/2011). Hurricanes that often hit the Gulf coast, halting over half of the Gulf of Mexico oil and gas production for prolonged periods of time (US Mineral Management Service, Release #3447, 12/29/2005)), are primary examples of natural disasters that generate exogenous shocks and volatility. International turmoil including recently announced oil embargoes are other such examples (New York Times, 1/4/2012).

[16] Similar results could be established using the framework by Decarolis [2009] where the cost could be modeled as being private with probability θ or have an effect from market sources with probability $(1 - \theta)$.

An alternative setup with pure private costs but risk-averse firms would yield qualitatively the same set of predictions as our model with possibly more pronounced quantitative effects. Under the assumption of risk-averse agents, Holt [1979] showed that when the government assumes part of the risk of individual contractors, bids become significantly more aggressive and less dispersed. In other words, this variation produces qualitatively similar results. It would be ideal to incorporate the degree of risk aversion of various firms participating in the process to the analysis. We are unfortunately unable to empirically evaluate a bidder's risk preference due to lack of data.

The projects cover a wide variety of tasks, ranging from grading, paving, and signaling to intersection modification and bridge rehabilitation. For each project the transportation agency provides detailed information, including a unique identification number, the project's precise location and a brief description of tasks involved. They provide estimates of the number of days to complete the work, and the engineer's cost for projects overall and for each task within a project. As required by ODOT, all firms interested in bidding for a project must first purchase the plan to qualify as potential bidders. Plans are becoming available at least three weeks before the monthly lettings. The names of plan-holders are released to the public prior to the auction. All projects are auctioned off using a low price sealed bid format and are subject to the same set of rules regarding the awarding process and ex post price adjustments. After the auction session is concluded, all bids submitted and the identities of bidders are posted on the website. Typically, two weeks after a winner is selected ODOT issues a "notice to proceed", marking the official beginning of construction. It takes a little over six months to complete an average project but large projects may go on for as long as several years.[17] Using these records, we constructed our data set so that each observation would correspond to a plan bought by a perspective contractor, a bid submitted when applicable, and all relevant characteristics of the project and the contractor. The panel is unbalanced since firms differ in their plan-holding frequencies considerably.

[Place Table I about here.]

Table I summarizes auction characteristics using project bids separately for the periods before and after June 2006. The clause applies to selective materials only. In the top section of Table I, we contrast measures on projects with eligible asphalt inputs (eligible projects) versus measures on projects without eligible asphalt inputs (ineligible projects). Asphalt is consistently a key component of the former group, making up 42% of the value before June 2006 and 40% of the value after.[18] Eligible projects are generally larger and take more calendar days to complete. Statistics on number of bidders or plan-holders appear stable over time. Eligible projects seem to attract a slightly larger number of participants, but the difference is insignificant. Other than a few small-sized, highly specialized builders, the majority of firms (62%) have participated in both eligible and ineligible auctions, resulting in 87% of bids submitted by the same bidders across categories. The last two rows of statistics reveal that, bids on eligible projects are lower in the second period than in the first period but not for ineligible projects. Standard kernel plots (A) and (B) of Figure 2 lend support to this observation, revealing an intertemporal shift to the left in the bid distribution of eligible projects but no such movement in ineligible projects. The same pattern is observed for winning bids.

[Place Figure 2 about here.]

The next comparison at a project level, presented in the bottom section of Table I, has a focus on asphalt and bridge projects to maintain homogeneity within groups. We chose these projects for two reasons. First, they are the most common types of work, and taken together they comprise 65% of auctions in the sample. Moreover, they differ distinctively in the extent of asphalt involvement. Applicable asphalt binder is used in nearly 86% of asphalt paving, and on average makes up 77% of the total contract value. In contrast, more than two thirds of bridge construction does not use any eligible items, and the remaining use them at a much lower intensity (11%). This translates

[17] The common uncertainty in costs therefore originates from the lapse of time between the project letting and delivery, and is escalated when input prices experience dramatic fluctuations. The two-period feature of our theoretical model is aiming to capture this time dimension.

[18] Calculations are based on the state engineer's cost estimates.

in a 3% involvement of asphalt work across all bridge projects in our sample. Bridge projects in general take longer to complete than asphalt paving and enlist broader participation judging by the number of plan holders and bidders. There is also a large number of firms bidding for both types of projects, acquiring 94% of plans sold and producing 85% of bids received. Participation statistics are comparable within either type through time, leading to an apparent yet roughly constant gap across groups. Finally, as shown in the final two entries, temporal changes in relative bids of asphalt paving projects become larger compared to those of eligible projects presented in the top section of Table I, while the same statistics on bridge projects do not have a statistically significant difference, exhibiting similar patterns to those of ineligible projects. These trends are again picked up by Figure 2 in plots (C) and (D).

The analysis presented so far is based upon auction level data. One could argue that some systematic group dissimilarities, rather than the adjustment clause, are responsible for the noted disagreement in relative bids. In an effort to clear up this ambiguity, we use itemized level observations to restrict attention to the group of eligible projects only. Itemized bids submitted by a single firm for a particular project are formulated under the same strategic considerations (such as project attributes, competition intensity, profit margin, etc.), relieving us from concerns about confounding errors unobserved by the econometrician. The upper left portion of Table II reproduces auction level characteristics of eligible projects, and the lower left portion contrasts itemized bids of asphalt against non-asphalt items from eligible projects. Mirrored by (E) and (F) of Figure 2, there is a compelling reduction in the bids on policy eligible asphalt items after June 2006, but not for other ineligible items.

[Place Table II about here.]

The last comparison pair, presented on the right part of Table II, employs an even more refined subgroup: projects involving eligible asphalt items and one particular class of ineligible items, namely diesel fuel related inputs. Both asphalt binder and diesel fuel are produced out of crude oil purification, so their costs, and bids accordingly, are intrinsically tied by the common influence of oil price fluctuation.[19] As a result, bid values on the two items are expected to fluctuate similarly throughout in the absence of any asymmetric interference. Nonetheless, we observe in (G) and (H) of Figure 2 that the distribution of fuel items has remained almost identical between periods, while for asphalt items, it has visibly shifted to the left and has become less dispersed in the post policy era, a change that we will argue is caused by the price adjustment applicable to asphalt. While visual inspection of Figure 2 suggests lower bids submitted on projects affected by the clause, we also need to be cautious in our interpretation since we have not yet introduced any controls for auction and rival characteristics, intensity of competition and economic conditions. One way to accomplish this is to utilize the nonparametric technique proposed by Racine and Li [2004] to provide the predicted distributions of bids before and after the policy change across group categories while incorporating various controls.

Maintaining the well-known merits of nonparametric estimations, this new method accommodates both continuous and discrete variables. With the choice of (continuous) bandwidths and (discrete) smoothing parameters based on least squares cross-validation, the Racine and Li method generates projections with higher predictive power than conventional parametric approaches when categorical variables are present. In our case, those variables are the letting months and project

[19] Indeed, prices of asphalt and fuel followed a similar trajectory between 2003 and 2009. Data acquired from Arizona Department of Transportation indicate that diesel fuel and asphalt price indices are closely correlated with a coefficient of 0.79 (see also Figure 1). ODOT did not report diesel fuel index until 2011.

types. In particular, we apply the following model empirically:

$$y_{iat} = g(X_{iat}) + u_{iat},$$

where $X_{iat} = (X^d_{iat}, X^c_{iat})$ represents the groups of continuous and discrete covariates, respectively, and $g(X_{iat})$ is a "mixed" kernel function smoothing over both sets of variables.

[Place Figure 3 about here.]

Projected relative bids ($\widehat{y}_{iat}$) are constructed conditional on the characteristics of bidders, the characteristics of auctions, and the proxies for the state of the general economy, separately for the periods prior to and after the policy change. The detailed description of these variables is provided in Table BI in the Appendix. Density plots of the estimated relative bids, $\widehat{y}_{iat}$, seem to be close enough to the unconditional kernel graphs for all four comparison groups. This is not surprising in consideration of the great similarities in the level of independent variables between pairs (as seen in Table I and Table II). Figure 3 is a presentation of panels contrasting the four comparison groups presented earlier. Discrepancies between treated and control groups continue to arise, both in terms of the shift at the mean level and the changes in the degree of concentration. Relative bids on asphalt paving projects are systematically lower in the period after the policy change, while the ones on bridge work projects remain virtually unchanged. Regarding the third and fourth panels (plots (E)-(H) in Figure 3), bids are both considerably lower and less dispersed upon the introduction of the price indexing policy. Notable differences between bids of treated and untreated items persist, underlying the impact of the policy on bidding.[20]

V. EMPIRICAL TESTS

In this section we apply two approaches to assess quantitatively the impact of the price adjustment clause on bidding and procurement costs. Our primary identification strategy is to use the difference-in-differences (DID) models. Due to few restrictions imposed and its straightforward intuition, the DID method has widely gained popularity among empirical researchers (see Imbens and Wooldridge [2008], Bertrand *et al.* [2004]). It manages to control for factors that are hard to measure otherwise by employing a separate group to approximate the "counterfactual" performance of the treated group. By taking double differences, both the time-invariant group gap and the treatment unrelated time trend are removed, leaving as unaccounted residuals the specific effects credited to the program intervention. Our second approach is to use the regression discontinuity design that capitalizes on the discrete nature of the policy change. This method focuses on treatment of eligible observations within a close neighborhood around the first implementation of the indexing policy.

V(i). *Difference-in-Differences Models*

The institutional details of the asphalt price adjustment clause enable us to apply the difference-in-differences method using data collected from the state of Oklahoma. The legislation provides an easy division of the entire sample based on policy eligibility and time of policy implementation. The standard DID specification, applicable to different subsets and stratifications of the data is set up as follows:

$$y_{iat} = \beta_1 T_t + \beta_2 A_a + \beta_3 (T_t \times A_a) + \mathbf{x}'_{iat}\gamma + \mathbf{z}'_{at}\delta + \mathbf{w}'_t\tau + \alpha_i + \varepsilon_{iat} \tag{3}$$

[20] Kolmogorov-Smirnov tests were performed of the hypotheses that the distributions are the same across predicted bids for all pairs. The test results are supporting the qualitative observations made above.

where each observation represents one bid submitted by firm i, in auction a, at time t. The relative bid, y_{iat}, is the ratio of a bid divided by corresponding engineering cost estimate (ECE) and is established as the main dependent variable to allow comparison among projects of various scales.[21] The time dummy T_t is equal to 1 for the period after June 2006, and the assignment indicator A_a is equal to 1 for projects or items that are adjustment eligible. The coefficient β_1 represents inter-period changes that are common across groups; β_2 absorbs the permanent inter-group difference; and β_3 captures the average distance between treated and controlled bids in the post enactment era. According to theoretical predictions, β_3 is expected to have a negative sign as participants who assume lower risks compete with increased aggressiveness.

The key assumption of the model ensuring unbiased treatment evaluation is that subtracting the difference in bids over time in the control group from that of the treatment group removes unobserved factors simultaneously associated with group assignment and potential outcomes. To this end, we first employ a rich set of independent variables that accommodates observed heterogeneity. We include controls for bidder specific characteristics in $\mathbf{x}$, auction specific characteristics in $\mathbf{z}$, and general economic conditions in $\mathbf{w}$, that encompass most of the established covariates in the literature (see Porter and Zona [1993], Jofre-Bonet and Pesendorfer [2003], DeSilva *et al.* [2003], Bajari and Ye [2003], Bajari *et al.* [2006]). These include the number of competitors, project type indicators, calendar days to complete a project, capacity utilization rates for firms, distance to project location and rival characteristics. Fluctuations in the general economy, relevant for the industry are captured by the seasonally adjusted unemployment rate, and measures of real volume of contracted projects and building permits.[22] All specifications include firm fixed effects and monthly dummies to control for individual idiosyncrasies and periodic cycles.[23] Further, we cluster standard errors by auction to avoid deflation due to latent auction specific residuals.

V(i) i. *Mean Level Estimation*

We start our analysis by considering all auctions in the sample as a benchmark. As was mentioned above, projects are distinguished by the use of selective asphalt materials, so bids on ineligible projects constitutes a natural reference to evaluate the influence of the adjustment clause on bidding behavior for eligible projects.

[Place Table III about here.]

Column (1) of Table III reports estimated coefficients from the base model. Overall, bids received before and after June 2006 are not systematically different judging from β_1. Firms tend to submit higher bids on eligible projects compared to ineligible projects, based on the estimate of β_2. The estimate of interest is the difference-in-difference parameter β_3 which is negative and statistically significant. It indicates that bids on the treatment group are on average 4.6% lower after policy enactment. This reduction is unmatched by bidding behavior in the control group. Such findings are consistent with the qualitative analysis in Section IV. Turning to other explanatory variables, the distance between a contractor and the project site tends to increase bids, as costs (such as the cost of transportation) generally rise with the need for longer commute. The number of bidders provides a good approximation of competition and thus is inversely related to bid values. Rivals' characteristics, including past winning records, distance to project and committed

[21] In an alternative specification, we use log of bids as a dependent variable in the regression. The results are similar across the two specifications. The logbid regression results are available upon request.

[22] Table BI of the Appendix provides detailed description for all.

[23] In the base specification, we also include interactive terms between task types and time periods to allow for additional flexibility in category specific trends.

backlog, all have expected signs, in line with the theory that firms bid more aggressively when faced with strong competitors. Relative bids are shown to fall with unemployment, probably due to the substitutability between government procurement contracts and outside business opportunities (commercial or residential construction). The other two measures of economic activity appear to have statistically insignificant effects on bidding behavior.[24]

We also present a comparison of bidding across project categories. The second column of Table III presents regression results of asphalt paving against bridge construction projects. Estimates are very comparable to those in the first column. While neither the time nor the assignment dummies exhibit significance at 0.1 level, the key parameter β_3 once again turns out to be significant both statistically and economically. The increase in the coefficient estimate from almost 5% in the benchmark case to a 9% here, can be explained by the combination of two factors: 1) the increased use of asphalt items in the new treatment group (almost doubled from 40% to 78%), and 2) a very small asphalt involvement in the new control group (3% across the sample).[25] Rivals' competitiveness, measured by their historical winning to plan-holder ratio, now plays a bigger role in shaping bids. A potential remaining confounding source is the price variation of inputs critical for bridge construction but seldom used in asphalt surfacing (such as reinforcement bars and structural concrete), an oversight of which may result in falsely attributing relevant influences to the policy intervention. The diff-in-diff coefficients prove robust after incorporating monthly price indices on steel and Portland cement to the regression.[26]

Column (3) displays results from the same diff-in-diff regression of column (2) except that we replace bridge construction with traffic signing as the control group. As with bridge projects, signing related work rarely requires asphalt materials (75% of projects have no eligible items) or use them to a limited extent (12% on average of those containing asphalt components, or 3% across the entire sample). Findings suggest substantially lower bids in eligible auctions after the policy enactment.

We now proceed to exploit our unique access to itemized bids and focus only on eligible projects, the treatment group in the benchmark case. Unlike auction level analysis, two dependent variables are constructed out of each eligible project: a weighted average of relative bids from eligible asphalt inputs and one from all other ineligible inputs.[27] If the decline in bids after June 2006 were a result of factors other than the clause affecting treated projects only, there would be no differential effects on itemized asphalt and non-asphalt bids over time. Otherwise, as evidenced by the $\hat{\beta}_3$ in column (1) of Table IV, the unbalanced trend should be attributed to the adjustment clause, which applies exclusively to eligible items. The magnitude of the difference in relative bids after the enactment of the policy rises to 12.7%, consistent with the increase in asphalt percentage between treatment and control groups.[28] Regarding the rest of the regressors, own and rival distance to work, intensity of competition, and unemployment rate carry on their roles in bid determination.

[24]Note that, the low value of R^2 in the regression is mostly attributable to the adoption of relative bid rather than the logarithm of bid as the dependent variable. Since ECEs are highly correlated with contracting costs, standardizing it out of the equation considerably lowers the model's explanatory power. Similar observations are documented in works based on Oklahoma data (De Silva *et al.* [2009]) as well as data from other states (De Silva *et al.* [2008], Bajari *et al.* [2006]).

[25]We argue that the stark difference in asphalt usage and the stability of involvement over time lend support to the selection of bridgework as a control group. An alternative specification, using bridge projects that do not involve eligible items produces similar findings.

[26]We further homogenized the control group of bridge work based on narrower categories of tasks (bridge and approaches, bridge rehabilitation, bridge repair, etc.) and sizes such that the refined groups would have a uniform percentage of steel and cement usage. In either case, findings are consistent with those presented here when the all-bridge sample is employed.

[27]Typically eligible projects contain a number of asphalt and non-asphalt items. We constructed for each group a composite measure of relative bids as the sum of dollar amounts of all items divided by the sum of ECEs.

[28]Here it is 100% treatment vs. 0% control, as opposed to 40% vs. 0% in the base model.

[Place Table IV about here.]

An alternative way to contrast eligible and ineligible items over time is to evaluate the ratio of the two relative bids. Continuing with the notation of the base model, we let y_1 denote relative bids on eligible asphalt items (treated) and y_0 denotes relative bids on ineligible items (untreated). When the two groups of eligible and ineligible components of a project are affected symmetrically, their ratio y_1/y_0 of itemized bids should remain roughly constant through time.[29] In column (2) of Table IV, the ratio y_1/y_0 is shown to project a significant decline in the second period, indicating that relative bids on eligible items have been disproportionately reduced in comparison to the relative bids on ineligible items. Another point worth noting is that rival characteristics matter more as far as bidding ratios are concerned. The fiercer the competition is the less room is left for firms to leverage between the bids on different components.

We further narrow down our analysis to the subgroup of projects that simultaneously involve asphalt and diesel fuel items.[30] In the absence of other driving forces, bids on asphalt are expected to have similar fluctuations to diesel fuel bids, both affected by the ups and downs of crude oil prices. Findings from the data, presented in column (3) & (4) of Table IV, support our earlier observation from the comparison of kernel densities. Prior to the policy change relative bids on asphalt and fuel items were tracking each other closely. However, the enactment of asphalt price adjustment in June of 2006 broke off the original balance by removing excessive uncertainty from asphalt products only. The negative signs on the parameters of interest suggest that bids on treatment items have been significantly reduced compared to untreated fuel bids upon policy implementation. This more refined subsample has also produced the largest β_3 at 14.5%, largely due to the heightened volatility in the price of fuel products experienced around 2008.

V(i) ii. *Bid Dispersion*

Theory predicts that, provided with additional insurance against price uncertainty, contractors will respond by adjusting their bidding strategies. Our results have provided evidence toward predictions related to the first moment: average bids are driven down when participants compete more vigorously. We now consider the second moment to examine whether bids become less dispersed after the policy implementation. We estimate four specifications considering both project and item bids, using this simple linear regression:

$$y_{at} = \alpha_i + \beta_1 T_t + \beta_2 A_a + \beta_3 (T_t \times A_a) + \mathbf{z}'_{at}\delta + \mathbf{w}'_t \tau + \varepsilon_{at} \tag{4}$$

where y_{at} is an indicator of the degree of bid concentration for auction a, at time t. For the first two specifications, "within auction bid dispersion" is employed, equal to the standard deviation of relative bids of a project. For the remaining specifications, the dependent variable is the ratio of two bid dispersions from the same auction, one on asphalt items and one on other (ineligible) items.[31,32] Bidder level heterogeneity is integrated out, leaving auction specific characteristics and general economic conditions as explanatory variables in the regressions. Estimated coefficients

[29] There are some advantages in utilizing this approach. Regressing ratios on the same set of covariates allows more flexibility as independent variables may assume different values for treatment and control groups. Moreover, considering a ratio helps eliminate potential firm-auction specific effects that are common across items but unobserved.

[30] Since diesel fuel is a common material used in most day-to-day constructions, we follow ODOT's classification to qualify only tasks involving fuel items heavily, such as burrow and excavation.

[31] The reason to use ratios is the same one mentioned earlier: since the two sets of bids come from the same auction, these ratios help to eliminate firm-auction specific effects that could potentially be hard to control for.

[32] We excluded projects receiving three or fewer bids to achieve a meaningful within auction dispersion. We also used the bid range, the difference between highest and lowest relative bid, instead of standard deviation and similar (slightly more significant statistically) results prevailed in all cases. The results are available upon request.

are presented in Table V.[33] In columns (1) and (2) relative bids appear to be more dispersed in the second period. Bids on asphalt projects are less dispersed than those on bridge work, in line with the previous literature (see Hong and Shum [2002], Bajari and Ye [2003]). Additionally, observations from the treated group display smaller variance after the policy is enacted, with the difference becoming statistically significant in the second column. From the last two specifications, bids for treated materials have smaller variance as price adjustment clauses reduce the level of uncertainty. Notice that, the change in the bid variance is more pronounced and becomes more visible if you compare asphalt items and fuel items that exhibit greater price uncertainty.

[Place Table V about here.]

V(i) iii. *Quantile Regression Analysis*

[Place Table VI about here.]

In Table VI, we apply quantile regression analysis (see Koenker [2004], [2005], Lamarche [2010]) to investigate more systematically if policy effects vary across the distributions of relative bids. We examine whether the policy has induced a location shift, consistent with the intervention affecting uniformly all bidders, or the impact is restricted to a particular quantile with the scale effects varying across the range. The upper part of Table VI presents regression results at 0.20, 0.5 and 0.80 quantiles derived for all of the four specifications. As in the previous sections, the dependent variable is the relative bid for the first two specifications, and the ratio between relative bids for the other two. The estimates of the parameters capturing policy effects (β_3 in the first two cases and β_1 in the last two) are consistently negative and significant for all three quantiles. An interesting finding is that the difference in coefficients across quantiles of the same model becomes much more prominent for the two specification furnishing itemized bid comparisons. It provides evidence that bidding aggressiveness is a response to the adjustment clause. The lower part of Table VI, presents fixed effects quantile regression estimates. A model with bidders' fixed effects would capture private cost differences among other time invariant latent factors, enabling us to examine more closely the effect of the price adjustment policy on bidding.[34] The results are robust qualitatively and quantitatively providing evidence that policy eligibility is not correlated with the level of firm productivity; policy effects remain virtually the same. This pattern is even more apparent in the four panels presented in Figure 4. While the continuous lines in all graphs show point estimates, the shaded regions represent .95 confidence intervals for these estimates. In Figure 4(A), we present bids on eligible items in comparison to those on ineligible items. Figure 4(B) is a plot of quantile estimates of relative bids after the policy enactment for the last specification contrasting asphalt and fuel items, which reveals that relative bids are reduced by 13.5% at the 0.2 quantile dropping significantly as we move towards the 0.8 quantile. This difference of estimates across the distribution is not surprising considering the daunting uncertainty in the cost of crude oil by-products and the expectation for higher prices. Figures 4(C)-(D) are corresponding plots of fixed effect quantile estimates of relative bids after the policy enactment. Those graphs exhibit similar fluctuations to the quantile regression plots Figure 4 (A)-(B).

[Place Figure 4 about here.]

[33] The variable, "average bidder's winning to plan holding ratio", calculated as the average past winning to plan holding ratio of all participants in an auction, is included as a proxy of competition intensity. It is insignificant and is not reported in the table.

[34] We followed the method of penalized quantile regression to allow flexibility in distributional shifts for each individual.

V(i) iv. *Robustness Checks*

We are now exploring the robustness of mean level estimation results from Section V(i) i. We are taking four directions to address common concerns raised by the literature. The first deals with the potential underestimation of standard errors due to overlooked intra-group or cross time correlation (Moulton [1990]). We follow procedures proposed by Bertrand *et al.* [2004] and collapse the 73-month panel down to two periods, aggregating data by firm and type. Findings similar to those in Tables III & IV are found in Table VII, columns (1) & (6). A second critique of these models is that bid reduction of treatment observations may result from a gradual but steady downward trend rather than the institutional break. In columns (2) & (7) of Table VII, we introduce a trend and an interactive term resulting in insignificant effects. We also examine the sensitivity of our results to the use of the actual number of bidders as an explanatory variable. Two instruments are employed: number of plan-holders and expected number of bidders, both correlated with competition intensity but known to firms before lettings take place. Estimations are displayed in columns (3) & (4) and (8) & (9), where parameters of interest prove robust to this modification. Finally, in column (5) of Table VII, we introduce to the baseline model the proportion of asphalt items in a project as a continuous measure of policy eligibility. The positive and statistically significant parameter indicates that as the proportion of eligible items increases bids are becoming lower.[35]

[Place Table VII about here.]

V(ii). *Regression Discontinuity*

An alternative method to evaluate the ODOT asphalt price indexing policy is through the regression discontinuity designs (RDD). Instead of comparing over time the behaviors of two groups one of which was not subjected to a policy, RDD tracks only the designated targets of a program, and focuses on observations within a close neighborhood around the time when the new policy kicked in. We limit attention to relative bids from eligible projects auctioned off immediately preceding and following June 2006, the time of enactment of the price adjustment clause. The idea is as follows: for lettings taking place right before and after the application of treatment, all factors are assumed to affect bidding behaviors in a smooth, continuous fashion except the institutional break, therefore, any discontinuity in the distribution of relative bids ought to be traced down to the discrete treatment. We apply the sharp regression discontinuity (SRD) framework considering the strict conformity of treatment status with the date variable, and including in the sample only those bidders who participated both before and after the policy change to remove self selection biases. Following the parametric setting of van der Klaauw [2008] and Hahn *et al.* [2001], we apply a linear equation to implement regression discontinuity. We let y_{iat} be the relative bid submitted by firm i in auction a held at time t. A is the dummy variable indicating presence of the adjustment policy, t denotes a continuous time trend, and X_{iat} is the vector of other covariates that includes variables on the characteristics of bidders, the characteristics of rivals, and general economic conditions. Our model is

$$y_{at} = \alpha_i + \beta_1 A + \varsigma_1 t + \varsigma_2 (A \times t) + X_{iat}\gamma + \varepsilon_{iat} \qquad s.t. \quad -h < t - t_0 < h \tag{5}$$

where h denotes the "bandwidth", indicating how far we stretch into the area around the cut-off point in time. Table VIII presents the estimates of β_1, representing discontinuous policy ef-

[35] As suggested by a referee, an additional robustness check was carried out to account for the short lived drop in asphalt index between October 2008 to March 2009. Since such changes were in opposite direction of the overall trend, it could lead to a temporary reversion in expectation. We exclude observations after October 2008 to avoid potential confusion. Results from this alternative setting are consistent with those based on the entire window, and are available upon request.

fects, when several bandwidths are applied.[36] These estimates are consistently negative for asphalt paving work, which intensively involves materials subject to price adjustment, and the coefficients are statistically different from zero when $h = 9$ and $h = 12$. On the other hand, after controlling for the forcing variable of date in bridge work projects, which sparsely contain policy affected items, the dummy variable used for policy presence fails to demonstrate significant impact in all three cases.

[Place Table VIII about here.]

V(iii). *Policy Implications on Procurement Costs*

In order to evaluate the policy effects on government procurement costs in our sample, we estimate the model using the set of winning bids, which is linked directly to ODOT's construction expenditures. Table IX reports on coefficients of the diff-in-diff framework applied to relative winning bids. Each column corresponds to one main specification explored in the previous section. For all four specifications, bids are shown to be significantly lower for the treatment than the control group after the policy enactment, indicating that the policy encourages more aggressive bidding among those who have won.

According to records provided by state engineers, ODOT approved a net payment to contractors of \$17 million between August 2006 and June 2009 in the form of asphalt price adjustments, equivalent to 5.05% of the total contracted value of those items. Since the reimbursement number is based on the subgroup of eligible projects in our analysis, the specification in column (3) of Table IX would be appropriate for calculating counterfactual costs and consequent savings. Suggested by the estimate of β_3, contracted prices of eligible items would have been 11.7% higher in the absence of any adjustment policy. This translates in an estimated potential increase of about \$40 million, resulting in net savings of roughly \$23 million for ODOT during this period.

[Place Table IX about here.]

The extent of potential benefits go beyond the scope of immediate savings in contract payments. Through clearly stipulated rules in the event of significant input price changes, an adjustment clause diminishes the prospects of ex-post negotiations, which are often costly and susceptible to strategic manipulations by contractors (Athey and Levin [2001], Bajari *et al.* [2006], Spulber [1994]). Moreover, indirect costs incurred by claims, disputes and litigations between parties and associated delays of completion motivated the state department to adopt the policy. Indexation of prices reduce the occurrence of such activities and promotes social welfare.

VI. CONCLUDING REMARKS

The introduction of asphalt adjustment clauses in public procurement contracting helps to reduce firms' risks from excessive price volatilities. Yet despite the growing popularity of the new legislation, there has been limited empirical research looking into its overall impact. From a theoretical perspective such a policy has both benefits and costs. This paper seeks to present some empirical evidence on the topic by employing a new detailed data set acquired from the Oklahoma Department of Transportation. The advantage of this data set is that it provides an opportunity to analyze overall project bid differences distinguishing among projects by the level of involvement of eligible items. With the help of unique itemized bidding information, we are also able to assess the policy

[36] Bandwidth selection is based upon the cross-validation criterion (Ludwig and Miller [2007]), and is achieved by minimizing the summed errors between actual and projected values. Nonetheless, it is instructive to see that results are robust to different bandwidth choices.

implication on targeted tasks closely. Our findings lend support to theoretical predictions on bidding behavior, confirming that, when uncertainty is reduced, firms do submit more aggressive bids with lower dispersion in the distribution. Reduction in bid spread is more pronounced and statistically significant for specifications with itemized bids. A comparison between the estimates with and without fixed effects suggests that policy eligibility and firm productivity are not correlated. The policy is not protecting firms that are less productive.

The favorable evidence of policy intervention, however, must be taken cautiously. Construction firms could utilize market instruments available at financial exchanges as an alternative to insure against volatile asphalt prices. Market imperfections[37] and the uncertain nature of demand (a firm does not know its demand with certainty when proposing a bid) increases even more the complexity and costs associated with hedging behaviors, especially for smaller sized firms which constitute the majority of procurement industry participants.[38] In discussions we had with state officials, they thought it was unlikely that firms have used private financial instruments in the past. The final decision on the implementation of price adjustments should account for the trade-off between incentives and efficiency, taking potential differences in risk attitude under consideration (Iossa *et al.* [2007]). Overall, our results point to the positive effects of this intervention. Additional work focusing on long term effects on entrants and small firm (typically facing more uncertainty) is needed to carry out a complete cost-benefit study and provide guidance for policymakers. Assuming that the benefits of this policy outweigh the costs, one would then need to examine the optimality of the threshold value that triggers the subsidy (currently at the 3% level).

APPENDIX

Derivation of Equilibrium Bidding Function

Here, we present how the optimal bidding function is derived. Consider a bidder's expected utility from participation:

$$U(b_{it}) = [b_{it} - s_{it} + E(\eta_{it+1}|s_t \geq B^{-1}(b_{it}))][1 - F_s(B^{-1}(b_{it}))]^{n-1}.$$

Notice that for any random variables Y and X,

$$\frac{\partial}{\partial x}E(Y|X \geq x) = \frac{\partial}{\partial x}\int_x^{x_H} E(Y|X \geq t)\frac{f_x(t)}{1 - F_x(x)}dt.$$

Following Leibnitz's rule for differentiation, we get:

$$\begin{aligned} \frac{\partial}{\partial x}E(Y|X \geq x) &= [\int_x^{x_H} E(Y|X \geq t)\frac{f_x(t)}{1 - F_x(x)}dt - E(Y|X = x)]\frac{f_x(x)}{1 - F_x(x)} \\ &= [E(Y|X \geq x) - E(Y|X = x)]\frac{f_x(x)}{1 - F_x(x)}. \qquad (6) \end{aligned}$$

Differentiating the objective function $U(b_{it})$ with respect to b (using (6)) and evaluating the expres-

[37] There is no standardized futures market for asphalt as a commodity (see page 11 of the Argus media LTD report available at www.ctaa.ca/docs/presentations_2007/2_NasreenEnergyCosts.ppt.)

[38] Small firms are faced with considerable fixed cost for such practices and higher liquidity constraints (see Haushalter [2000]).

sion at the optimal choice we have:

$$\frac{\partial U}{\partial b_{it}}|_{b_{it}=B(x)} = \left[1+[E(\eta_{it+1}|s_t \geq x) - E(\eta_{it+1}|s_t = x)]\frac{1}{B'(x)}\frac{f_s(x)}{1-F_s(x)}\right][1-F_s(x)]^{n-1}$$
$$-[B(x) - s_{it} + E(\eta_{it+1}|s_t \geq x)](n-1)[1-F_s(x)]^{n-2} f_s(x)\frac{1}{B'(x)} = 0.$$

Simplifying we get:

$$\left[\frac{B'(x)}{n-1}\frac{1-F_s(x)}{f_s(x)} + \frac{1}{n-1}[E(\eta_{it+1}|s_t \geq x) - E(\eta_{it+1}|s_t = x)]\right]$$
$$-B(x) + s_{it} - E(\eta_{it+1}|s_t \geq x) = 0. \tag{7}$$

We can now show that the following function is indeed the symmetric equilibrium bidding strategy for bidder i in the first price auction:

$$B(x) = -E(\eta_{it+1}|s_t \geq x) + E(y_{1t}|y_{1t} \geq x). \tag{8}$$

Differentiating this expression we get:

$$B'(x) = -[E(\eta_{it+1}|s_t \geq x) - E(\eta_{it+1}|s_t = x)]\frac{f_s(x)}{1-F_s(x)} + [E(y_{1t}|y_{1t} \geq x) - x]\frac{f_{y_1}(x)}{1-F_{y_1}(x)}. \tag{9}$$

Using the fact that $f_{y_1}(x) = (n-1)(1-F_s(x))^{n-2} f_s(x)$ and $1 - F_{y_1}(x) = (1-F_s(x))^{n-1}$ which implies that $\frac{f_{y_1}(x)}{1-F_{y_1}(x)} = \frac{(n-1)f_s(x)}{1-F_s(x)}$, and replacing (8) and (9) into (7) we get:

$$-\frac{1}{n-1}[E(\eta_{it+1}|s_t \geq x) - E(\eta_{it+1}|s_t = x)] + [E(y_{1t}|y_{1t} \geq x) - x] + \frac{1}{n-1}[E(\eta_{it+1}|s_t \geq x)$$
$$-E(\eta_{it+1}|s_t = x)] + E(\eta_{it+1}|s_t \geq x) - E(y_{1t}|y_{1t} \geq x) + s_{it} - E(\eta_{it+1}|s_t \geq x) = 0.$$

$\iff s_{it} = x$.
Together with the monotonicity of B, we show that $B(s_{it})$ is the bidder's unique optimal strategy, i.e.:

$$B(s_{it}) = E(y_{1t}|y_{1t} \geq s_{it}) - E(\eta_{it+1}|s_t \geq s_{it}).$$

The Effect of λ on the Variance of Bids
The variance of bids is:

$$V[B(s_{it}|\lambda)] = V[E(y_{it}|y_{it} \geq s_{it}, \lambda) - E(\eta_{it+1}|s_t \geq s_{it})]$$
$$= V[E(y_{it}|y_{it} \geq s_{it}, \lambda)] + V[E(\eta_{it+1}|s_t \geq s_{it})] - 2cov[E(y_{it}|y_{it} \geq s_{it}, \lambda), E(\eta_{it+1}|s_t \geq s_{it})].$$

Taking the derivative of the variance with respect to the policy threshold yields:

$$\frac{\partial V[B(s_{it}|\lambda)]}{\partial \lambda} = \frac{\partial V[E(y_{it}|y_{it} \geq s_{it}, \lambda)]}{\partial \lambda} + \frac{\partial V[E(\eta_{it+1}|s_t \geq s_{it})]}{\partial \lambda}$$
$$-2\frac{\partial cov[E(y_{it}|y_{it} \geq s_{it}, \lambda), E(\eta_{it+1}|s_t \geq s_{it})]}{\partial \lambda} > 0.$$

Note that, the second term in this expression is zero. The covariance is negative and becomes more so as λ increases since $E(y_{it}|y_{it} \geq s_{it}, \lambda)$ increases in λ while $E(\eta_{it+1}|s_t \geq s_{it})$ is unaffected.

REFERENCES

Athey, S. and Levin, J., 2001, 'Information and Competition in U.S. Forest Service Timber Auctions,' *Journal of Political Economy*, 109(2), pp. 375–417.

Bajari, P. and Ye, L., 2003, 'Deciding Between Competition and Collusion,' *Review of Economics and Statistics*, 85(4), pp. 971–989.

Bajari, P.; Houghton, S. and Tadelis, S., 2006, 'Bidding for Incomplete Contracts: An Empirical Analysis,' NBER working papers 12051.

Bajari, P.; McMillan, R. and Tadelis, S., 2009, 'Auctions Versus Negotiations in Procurement: an Empirical Analysis,' *Journal of Law, Economics, and Organization*, 25(2), pp. 372–399.

Bertrand, M.; Duflo, E. and Mullainathan, S., 2004, 'How Much Should We Trust Differences-in-Differences Estimates?' *Quarterly Journal of Economics*, 119(1), pp. 249–75.

Crocker, K. J. and Reynolds, K. J., 1993, 'The Efficiency of Incomplete Contracts: An Empirical Analysis of Air Force Engine Procurement,' *RAND Journal of Economics*, 24(1), pp. 126–146.

De Silva, D. G.; Dunne, T. and Kosmopoulou, G., 2003, 'An Empirical Analysis of Entrant and Incumbent Bidding in Road Construction Auctions,' *Journal of Industrial Economics*, 51(3), pp. 295–316.

De Silva, D. G.; Dunne, T.; Kankanamge, A. and Kosmopoulou, G., 2008, 'The impact of public information on bidding in highway procurement auctions,' *European Economic Review*, 52(1), pp. 150–181.

De Silva, D. G.; Dunne, T.; Kosmopoulou, G. and Lamarche, C., 2010, 'Disadvantaged Business Enterprise Goals in Government Procurement Contracting: An Analysis of Bidding Behavior and Costs,' Working Paper.

De Silva, D. G., Kosmopoulou, G. and Lamarche, C., 2009, 'The Effect of Information on the Bidding And Survival of Entrant in the Procurement Auctions,' *Journal of Public Economics*, 93(1), pp. 56–72.

Decarolis, F., 2009, 'When the Highest Bidder Loses the Auction: Theory and Evidence from Public Procurement,' Temi di discussione (Economic Working Papers) 717, Bank of Italy, Economic Research and International Relations Area.

Eckert, C. and Eger, R., 2004, 'A Study of Liquid Asphalt Price Indices Applications to Georgia Pavement Contracting,' Georgia Tech Research Institute A-7319 no.2.

Goeree, J. K. and Offerman, T., 2003, 'Competitive Bidding in Auctions with Private and Common Values,' *Economic Journal*, 113(489), pp. 598–613.

Hahn, J.; Todd, P. and van der Klaauw, W., 2001, 'Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design,' *Econometrica*, 69(1), pp. 201–209.

Haushalter, G. D., 2000, 'Financing Policy, Basis Risk, and Corporate Hedging: Evidence from Oil and Gas Producers,' *Journal of Finance*, 55(1), pp. 107–152.

Holt, C. A. J., 1979, 'Uncertainty and the Bidding for Incentive Contracts,' *American Economic Review*, 69(1), pp. 697–705.

Hong, H. and Shum, M., 2002, 'Increasing Competition and the Winner's Curse: Evidence form Procurement,' *Review of Economic Studies*, 69, pp. 871–898.

Imbens, G. M. and Wooldridge, J. M., 2008, 'Recent Developments in the Econometrics of Program Evaluation,' NBER Working Paper 14251.

Iossa, E.; Spagnolo, G. and Vellez, M., 2007, 'Public-Private Partnerships,' Report prepared for the World Bank.

Jofre-Bonet, M. and Pesendorfer, M., 2003, 'Estimation of a Dynamic Auction Game,' *Econometrica*, 71(5), pp. 1443–1489.

Koenker, R., 2004, 'Quantile Regression for Longitudinal Data,' *Journal of Multivariate Analysis*, 91(1), pp. 74–79.

Koenker, R., 2005, *Quantile Regression*(Cambridge Books, New York).

Lamarche, C., 2010, 'Robust Penalized Quantile Regression Estimator for Panel Data,' *Journal of Econometrics*, 157, pp. 396–408.

Ludwig, J. and Miller, D. L., 2007, ‘Does Head Start Improve Children’s Life Chances? Evidence from a Regression Discontinuity Design,’ *The Quarterly Journal of Economics*, 122(1), pp. 159–208.

Marion, J. ,2007, ‘Are Bid Preferences Benign? The Effect of Small Business Subsidies in Highway Procurement Auctions,’ *Journal of Public Economics*, 91, pp. 1591–1624.

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), pp. 334–338.

Naegelen, F. and Mougeot, M., 1998, ‘Discriminatory Public Procurement Policy and Cost Reduction Incentives,’ *Journal of Public Economics,* 67(2), pp. 349–367.

Porter, R. H. and Zona, J. D., 1993, ‘Detection of Bid Rigging in Procurement Auctions,’ *Journal of Political Economy*, 101(3), pp. 518–538.

Racine, J. and Li, Q., 2004, ‘Nonparametric Estimation of Regression Functions with Both Categorical and Continuous Data,’ *Journal of Econometrics*, 119(1), pp. 99–130.

Spulber, D. F., 1994, ‘Economic Analysis and Management Strategy: A Survey Continued,’ *Journal of Economics & Management Strategy*, 3(2), pp. 355–406.

Thomas, C. J. and Wilson, B. J., 2002, ‘A Comparison of Auctions and Multilateral Negotiations,’ *RAND Journal of Economics*, 33(1), pp. 140–155.

van der Klaauw, W., 2008, ‘Regression-Discontinuity Analysis: A Survey of Recent Developments in Economics,’ *Labour*, 22(2), pp. 219–248.

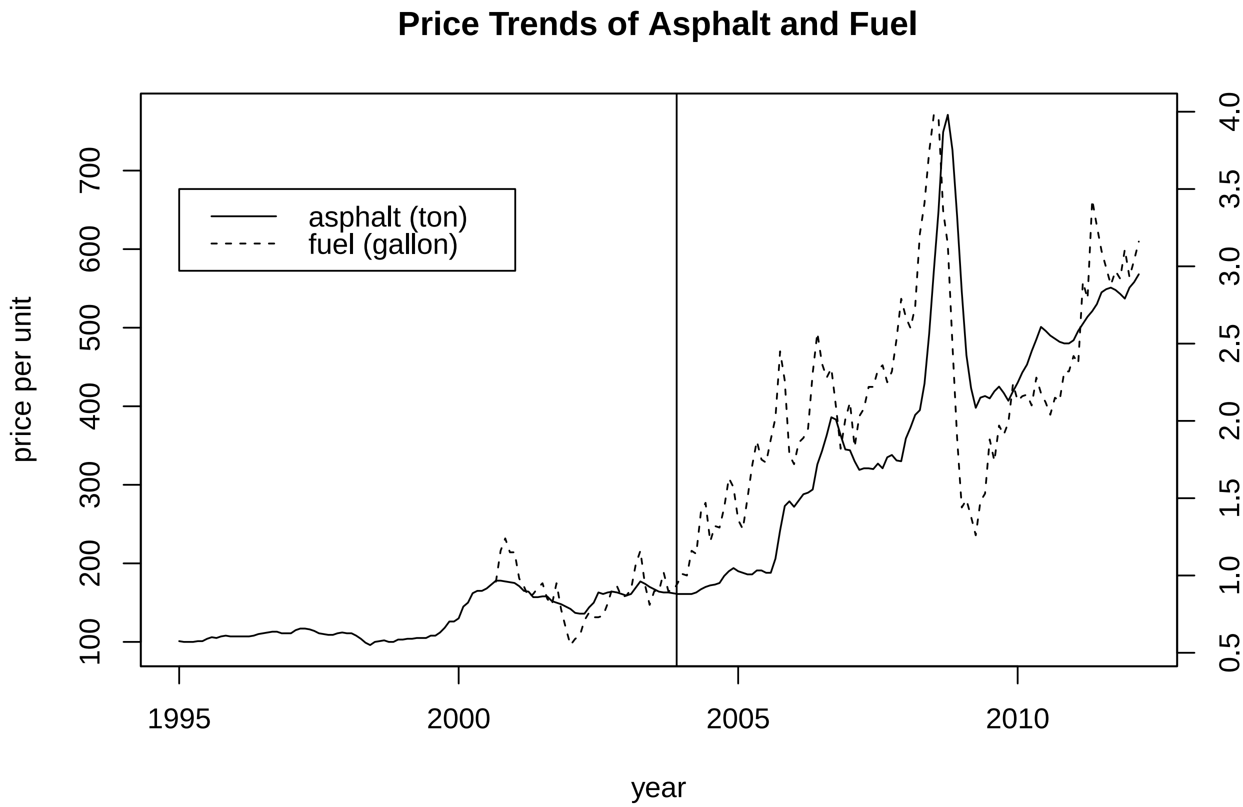

Figure 1: Time series plot of asphalt and fuel price indices. Source: Arizona Department of Transportation. The left scale indicates asphalt prices ($/ton) and the right scale fuel prices ($/gallon). The vertical line represents the beginning of our data collection period.

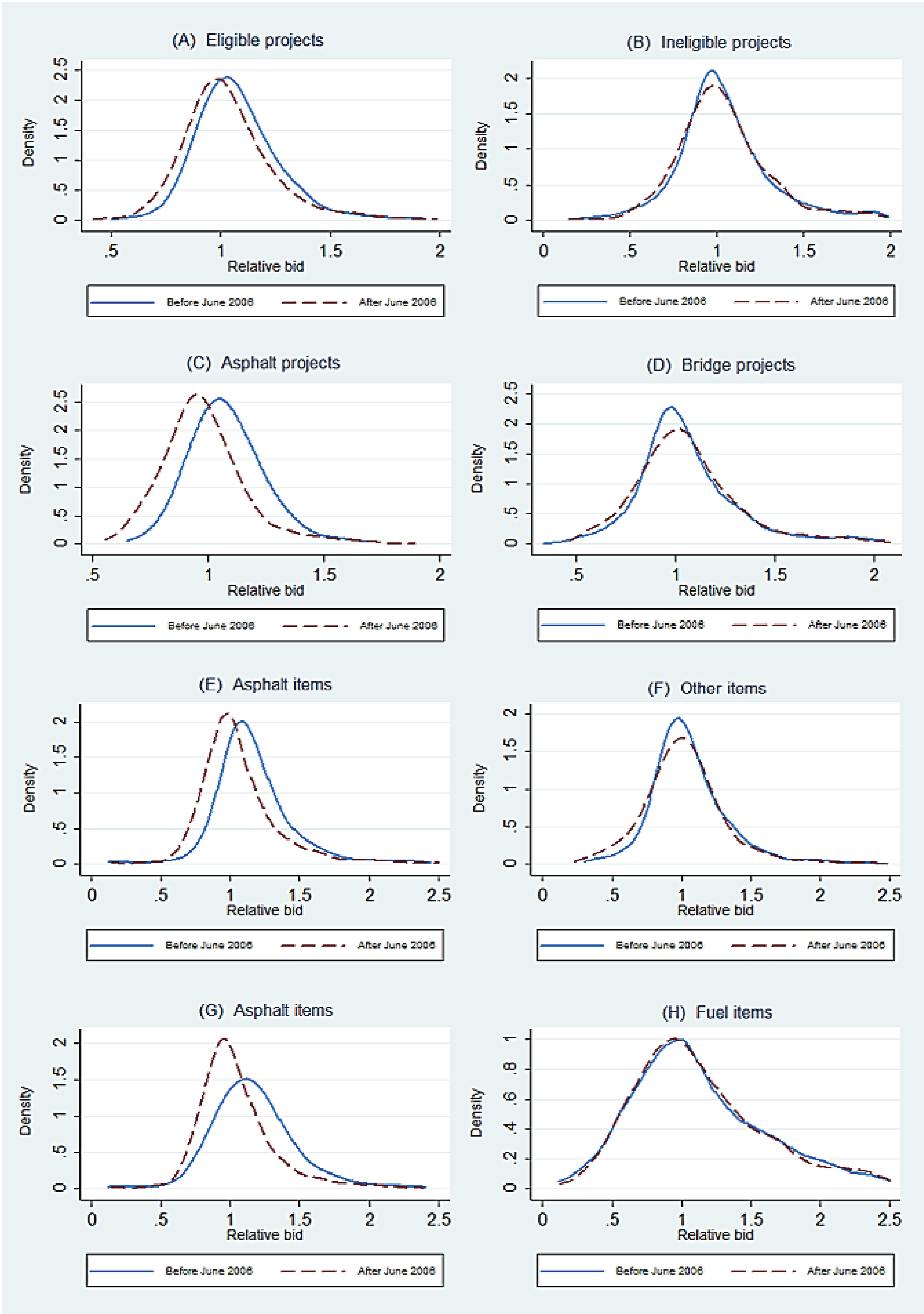

Figure 2: Unconditional kernel densities

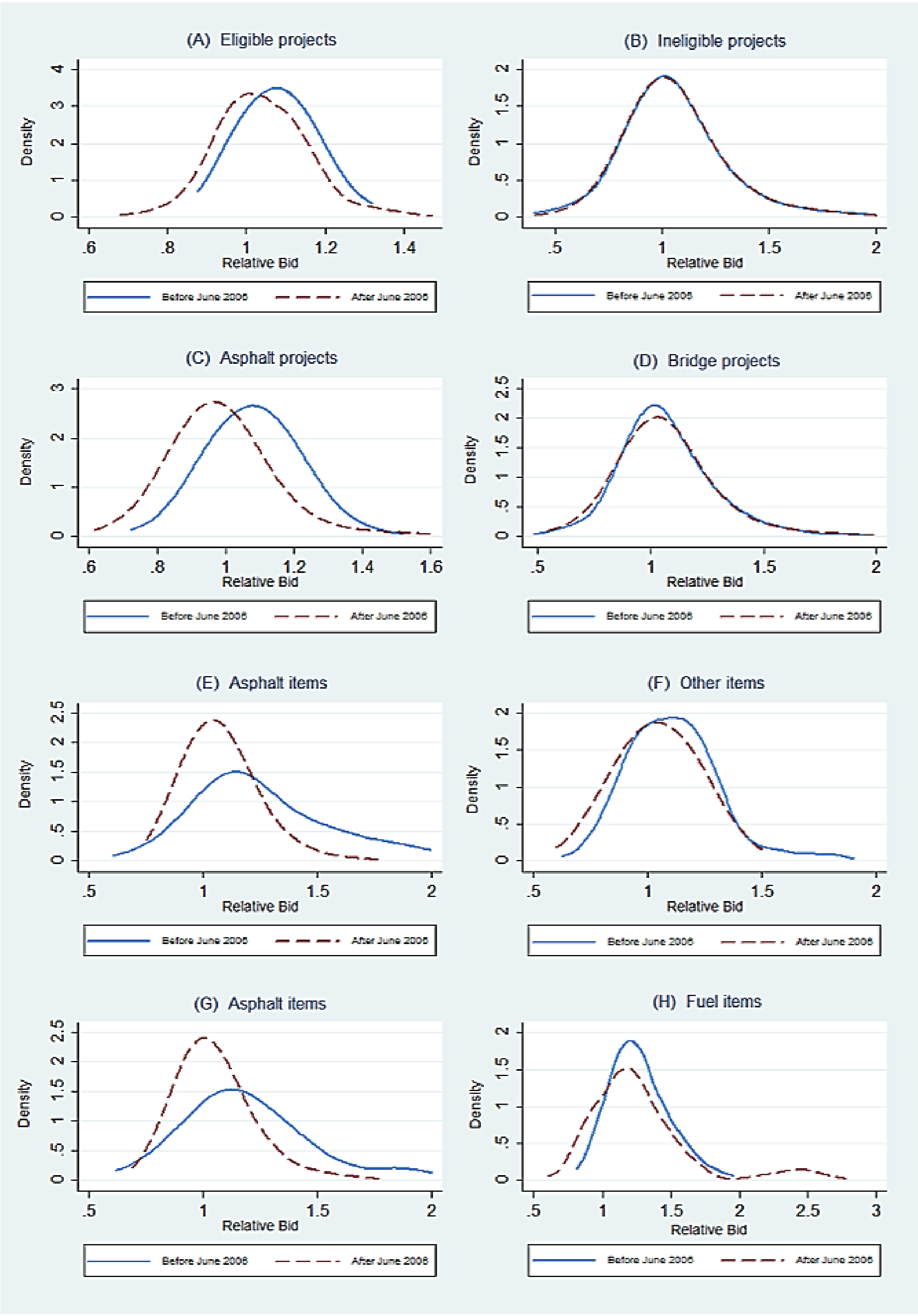

Figure 3: Conditional kernel densities

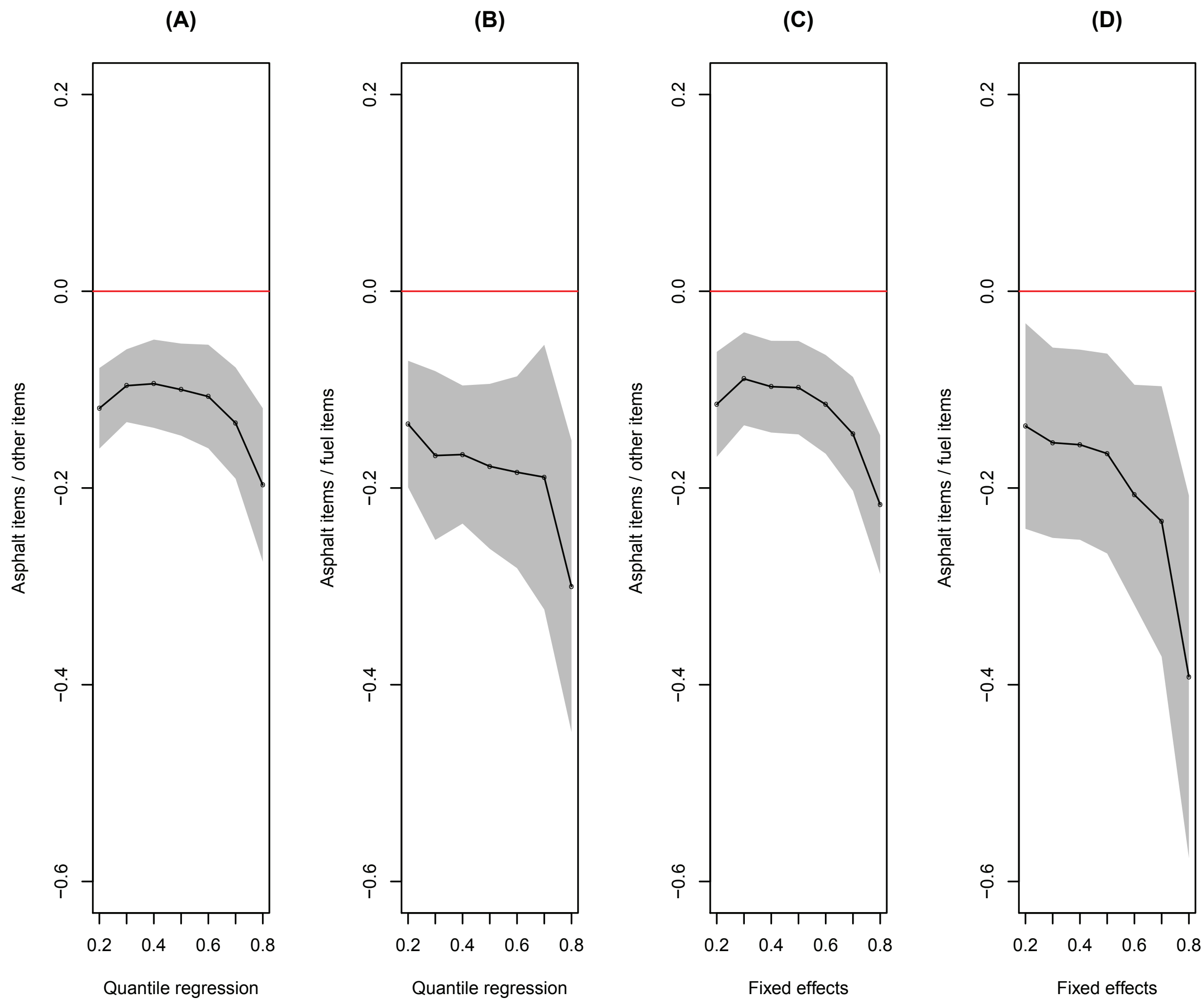

Figure 4: Quantile regression and fixed effects quantile regression results on relative bids. Continuous lines show the point estimates, and shaded area represents a 0.95 (pointwise) confidence interval.

Table I: Summary statistics of project bids.

Variables	Comparison groups			
	All projects (base model)			
	eligible		ineligible	
	before	after	before	after
Number of contracts auctioned off	396	622	377	489
Percentage of asphalt items per auction	41.8	39.8	0	0
	(34.2)	(33.4)	n/a	n/a
Number of calendar days allocated	149.2	163.4	94.3	101.7
	(112.5)	(114.9)	(73.6)	(70.2)
Number of plan holders per auction	6.439	6.362	5.942	6.029
	(3.315)	(2.987)	(2.418)	(2.716)
Number of bidders per auction	3.207	3.270	3.490	3.527
	(1.468)	(1.622)	(1.573)	(1.597)
Expected number of bidders per auction	3.642	3.577	3.285	3.339
	(1.770)	(1.691)	(1.449)	(1.526)
Average value of relative bid	1.078	1.038	1.065	1.093
	(0.195)	(0.235)	(0.343)	(0.624)
Average value of winning relative bid	1.003	0.961	0.913	0.940
	(0.152)	(0.163)	(0.216)	(0.500)
	Asphalt and bridge type			
	asphalt paving		bridge construction	
	before	after	before	after
Number of contracts auctioned off	182	268	354	431
Percentage of asphalt items per auction	78.9	75.7	10.2	12.8
	(17.8)	(21.7)	(7.9)	(8.1)
Number of calendar days allocated	92.9	100.7	114.6	119.0
	(64.3)	(70.8)	(77.8)	(77.8)
Number of plan holders per auction	4.798	5.011	6.522	6.591
	(2.457)	(2.427)	(2.418)	(2.562)
Number of bidders per auction	2.820	3.011	3.710	3.812
	(1.254)	(1.525)	(1.617)	(1.843)
Expected number of bidders per auction	2.688	2.779	3.668	3.749
	(1.241)	(1.361)	(1.366)	(1.509)
Average value of relative bid	1.079	0.986	1.084	1.077
	(0.154)	(0.157)	(0.324)	(0.347)
Average value of winning relative bid	0.992	0.921	0.947	0.955
	(0.115)	(0.153)	(0.202)	(0.208)

Standard deviations are in parenthesis. For variable definition and construction, refer to Table BI.

Table II: Summary statistics of itemized bids.

Variables	Comparison groups							
	projects with asphalt items				projects with asphalt and fuel items			
	before		after		before		after	
Number of contracts auctioned off	396		622		241		346	
Percentage of asphalt items per auction	41.8 (34.2)		39.8 (33.4)		31.8 (27.4)		25.6 (22.1)	
Number of calendar days allocated	149.2 (112.5)		163.4 (114.9)		196.3 (118.0)		210.6 (121.8)	
Number of plan holders per auction	6.439 (3.315)		6.362 (2.987)		7.232 (3.298)		7.220 (3.153)	
Number of bidders per auction	3.207 (1.468)		3.270 (1.622)		3.320 (1.520)		3.341 (1.689)	
Expected number of bidders per auction	3.642 (1.770)		3.577 (1.691)		4.074 (1.902)		4.076 (1.782)	
	asphalt items	other items	asphalt items	other items	asphalt items	fuel items	asphalt items	fuel items
Average value of relative bid	1.272 (0.857)	1.114 (0.831)	1.075 (0.386)	1.104 (0.679)	1.273 (0.902)	1.255 (0.767)	1.042 (0.331)	1.235 (0.792)
Average value of winning relative bid	1.195 (0.763)	0.991 (0.322)	1.103 (0.334)	0.941 (0.289)	1.182 (0.702)	1.075 (0.638)	1.015 (0.335)	1.092 (0.670)

Standard deviations are in parenthesis. For variable definition and construction, refer to Table A1.

Table III: Fixed effects diff-in-diff regressions of project level bids.

Variables	Base model with asphalt vs. no asphalt (1)	Across task types: asphalt paving vs. bridge construction (2)	Across task types: asphalt paving vs. traffic signing (3)
Bids after policy enactment (β_1)	0.007(0.031)	-0.035(0.026)	0.020(0.035)
Bids from treatment group (β_2)	0.046**(0.017)	0.039(0.035)	-0.099**(0.043)
Bids from treatment group after policy enactment (β_3)	-0.046*(0.025)	-0.090**(0.039)	-0.125**(0.042)
Capacity utilization rate	0.044*(0.025)	-0.012(0.016)	-0.008(0.018)
Distance to project location	0.018**(0.008)	0.017**(0.005)	0.024**(0.004)
Number of bids submitted	-0.018**(0.003)	-0.022**(0.003)	-0.009*(0.004)
Average rivals' winning to plan holding ratio	-0.047(0.217)	-0.388**(0.148)	-0.060(0.117)
Closest rival's distance to project location	0.003(0.008)	-0.001(0.006)	0.016**(0.004)
Rivals' minimum backlog	0.002*(0.001)	0.033**(0.009)	0.002*(001)
Seasonally adjusted unemployment rate	-0.048**(0.009)	-0.005(0.022)	-0.059**(0.010)
Three month average of real volume of projects	0.007(0.017)	-0.007(0.035)	-0.021(0.021)
Three month average of number of building permits	-0.020(0.028)	-0.085**(0.035)	-0.009(0.038)
Number of observations	6441	4239	1674
Adjusted R^2	0.029	0.057	0.151

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] Clustered standard errors by auction are provided. All regressions include firm fixed effects, categorical and monthly dummy variables.

In the base model (1) category specific trends are allowed. In cross type model (2), steel and Portland cement indices are included.

Table IV: Fixed effects diff-in-diff regressions of itemized bids.

Variables	Asphalt items vs. Other items		Asphalt items vs. Fuel items	
	relative bid	ratio	relative bid	ratio
	(1)	(2)	(3)	(4)
Bids after policy enactment (β_1)	-0.094*(0.051)	-0.241**(0.044)	0.015(0.036)	-0.254**(0.054)
Bids from treatment group (β_2)	0.106**(0.056)		-0.018(0.045)	
Bids from treatment group after policy enactment (β_3)	-0.127**(0.056)		-0.145**(0.038)	
Capacity utilization rate	0.008(0.037)	-0.048(0.053)	0.034(0.040)	-0.055(0.062)
Distance to project location	0.013**(0.006)	-0.008(0.012)	0.011(0.009)	0.008(0.014)
Number of bids submitted	-0.010*(0.005)	0.006(0.008)	0.022**(0.005)	0.030(0.480)
Average rivals' winning to plan holding ratio	-0.009(0.021)	-0.852**(0.365)	0.103(0.268)	-0.032**(0.009)
Closest rival's distance to project location	0.031**(0.008)	0.018**(0.010)	-0.003(0.009)	0.038**(0.012)
Rivals' minimum backlog	0.001(0.001)	0.006**(0.003)	0.002(002)	0.002(0.003)
Seasonally adjusted unemployment rate	-0.057**(0.011)	-0.008(0.018)	-0.037**(0.014)	-0.024(0.022)
Three month average of real volume of projects	-0.033(0.022)	0.121**(0.044)	0.029(0.027)	0.066(0.052)
Three month average of number of building permits	-0.035(0.036)	-0.131**(0.063)	0.032(0.045)	0.111(0.077)
Number of observations	6585	3284	3884	1939
Adjusted R^2	0.041	0.032	0.040	0.056

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] Clustered standard errors by auction are provided. All regressions include firm fixed effects, categorical and monthly dummy variables.

Table V: Dispersion of relative bids.

Variables	Base model (1)	Asphalt paving vs. Bridge construction (2)	Asphalt items/ Other items (3)	Asphalt items/ Fuel items (4)
Bids after policy enactment (β_1)	0.023(0.037)	0.305(0.345)	-0.073*(0.039)	-0.083*(0.051)
Bids from treatment group (β_2)	-0.056*(0.032)	-0.020(0.047)		
Bids from treatment group after policy enactment (β_3)	-0.028(0.027)	-0.062*(0.036)		
Number of bids submitted	-0.012(0.008)	-0.009(0.007)	-0.101(0.135)	-0.009(0.015)
Seasonally adjusted unemployment rate	0.001(0.013)	0.021(0.018)	-0.108(0.180)	-0.009(0.021)
Three month average of real volume of projects	-0.034(0.034)	-0.014(0.030)	-0.763(0.489)	-0.010(0.052)
Three month average of number of building permits	0.040(0.052)	0.072(0.065)	-0.015(0.065)	-0.148*(0.082)
Number of observations	777	533	381	203
Adjusted R^2	0.114	0.107	0.021	0.077

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] Clustered standard errors by auction are provided. All regressions include firm fixed effects, categorical and monthly dummy variables. In the base model (1) category specific trends are allowed. In cross type model (2), steel and Portland cement indices are included.

[c] For itemized regressions in columns (3)&(4), two observations arise from each project, with the 3 exceptions that use 100% eligible asphalt items excluded.

Table VI: Quantile regression results for relative bids.

Variable	Base model			Asphalt vs. bridge			Asphalt items/other items			Asphalt items/fuel items		
	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Method:Quantile Regression												
Bids after policy	-0.014	-0.015	-0.023	-0.020	-0.023	-0.028	-0.119**	-0.100**	-0.192**	-0.135**	-0.178**	-0.300**
enactment (β_1)	(0.013)	(0.013)	(0.027)	(0.024)	(0.023)	(0.022)	(0.021)	(0.024)	(0.040)	(0.033)	(0.043)	(0.076)
Bids from treatment	0.074**	0.061**	0.034**	0.139	0.031	-0.016						
group (β_2)	(0.010)	(0.010)	(0.017)	(0.132)	(0.016)	(0.013)						
Bids from treatment	-0.041**	-0.050**	-0.053**	-0.085**	-0.102**	-0.112**						
after enactment (β_3)	(0.013)	(0.011)	(0.022)	(0.036)	(0.036)	(0.033)						
No. of observations	6441	6441	6441	4239	4239	4239	3284	3284	3284	1956	1956	1956
Method: Fixed Effects Quantile Regression												
Bids after policy	-0.020	-0.017	-0.015	-0.026	-0.036	-0.016	-0.115**	-0.098**	-0.217**	-0.137**	-0.165**	-0.392**
enactment (β_1)	(0.015)	(0.016)	(0.024)	(0.017)	(0.027)	(0.020)	(0.024)	(0.036)	(0.021)	(0.54)	(0.052)	(0.095)
Bids from treatment	0.078**	0.070**	0.047**	0.095**	0.013	-0.030						
group (β_2)	(0.011)	(0.014)	(0.017)	(0.046)	(0.024)	(0.033)						
Bids from treatment	-0.048**	-0.046**	-0.059**	-0.108**	-0.105**	-0.142**						
after enactment (β_3)	(0.016)	(0.015)	(0.019)	(0.016)	(0.013)	(0.026)						
No. of observations	6441	6441	6441	4239	4239	4239	3284	3284	3284	1956	1956	1956

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] All regressions include monthly dummy variables. In the base model (1-3) category specific trends are allowed. In cross type model (4-6), steel and Portland cement indices are included.

Table VII: Alternative specifications for robustness checks.

Variables	Base model					Asphalt items vs. Other items			
			relative	bid		relative bid		ratio of relative bids	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bids after policy enactment (β_1)	0.113**		-0.005	-0.001	0.001	-0.014		-0.186**	-0.191**
	(0.056)		(0.031)	(0.031)	(0.023)	(0.050)		(0.039)	(0.039)
Bids from treatment group (β_2)	0.035	-0.033	0.056**	0.055**		0.107**	0.184**		
	(0.036)	(.031)	(0.017)	(0.017)		(0.031)	(.056)		
Bids from treatment after policy enactment (β_3)	-0.073**		-0.047**	-0.045*		-0.121**			
	(0.037)		00.025)	(0.024)		(0.041)			
Time		-0.008					0.033		
		(0.009)					(0.024)		
Time* bid from treatment		0.003*					-0.004		
		(0.002)					(0.004)		
Number of plan holders			-0.015**					-0.022**	
			(0.003)					(0.005)	
Expected number of bids				-0.023**					-0.043**
				(0.004)					(0.008)
Proportion of eligible items					0.108**				
					(0.045)				
Proportion of eligible items from projects after enactment					-0.128**				
					(0.028)				
Number of observations	904	2585	6441	6441	6441	901	2530	3284	3284
Adjusted R^2	0.029	0.094	0.042	0.044	0.042	0.096	0.059	0.038	0.040

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] All regressions include monthly dummy variables. In the baseline specifications (1),(3),(4), category specific trends are allowed.

Table VIII: RD fixed effects of project relative bid from asphalt and bridge types.

Bandwidth	Dependent variable: project relative bid from asphalt and bridge types	
	asphalt paving	bridge construction
6 months	-0.442	0.103
	(2.007)	(1.809)
9 months	-0.770*	0.069
	(0.390)	(0.449)
12 months	-0.659*	0.263
	(0.365)	(0.436)

* denotes statistical significance at 10% level. Robust clustered standard errors by firms are provided.
Number of observations and adjusted R^2 for the three specifications are 157(0.2130), 267 (0.1889), 280(0.1879); and 627(0.0155), 871 (0.0360), 1117(0.0432) for asphalt paving and bridge construction respectively.

Table IX: Fixed effects diff-in-diff regressions of winning bids.

Variables	Base model (1)	Asphalt paving vs. Bridge construction (2)	Asphalt items vs. Other items (3)	Asphalt items vs. Fuel items (4)
Bids after policy enactment (β_1)	0.062(0.057)	0.005(0.039)	-0.066*(0.040)	-0.033(0.057)
Bids from treatment group (β_2)	0.082**(0.020)	-0.027(0.196)	0.205**(0.028)	-0.093**(0.038)
Bids from treatment group after policy enactment (β_3)	-0.111**(0.044)	-0.113**(0.051)	-0.117**(0.036)	-0.149**(0.049)
Capacity utilization rate	0.023(0.054)	-0.023(0.029)	-0.012(0.045)	-0.010(0.065)
Distance to project location	0.014(0.018)	0.006(0.008)	0.003(0.010)	-0.006(0.013)
Number of bids submitted	-0.028**(0.004)	-0.032**(0.003)	-0.015**(0.007)	-0.034**(0.010)
Average rivals' winning to plan holding ratio	-0.142(0.174)	-0.139(0.109)	-0.270(0.245)	-0.010(0.039)
Closest rival's distance to project location	0.019*(0.011)	0.004(0.005)	0.013(0.008)	0.000(0.011)
Rivals' minimum backlog	0.002(0.012)	0.002(0.001)	0.001(002)	0.002(003)
Seasonally adjusted unemployment rate	-0.048**(0.017)	-0.018**(0.010)	-0.043**(0.015)	-0.056**(0.023)
Three month average of real volume of projects	-0.012(0.020)	-0.015(0.019)	-0.051(0.035)	-0.045(0.052)
Three month average of number of building permits	-0.049*(0.027)	-0.023(0.035)	-0.081*(0.049)	-0.026(0.071)
Number of observations	1884	1226	2030	1164
Adjusted R^2	0.048	0.165	0.079	0.053

[a] ** denotes statistical significance at 5% and * denotes statistical significance at 10%.

[b] Clustered standard errors by auction are provided. All regressions include firm fixed effects, categorical and monthly dummy variables. In the base model (1) category specific trends are allowed. In cross type model (2), steel and Portland cement indices are included.

[c] For itemized regressions in column (3)&(4), two observations arise from each project, with the 3 exceptions that use 100% eligible asphalt items excluded.

Table BI: Regression Variables

Variable	Description and Construction of the Variable
Relative bid	Bid divided by engineer's estimated cost.
Itemized bid	A firm submits bids for an exhaustive list of materials used in each project. The project bid equals the weighted sum of unit prices (the bids) and quantities allocated to each item on the list. Itemized bids simply refer to these detailed bids at item level. As opposed to the total bid, a project could have more than 1 itemized bid when it uses multiple items for construction, which is the norm.
Within auction bid dispersion	This variable measures the dispersion of bids submitted in an auction, taking the value of standard deviation of relative bids.
Eligible projects	Projects use bituminous products prescribed in ODOT special provision 109.12.
Eligible items	Bituminous AC products prescribed in ODOT special provision 109.12; used interchangeably with "asphalt items" and "bituminous items".
Bids after policy enactment	A dummy variable that identifies bids submitted after June 2006.
Bids from treatment group	A dummy variable that identifies bids from a group subject to policy influences involving eligible items. The only exception is in the comparison between "bridge" and "signing" projects.
Bids from treatment group after policy enactment	A dummy variable identifying bids from a group subject to policy influences for auctions held after June 2006.
z	*Auction Specific Characteristics*
Number of plan holders	The number of firms who have purchased plans and qualified as potential bidders for a project prior to the actual auction.
Number of bidders	The number of firms who have submitted bids; used interchangeably with "number of bids submitted".
Expected number of bidders	Based on its own bidding records of the past 12 month, each firm is assigned a probability of submitting bids conditional on being a plan holder. Consequently, the expected number of bidders in an auction is the summation of the entry probabilities for all firms that hold plans. See De Silva *et al.* [2008].
Project type dummies	All projects are categorized into seven groups based on brief descriptions provided by ODOT, which are asphalt paving, bridge related work, traffic signing and lighting, grading and draining, clearance, concrete work, and miscellaneous projects such as landscaping. The omitted group in regression is miscellaneous projects.
Calendar days	The number of calendar days that are needed to complete the project according to the plans.

Table continues on next page...

...Table BI Continued: Regression Variables

Variable	Description and Construction of the Variable
x	*Bidder Specific Characteristics*
Capacity utilization rate	The ratio of a firm's current backlog over its capacity. Projects are assumed to be completed in a uniform fashion over its designated contract time. A project's backlog equals the monetary value of yet to be finished part. A firm's backlog equals the sum of backlog values from all of its ongoing projects, which goes to zero upon completion of engaged work and becomes positive when new ones are undertaken. A firm's capacity is assumed to be the maximum of its backlog amounts during the sample period. Historical bidding records (Sep 2001 to Aug 2003) are used to calculate the initial values of capacity utilization rate. For firms that have not undertaken any projects, this variable is set to 0. See also Porter and Zona [1993].
Distance to project location	The logarithm of distance (in mile) between the city where the firm's is located and the city where the project is located. City location is represented by the longitude and latitude of its center. See Porter and Zona [1993].
Average rivals winning to plan holder ratio (ARWP)	ARWP captures the average success rate of rivals' past bidding. First a ratio of winning times to plan holding times in the past 12 months is created for each firm (note that this is a moving window and updated monthly). Then the average of rivals' ratios gives the ARWP for a firm faced with a particular set of competitors. This variable incorporates two aspects of rivals' behaviors: the probability of bidding conditional on purchasing a plan and the probability of winning conditional on bidding. See Jofre-Bonet and Pesendorfer [2003] and De Silva *et al.* [2003].
Rival's minimum distance to work site	The logarithm of distance (in mile) from the work site to the location of the closet rival. See Bajari and Ye [2003].
Rivals minimum backlog	The logarithm of the minimum of all rivals' backlog amounts. See capacity utilization rate for the construction of backlog amounts. See Bajari and Ye [2003].
w	*Variables on General Economic Conditions*
Seasonally adjusted unemployment rate	Monthly unemployment rate for the state of Oklahoma, adjusted for seasonal fluctuations; collected from the Bureau of Labor Statistics (BLS).
Three month average of the real volume of contracted projects	Monthly volume of contracted projects is measured by the logarithm of the amount of all awarded projects at a given month; deflated by the monthly index of producer's prices published by BLS.
Three month average of the number of building permits issued	The logarithm of 3-step moving average of monthly building permits issued to the state of Oklahoma; obtained from the Bureau of Economic Analysis.
Monthly dummies	There are in total 10 monthly dummies since ODOT holds no December lettings.