Price Adjustment Policies and Firm Size*

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Abstract

A number of U.S. State Departments of Transportation have adopted a price adjustment policy designed to limit cost fluctuations of oil based inputs in government procurement. Similar policies are common in defense contracting, and have been used to offset financial losses of health insurance companies in Medicare and the Affordable Care Act. We show that while all bidders submit lower bids after the policy is introduced, the extent of bid reduction diminishes with firm size. Small new firms are able to compete more frequently, promoting auction competition and efficiency (H4, H57, D44).

Keywords: Government procurement, firm size, survival analysis.

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1 Introduction

By the fall of 2009, several State Departments of Transportation in the U.S. adopted price adjustment policies to mitigate significant fluctuations in the cost of oil based inputs in government procurement. Price escalation in oil-based materials, such as asphalt binder or fuel, was the main cause behind the trend. Firms increased bids to offset higher input prices, adversely affecting procurement costs (Damnjanovic *et al.* (2008)). Because inputs like asphalt experienced significant cost increases (e.g., the price of alphalt increased by 31% in 2005 alone), it is not surprising that contractors in general, and small firms in particular, struggled with construction budgets. In response to the growing uncertainty, many states introduced price adjustment policies for related inputs, effectively dampening losses and profits at times of unanticipated cost fluctuations.[1] While the latter part of last decade saw notable oil price increases, in the recent months firms enjoyed cost savings, a percentage of which can be passed on to Departments of Transportation with the establishment of this policy. Going beyond industries directly impacted by uncertainty in oil prices, the provisions investigated in this paper are common in defense contracting, and were added to the health care law in what came to be known as "risk corridors".[2] As an example, the Department of Defense has embedded such provisions in fixed-price contracts with economic price adjustment (FPEPA). These measures are designed to limit contractors' exposure to economic uncertainty and market volatility prevalent in long-term fixed-price arrangements.[3] In the same spirit, the Regional Greenhouse Gas Initiative (RGGI), an emission permit trading program involving nine northeastern states in the US, held down price escalations by placing a price collar on allowances that limits variability. We investigate the effect of the price adjustment policy on firm bidding behavior and competition intensity in road construction in Oklahoma, which can offer insights on the effectiveness of implementing such policies across industries.

[1]For selected materials, these policies state that if the price deviates beyond a certain range of the baseline index, contractors are guaranteed an adjustment in payment by the government, the direction and amount of which are contingent on the triggering price change.

[2]"Risk corridor" provisions have been in place as Part D in Medicare since 2003, and are utilized in the recent ACA reform. See Lucarelli, Prince, and Simon (2012).

[3]Information on FPEPA defense contracting practices can be found on the Acquisition Community Connection website (https://www.fpds.gov/fpdsng_cms/).

We use data on public construction auctions to study the effect of this policy on firms of different sizes, where size heterogeneity is a defining characteristic of the market (Cho (1986)). The construction industry displays market concentration featuring a small number of strong contenders. From the pool of over 150 participants in our sample, the 11 firms that won most frequently were awarded over a quarter of auctioned projects and more than 38% of contracted value. Compared with the manufacturing sector surveyed in Audretsch and Mahmood (1995), a notably higher percentage of new construction companies end up failing. Many undersized and start-up builders compete on the margin and have a low chance of making it to the list of long-term players. The literature has identified a strong correlation between firm size and financial solvency in association with firm survival and growth (see Brito and Mello (1995) and Hubbard (1998)). In what follows, we frame our empirical analysis with a theoretical model highlighting this connection. As noted by Gertler and Gilchrist (1994) and Martinelli (1997), there are asymmetric changes in firms' borrowing costs when financial constraints are tightening in the face of uncertainty, and they depend on the level of capital accumulation. As a result, high volatility in input prices is likely to reinforce the imbalance among competitors of different sizes.[4] Price adjustment policies help to level the playing field between small and large firms without invoking differential treatment towards a group. Finally, there has been considerable interest in the literature in various policies that Departments of Transportation around the country use to help small businesses, such as bid preference policies and set-asides (see, for instance, the work of Denes (1997), Marion (2009), Krasnokutskaya and Seim (2011), and Athey, Coey, and Levin (2013)). Their conclusions on the effectiveness of these programs vary across researchers. As we show here, price adjustment policies, intended to help all firms cope with input price volatility, benefit disproportionately small competitors.

In particular, we find that the reduction in uncertainty asymmetrically impacts small and large firms, and that the differences are more pronounced at the upper tail of the conditional distribution of bids. Our identification strategy capitalizes on the asphalt price adjustment clause which constitutes an exogenous change relevant to all participating firms. Since the prices of asphalt and fuel

[4]While major contractors manage to share financial risk with input suppliers, fringe firms are less able to do so and often have to build a premium into their bids.

items are intrinsically linked to the price of oil, albeit the policy applies to asphalt but not fuel, we estimate distributional effects by comparing policy eligible asphalt items with policy ineligible fuel items before and after the policy is introduced. Kosmopoulou and Zhou (2014) employ a similar method and discover that, at the project level, all firms bid more aggressively if the degree of uncertainty is reduced, a change favoring government agencies as buyers. We find, however, that after the introduction of the policy, small firms reduce bids on selected asphalt materials substantially more than large firms. We also examine how the policy has affected the intensity of competition, as measured by the number of bids submitted by a firm during a period of time. By estimating standard count models, we find that the introduction of the policy enhances the competitiveness of the procurement process.

The remainder of this paper proceeds as follows. Section 2 offers details on the price adjustment policy and a theoretical framework guiding our empirical analysis. Section 3 investigates the distributional effect of the policy. It also documents how bidding frequencies are affected by the policy. Section 4 offers concluding remarks.

2 Background, Data and Theoretical Framework

Project and item level data are collected from monthly lettings held by the Oklahoma Department of Transportation (ODOT) between September 2003 and September 2009, providing access to contract information as well as bidder characteristics.[5] Procurement lettings are held on a monthly basis (except for December) using the format of first price sealed-bid auction. A firm with the lowest bid is typically awarded the contract.[6]

[5]Congress approved a stimulus package to state transportation agencies nationwide in February 2010 and the funds were first introduced in Oklahoma's procurement auctions in March 2010. Therefore, our sample is not influenced by the stimulus package.

[6]ODOT may reject the winning offer and schedule a re-auction later. According to state engineers, rejections can be caused by unresponsiveness afterwards or materially unbalanced bids. We have dropped rejected projects from our database.

2.1 Auction level data

Firms interested in bidding for a project must purchase a plan. The list of plan-holders is released before the actual letting to inform participants of potential competition. The observations in our database are generated when a potential contractor buys a plan.[7] We have information on the identity of the plan-holder, the project of interest, whether the firm submits a bid, and whether the firm has won an auction. Each entry is matched with a number of relevant factors, including characteristics of the project (such as the nature of work, the engineering cost estimate (ECE) and time allocated for completion of the project), the plan-holder's own attributes, rival plan-holders' attributes, and variables describing the general economic environment at the time of letting. Data between January 2002 and August 2003 are used to construct firms' backlog, bidding and winning histories. A description of all variables used in this study is provided in Table A1 in the Appendix.

2.2 Item level data

Each project employs a number of items as building materials. State engineers prepare a pair of unit price and quantity for each item in the plan. When bidding, contractors are required to submit a unit price for every pay item on the plan list at the quantity determined by engineers.[8] Hence, a bid for a project is not merely a single number but a vector of unit prices corresponding to predefined quantities. The bidder with the lowest total amount, i.e. the sum of proposed unit prices multiplied by the predetermined quantities, is awarded the contract. To illustrate the relationship between project level and item level data, we present in Table 1 the bidtab report of an asphalt resurfacing work auctioned in March 2008. According to the table, this resurfacing project uses four items, namely, asphalt concrete, traffic stripes, cold milling pavement, and construction traffic control. The total ECE is $455,600. Both bidders submitted unit prices for all four items on the list, and firm B was awarded the project with a total bid of $475,300. The set of unit prices are hereinafter referred to as itemized bids, which is distinguished from the overall bid (total bid) of a project.

[7] It is quite common for a firm to acquire a plan but not to participate in the bidding. Based on our data, plan-holders submit bids approximately 56% of the time.

[8] Failure to conform may result in rejection of the offer.

Table 1

Item bid and total bid – example using an asphalt resurfacing project.

Item	Description	Quantity	Unit price	Estimate	Unit price	Bid	Unit price	Bid
			ODOT		Bidder A		Bidder B	
1.	Asphalt concrete (tons)	12,000	$35	$420,000	$35.75	$453,000	$37.5	$450,000
2.	Traffic stripe (linear ft.)	100,000	$0.3	$30,000	$0.25	$25,000	$0.2	$20,000
3.	Cold milling pavement (sq. yds.)	800	$2	$1,600	$2	$1,600	$1.5	$1,200
4.	Traffic control (lumpsum)	1	$4000	$4,000	$1600	$1,600	$4150	$4,150
5.	Project estimate/Total bid:			$455,600		$481,200		$475,350

2.3 Special provision 109.7 and firm size

The asphalt price adjustment policy was introduced in the state of Oklahoma in June 2006. An amendment to the general instruction manual, special provision 109.7 guarantees that, for applicable asphalt binder materials, an adjustment in payment will be made if the asphalt price index at delivery is different by 3% or more from the value at letting. If the current price index exceeds the base value by more than 3%, a lump-sum adjustment is transferred from ODOT to the contractor, the amount determined by the quantity of asphalt items involved and the extent of price deviation. The direction of payment is reversed if the current index declines by 3% or more compared to its base value.[9] Applicable items include asphalt binders of several types and grades. A complete list can be found at the ODOT website.[10]

Between 2003 and 2009, 1884 projects were awarded with more than $3 billion in contract value. A total of 11658 plans were purchased and 6441 bids were submitted by 207 prequalified bidders, most of whom are based in Oklahoma or its neighboring states. The department granted a net payment of $17 million to contractors as asphalt price adjustments from August 2006 through June 2009, equivalent to under $6 million in annual transfers, or 5.05% of the total contracted value of asphalt items in the period. Of the 1884 awarded projects, 1018 prescribe eligible asphalt items (54%). When the observation window is divided to two by the policy initiative, the frequency of asphalt projects remains rather comparable before (52%) and after (56%).

As our interest lies in the asymmetric effect of a price adjustment policy on contractors of different sizes, firms are grouped into large and small for comparison. Following the empirical literature, we define size by the number of employees, which is obtained from the National Establishment Time-Series Database (NETS) by Walls & Associates.[11] Similar to Dean *et al.* (1998) and Hancock and Wilcox (1998) among others, a large firm is defined as an establishment with 100

[9] For calculation of transfers, ODOT utilizes a price index published in "Asphalt Weekly Monitor" by Poten & Partners, a consulting company of the energy industry.

[10] http://www.okladot.state.ok.us/c_manuals/specprov2009/oe_sp_2009-109-7.pdf.

[11] NETS database is created from publications of Dun and Bradstreet (D&B) and annual surveys conducted by Duns Marketing Information (DMI) and Walls & Associates.

TABLE 2
Descriptive statistics for the bid data by firm size before and after the introduction of the price adjustment policy.

Variables	Large Firms		Small Firms	
	Before	After	Before	After
Relative bid on asphalt items	1.147	1.032	1.202	1.070
	(0.344)	(0.290)	(0.415)	(0.385)
Relative bid on fuel items	1.303	1.250	1.283	1.336
	(0.757)	(0.698)	(0.665)	(0.768)
Winning relative bid on asphalt items	1.067	1.002	1.145	1.017
	(0.284)	(0.283)	(0.447)	(0.321)
Winning relative bid on fuel items	1.122	1.110	1.175	1.198
	(0.610)	(0.578)	(0.162)	(0.595)

Standard errors are in parenthesis. The adjustment policy on asphalt was introduced in June 2006. A firm is considered large if it has 100 or more employees, and small otherwise. A total of 2815 (4873) asphalt and 1235 (1900) fuel bids are submitted by 16 (75) large (small) firms.

or more employees.[12] We concentrate on firms headquartered in Oklahoma since we have access to the NETS Oklahoma section. However, we expect that our findings extend to out-of-state firms as all bidders compete on an equal footing in ODOT lettings regardless of their primary locations. A total of 8622 plans were purchased and 4938 bids were submitted by 91 in-state firms. Naturally, the sample size dramatically increases when item level data are used, reaching 10823 observations. Out of 91 in-state firms, 82% have under 100 employees. Of those, 21% have no more than 10 employees and 66% have between 11 and 50.

We consider only projects with asphalt items, and then identify fuel items from these asphalt projects. Descriptive statistics for relative bids on these items, which are ratios of dollar bids divided by engineering estimates, are presented in Table 2. The costs of asphalt and fuel items, and therefore bids, are linked by the common influence of oil price fluctuation, and would trend similarly throughout the period in the absence of any intervention. After the policy, however, the cost of asphalt items is bounded by ex post price adjustments, while the cost of fuel items is left exposed to the full range of market price fluctuation. Table 2 shows that the average bid on asphalt

[12]Due to the longitudinal nature of our data, it is possible for a firm to expand or downsize its employment, and hence to be categorized as large in some years and small in others. Fortunately, most firms in our sample maintained a stable payroll during the period of observation, and only once did a contractor cross the threshold of 100 and went from 200 employees to a number below 100. It is categorized as a large firm, but our analysis is not sensitive to this treatment.

items is significantly lower for both large and small firms after June 2006, and this intertemporal shift carries over to the subset of winning bids, albeit at a smaller magnitude.[13] Meanwhile, changes in fuel bids after June 2006 appear either insignificant or reversed in direction.[14]

2.4 A modeling framework

We now consider a simple theoretical model of auction competition framing the analysis of bidding behavior that follows.[15] A number of bidders, n, compete in a low price sealed bid auction held at time t, for a contract to be completed in the next period, $t + 1$.[16] Bidders are risk neutral. Bidder i has only an estimate of the cost, c_{it}^e, at the time of bidding. We assume that the construction cost c_{it+1} depends on the realizaton of a continuous random variable d_{t+1} with mean zero, a fluctuation representing exogenous shocks in the price of basic inputs common across local suppliers. The ODOT price adjustment policy limits those cost fluctuations to bidders. The estimate c_{it}^e for bidder i is drawn from a twice continuously differentiable distribution F_t^e with strictly positive density f_t^e on the support $[c_t^{eL}, c_t^{eH}]$. Each firm has some capital available at the time of bidding denoted by w_{it} that depends on its size, i.e., $w_{it} = w(z_{it})$ with $w' > 0$. Firm size $z_{it} \in [\underline{z}, \overline{z}]$ is distributed according to f_z, that is twice continuously differentiable on its support.

Let c_{it}^e and z_{it} be independent. We abstract away from possible economies of scale to highlight one single channel of differential behavior among firms of different sizes that is most critical in the presence of uncertainty, namely the cost of borrowing. This is consistent with the observation of State Department of Transportation officials that small firms were more constrained and prone to

[13]To carefully examine the utilization of the price adjustment clause by large and small firms, we compare the percentages of eligible asphalt items in projects won by each group before and after the policy, and find no evidence that small firms are exploiting contracts subject to *ex post* transfers, which potentially could lead to higher procurement costs for the state. In addition, we learned from discussion with ODOT staff that there was no systematic observation that projects eligible for price adjustment were associated with late completion.

[14]It should be pointed out that any ex post adjustment in payments is based on the price index published in "Asphalt Weekly Monitor", and is therefore independent of bids submitted by firms. Explicit contingency clauses such as this one do not enhance incentives for strategic maneuvering (Iossa *et al.* (2007)).

[15]This model extends Kosmopoulou and Zhou (2014) to incorporate asymmetries in cash position.

[16]Typically, two weeks after a winner is selected by competitive auction, 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 ones may go on for as long as several years. The two-period feature of our model is aiming to capture this time dimension.

bankruptcy right before the policy took effect. A bidder may finance future projects by borrowing at a cost dependent on its size and need for capital through the function $R(c_{it}^e - w(z_{it}), \lambda)$ with $R(\cdot, \lambda) > 0$ for $c_{it}^e - w(z_{it}) > 0$ and zero otherwise. The parameter λ is the minimum percentage fluctuation in d_{t+1} that triggers ex post adjustments according to the policy. With price indexation in place d_{t+1} becomes:

$$d_{t+1}^* = \begin{cases} d_{t+1} & \text{if} \quad -\lambda\bar{c}_t \leq d_{t+1} \leq \lambda\bar{c}_t \\ \lambda\bar{c}_t & \text{if} \quad d_{t+1} > \lambda\bar{c}_t \\ -\lambda\bar{c}_t & \text{if} \quad d_{t+1} < -\lambda\bar{c}_t, \end{cases}$$

where $\bar{c}_t$ denotes the average cost of asphalt in period t based on suppliers' data. The overall cost of the project becomes $c_{it+1} = c_{it}^e + d_{t+1}^* + R(c_{it}^e - w(z_{it}), \lambda)$.[17]

Bidder i, who wins the auction by submitting a bid b_{it}, receives a payoff of $u(b_{it}, c_{it}^e, d_{t+1}^*, z_{it}, \lambda) = b_{it} - c_{it}^e - d_{t+1}^* - R(c_{it}^e - w(z_{it}), \lambda)$. Let $s_{it} = c_{it}^e + R(c_{it}^e - w(z_{it}), \lambda)$ be its privately observed component of c_{it+1} at the time of bidding, and let y_{1t} be the infimum of the remaining $n-1$ estimates of s_t. Under the assumption that densities f_t^e and f_z are logconcave,[18] the unique equilibrium bidding strategy for i in the first price auction held at t is:

$$B(s_{it}|\lambda) = E(y_{1t}|y_{1t} \geq s_{it}, \lambda) + E(d_{t+1}^*|s_t \geq s_{it}, \lambda). \tag{1}$$

The cost of borrowing depends on the size of the firm and its risk exposure, where $R'_z(\cdot) < 0$ and $R'_\lambda(\cdot) > 0$. As noted by Gertler and Gilchrist (1994) and Martinelli (1997), there are asymmetric changes in firm borrowing costs when financial constraints are tightening and they depend on the level of capital accumulation. Hence, we assume that $\frac{\partial^2 R(\cdot)}{\partial z_{it} \partial \lambda} < 0$. Under these assumptions, a reduction in λ reduces uncertainty and the cost of borrowing asymmetrically among bidders of dif-

[17]We can think of the situation without ex-post transfers as one in which λ is set at an unrealistically high level. Therefore, implementing the policy is equivalent to lowering the threshold value.

[18]The assumption of logconcavity is discussed in detail in Goeree and Offerman (2003). It guarantees that a lower privately observed cost implies, on average, a lower overall cost thus ensuring monotonicity and existence of equilibrium. The derivation is delineated in the appendix.

ferent sizes, leading to lower bids across firms but more so for those facing financial constraints. In the Appendix, we present derivations showing that a reduction in bid dispersion, more prominent for smaller firms, is possible under the previous assumptions and a positive association between interest spread and credit risk.[19]

3 The Distributional Effect of the Policy on Bidding

We exploit the fact that the adjustment policy constitutes a source of exogenous variation to all firms. As policy ineligible fuel items offer a natural comparison for policy eligible asphalt items, we estimate the following standard difference-in-differences equation:

$$y_{ijat} = \beta_1 A_j + \beta_2 T_t + \beta_3 (A_j \times T_t) + \boldsymbol{h}'_{ijat}\boldsymbol{\theta} + \alpha_i + \nu_j + m_t + \epsilon_{ijat}. \tag{2}$$

The dependent variable is y_{ijat}, the relative bid by firm i for item j in auction a at time t. Policy eligibility A_j is set to 1 for asphalt items, and the time dummy T_t is equal to 1 if observed after the introduction of the policy in June 2006. The variables in $\boldsymbol{h}_{ijat}$ control for factors that may influence bids, including capacity utilization, distance to work site, the firm's and its rivals' past winning to bidding ratios, work type and duration, expected number of bidders of the project, unemployment rate, and three-month average of building permits and contracted value. The vectors α_i, ν_j, and m_t represents bidder effects, item effects (i.e. various types of asphalt and fuel items, such as superpave type S3 and superpave type S4), and time effects. We estimate a linear conditional quantile function associated with equation (2) separately for small and large firms:

$$Q_{Y_{ijat}}(\tau | A_j, T_t, \boldsymbol{h}_{ijat}, \boldsymbol{\psi}_{ijt}) = \beta_1(\tau) A_j + \beta_2(\tau) T_t + \beta_3(\tau)(A_j \times T_t) + \boldsymbol{h}'_{ijat}\boldsymbol{\theta}(\tau) + \boldsymbol{e}'\boldsymbol{\psi}_{ijt}(\tau), \tag{3}$$

[19] An alternative framework with risk-averse bidders is expected to produce qualitatively similar and quantitatively stronger results, but adds a dimension to the modeling effort that we are unable to control for empirically. Nevertheless, projecting from the work of Holt (1979), the increase in bidding aggressiveness and the decline in bid dispersion would be more pronounced, as risk-averse bidders derive higher utility from the uncertainty-reducing policy. Assuming that small firms are more risk averse, this theory provides a different avenue for establishing our results.

where $Q_{Y_{ijat}}(\tau|\bullet)$ is the quantile function, τ is a quantile, and the vector $\boldsymbol{\psi}_{ijt}(\tau)$, which is equal to $(\alpha_i(\tau), \nu_j(\tau), m_t(\tau))'$, denotes quantile-specific fixed effects of bidder, item and time with $\boldsymbol{e} = (1, 1, 1)'$.

Our primary interest concerns the estimation of $\beta_3(\tau)$ for small and large firms. The parameter measures the distance between the conditional quantiles of asphalt and fuel bid distributions in the period after the policy is implemented:

$$\beta_3(\tau) = [Q_Y(\tau|A=1, T=1, \boldsymbol{h}, \psi) - Q_Y(\tau|A=0, T=1, \boldsymbol{h}, \psi)] - [Q_Y(\tau|A=1, T=0, \boldsymbol{h}, \psi) - Q_Y(\tau|A=0, T=0, \boldsymbol{h}, \psi)].$$

By estimating $\beta_3(\tau)$ for small firms and large firms, we are able to investigate the group specific distributional impact of the policy, and to infer from the quantile estimates whether there are changes in the location, scale, and possibly the shape of the conditional distribution of relative bids.

The quantile regression model in (3) can be estimated by employing a version of Koenker (2004) panel data estimator:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{J} \sum_{t=1}^{T} \rho_\tau(y_{ijt} - \beta_1 A_j - \beta_2 T_t - \beta_3(A_j \times T_t) - \boldsymbol{h}'_{ijt}\boldsymbol{\theta} - \psi_{ijt}),$$

where $\rho_\tau(u) = u(\tau - I(u < 0))$ is the quantile regression "check function". Koenker (2005) discusses several methods for inference on quantile regression, including rank-based methods, resampling approaches, and estimation of the asymptotic covariance matrices. However, there might be within project dependence that needs to be accounted for. As a result, we estimate standard errors by block bootstrap with blocks constructed at the auction level.[20]

[20]There are a few recent advances in quantile regression models with cross-sectional data. Parente and Santos Silva (2016) propose a variation of the asymptotic covariance matrix that accommodates to clustering, and Hagemann (2015) investigates a cluster-robust bootstrap approach for inference. In panel quantiles, it is standard to use a block or panel bootstrap approach. We estimated the models using both Parente and Santos Silva (2016) and block bootstrap and found that the results are similar whether we estimate the asymptotic covariance matrix or we estimate the covariance matrix by bootstrap. The results are available upon request.

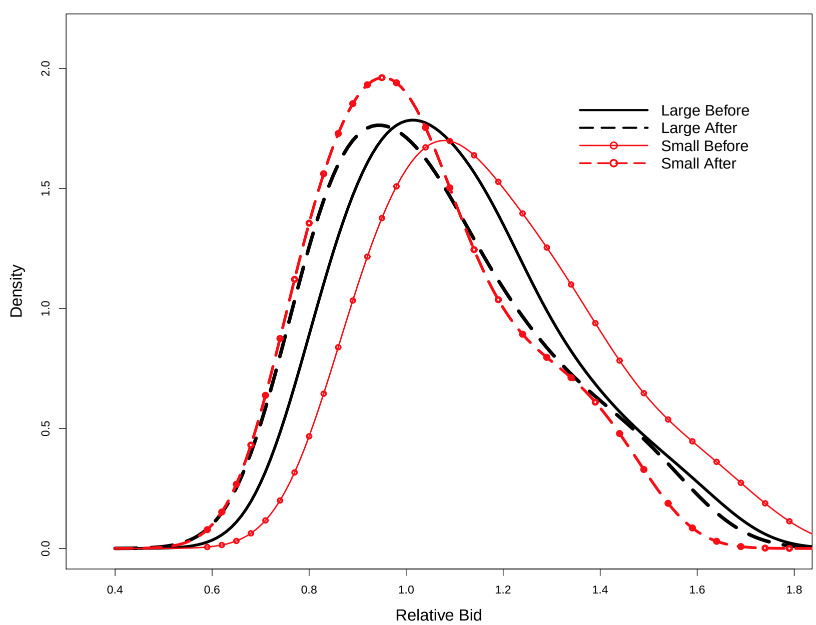
TABLE 3
Price adjustment policy and firm size: the distributional effect on bidding.

	Quantiles (τ)					
Variable of interest	0.1	0.25	0.5	0.75	0.9	Mean
	Large Firms					
After policy	-0.019	-0.058	-0.089	-0.109	-0.170	-0.088
(β_{1l})	(0.044)	(0.046)	(0.055)	(0.113)	(0.195)	(0.073)
Asphalt items	0.376*	0.285*	0.085	-0.262†	-0.571*	-0.066
(β_{2l})	(0.053)	(0.058)	(0.078)	(0.133)	(0.225)	(0.081)
After policy on asphalt items	-0.054	-0.039	-0.040	-0.043	-0.025	-0.052
(β_{3l})	(0.041)	(0.042)	(0.054)	(0.115)	(0.184)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time/Firm/Item Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	4050	4050	4050	4050	4050	4050
	Small Firms					
After policy	0.012	0.008	0.016	0.015	-0.002	0.023
(β_{1s})	(0.040)	(0.040)	(0.042)	(0.077)	(0.148)	(0.059)
Asphalt items	0.344*	0.164*	0.060	-0.313*	-0.733*	0.038
(β_{2s})	(0.044)	(0.054)	(0.044)	(0.135)	(0.159)	(0.075)
After policy on asphalt items	-0.124*	-0.122*	-0.136*	-0.175†	-0.254‡	-0.185*
(β_{3s})	(0.036)	(0.038)	(0.036)	(0.073)	(0.137)	(0.057)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time/Firm/Item Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	6773	6773	6773	6773	6773	6773

Standard errors (in parentheses) are clustered at the auction level. ‡,†,$*$ denote statistical difference from zero at 0.10, 0.05 and 0.01 levels of significance. A large firm is an establishment with 100 or more employees.

Regression coefficients are presented in Table 3. Overall, the impact of price adjustment is negative. At the mean level, large firms have responded to the policy by submitting lower bids, with a change not statistically different from zero, while the reduction in bids observed from smaller firms is much larger and statistically significant. It appears that the asymmetric effect of the policy is evident from mean level results, but inspection of the quantile estimates reveals a much more detailed picture of such asymmetry. At the 0.1 quantile, an asphalt bid after June 2006 is 5% lower among large bidders and 12% lower among small ones. The difference in policy response becomes more pronounced as we move across quantiles. For small firms, β_3 increases in absolute value from 12% at 0.1 quantile to 13% at 0.5, 17% at 0.75, and 25% at 0.9. In contrast, the policy effect diminishes for large firms moving up quantiles, and is statistically insignificant throughout.

FIGURE 1
Price adjustment policies and relative bid distributions by firm size.



Data points are generated by employing estimated coefficients from quantile regressions and mean values of covariates.

In Figure 1, we simulate bids using quantile coefficients and mean values of covariates (except for the effect of the policy), to present a graphical visualization of the effect of the price adjustment clause on the conditional bid distributions. Both groups experienced a reduction in bids, but the change is notably larger for small firms, with a displacement of considerable mass from the right end toward the center of the distribution. In fact, the bid variance from small firms is reduced by 28% after the policy.

3.1 The distributional effect for winning bids

In this section, we investigate whether the effect of the adjustment policy carries over to the subset of winning bids, a more relevant signal of procurement cost. To this end, we estimate the same set of regressions as in Table 3 employing the group of itemized fuel and asphalt bids from contractors. The regression results are reported in Table 4.

TABLE 4
Price adjustment policy and firm size: the distributional effect for winning bids.

	Quantiles (τ)					
Variable of interest	0.1	0.25	0.5	0.75	0.9	Mean
	Large winning firms					
After policy	0.017	-0.070	-0.083	-0.076	-0.256	-0.067
(β_{1l})	(0.066)	(0.069)	(0.075)	(0.130)	(0.224)	(0.063)
Asphalt items	0.355*	0.319*	0.214†	0.023	-0.324	0.056
(β_{2l})	(0.066)	(0.082)	(0.108)	(0.176)	(0.215)	(0.068)
After policy on asphalt items	-0.084	-0.020	-0.070	-0.073	0.089	-0.039
(β_{3l})	(0.061)	(0.064)	(0.062)	(0.126)	(0.222)	(0.062)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time/Firm/Item Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1288	1288	1288	1288	1288	1288
	Small winning firms					
After policy	0.006	-0.004	0.014	0.077	-0.256	-0.036
(β_{1s})	(0.055)	(0.070)	(0.063)	(0.090)	(0.174)	(0.059)
Asphalt items	0.309*	0.153	0.015	-0.151	-0.761†	-0.040
(β_{2s})	(0.054)	(0.115)	(0.079)	(0.147)	(0.309)	(0.098)
After policy on asphalt items	-0.106†	-0.115‡	-0.108†	-0.232*	-0.041	-0.123†
(β_{3s})	(0.051)	(0.065)	(0.053)	(0.083)	(0.163)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time/Firm/Item Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2135	2135	2135	2135	2135	2135

Standard errors are (in parentheses) clustered at the auction level as multiple itemized bids may be observed from the winner in an auction. ‡,†,$*$ denote statistical difference from zero at 0.10, 0.05 and 0.01 levels of significance. A large firm is an establishment with 100 or more employees.

Overall, the results based on winning bids have retained the patterns of the full sample between large and small firms. The estimates of the parameter of interest, β_3, are smaller for small firms than for large firms, indicating a larger reduction in winning bids by small contractors after the policy implementation. A noticeable difference with Table 3 arises at the 0.9 quantile for small winning firms, where the policy effect is no longer statistically significant. It should be noted, nonetheless, that a decline in winning bids for selective items may not necessarily lead to a reduction in aggregate procurement cost for ODOT as these may coincide with increases in bids for fuel or simultaneous changes in bids for other construction items.

3.2 The Effect of the Policy on Bidding Intensity

As small firms behave much more comparably to large firms on asphalt materials after the price adjustment policy is introduced, a natural follow up question is: does this policy help small firms to compete more frequently in the market, potentially promoting competition and efficiency? Small and new participants in auctions play a key role in limiting the leverage of large firms and safeguarding against collusion. Between 2003 and 2009, a total of 90 firms entered the ODOT lettings, and 48 of them were based in Oklahoma. Putting the size of new firms into perspective, all except one in-state entrants have under 100 employees. Although examination of winning patterns show that the likelihood to win by small firms is not increased after the policy, small firms can help enhance competition in this highly concentrated industry through their participation. Intuitively, the price adjustment of asphalt materials may encourage bidding since it effectively limits potential losses firms are subject to in the event of unexpected cost overruns. As such, we take a step forward to examine how the adjustment has affected the participation frequency of entrants in the market, a group that consists of small firms predominantly.[21]

We continue to employ the same identification strategy in the analysis of the impact of the adjustment policy on monthly participation activities for small new firms and existing firms.[22] We

[21] There is considerable research on the effect of entry in procurement auctions but less so on participation patterns. Among the papers emphasizing strategic effects of entry on market outcomes are the seminal theoretical works by McAfee and McMillan (1987) and Levin and Smith (1994) and recent empirical work by Marmer, Shneyerov, and Xu (2013), Coviello and Mariniello (2014) and Branzoli and Decarolis (2014). Studying market survival, De Silva *et al.* (2009) highlighted the impact of information release policies on entrants bidding patterns and longevity.

[22] We have also estimated survival models using non-parametrics and parametric models. We found that while the

TABLE 5

Competition intensity: bidding frequency in a panel Poisson regression with fixed effects.

Variable of interest	Small new firms			All existing firms		
	1-month	3-month	6-month	1-month	3-month	6-month
After policy	0.053	0.211	1.144†	-0.047	0.261†	0.489
(β_1)	(0.193)	(0.357)	(0.576)	(0.116)	(0.115)	(0.253)
Asphalt projects	-0.087	-0.585*	-0.979*	0.180†	-0.108	-0.208‡
(β_2)	(0.117)	(0.182)	(0.248)	(0.081)	(0.118)	(0.122)
After policy on asphalt projects	0.262†	0.528†	0.668*	0.036	0.023	0.061
(β_3)	(0.126)	(0.257)	(0.193)	(0.080)	(0.112)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time and Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	3082	1125	598	7906	2950	1534

Standard errors are in parenthesis. ‡,†,$*$ denote statistically different from zero at 0.10, 0.05 and 0.01 levels of significance. Three choices of period length are used to count the number of submitted bids: a one-month period, a three-month period and a six-month period.

are able to observe participation intensity through bidding entries (i.e., no bidding, single-bid or multiple-bid) during a period of time. Bidding a single time versus bidding multiple times by a firm have different implications for market competitiveness as well as the firm's profit potential. As a result, we propose to evaluate the impact of the policy on competition intensity by comparing a firm's bidding frequency before and after policy implementation between policy eligible and policy ineligible projects. We estimate a panel Poisson count model with fixed effects for the number of bids during a period of time using the same covariates as in Table 3, and employ specifications based on a one-month period, a three-month period and a six-month period model.

The regression coefficients are reported in Table 5. We are most interested in the product of bidding "after policy" and bidding in "asphalt projects", because it represents the policy effect on bidding frequencies. For small new firms, the impact is positive, of considerable magnitude, and statistically different from zero in all variants of the specifications. The results suggest that small firms participate more frequently after the policy implementation. As the group of incumbents is

probability of staying in the market for one year is 57% before the adjustment policy, it is 85% in the period after. Entrants who were bidding on asphalt projects after the policy is introduced exhibit higher survival probabilities 12 months after they enter the procurement market. In our parametric specifications, we found that while entry after June 2006 or participation in asphalt projects alone shows no significant impact on survival, contractors bidding on policy eligible asphalt projects after the policy have favorable survival prospects relative to those bidding on policy ineligible non-asphalt projects. The results are available upon request.

most likely to include established contractors who are major players in the market, the policy can lead to more leveled competition and promote market efficiency.

4 Conclusion

This paper studies the impact of a price adjustment policy in road construction, designed to mitigate the adverse effects of volatile input prices, through analysis of firms' bidding and participation patterns.

We find that the policy has a differential effect on small and large firms, where small-sized competitors are shown to be more responsive in both bid reduction and intensified participation frequencies after the policy introduction than their large counterparts. The impact of the price adjustment policy has fundamental implications for the market of public procurement and others likewise. In an industry as concentrated as road construction, implementing policies of the same spirit has the potential to markedly increase the bidding frequency of new and small firms, serving to enhance the competitiveness and efficiency of the procurement process.

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A Appendix

Simplifying notations

$V_B(\lambda) = V[B(s_{it}|\lambda)]$

$V_y(\lambda) = V[E(y_{it}|y_{it} \geq s_{it}, \lambda)], \quad V_d(\lambda) = V[E(d^*_{it}|s_t \geq s_{it}, \lambda)]$

$\Delta V_B(\lambda) = V_B - V_B(\lambda), \qquad \Delta V_y(\lambda) = V_y - V_y(\lambda), \qquad \Delta V_d(\lambda) = V_d - V_d(\lambda)$

$\Omega = cov[E(y_{it}|y_{it} \geq s_{it}), E(d^*_{t+1}|s_t \geq s_{it})], \quad \Omega(\lambda) = cov[E(y_{it}|y_{it} \geq s_{it}, \lambda), E(d^*_{t+1}|s_t \geq s_{it}, \lambda)]$

A.1 Derivation of the equilibrium bidding function

Here we present derivations of the optimal bidding function in (1). Consider a bidder's expected utility from participation:

$U(b_{it}|\lambda) = [b_{it} - s_{it} - E(d^*_{t+1}|s_t \geq B^{-1}(b_{it}|\lambda), \lambda)]\ [1 - F_s(B^{-1}(b_{it}|\lambda))]^{n-1}.$

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:

$$\begin{aligned} \frac{\partial}{\partial x} E(Y|X \geq x) &= \left[-\int_x^{x_H} E(Y|X \geq t) \frac{f_x(t)}{1 - F_x(x)} dt - E(Y|X = x) \right] \frac{f_x(x)}{1 - F_x(x)} \\ &= [-E(Y|X \geq x) - E(Y|X = x)] \frac{f_x(x)}{1 - F_x(x)}. \end{aligned} \tag{4}$$

Differentiating the objective function $U(b_{it}|\lambda)$ with respect to b (using equation (4)) and evaluating the expression at the optimal choice, we have:

$$\frac{\partial U}{\partial b_{it}}\Big|_{b_{it}=B(x|\lambda)} =$$
$$\left[1 - [E(d^*_{t+1}|s_t \geq x, \lambda) - E(d^*_{t+1}|s_t = x, \lambda)]\frac{1}{B'(x|\lambda)}\frac{f_s(x)}{1 - F_s(x)}\right][1 - F_s(x)]^{n-1}$$
$$- [B(x|\lambda) - s_{it} - E(d^*_{t+1}|s_t \geq x, \lambda)](n-1)[1 - F_s(x)]^{n-2} f_s(x)\frac{1}{B'(x|\lambda)} = 0$$

Simplifying, we get:

$$\left[\frac{B'(x|\lambda)}{n-1}\frac{1 - F_s(x)}{f_s(x)} - \frac{1}{n-1}[E(d^*_{t+1}|s_t \geq x, \lambda) - E(d^*_{t+1}|s_t = x, \lambda)]\right] - B(x|\lambda) + s_{it} + E(d^*_{t+1}|s_t \geq x, \lambda) = 0 \quad (5)$$

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

$$B(x|\lambda) = E(d^*_{t+1}|s_t \geq x, \lambda) + E(y_{1t}|y_{1t} \geq x, \lambda). \quad (6)$$

Differentiating this expression, we get:

$$B'(x|\lambda) = [E(d^*_{t+1}|s_t \geq x, \lambda) - E(d^*_{t+1}|s_t = x, \lambda)]\frac{f_s(x)}{1 - F_s(x)} + [E(y_{1t}|y_{1t} \geq x, \lambda) - x]\frac{f_{y_1}(x)}{1 - F_{y_1}(x)} \quad (7)$$

Given 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 imply

$\frac{f_{y_1}(x)}{1-F_{y_1}(x)} = \frac{(n-1)\, f_s(x)}{1-F_s(x)}$, we replace (6) and (7) into (5) and get:

$$\frac{1}{n-1}[E(d^*_{t+1}|s_t \geq x, \lambda) - E(d^*_{t+1}|s_t = x, \lambda)] + [E(y_{1t}|y_{1t} \geq x, \lambda) - x]$$
$$- \frac{1}{n-1}[E(d^*_{t+1}|s_t \geq x, \lambda) - E(d^*_{t+1}|s_t = x, \lambda)] - E(d^*_{t+1}|s_t \geq x, \lambda)$$
$$- E(y_{1t}|y_{1t} \geq x, \lambda) + s_{it} + E(d^*_{t+1}|s_t \geq x, \lambda) = 0$$

$\iff s_{it} = x.$

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

$$B(s_{it}|\lambda) = E(y_{1t}|y_{1t} \geq s_{it}, \lambda) + E(d^*_{t+1}|s_t \geq s_{it}, \lambda).$$

A.2 Effect of the threshold parameter (λ) on bid variance

The derivative of bid variance with respect to the policy threshold is expressed as:

$$\frac{\partial V_B(\lambda)}{\partial \lambda} = \frac{\partial V_y(\lambda)}{\partial \lambda} + \frac{\partial V_d(\lambda)}{\partial \lambda} + 2 \cdot \frac{\partial \Omega(\lambda)}{\partial \lambda}.$$

Assuming that the spread of the interest rate, a component of $V_y(\lambda)$, increases with the degree of credit risk λ (established empirically in Krainer (2004), Kaplin *et al.* (2009), Edelberg (2006), and Hubbard (1998) among others), $\frac{\partial V_y(\lambda)}{\partial \lambda} > 0$.

Replacing d^*_{t+1} in $V_B(\lambda)$ and taking the derivative w.r.t. λ, we have:

$$\frac{\partial V_d(\lambda)}{\partial \lambda} = V(d_{t+1} + \bar{c}_t) \cdot 2P(-\lambda\bar{c}_t \leq d_{t+1} \leq \lambda\bar{c}_t) \cdot \frac{\partial P(-\lambda\bar{c}_t \leq d_{t+1} \leq \lambda\bar{c}_t)}{\partial \lambda}.$$

Noting that $\frac{\partial P(-\lambda\bar{c}_t \leq d_{t+1} \leq \lambda\bar{c}_t)}{\partial \lambda} > 0$, it follows that $\frac{\partial V_d(\lambda)}{\partial \lambda} > 0$.

Regarding the last term of the derivative, both $\frac{\partial E(d^*_{t+1}|s_t \geq s_{it}, \lambda)}{\partial \lambda}$ and $R\,'(\cdot)$ are greater than zero, implying that $\Omega(\lambda) > 0$. Given the convex change in borrowing cost ($\frac{\partial^2 R(c^e_{it} - w(z_{it}), \lambda)}{\partial z_{it} \partial \lambda} < 0$) and the linear change in input cost fluctuation ($\frac{\partial^2 E(d^*_{t+1}|s_t \geq s_{it}, \lambda)}{\partial^2 \lambda}$), it follows that $\frac{\partial \Omega(\lambda)}{\partial \lambda} > 0$. Q.E.D.

A.3 Effect of firm size (z_{it}) on bid variance

Using equations (1), we can express the derivative of the variance with respect to z_{it} as follows:

$$\frac{\partial \Delta V_B(\lambda)}{\partial z_{it}} = \frac{\partial \Delta V_d(\lambda)}{\partial z_{it}} + \frac{\partial \Delta V_y(\lambda)}{\partial z_{it}} + 2 \cdot \frac{\partial(\Omega - \Omega(\lambda))}{\partial z_{it}}.$$

The first term of this expression equals zero ($\frac{\partial \Delta V_d(\lambda)}{\partial z_{it}} = 0$) due to the independence between firms' establishment size and exogenous price shocks. Assuming positive correlation between the interest rate spread and credit risk it follows that $\frac{\partial \Delta V_y(\lambda)}{\partial z_{it}} < 0$. Lastly, since c^e_{it} and z_{it} are independently distributed $\frac{\partial(\Omega - \Omega(\lambda))}{\partial z_{it}} = 0$, which implies that $\frac{\partial \Delta V_B(\lambda)}{\partial z_{it}} < 0$. Q.E.D.

Table A1
Regression variables

Variable	Description and construction of variables
Project relative bid	Project bid divided by engineering cost estimate(ECE).
Item relative bid	Unit price divided engineering estimate for items used in a project.
Large firm	Establishment that has over one hundred employees; otherwise small.
Asphalt item	Asphalt concrete products prescribed in ODOT Special Provision 109.7; interchangeable with "eligible item".
Fuel item	Diesel fuel related products prescribed in ODOT Special Provision 109.3.
Asphalt project	A project that prescribes asphalt items in the plan; same as "eligible project".
Entrant	Contractors who submit bids for the first time after September 2003.
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 the contract period. Backlog equals the monetary value of unfinished part. A firm's backlog sums up the backlog values of all its ongoing projects, which goes to zero upon completion of existing work and becomes positive when new ones are undertaken. A firm's capacity is assumed to be the maximum of its backlog in the sample period. Data between Jan 2002 to Aug 2003) are used to initialize capacity utilization. For firms that have never one, the variable is set to zero.
Distance to work site	The logarithm of distance in miles between the city that the firm's is located and the city that the project is located. City location is represented by the longitude and latitude of its center.
Winning to bidding ratio (WB)	The ratio of times won to plan-holding times in the past 12 months (note that this is a moving window and updated monthly); an indicator of individual bidding strength.
Average rivals' winning to plan holding ratio (ARWP)	A measure to capture the average success rate of rivals' past bidding. Based on each firm'sinning to plan-holding ratio as constructed above, the average of all rivals' value gives the ARWP for a firm faced with a particular set of competitors. It incorporates two aspects of rivals' behaviors: the probability of bidding conditional on purchasing a plan and the probability of winning conditional on bidding.
Rival's min distance	The logarithm of distance in miles between project location and the closest rival.
Rival's min backlog	The logarithm of the minimum of rivals' backlog. See capacity utilization rate for backlog construction.
Auction specific characteristics	
Expected number of bidders	Each firm has a probability of bidding conditional on holding plans based on its past twelve months' record. Expected number of bidders in an auction is thus the sum of plan holders' individual probabilities.
Project type dummy	Projects are categorized according to work nature into 7 groups: asphalt paving, bridge work, clearance, concrete, grade & drain, traffic & signing, and miscellaneous (e.g. landscaping). The miscellaneous are omitted in regression.
Calendar days	The number of calendar days indicated in the plan that contractors are allowed to complete the project.
Variables on general economic conditions	
Seasonally adjusted unemployment rate	Monthly unemployment rate for the state of Oklahoma, adjusted for seasonal fluctuations. Source: Bureau of Labor Statistics.
Three month average of contract value	The logarithm of total value of successfully awarded and contracted projects in a month, adjusted for inflation.
Three month average of building permits issued	The logarithm of three-step moving average of monthly building permits issued by the state of Oklahoma. Source: Bureau of Economic Analysis.