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XUEQI ZHOU
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THREE ESSAYS ON CONSTRUCTION PROCUREMENT INDUSTRY AND PUBLIC POLICIES

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BY

Dr. Georgia Kosmopoulou, Chair

Dr. William Megginson

Dr. Carlos Lamarche

Dr. Gregory Burge

Dr. Qihong Liu

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ABSTRACT

This study analyzes construction procurement auctions conducted by Oklahoma Department of Transportation (ODOT) focusing on mechanism design and its impact on functioning of the market. First we investigate a recent policy that was enacted to reduce cost uncertainty in road construction and its implications upon competitive bidding and firms' survival. Then we consider time incentive bidding designs and the impact on bidding and project completion. Using data from the period extending from 2002 to 2010 and modern econometric techniques, this thesis presents a study of the dynamic interactions between private and public sectors.

The first essay, "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior," examines the effects that asphalt price adjustment clauses have on the bidding behavior of firms and the procurement cost accrued for ODOT. Based on a newly constructed, detailed panel of observations, we compare bidding behaviors across projects and time, but also across items within projects. Employing difference-in-difference estimations, we find that bids become more aggressive and less dispersed after the implementation of adjustment policy. Quantile regression confirms that the reduction in bids is not restricted to a particular range but rather permeates the entire distribution. The increased bidding aggressiveness grows more pronounced when we consider bids at item level than at project level. Alternative approaches of regression discontinuity and nonparametric estimation are applied and yield consistent results.

The second essay, " On the Distributional Impact of Price Adjustment Policies: Bidding Patterns and Survival in the Market," continues to study the risk discounting

asphalt price adjustment clauses, with a concentration on potential asymmetric impacts on firms of different sizes and levels of experience. Theory argues that, by removing excessive volatility, adjustment clauses may shadow the information rents enjoyed by large or existing firms and elevate the performances of the small and less experienced. Based on a rich micro level sample almost a decade long, we first carry out quantile regressions to show that entrants and small incumbents, regardless of their relative efficiency, respond more positively to the indexation policy by submitting disproportionally lowered bids. In addition, the presence of contingent adjustments is expected to increase new and small firms' inclinations toward participation and improve their chance of winning overall. Classical survival analysis is then employed and reveals that entrants do demonstrate statistically reduced failure rates and extended durations in the market.

In the third essay, "Speed Incentives in Public Procurement Auctions," we study the usage of two innovative contracting methods which incorporate completion time into competitive auctions: incentive/disincentive milestone and A+B bidding. It is a well known fact that faster execution of road construction work reduces negative externality due to delayed traffic and thus promotes social welfare. With an exhaustive sample collected from ODOT, we find favorable effects of the creative designs. On the one hand, both special provisions are likely to lead to shortened construction time. At the same time, through program evaluation methods of linear regression and matching technique, we show that the innovative contracting mechanisms do not statistically inflate bids submitted by winning contractors or significantly increase the procurement costs of public transportation agencies.

CHAPTER 1

INTRODUCTION

Auction as an institution of allocating resources could date back over two thousand years to ancient Greece. Nowadays, it has been widely applied to numerous organizations and contexts thanks to its competitive feature that leads to low prices and high efficiency, limits favoritism and political influences, and promotes equal opportunities. Such benefits have been strongly advocated by economists. Road construction projects, as well as sales of forest timber and mineral rights, are leading examples which make the most extensive use of auction mechanism by the public sector. Principles and regulations such as the Federal Acquisition Regulations (FAR) favor auctions so much that most public construction projects in most U.S. are procured via competitive bidding. Auction is also a frequently used method in privatizing government assets.

With applications spreading, auction-related studies have emerged as an increasingly important field of the economics spectrum in the past several decades. Theoretical literature produces critical contributions concerning basic structures, fundamental valuations, effectiveness and efficiency of outcomes and optimal mechanism designs, to name a few among the voluminous collection. Meanwhile, empirical research is also flourishing, for the well-defined auction environment provides a rare opportunity to test classical economic theories, especially those of game theory.

The object of my dissertational study, government construction contracts, including those administered in the state of Oklahoma, typically follow the format of competitive first price sealed-bid auction. Data used in this study are collected via the official website of Oklahoma Department of Transportation. A unique yet valuable feature of the dataset is that observations are broken down at item level rather than project level, which warrants more targeted analysis of policy implications since items within projects are the direct recipients of any government intervention.

Empirically studying the practice of auction in the industry of public construction presents new challenges, but also may accumulate generous returns. Firstly, procurement contracts of highway and bridge work is an important component of government spending, taking up a nontrivial portion of GDP.[1] Examinations of existing policies and search for optimal means of regulations could lead to considerable benefits for the society. Secondly, empirical research can more effectively accommodate practical situations that haven't been fully framed by theorists. For example, players in this market can possess strong asymmetries information wise or valuation wise, an attribute that may posit difficulties for pure theoretical formalizations. Thirdly, the market of highway construction constantly involves interactions between public and private parties. Federal and state government agencies are the main buyer, whereas construction firms, mostly private ownership, are the main seller. When transportation departments introduce new rules, there will a direct and immediate response from the private side and later a series of ripple effects, all of which may influence the final outcomes. Therefore, understanding dynamics of this process is crucial for a comprehensive evaluation of public policies.

[1] It is reported by the American Association of State Highway and Transportation (AASHT) and Federal Highway Administration (FHWA) that the U.S. federal and state governments spent over 100 billion dollars on road construction projects, equivalent of slightly under 1% of the nominal GDP.

History has demonstrated a tendency that financial challenges are conducive to innovations. Put in context of the current study, the ongoing financial crisis, together with concerns of rising energy prices, has lead transportation departments across the U.S. to amend general specifications of public procurement by adding various special provisions in pursuit of achieving low costs and high efficiency in the maintaining and construction of social infrastructure.

In the thesis, we study two of such initiatives introduced in the past decade that are gaining popularity nationwide, taking as a case study the procurement lettings conducted by Oklahoma Department of Transportation. One is the price adjustment clauses concerning hot mixed asphalt (HMA) products, and the other is special provisions that incorporate completion speed into the standard contracting mechanism, labeled as incentive/disincentive milestone and A+B bidding. A detailed micro level panel is utilized to investigate how private contractors adjust their bidding strategies in response to the implementation of policies and the associated effects on construction costs accrued to ODOT, long run development of the market and allocation of social resources. By doing so, this project not only fills in several gaps in the literature of auction and highway contracts, but also sheds light on effective policy designs and social welfare advancement.

The first two papers are an unprecedented attempt to evaluate the impacts of asphalt price adjustment quantitatively and rigorously. In contrast to the widespread applications and continuous discussion over costs versus benefits, there has been little systematic research devoted to this topic. We seek to fill in this gap between real world and academic community. The interest of our study extends even beyond the current scope of construction industries. For example, in the recent health care reform, similar clauses of contingent price adjustments are included in the legislation. In the third essay we materialize, for the first time, on two creative time-incentivized contract designs, namely incentive/disincentive milestone and A+B bidding. Based data from Oklahoma, our findings complement existing literature by assembling evidence from a less populated area, which provide useful reference for policy generalization in the future. Taking into account the high stake of highway construction work, proper usage of the aforementioned initiatives may amount to notable gains of social welfare.

Chapter 3 prefaces the main body of three essays by describing the huge dataset that forms the foundation for all of empirical endeavors. Collection procedures and basic summary statistics are provided to convey a general impression. This chapter can also be viewed as a convenient glossary for specific terminologies used in subsequent chapters.

Chapter 4, "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior," deals with asphalt price adjustment clauses introduced by state Departments of Transportation (DOTs). Incentivized by recent unsettling of energy prices, they are primarily designed to alleviate contractors' excessive risks. Employing various econometric methods, we compare firms' bidding behaviors across projects at different times, but also more carefully at item level within each project. Nonparametric estimations first provide visual evidence that bidding differentials are observed in the group affected by the policy while none in the other. Parametric estimations are then presented to quantify the policy impacts. Our results show that, after enactment of clauses bids are on average 5% lower at project level and 14.5%

lower at item level. Besides, the distribution of bids has become more centralized. Furthermore, the decline in submitted bids from the period after is shown to stretch across all bidders and estimated to be at least twice as large as the direct reimbursement cost of the transportation agency.

Chapter 5, "On the Distributional Impact of Price Adjustment Policies: Bidding Patterns and Survival in the Market," continues to study this risk discounting special provision. This chapter concentrates on its potential asymmetric impacts on firms of various characteristics, such as dissimilar sizes, levels of experience and leverage abilities. In the construction industry, new and small businesses are commonly believed to be disadvantaged due to less well informed price prospect and limited access to external financing. Theory suggest that adjustment clauses, by removing excessive volatility in costs, may shadow the comparative advantage enjoyed by large established firms and elevate performances of small and less experienced ones, which are conducive to long run competitions. Based on a decade long observation window, we first carry out quantile regressions to show that small contractors, regardless of their relative efficiency, adjust their bids downward to a larger extent than the large. In addition, the increased aggressiveness intensifies moving up the bid distribution. Upon policy implementation, small firms are more inclined toward submitting bids and stand a better chance of winning overall. New firms are shown to respond to the adjustment clauses in similar patterns as small firms. We new employ classical survival analysis to reveal that entrants do display statistically lower failure rates and extended duration in the market in the period after policy enactment.

The sixth chapter, "Speed Incentive in Public Procurement Auctions," studies the usage of two innovative contracting methods known as special provisions of incentive/disincentive and A+B milestones. Using data collected from ODOT construction auctions, we have demonstrated that both designs are likely to contribute to faster execution of highway contracts and reduction in commuters' traffic delay. In particularly A+B structure on average accelerates projects completion by 18.5%, or 49.5 days if translated to time. In the meantime, the shortened duration does not significantly increase procurement costs incurred by the state department. We have reported that there are no statistically significant differences between the winning bids received under the creative structures and those under the conventional structure. When we combine impacts from both sides, the new incentive/disincentive and A+B contracting methods result in reduced negative externality and improved social welfare.

The rest of this study is organized as follows. Chapter 2 briefly reviews the theoretical as well as empirical literature pertaining to auctions in general and public procurement auctions in particular. Chapter 3 highlights the collection, special features and summary statistics of the unique dataset. Chapter 4 presents the first essay, "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior." In chapter 5, the second essay examines the distributional impact of price adjustment policies on bidding patterns and survival in the market. The third essay, "Speed Incentive in Public Procurement Auctions," is presented in chapter 6. In chapter 7, we offer concluding remarks.

CHAPTER 2

LITERATURE AND BACKGROUND

This chapter first provides an introduction to the general literature of auction, and then a more specific review of auction applications in the sector of public construction procurement.

2.1 Auction Literature: An Overview

There are four most common forms of auctions: the English auction, also called progressive or ascending auction, the Dutch auction, also known as descending auction, the first-price sealed bid auction, and the second-price sealed bid auction, usually accredited as Vickrey auction. As suggested by its name, first-price sealed bid auction requires bidders to simultaneously and confidentially submit their bids to the auctioneer (sealed), and the highest bidder is awarded the object for the price he or she puts forward (first-price). Procurement auctions of public construction work administered by state Departments of Transportation usually employ this format and follow the rules outlined above, except that the low bidder is deemed winner, representing the lowest (projected) cost for the agency to contract a project. This is a format that limits the information that bidders can exchange during the auction and therefore limits collusions.

In what follows we outline some of the landmark research that has helped shape people's understanding of auctions and how they work.

Vickrey (1961) was the first to use game theory in an effort to explain the dynamics of auctions and equilibrium behaviors. Following Wilson (1977), auction designing rules are commonly divided into polar cases based on the underlying valuation among bidders: independent private value (IPV) models, where bidders' valuations depend on their preferences alone, and common value models, where all bidders value the object by the same amount but they receive a signal of the value rather than knowing it with full certainty. Under the framework of IPV and symmetry, Riley and Samuelson (1981) and Myerson (1981) separately formalize the revelation principle and establish the revenue equivalence theorem (RET) that all four basic types of auctions generate the same expected payoff for the seller. The seminal paper by Milgrom and Weber (1982) expands previous analysis by creating a more realistic model of affiliated values and shows that the revenue equivalence result no longer holds. Many studies have been devoted to evaluating the performance of various auction rules assuming different types of valuation: private value, common value, or a combination of them, with an emphasis on the critical role played by information and uncertainty in payoff realization (McAfee and McMillan 1987, Kagel and Levin 1999, Lebrun 1999, Klemperer 1999, Goeree and Offerman 2003). Challenging other standard assumptions, Engelbrecht-Wiggans, Milgrom and Weber (1983) brings in the notion of asymmetry among participants. Maskin and Riley (2000) build upon it and further develop the equilibrium when bidders are asymmetric with values drawn from different distributions. Since then, researchers have engaged in empirical explorations under less and less restrictive assumptions to study strategic movements and market outcomes, such as when valuations are interdependent, when there are synergies, when the game setting is sequential and more, to better accommodate the complicated real situations where asymmetry is ubiquitous.

2.2 A Survey of Literature on Optimal Procurement Auction Designs

As mentioned earlier, many State Transportation Agencies conduct periodic auctions to let infrastructure projects. As a result, how to minimize procurement costs by carefully formulating rules has been the objective of both government practices and experiments and extensive studies of the academic world. The variety of public policies that have been scrutinized by researchers include: the timing of information release, ex-post renegotiations, scoring rules that internalize completion time into reward consideration, and preferential treatment programs favoring certain groups (such as minority owned business or domestic suppliers) over others. In this section we will review the empirical literature where a multitude of issues of policy designing in the public construction procurement industry are addressed.

De Silva, Dunne, Kankanamge and Kosmopoulou (2008) evaluate the impacts of additional information in the public procurement auction based on letting records of Oklahoma and Texas between 1998 and 2003. Capitalizing on an ODOT policy change taking place in 2000, they compare bidding behaviors of participants with and without the advance release of state engineer's own estimated cost, information that could be utilized by bidders to shadow the common value component of overall costs. Observations from Texas, a contiguous neighboring state of Oklahoma, are employed as a proper control group, where a uniform releasing information policy is maintained throughout the period. Their meticulously executed empirical tests lend supportive evidence that when the weight of uncertain common value component is reduced by additional information, bidders adjust their strategies to submit more aggressive bids: the bidding average is statistically lower after the release of information about engineers' internal cost prior to lettings. The decline is larger for projects with a serious concern for common uncertainty and hence winner's curse. As a robustness check, they take advantage of "recurring auctions", a special group which were not successfully contracted initially and hence have to go on letting a second time. For these auctions, bidders were able to learn engineer's estimate in the failed first auction. Consequently their bids submitted the second time around ought to be least affected by the newly released information. Findings from actual data confirm their expectation that bids received for recurring projects do not differ statistically before and after the policy change.

Utilizing the same institutional break, De Silva, Kosmopoulou and Lamarche (2009) consider the topic of bidder asymmetry in the dimension of entrants versus incumbents. Theory argues that entrants are positioned disadvantageously because they only have limited experiences. Therefore they are more likely to fall prey of the winner's curse in common value situations by competing over aggressively and proposing bids that are too costly to commit. As a result, their profit margins are generally lower than incumbents, which in turn hurt their performances and survival probability in the market. Empirical analysis in De Silva, Kosmopoulou and Lamarche (2009) confirm the theoretical prediction that entrants display a higher tendency to submit unrealistically low bids than the more experienced, reflected by a stochastic dominance between bid distributions at the lower end. However, the stochastic difference is narrowed downed after the release of state engineer's cost estimate, indicating that new firms have absorbed the new formation and adjusted their bids upward, especially those who used to underestimate costs. Thanks to the increased profit margin and non-decreased winning probability, entrants now enjoy a better surviving prospect in the market. This development may have positive influences in the long run when the credible threat exerted by successful entrants enhance competition and prevent collusive behaviors from existing firms.

Standard procurement contracts are often incomplete since initial plans up for bidding are subject to changes and revisions after the winner is selected by competitive auction. Since post award negotiations are common or even prevalent in practice, contractors usually specifically accommodate this possibility and costs associated with it in forming optimal bidding strategies, leading to different procurement costs to the government had firms not accounted for ex post renegotiation. To provide quantitative evidence to the argument, Bajari, Houghton and Tadelis (2009) set up a structural model where firms are able to explicitly take into account the renegotiation afterward and resulted adaption costs in maximizing expected utility. Based on data collected from the California Department of Transportation (Caltran) during 1999 and 2000, they confirm that rational firms' equilibrium strategy is to submit higher bids in order to cover subsequent costs of renegotiation. In particular, their estimates suggest that government procurement costs may be inflated by as large as 10% because of contractors' anticipation of adaptation costs, even if the project turns out to involve no revisions at all. In a related study of bidding manipulation in the U.S. timber industry, Athey and Levin (2001) show that for risk-neutral bidders, their optimal strategy should be to submit extremely unbalanced bids in competitive auctions, with the intention of recovering a much larger windfall payment when inaccurate estimations in initial plans are straightened out through contact execution.

Bidding preference toward certain groups, such as local suppliers and minority operated firms, is a common instrument used by Departments of Transportation to assist otherwise disadvantaged businesses, which has been the focus of a number of papers. With the general consensus being that discriminatory policies are counterproductive and should be eliminated, Naegelen and Mougeot (1998) analyze the trade-off between local preferences and social costs imposed by a protectionist policy, and conclude that special treatment may be justified as boosting competitive behaviors. However, to insure the benefits government must formulate payment rules such that greater effort will be induced from favored firms. Structural estimates from Marion (2007) show that highway construction costs paid by the Caltran between 1996 and 2002 are significantly increased by the discriminatory provision favoring small firms. This is primarily because many large firms are discouraged by the special treatment and withdrawn from the market, undermining competition. With the feature which puts auction ahead of other mechanisms in jeopardy, the loss of social surplus overwhelmingly outweighs the higher profits enjoyed by the small pool of favored firms. De Silva, Dunne, Kosmopoulou and Lamarche (2010) investigate a specific preference program known as Disadvantaged Business Enterprises (DBE), focusing on the impacts of minimum DBE subcontracting requirement. With data obtained from Texas Department of Transportation (TxDOT), a well-defined structural model and newly developed estimation approaches, they find that for both projects with and without assigned DBE goal, firms' underlying cost distributions do not seem to differ significantly. Robustness of such findings is confirmed when even smaller gap between recovered cost distributions is reported based on a prudently selected, highly homogenous subsample.

The studies reviewed above have analyzed many of the current policies Departments of Transportation apply to regulate the market of highway construction. However, one of the most widely used special provisions, price adjustment on selective inputs, has largely been overlooked by the literature. It will be carefully explored in this project.

CHAPTER 3

DATA COLLECTION PROCESS

Access to rich, detailed and reliable data sources usually provide unique opportunities to empirically test theories about market functioning and industry evolutions or to explore areas that haven't been fully addressed by theoretical predecessors. However, microeconomic records, especially those broken down at industry or even firm level, may be difficult to acquire[2] and overwhelming to collect. Therefore, before turning into the three essays, it might be useful to provide an overview of the dataset upon which this thesis is based: to introduce the ODOT letting environment where all auctions take place, to describe data collection and variable construction, and to summarize some basic statistics.

3.1 ODOT Lettings Structure and Data

The panel used in this project is collected from ODOT official pages online.[3] It stretches from January 2002 to December 2010 and encompasses all public construction projects auctioned off by ODOT in this period. Each of the three essays covers a segment of this entire window, as is clarified in corresponding chapters. Unless otherwise noted, records between January 2002 and August 2003 are utilized as history, mainly to construct state variables and identify participants' past performances. Construction projects let between September 2003 and December 2010 constitute the primary object of this study.

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[2] Firm level data are usually private information and may take thousands of dollars to purchase from market research companies.

[3] Available at http://www.okladot.state.ok.us/contracts/index.htm

As briefly mentioned in section 2.1, ODOT procurement lettings are held on a monthly basis (except for December) using the format of first price sealed bid auction. Procured projects cover a wide variety of tasks, ranging from grading, paving, and signaling to intersection modification and bridge work. For each project on the agenda, ODOT provides its detailed information, including a unique identification number, the project's specific location, a brief description of the nature of the work, a detailed engineer cost estimate, and the number of days to complete the project. As required by ODOT, all firms interested in bidding for a project must purchase its plan in advance to qualify as potential bidders (i.e. planholders), and the complete list of planholder names is released to public before the actual letting to inform participants of potential competition. After auction sessions are concluded, all bids submitted including the winning bids are posted on the website. A firm with the low bid is normally deemed winner (equivalent to the lowest cost for the state to contract the work), although ODOT may reject the winning offer and schedule a re-auction later. According to state engineers' comments, rejections are usually based on individual grounds, such as materially unbalanced bids, and there are no specific rules to guide these decisions. We have dropped rejected projects from our database.

Based on the auction setting, observations in the database are generated when a perspective contractor purchases a plan. We know the identity of the planholder and who its rivals are, attributes of the project of interest, a bid if the firm submitted one, and the auction outcome, i.e. whether the firm has won or not. To put it another way, we construct the dataset in a way such that each observation would correspond to a plan purchased by some contractor, a bid (whenever applicable), and all relevant characteristics of the project, the contractor the set of rivals. The panel structure is fairly unbalanced since firms differ considerably in their planholding frequencies. For example, the most frequently observed firm has purchase more than 300 plans and bid over 200 times, while some fringe firms may have purchased as few as one plan.

Table 3.1 details how variables used in the empirical sections are constructed from raw data collected from various ODOT's publications. In most regressions, we adopt relative bid as the primary dependent variable. As the ratio between absolute bid and state engineer's estimate, it facilitates comparisons of bids from different scales. For explanatory variables, there are three major groups: characteristics of bidders, characteristics of rivals and general business conditions. For some variables, references are provided to show common practices in the literature.

3.2 A Special Feature: Data at Item Level

Our vast database is further enriches by the availability of item level data. For every project let by ODOT, its construction may employ a number of items as building materials. In the plan prepared by state engineers, the cost estimate consists of a series of unit price and quantity. Contractors are required to submit a separate bid for each item on the list. Hence, a bid is not merely a single number but a vector of unit prices corresponding to specified quantities. The bidder who submits the lowest total amount, the sum of proposed item bids multiplied by the estimated quantities, is awarded the contract. To illustrate the relationship between bids of items and projects, Table 3.2 presents the bidtab report of an asphalt resurfacing work auctioned off in March 2008. According to the report, the resurfacing project uses 4 items, namely asphalt concrete, traffic stripe, cold milling pavement, and construction traffic control. The total estimated cost across all items is $455,600. Both bidders propose unit prices for every item, and firm B wins the auction with a total bid of $475,300. The set of unit prices on all contracted items are hereafter referred to as itemized bids, to distinguish them from the overall/total bid of a project.

3.3 Summary Statistics: On the Entire Sample

Overall, the full sample includes nearly 2300 projects with a total worth of more than $470 million. Out of the 14058 plans purchased, a total of 7402 bids are submitted by 259 pre-qualified contractors, most of whom are based in Oklahoma.

In general, there are 6.15 planholders for each project, 3.41 of them later submit a bid and one is eventually selected as the winner. It takes a contractor approximately 131 days to complete an average project. The mean value of all projects, measured by engineers' cost estimates, is $2.06 million, with the largest over $88 million and the smallest merely $3800. While the average winning bid is slightly above $2.02 million, the average relative winning bid is 1.06, demonstrating the superb predicting power of engineers' estimates on bids.

Table 3.1 Variable Construction

Variable	Description and Construction of the Variable
Project relative bid	Bid divided by engineer's estimated cost.
Itemized relative 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 refer to these detailed bids at item level. As opposed to the total bid, a project could have more than one itemized bid when it uses multiple items for construction, which is the norm.
Large and small firms	Division based on market share over 1% or not.
Entrants	Contractors who submit first bids after September 2003.
Asphalt items	Bituminous Asphalt Concrete products, as prescribed in ODOT Special Provision 109-7(a-b) 99; used interchangeably with "eligible items" and "bituminous items" in the text.
Fuel items	Construction items heavily using diesel fuel, as prescribed in ODOT Special Provision109-3(a-c) 09.
Asphalt projects	Projects that include asphalt items in plans.
Non-asphalt projects	Projects that don't include asphalt items in plans.
Bids after policy	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	A dummy variable use to identify bids from the group of held after June 2006 and subject to policy influences.
x	*Bidder Specific Characteristics*
Capacity utilization	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 the "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 (Jan 2001 to Aug 2003) are used to calculate the initial values of capacity utilization rate. For firms that have never undertaken any projects, this variable is set to 0. See Porter and Zona (1993).

Distance to project	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).
Past winning to bidding ratio (WP)	Firms' ratio of winning times 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 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 as an evaluation of the particular set of competitors a firm is faced with. 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 values. See capacity utilization for the construction of backlog values. See Bajari and Ye (2003).
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).
Within auction bid dispersion	This variable measures the dispersion of bids submitted in an auction, taking the value of standard deviation of relative bids.
Project type dummies	All projects are categorized into seven groups based on the brief description in the plan. They 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.
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 (BEA).
Monthly dummies	There are in total 10 monthly dummies since ODOT holds no December lettings.

Table 3.2: Item Bid and Total Bid – An Example from A Resurface (Asphalt) Project

Item	Description	Quantity	Unit price	Amount	Unit price	Amount	Unit price	Amount
			(engineer's estimate)		(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(square 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
			Overall / Total bid:			$481,200		$475,350

CHAPTER 4

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

4.1 Introduction

This chapter compares the bidding records in ODOT highway procurement auctions held before and after the enactment of price adjustment clauses in 2006, based on observations between September 2003 and September 2009.[4]

The prices of crude oil and its byproducts 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 fuel-based inputs and rely on the public procurement process for most of their business activities. One such example is the road construction industry. Unpredictable oil prices are a significant concern for contractors when projecting costs to propose bids. Firms are faced with a much greater risk of losses and forced to inflate their bids.

In an effort to reduce the risk faced by contractors, the US Federal Highway Administration (FHWA) and several state Departments of Transportation 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

[4] This chapter is based on a working paper coauthored with Georgia Kosmopoulou, to whose guidance, support and encouragement I am greatly indebted. I am grateful to Carlos Lamarche for generously sharing his programs on panel quantiles. I would also like to thank Xin Huang and Gregory Burge for helpful comments.

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 an indexed price system give a state agency the additional role of an insurer, raising construction and operational costs. Besides, is this policy providing primarily protection and support to less productive firms?

Despite the increasing popularity of these clauses among transportation agencies and the ongoing debate about costs versus benefits, there has been little systematic study on how the behaviors of construction firms are affected by the presence of price indexing clauses. This paper seeks to fill the gap in the empirical literature by evaluating the price adjustment clauses that were applied to selected fuel-based construction materials (bituminous) in Oklahoma since June 2006. This recent policy change provides an appropriate object for the case study for a number of reasons. First, Oklahoma is among the early states to institute price adjustments, generating a sufficiently long window for policy analysis and impact assessment. Second, to this date the special provision on asphalt and related materials is the only price adjustment ever implemented by ODOT, which frees us from the complication of multiple contemporary policy changes. Third, detailed project level information is available to control for individual heterogeneity that may not have been possible otherwise. The dataset is further enriched by item level data as described in section 3.2. This unique feature allows us to assess the policy effects of adjustment clauses on targeted tasks more closely.

The study of input price adjustment clauses may have important implications outside U.S. road construction industries. One example is the practice of Public-Private-

Partnership (PPP) in Europe. Currently, the usage in PPP is quite limited, partially attributable to the frequent and potentially costly renegotiations taking place after contracts are awarded. If contingent clauses for anticipated changes were included in the original plan to make it as complete and exhaustive as possible, some important downsides of PPP's could be avoided to promote its applications. The potential gains even extend beyond sectors where daily operation is heavily influenced by fluctuations in oil prices. In the recent federal health reform, a legislation known as Medicare part D was enacted in 2003 through the Medicare Prescription Drug, Improvement and Modernization Act and included provisions similar to ODOT asphalt price adjustment clauses. 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." With the stipulation in place, US federal government is essentially setting up "risk corridors" that would the amount of profits or 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 costs of medical insurance.

The remainder of the chapter is organized as follows. Section 4.2 reviews background and literature. Section 4.3 lays out a modeling framework. Section 4.4

describes data wile Section 4.5 carries out econometric analysis. Section 4.6 offers concluding remarks.

4.2 Background

4.2.1 ODOT Price Adjustment for Asphalt Binder

A distinguishing trait of Industrial Organization is that every research question stems from a relatively unique environment. Hence, background information is very important in understanding the context of each inquiry.

Due to increasing demand from contractors, ODOT amended its standard specification to include special provision 109.12 on price adjustment for asphalt binder, effective with 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, when the current index ($\bar{c}_{t+1}$) increases by more than 3% from the base index ($\bar{c}_t$), a lump-sum payment is automatically triggered from the department 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. For example, the reimbursement amount per unit of eligible item is $r_{t+1} = \bar{c}_{t+1} - 1.03\bar{c}_t$ when the index increases by more than 3% from its base value.

As of September 2009, 40 states apply price adjustment for asphalt products in their procurement contracts and two 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: 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 Oklahoma, Colorado, Illinois, and Michigan implemented the new policy in the recent wave.

Early in 2009, ODOT drafted a similar clause intended for items of diesel fuel but didn't officially enact it until July 2011. We collected information on itemized bids for all policy eligible asphalt and fuel materials that either have been or would be subject to price adjustments. Since asphalt and diesel fuel are both products out of crude oil refinement, their bids, primarily built upon costs, ought to exhibit similar fluctuations through time. In the empirical analysis section, we take advantage of this highly homogenous pair and investigate whether the expected similar paths hold up.

4.2.2 Related Literature

At first glance, by shifting risk from contractors to the government agency, the price indexing system benefits private firms only, and increases the immediate cost of procurement. One perceivable direct return to the government is the savings when prices drop. On the other hand, 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 the risks. Goeree and Offerman (2003) shows that bidders bid more aggressively when uncertainty is reduced, even if they are risk neutral, and this bidding behavior can benefit government agencies as buyers.

The auction literature has been prolific of studies on the effectiveness of mechanisms used to procure construction contracts and the impact of various regulations. Based on state auctioned contracts offered between 1997 and 2003 in Oklahoma and Texas, De Silva et al. (2008) look at the release of information policy concerning internal cost estimates. Discriminatory treatment and preference toward certain groups have been investigated in multiple settings (Naegelen and Mougeot, 1998; Marion, 2007; De Silva et al., 2010). Thomas and Wilson (2002) and Bajari, McMillan and Tadelis (2009) compare competitive auctions with bilateral negotiations in search for the optimal mechanism, and conclude that auction competition is generally favored from an efficiency point of view but negotiations facilitate communication and may be superior in environments with high uncertainty. Bajari, Houghton and Tadelis (2009) examine the impacts of ex post renegotiation and adaptation costs frequently incurred in competitive auctions.

This paper is among the first empirical attempts to evaluate the impacts of price adjustment clauses on government procurement auctions of construction contracts. Eckert & Eger (2004) approach the question by consulting state engineers and government employees who participated in similar programs in Georgia's neighboring states (Alabama, Florida, etc), and base 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.

4.3 A Modeling Framework

We consider a simple theoretical model of auction competition to formalize the impact of price adjustment clauses on the bidding outcome. Bidders are assumed to be risk neutral. A bidder has only an estimate $c^e_{i,t+1}$, for the cost at the time of bidding. Assume that the true cost $c_{i,t+1} = c^e_{i,t} + d_{t+1}$, where d_{t+1} represents the difference between estimated and actual costs affected by market factors beyond the immediate control of the firm. The cost $c^e_{i,t}$ is drawn from a twice continuously differentiable distribution with a strictly positive density. The uncertainty in the price of volatile inputs, in this case asphalt mixture product, may cause the actual fulfillment cost of firms to be different from $c^e_{i,t}$. Let $d_{t+1} = \bar{c}_{t+1} - \bar{c}_t$ where $\bar{c}_{t+1}$ and $\bar{c}_t$ are indices at the time of construction completion (next period) and letting (this period) respectively. $\bar{c}_{t+1}$ is a random variable with a known distribution ex ante. One can think of cost realizations in the following way: A firm receives a quote from a supplier at time t on the price of asphalt at $t+1$ which is uncertain and depends on market forces beyond the control of local suppliers. The price index represents the average price across suppliers at a specific time period affected by exogenous shocks. The differences in the cost index through time capture potential fluctuations in the cost that cannot be controlled by the supplier at time t.

The bidder who bids b_{it} and is awarded the contract receives a utility of $u(b_{it}, c_{it+1}) = b_{it} - c^e_{it} - d_{t+1}$. Let $s_{it} = c^e_{it}$ be the privately observed component of the cost and y_{1t} denote the infimum of the remaining estimates of s_t. The unique symmetric equilibrium bidding strategy for bidder i in the first price auction held at t is:

$$B(s_{it}) = E(d_{t+1} \mid s_t \geq s_{it}) + E(y_{1t} \mid y_{1t} \geq s_{1t}), \tag{4.1}$$

The adjustment clauses transform the difference between initial estimates and the realized costs and it becomes:

$$d^*_{t+1} = \begin{cases} \bar{c}_{t+1} - \bar{c}_t & \text{if } -1 \leq \frac{\bar{c}_{t+1} - \bar{c}_t}{\lambda \bar{c}_t} \leq 1 \\ \lambda \bar{c}_t & \text{if } \frac{\bar{c}_{t+1} - \bar{c}_t}{\lambda \bar{c}_t} > 1 \\ -\lambda \bar{c}_t & \text{if } \frac{\bar{c}_{t+1} - \bar{c}_t}{\lambda \bar{c}_t} > -1 \end{cases}$$

where λ is the proportion of price adjustment specified by the indexing policy (λ is set to be 0.03 in the case of asphalt binder adjustment). Without loss of generality, we assume λ is bounded between zero and one.

It is obvious from this expression, that the distribution of realized common cost is now becoming less dispersed. Note also that the likelihood of cost overruns increased substantially in the past ten years. Overall oil prices have a persistent upward trend. 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 imminent closure of some nuclear facilities (Washington Post 3/17/2011) is creating expectations for a substantial increase in demand for petroleum products in the future (Associated Press 4/11/2011). Assuming rational expectations it follows that $E(d_{t+1} \mid s_t \geq s_{it}) \geq E(d^*_{t+1} \mid s_t \geq s_{it})$. The variance of d^*_{t+1} is lower in relative terms. When there is expectation of price fluctuations leading to higher costs, the distribution of d^*_{t+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; and (3) the smaller the component is in the total cost, the smaller the effect of the policy on bidding behavior.

4.4 Qualitative Analysis

The panel generated for this study was based on data collected from Oklahoma Department of Transportation online site and includes all public construction projects auctioned off between September 2003 and September 2009. As explained in section 3.1, the panel structure is unbalanced since firms differ in their participation frequencies.

Table 4.1 provides a summary of auctions for the pre and post-adjustment periods separately, broken down by several comparison groups. Since the adjustment enacted in June of 2006 is applicable to certain materials only, projects naturally fall into one group or the other depending on whether they involve relevant items, and hence are subject to ex-post payment transfers. The top section of Table 4.1 contrasts measures on projects with eligible asphalt inputs (eligible projects) versus measures on projects without eligible asphalt inputs (ineligible projects). Auctions in both categories are roughly balanced across time. All measures are not significantly different across categories except for the average relative bid. Plots (A)-(B) in Figure 4.1 present an inter-temporal shift in the distribution of relative bids for eligible projects in the period after the policy enactment but no such movement for ineligible projects in the same period. The next comparison group presented in Figure 4.1(C)-(D) has a focus on projects by type, to maintain homogeneity within group more effectively. We elect here asphalt paving and bridge work projects for two reasons. First, they are the two largest categories and together take up 65% of the whole sample. Further, they differ considerably in the percentages of eligible projects. Applicable asphalt products are involved in nearly 86% of asphalt paving, and on average constitute 74% of the total contract value. On the other hand, two thirds of bridge construction projects do not use any eligible items, and those that do, use them at a much lower intensity (11%). Compared to bridge related construction, asphalt work has fewer plan holders and bidders in both periods. As one can see from the table, the difference in relative bids became more pronounced after June 2006. This trend is again picked up by plots (C) and (D) of Figure 4.1.

The comparisons made so far were at the project level. One could still argue that other systematic differences between the two groups, not the presence of adjustment, are responsible for the noted disagreement. In an effort to clear up this ambiguity, we restrict attention to eligible projects alone. In the third section of Table 4.1 we compare relative bids on eligible items to relative bids of ineligible items within the same projects. As seen in Figure 4.1(E) and (F), there is a significant difference in the distribution of eligible items but not in those of ineligible items. Our last comparison group consists of eligible asphalt items and ineligible diesel fuel items within the same projects. Both asphalt binder and diesel fuel are produced during the process of refining crude oil, so their costs are subject to common risk of future fluctuations. In fact, the indexes for asphalt and fuel follow a similar trajectory. Data on those indexes are not available for Oklahoma (not for the entire period of analysis) but they are available for Arizona, where the coefficient of correlation between the crude oil index and the asphalt price index is 0.79. As a result, bids on the two items are expected to behave similarly through time in the absence of any asymmetric interference. Nonetheless, we observe in plots (G) and (H) of Figure 4.1 that the bid distribution of diesel related items has remained roughly identical between the two periods, while the bid distributions of bituminous products from the post-policy interval has visibly shifted to the left and became less dispersed, a change that we will argue is caused by the price adjustment for asphalt alone. While the panels in Figure 4.1 suggests that bidders submit lower bids on the item 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.

Maintaining the well-known merits of nonparametric estimations, this new method has been improved to accommodate both continuous and discrete variables. With the choice of (continuous) bandwidth and (discrete) smoothing parameter based on least squares cross-validation, the Racine and Li method was shown to generate 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 types. In particular, we apply the following model empirically:

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

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

Projected relative bids, denoted by $\hat{y}_{iat}$, 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 available in Table 3.1. Distribution plots of $\hat{y}_{iat}$ seem to be close enough to the unconditional kernel graphs for all four specifications. This is not surprising in consideration of the great similarities in the level of independent variables between pairs (as seen in Table 4.1). Figure 4.2 presents 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 remained virtually unchanged. Regarding the third and the fourth panels (plots (E)-(H) in Figure 4.2), bids are both considerably lower and less dispersed upon the introduction of the price index. Notable differences between treated and untreated bids persist, underlying the impact of the price indexing policy on bidding.

The final step in this analysis is to perform a number of Kolmogorov-Smirnov tests of the hypothesis that the distributions are the same across predicted bids. The tests on the treatment groups were rejected for all cases considered, at 1% confidence level. When control groups were tested, we failed to reject the null hypothesis for eligible versus ineligible projects and asphalt versus bridge work, while we concluded that there is some inequality in the distributions of itemized bids on fuel materials and other items at the 5% significance level. However, the revealed differences in bids before and after the policy enactment are much smaller compared to the control groups, and the direction of change is reversed for fuel items. Some bidders submitted considerably less aggressive bids for fuel items in the lack of any policy intervention reflecting the risk that the firms were taking while submitting bids under highly volatile prices between 2006 and 2008.

4.5 Empirical Tests

In this section, we present two approaches on how to assess quantitatively the impact of price adjustment clauses on bidding and procurement costs. First, we propose to apply the difference-in-difference (DID) regression strategy. Due to few restrictions and straightforward intuition, DID methods have quickly gained popularity among empirical researchers (Imbens and Wooldridge 2008, Bertrand et al. 2004). This approach manages to control for factors that are hard to measure otherwise by employing a separate (control) group to approximate the "counterfactual" performance of the treated group. By applying double differences, both the time-invariant group gap and temporal change along the timeline are removed, leaving as unaccounted residuals the specific effects ascribed to the program intervention. Our second route is to use regression discontinuity designs that capitalize on the discrete nature of the policy change. This method focuses on observations within a close neighborhood around the time of the new policy implementation.

4.5.1 Difference-in-Difference Models

The institutional detail of asphalt price adjustment clauses enables us to apply the difference-in-difference method based on data collected from Oklahoma. The standard DID specification, applied to different subsets and stratifications of our data set is as follows:

$$y_{iat} = \alpha_i + \beta_1 T_{it} + \beta_2 A_t + \beta_3 (T_{it} \times A_t) + x_{iat}^{'}\gamma + z_{at}^{'}\delta + w_t^{'}\zeta + \varepsilon_{iat}, \tag{4.2}$$

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 engineer's estimated cost and is employed as the dependent variable, to allow a comparison among projects of various scales. T_{it} takes the value of 1 for projects or items in the treatment group; A_t the time dummy takes the value of 1 for bids submitted after June 2006. Apparently β_1 captures the permanent intra-group difference; β_2 absorbs intra-period changes that are common across; and β_3 measures the change in bids between the treatment and control groups in the post-policy enactment period. According to theoretical predictions, β_3 is expected to have a negative sign when participants assume lower risks and bid less aggressively. The key assumption ensuring an unbiased estimate is that β_3 would be equal to zero if treatment had no asymmetric impact across categories, i.e. $E(\varepsilon_{iat} \mid x, z, w, A_t = 1, T_{it} = 1) = 0$.

A set of independent variables are included to control for observed heterogeneity across firms and auctions, which are classified into three main categories: bidder specific characteristics (captured by the covariates in x), auction specific characteristics in z and variables reflecting general economic conditions in w. As mentioned earlier, Table A1 provides a detail description of all variables.

All specifications include firm fixed effects and monthly dummies to remove the influence of individual idiosyncrasies and seasonal factors. Standard errors are clustered by auction, to ensure robustness to latent auction-specific residuals. The legislation on the price indexing system provides an easy division of the entire panel into two periods, and we employ several treatment-control pairs to study how firms adjust their bids in the presence of the new policy.

4.5.1.1 Mean Level Estimation

We start our analysis by considering the entire pool of auctions as a benchmark. Based on the distinction of involving applicable items or not, all projects fall into one of the two categories: (1) projects that use eligible items and are subject to ex-post adjustments and (2) projects without eligible items that are not subject to the current intervention. The latter category constitutes a natural control group for program evaluation, and the former can be viewed as a treatment group that bears potential influences.

Column 1 of Table 4.2 reports parameter values of the base model. Overall, considering β_1 bids submitted after the policy was enacted are not systematically different from the ones submitted before. Firms tend to offer slightly higher bids on eligible projects, according to β_2. The estimator of interest is the difference-in-difference parameter β_3 representing any change in bidding across time but unique to the treatment group only. This key parameter is negative and statistically significant, suggesting an unmatched reduction in bids from the treatment group after June 2006, in the period after the policy change. The magnitude of this reduction is 4.7%. As far as other explanatory variables are concerned, the distance between a firm and the project undertaken is positively related to the bid submitted; costs increase as distance grows further. As capacity utilized rises, bids increase indicating that costs may rise if firms are already involved in major works elsewhere. The number of bids submitted is a rough indicator of the intensity of competition and is driving bids down. Competition typically induces more aggressive bidding behavior. Rivals characteristics such as their distance to a work site or capacity commitment affect bidding decisions. Long commuting distance and large workload attenuate competition. Bids tend to fall as the unemployment rate rises, since government procurement projects become more attractive to bidders when outside business opportunities decrease. Other variables describing economic activities appear to have statistically insignificant effects on bidding behaviors.

We also consider projects by type (asphalt, bridge and signing projects) and present a comparison of bidding across project categories. One advantage of this approach is that projects of the same type are more homogenous in nature, and thus such comparisons will spare us of important but hard to quantify within-group heterogeneities. The second column of Table 4.2 provides regression results using asphalt paving and bridge work projects. The two subsamples differ markedly in the usage of asphalt materials eligible for ex post price adjustments. Eligible materials are involved in approximately 86% of asphalt paving work and are taking up three quarters of the total contract value on average. This is in comparison to a mere 30% involvement in bridge work accounting for 11% of bridge work relevant contract values. As a result, observations from asphalt paving form the treatment group and those from bridge work are used as controls. Estimators obtained are fairly consistent with the base model. While neither the time dummy nor the treatment group dummy exhibits significance, the difference-in-difference parameter β_3 remains statistically and economically significant, exceeding 10% in magnitude. Rivals' competitiveness, based on winning to plan holder ratios, becomes much more critical in shaping the bids submitted. Column 3 displays results from the same specification except for using signing work as the control group. Most signing projects do not contain eligible items. The results reported in column 3 are in line with those in the first two columns. The estimate of β_3 continues to be significant both statistically and economically. Once more, bids from the treatment group have been significantly lowered in the period after the policy implementation. Rivals distance to work site becomes an important factor. In the last column, we apply the DID approach to bridge and signing work. Both project types have been employed as controls when studying asphalt paving work as they infrequently involve eligible items. Theoretically, since neither is intensely affected by the new legislation, we should not expect the parameter β_3 to be significant in the comparison between these types.[5] Indeed, in column 4 the estimate of β_3 is not

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[5] 75% of signing projects have no eligible items. If there is any small difference in the estimates of β_3, it should be

significant.

We now restrict attention to projects using applicable asphalt items alone. Having access to itemized bid data, we could construct for each eligible project two itemized relative bids, one is a weighted relative bid from eligible asphalt materials and one is a corresponding relative bid from all others ineligible items. There are actually 3 exceptions in the entire sample which use 100% of eligible asphalt items, and don't have a relative bid on ineligible items. They are excluded from this particular subsample. Relative bids on eligible items serve as the treatment group and relative bids on the rest are controls. If the significance of the bid decline in the previous table were attributed to other factors affecting the entire group of projects, the pair should have been affected similarly and should have exhibited comparable fluctuations throughout the time window. Nevertheless, as shown in the first column of Table 4.3, the key parameter of DID continues to be statistically different from zero. This asymmetric trend over time could be attributed to the adjustment clauses as they only take effect on one group. In regard to other independent variables, travel distance, competition intensity, and rate of unemployment carry on their significance in determining the bids.

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). If the two groups, eligible and ineligible components of a project, are affected symmetrically, their ratio $\frac{y_1}{y_0}$ should remain roughly constant through time. There are some advantages in utilizing this approach.

negative, indicating that a slightly higher proportion of bridgework than signing projects have eligible items.

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 firm-auction specific effects that are common across items but unobserved. In column 2 of Table 4.3 the ratio $\frac{y_1}{y_0}$ is shown to have a significant decline in the second period, indicating that relative bids on eligible items have been disproportionally 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 there left for firms to leverage between the bids on different components.

We also narrow down our analysis to the subgroup of projects that simultaneously involve asphalt and diesel fuel items.[6] Both items are produced out of crude oil and their price fluctuations are closely tied together. This strategy will enable us to examine how relative bids of asphalt items and fuel items change over time. 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 dataset support that, 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. It removed excessive fluctuations in asphalt item bids while leaving diesel fuel items by themselves. It is obvious from the bottom panel in Table 4.1 that the relative bids on two groups have diverged as a response to the adjustment policy. Relative bids on asphalt are

[6] 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.

significantly lower in the second period, while relative bids on fuel stay essentially unaffected. This change in pattern between periods speaks for the potential effects of the price adjustment clauses on treated items. Results from DID analysis, shown in Table 4.3, further underline the policy impact, which is statistically and economically significant when other factors are taken into account.

4.5.1.2. Bid Dispersion

Theory predicts that, provided with additional insurance against price uncertainty, contractors will respond by adjusting their bidding strategies. Our results have provided affirmative 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 see whether bids become less dispersed after the policy implementation. We estimate four specifications considering both project and item bids, using this simple linear regression:

$$y_{at} = \alpha_i + \beta_1 T_{it} + \beta_2 A_t + \beta_3 (T_{it} \times A_t) + z_{at}^{'}\delta + w_t^{'}\zeta + e_{at}, \qquad (4.3)$$

where y_{at} is an indicator of the degree of bids 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 items. 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. We exclude 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. As a result sample size is further reduced. Regarding the right hand side, bidder level heterogeneity is integrated out, leaving auction specific characteristics and general economic conditions as explanatory variables.

Estimated coefficients are presented in Table 4.4.[7] 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 (Hong and Shum 2002, Bajari and Ye 2003). Additionally, observations from the treated group display smaller variance after the policy becomes effective, with the difference becoming statistically significant in the second column. The last two specifications use the ratio of bid dispersions to capitalize on itemized bids. The coefficients of the time dummy is negative and significant in both cases, supporting the theory concerning the second moment: bids have smaller variance for treated materials as price adjustment clauses lower the level of uncertainty. One thing worth pointing out is that change in bid variances becomes more visible when comparing asphalt items with fuel items (rather than ineligible items in general), because they are subject to greater price uncertainty.

4.5.1.3 Quantile Regression Analysis

So far we have shown noticeable policy influences on bidding behaviors at the mean level. In Table 4.5, we apply quantile regression analysis (Koenker 2005, Lamarche 2010) to investigate if such effects vary across the distributions of relative

[7] 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.

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 quartile with the scale effects varying across the range.

The upper part of Table 4.5 presents regression results at 0.20, 0.50 and 0.80 quartiles 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 is the ratio between relative bids for the other two. The parameters capturing asymmetric policy effects, β_3 in the first two cases and β_1 in the last two, are consistently negative and significant for all three quartiles. Relative bids are roughly reduced by about 4% in eligible projects compared to ineligible projects, 10% in asphalt projects compared to bridge projects, and beyond 10% in eligible asphalt items compared to ineligible fuel items. Consistent with results at the mean level, as contrasting pairs get more refined, the magnitude of the policy impact becomes more pronounced. An interesting finding is that difference in coefficients across quartiles of the same model becomes much more prominent for the final specification (asphalt items/fuel items), and is statistically significant at 5% confidence level. This magnified gap could be caused by behaviors of those at the higher end of distribution of relative bids. If these firms were inflating bids drastically to cover losses due to price volatility, they would derive most benefits under the indexed prices. This piece of evidence offers additional support that enhanced bidding aggressiveness is a response to adjustment clauses, and is not confined to certain firms but rather permeates through bidders at all levels. The lower part of Table 4.5, 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. 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 4.3. While the continuous line shows point estimates, the shaded region represents a .95 confidence interval for these estimates. In Figure 4.3(A) we present bids on eligible items in comparison to those on ineligible items. Figure 4.3(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 byproducts and the expectation for higher prices. As bids at lower quantiles are moderately reduced due to the policy change those at upper quantiles are dropping dramatically. Consistent with results in 4.5.1.2, bids become less dispersed in the second period. Theory shows a disproportionate reduction of costs estimates on eligible items ex ante due to the policy followed by a disproportionate reduction in bids. Figures (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 (A) & (B).

4.5.1.4 Robustness Checks

We are now exploring the robustness of results from section 4.5.1.1. One of the pressing concerns of the literature is potential underestimation of the standard error due to intra-group correlation or correlation across time, and the resulted spurious causality. Even though we have provided standard errors clustered by auctions throughout to correct the inflated t-statistic caused by intra-group correlation (Moulton 1990), there is still potential correlation in the time dimension. With regard to this issue we follow the procedure proposed by Bertrand et al. (2004) and collapse the 73-month panel down to two periods, aggregating data by firm and type. In this way, heterogeneity among main task groups remains intact, while temporal correlation is eliminated when each firm only submits one "composite" bid in each period of the collapsed dataset. Judging by the 2-period regression results presented in columns (1) and (5) of Table 4.6, the coefficient β_3 is robust to this alternative specification.[8]

If the reduction of bids from the treated group was caused by a gradual but steady downward trend, splitting the sample period in two could mistakenly attribute a progressive change to the institutional policy break. To test this hypothesis, we add to the existing model a continuous time trend and the interaction between the trend and treated group and present results in Table 4.6 under columns (2) and (6). In either column, we don't observe the trend or the interacted term to be statistically different from zero, confirming that the negative sign of the DID parameter is indeed caused by a sudden jump rather than a continuous movement. In fact, if we look at the interaction term of the base model, the positive coefficient hints a modest increase in the relative bids for eligible projects over time, conditional on other controls.

We also examine the sensitivity of previous findings on the usage of actual number of bidders as an independent variable. Since firms do not know whom they are

[8] Parameters of other independent variables appear smaller in magnitude. This is possibly due to the reduction in variation caused by the integration of observations across multiple periods.

bidding against in an auction until after submitting their bids, the exact number of competitors is not known at the time of decision making. To examine how much our conclusions depend on the implicit assumption of a given number of bidders, two proxies are considered. The first is the number of plan holders, made available to all firms on ODOT.s website before the auctions are taking place. This measure is representing the number of possible entrants and is obviously correlated with competition intensity. Second, the expected number of bidders is employed in place of the de facto number, making use of information on both the pool of potential participants and their past bidding frequencies. Specifically, for each firm, the ratio of number of bids submitted over the number of plans purchased in the past twelve months renders its entering likelihood. The expectation of the total number of entrants in a letting is simply the summation over bidding probabilities of all plan holders (De Silva et al., 2008). Estimations are displayed in columns (3)-(4) and (7)-(8), where our key parameters of β_1 (for (3)-(4)) and β_3 (for (7)-(8)) remain essentially unchanged to this modification. The same procedures are applied to other models (asphalt/bridge projects and asphalt/fuel itemized bids), whose results are consistent with previous finding and are available upon request.

Finally, in Table 4.7 we introduce the proportion of applicable items in a project to replace the dummy variable indicating adjustment eligibility. The proportion of eligible items is calculated based on the benchmark value of engineering estimates to provide a continuous and more precise measure of the involvement of eligible materials in each contract that is subject to ex-post transfers. Table 4.7 presents estimation results on relative bid regressions applied to all projects in column (1) and asphalt paving projects in column (2). Estimates of β_3 in both columns are similar. These estimates are showing that in the period after the policy enactment a higher proportion of eligible items is reducing the cost of contracting on average by an amount close to 12% relative to the period before. Estimates on the effects of other independent variables on relative bids are consistent to those reported in specifications presented earlier.

4.5.2 Regression Discontinuity

An alternative method to evaluate ODOT asphalt price index 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 adjustment clauses. The idea is as follows: for lettings taking place right before and after the application of treatment, all factors are assumed to affect bidding behavior 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), we apply a linear equation to implement regression discontinuity. We let be the relative bid submitted by firm i in auction a at time t. A is the dummy variable indicating presence of the adjustment policy, t denotes a continuous time trend, and 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:

$$y_{iat} = \alpha_i + \beta_1 A + \delta_1 t + \delta_2 (A \times t) + X_{iat}\gamma + e_{iat} \qquad s.t. \quad -h < t - t_0 < h \qquad (4.4)$$

where h denotes the "bandwidth", indicating how far we stretch into the area around the cutoff point in time. Table 4.8 presents the estimates of β_1, representing discontinuous policy effects, when several bandwidths are applied. Bandwidth selection is based upon the cross-validation criterion (Ludwig and Miller, 2005), 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. 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.

4.6 Concluding remarks

The introduction of asphalt adjustment clauses in public procurement contracting intends to liberate firms 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. A common justification for the use of incentives in contracting is the potential reduction in costs. This paper seeks to present some empirical evidence on the topic by employing a new detailed dataset acquired from 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 implication on targeted tasks closely.

Our findings lend support to theoretical predictions on bidding behavior, confirming that firms do submit more aggressive bids with lower dispersion in the distribution, if risks are reduced. In general, bids submitted on eligible projects are 5% lower in the presence of an adjustment policy relative to bids on ineligible projects. When we consider itemized bids (as opposed to the overall project bids), eligible items received approximately 12.7% lower bids than other items. In comparison to fuel items, eligible asphalt items received 14.5% lower bids on average after the policy was enacted than before. The cost of fuel items is subject to similar price fluctuations as that observed in eligible items. 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.

A more accurate measure of potential savings to the state department is to build on the subgroup of bids of awarded contractors rather than the entire pool. Table 4.9 provides results of DID regression applied to winning relative bids only. For the treated group in the period after, bids continue to be statistically significant and lower than that of the control, indicating that the policy does encourage more aggressive behaviors even from bidders that have won. As mentioned earlier, ODOT approved a net payment to firms equal to 5.05% of the contracted values of items eligible for adjustment from August 2006 to June 2009. Based on our analysis, we estimate a $22 million potential net savings for ODOT during this period.[9]

The evidence, however, in favor of policy intervention must be taken cautiously. Construction firms could utilize market instruments available at financial exchanges as an alternative to insure against volatile asphalt prices. Nonetheless, market imperfections (no standardized futures market for asphalt as a commodity) 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.[10] In discussions we had with state officials, they thought it was unlikely that firms have used private financial instruments in the past. Instead, it is possible that a few may have signed long term contracts for key commodity inputs or may have been on occasion pre buying these inputs at a discount. The fact remains that, price adjustment policies transfer risks from individual contractors to state departments, undoubtedly exposing government agencies to great fluctuations in payments and making it hard for them to plan their budgets. The final decision should account for the trade-off between incentives and efficiency, taking potential differences in risk attitude under consideration (Iossa, Spagnolo and Vellez, 2007).

To the best of our knowledge, this project is the first attempt on program

[9] The calculation is based on the total value of contracted projects, proportion of stipulated eligible items, and the estimated coefficients.

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

evaluation of price adjustment clauses in the procurement auctions related to construction. Overall, results point to the positive effects of this intervention. Nevertheless, it is unlikely that the effects are uniformly dispersed among firms given their asymmetric nature. The exact distribution in addition to the overall effects may be essential when it comes to policy appraisal and government decision making. In the next chapter, we will investigate the differential effects of asphalt adjustment policies on the pool of various participants of procurement auctions.

4.7 Appendix

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

$$\pi(b)=\{b-s-E[D\mid s\geq B^{-1}(b)]\}\{1-F_s[B^{-1}(b)]\}^{n-1}$$

Differentiating the expected payoff with respect to b and evaluating the expression at the optimal choice we have:

$$\left.\frac{\partial\pi}{\partial b}\right|_{b=B(x)}=\left\{1-[E(D\mid s\geq x)-E(D\mid s=x)]\frac{1}{B'(x)}\frac{f_s(x)}{1-F_s(x)}\right\}[1-F_s(x)]^{n-1}$$
$$-[B(x)-s-E(D\mid s\geq x)](n-1)[1-F_s(x)]^{n-2}f_s(x)\frac{1}{B'(x)}=0$$

Simplifying we get:

$$\begin{aligned}&\{\frac{1}{n-1}-\frac{1}{n-1}[E(D\mid s\geq x)-E(D\mid s=x)]\frac{1}{B'(x)}\frac{f_s(x)}{1-F_s(x)}\}[1-F_s(x)]-\\&[B(x)-s-E(D\mid s\geq x)]\frac{f_s(x)}{B'(x)}=0\Leftrightarrow\end{aligned}\tag{4.5}$$

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

$$B(x)=E[D\mid s\geq x]+E[y_1\mid y_1\geq x]\tag{4.6}$$

Differentiating this expression we get:

$$B'(x) = [E(D \mid s \geq x) - E(D \mid s = x)]\frac{f_s(x)}{1 - F_s(x)} + [E(y_1 \mid y_1 \geq x) - x]\frac{f_{y_1}(x)}{1 - F_{y_1}(x)} \quad (4.7)$$

Using the fact that $\frac{f_s(x)}{1-F_s(x)} = \frac{1}{n-1}\frac{f_{y_1}(x)}{1-F_{y_1}(x)} + \circ(\frac{f_{y_1}(x)}{1-F_{y_1}(x)})$ and replace (4.6) and (4.7) into (4.5) we get:

$$\frac{1}{n-1}[E(D \mid s \geq x) - E(D \mid s = x)] + (E(y_1 \mid y_1 \geq x) - x)$$
$$-\frac{1}{n-1}[E(D \mid s \geq x) - E(D \mid s = x)] - E(D \mid s \geq x)$$
$$-E(y_1 \mid y_1 \geq x) + s + E(D \mid s \geq x) = 0$$

$$[s - x] = 0 \Rightarrow s = x.$$

Together with the monotonicity of B, we show that $B(s_i)$ is the bidder's unique optimal bid, i.e. $B(s_i) = E[D \mid s \geq s_i] + E[y_1 \mid y_1 \geq s_i]$.

Figure 4.1: Unconditional Kernel Densities

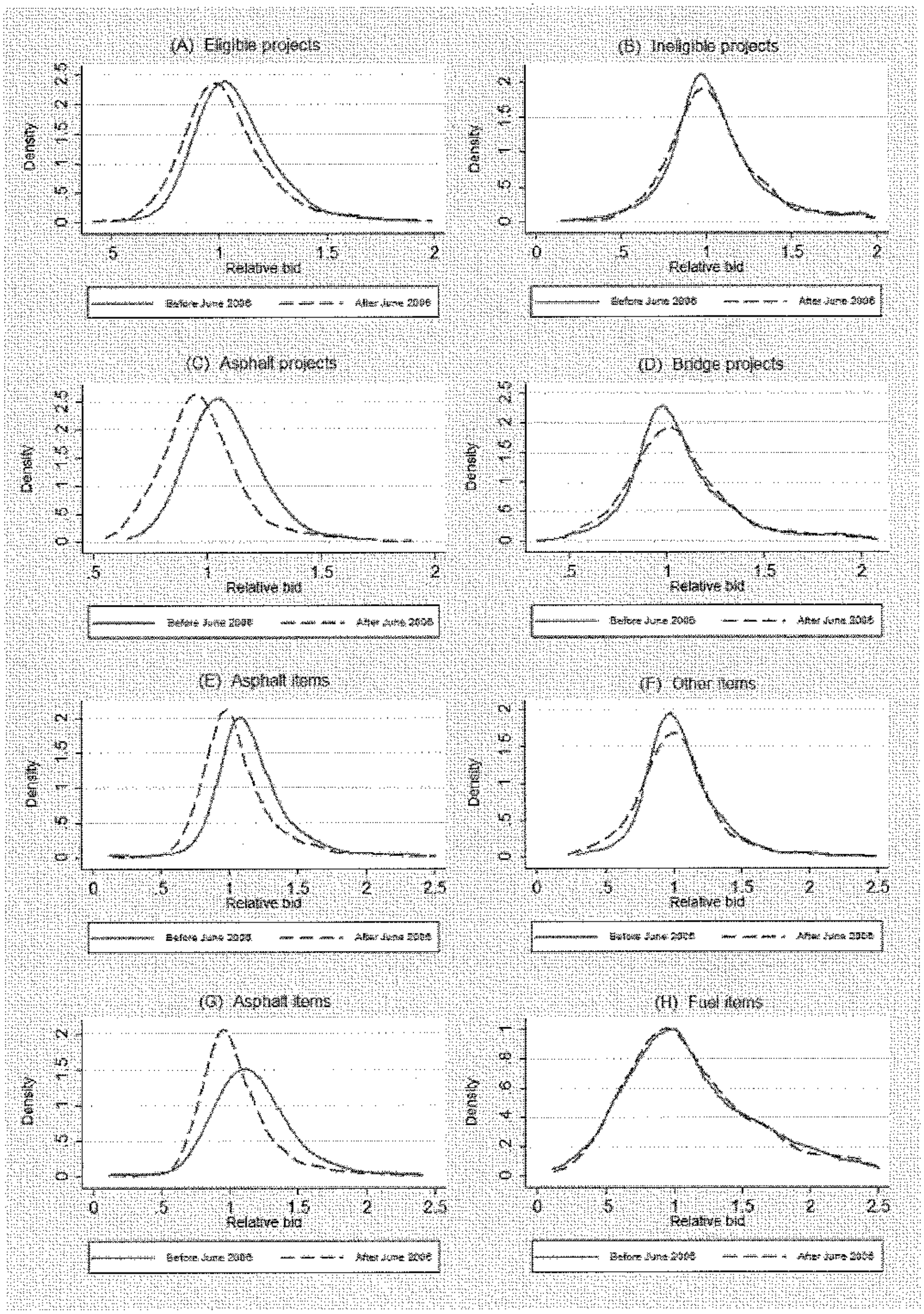


Figure 4.2: Conditional Kernel Densities

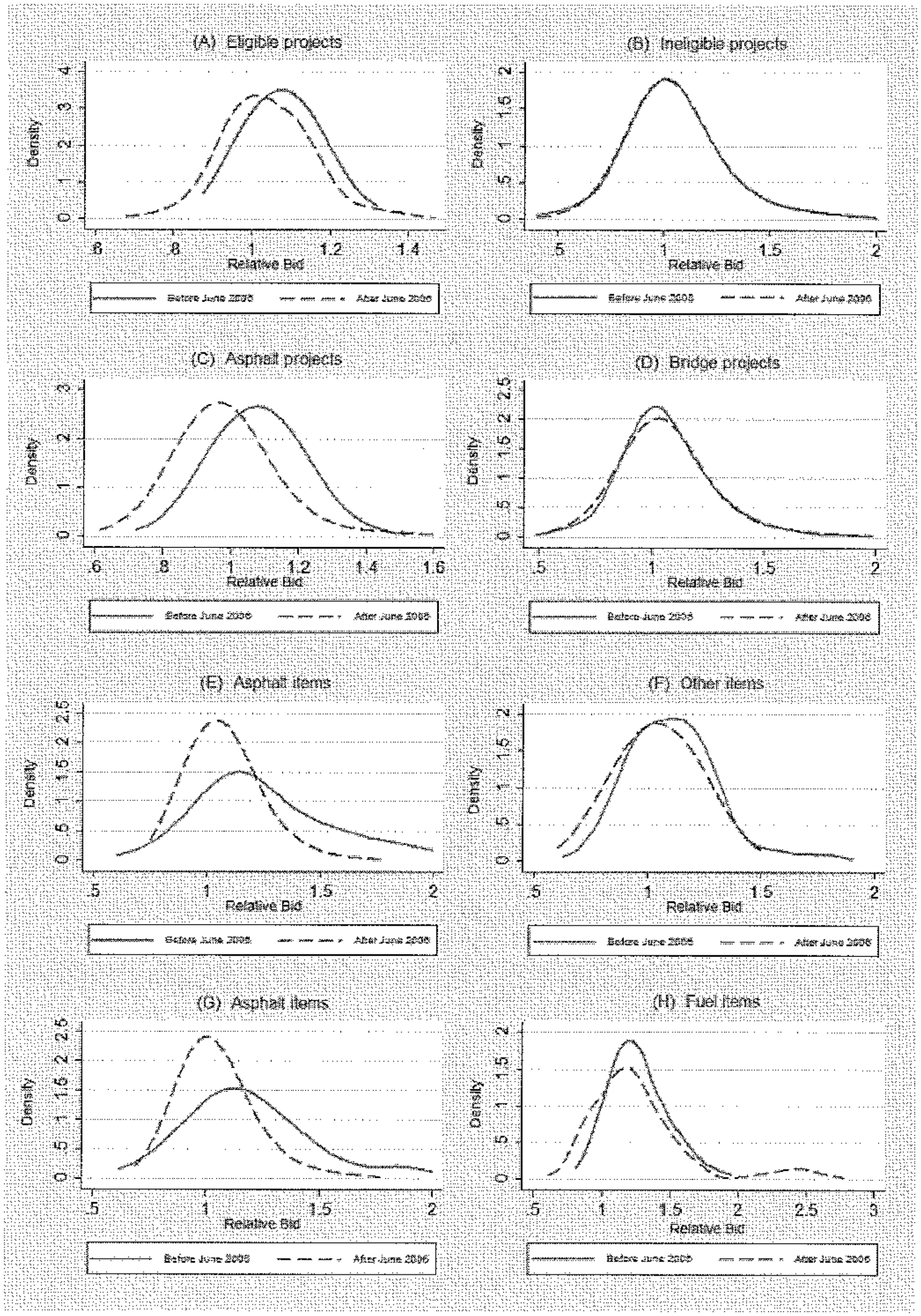
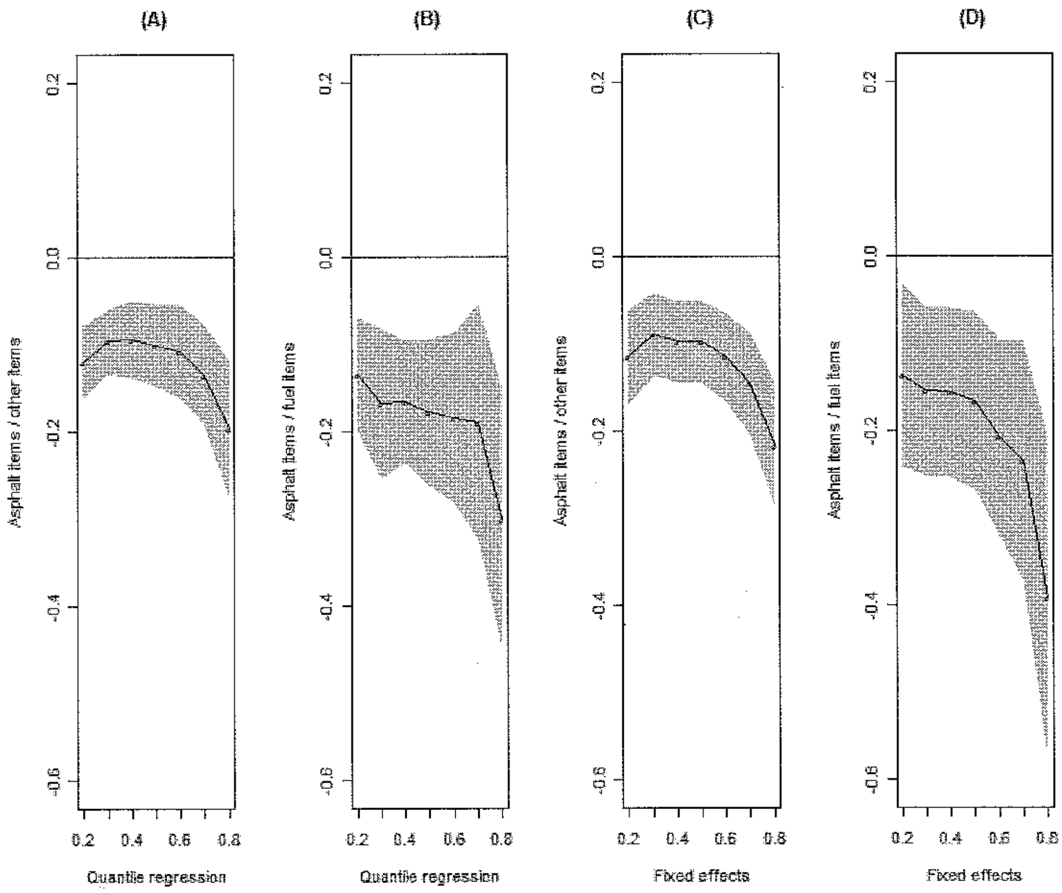


Figure 4.3: Quantile Regression and Fixed Effects Quantile Regression Results on Relative Bids.



Continuous lines show the point estimates, and shaded area represents a 0.95 (point-wise) confidence interval.

Table 4.1: Summary Statistics

Variables	Comparison groups			
	All projects			
	Before June 2006		After June 2006	
	Eligible	Ineligible	Eligible	Ineligible
Total number of auctions	396	377	622	489
Average number of plan holders	6.439 (3.135)	5.942 (2.564)	6.362 (2.987)	6.029 (2.716)
Average number of bidders	3.207 (1.468)	3.490 (1.573)	3.270 (1.622)	3.527 (1.597)
Average relative bid	1.078 (0.195)	1.065 (0.343)	1.038 (0.235)	1.092 (0.624)
	Asphalt and bridge projects			
	Before June 2006		After June 2006	
	Asphalt	Bridge	Asphalt	Bridge
Total number of auctions	182	354	268	431
Average number of plan holders	4.798 (2.457)	6.522 (2.418)	5.011 (2.427)	6.591 (2.562)
Average number of bidders	2.820 (1.254)	3.710 (1.617)	3.011 (1.525)	3.812 (1.843)
Average relative bid	1.079 (0.154)	1.084 (0.324)	0.986 (0.157)	1.077 (0.347)
	Eligible projects			
	Before June 2006		After June 2006	
Total number of auctions	396		622	
Average number of plan holders	6.439 (3.135)		6.362 (2.987)	
Average number of bidders	3.207 (1.468)		3.270 (1.622)	
	Asphalt items	Other items	Asphalt items	Other items
Average relative bid	1.272 (0.857)	1.114 (0.831)	1.075 (0.386)	1.104 (0.679)
	Eligible projects with fuel items			
	Before June 2006		After June 2006	
Total number of auctions	241		346	
Average number of plan holders	7.232 (3.298)		7.220 (3.153)	
Average number of bidders	3.320 (1.520)		3.340 (1.689)	
	Asphalt items	Fuel items	Asphalt items	Fuel items
Average relative bid	1.273 (0.902)	1.255 (0.767)	1.042 (0.331)	1.235 (0.792)

Standard deviations are in parenthesis

Table 4.2: Fixed Effects Difference in Difference on Project Relative Bids

Variables	Base model	Comparison across types		
	Eligible vs. Ineligible (1)	Asphalt vs. Bridge (2)	Asphalt vs. Signing (3)	Bridge vs. Signing (4)
Bids after policy enactment (β_1)	0.001 (0.025)	-0.033(0.026)	0.006 (0.035)	0.016 (.040)
Bids from treatment group (β_2)	0.045** (0.020)	0.028 (0.030)	-0.057 (0.040)	0.020 (0.054)
Bids from treatment group after policy enactment (β_3)	-0.047* (0.026)	-0.114** (0.023)	-0.137** (0.035)	-0.043 (0.040)
Capacity utilization rate	0.043 (0.033)	-0.012 (0.016)	-0.007 (0.019)	0.001 (0.022)
Distance to project location	0.018** (0.004)	0.017** (0.005)	0.022** (0.004)	0.022** (0.008)
Number of bids submitted	-0.018** (0.003)	-0.022** (0.003)	-0.009* (0.005)	-0.027** (0.004)
Average rivals winning to plan holder ratio	-0.033 (0.231)	0.395** (0.148)	-0.033 (0.119)	-0.337* (0.186)
Closest rival's distance to project location	-0.003 (0.009)	-0.001 (0.006)	0.016** (0.005)	-0.002 (0.008)
Rivals minimum backlog	0.002* (0.001)	0.001 (0.001)	0.002* (0.001)	0.002 (0.002)
Seasonally adjusted unemployment rate	-0.047** (0.016)	-0.034** (0.009)	-0.059** (0.009)	-0.025** (0.012)
Three month average of the real volume of projects	0.007 (0.024)	-0.007 (0.022)	0.006 (0.020)	-0.001 (0.029)
Three month average of the number of building permits	-0.015 (0.033)	-0.085** (0.033)	-0.045 (0.037)	-0.091** (0.042)
Number of observations	6441	4239	1674	3285
Adjusted R^2	0.028	0.054	0.145	0.028

** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors by auction are provided. All regressions include firm-level fixed effects and 10 monthly dummy variables.

Table 4.3: Fixed Effects Difference in Difference on Itemized Relative Bids

Variables	Eligible projects		Eligible projects with fuel items	
	Asphalt items vs. other items		Asphalt items vs. fuel items	
	Relative bids	Ratio of relative bids	Relative bids	Ratio of relative bids
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 holder 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 (0.002)	-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 the real volume of projects	-0.033 (0.022)	0.121** (0.044)	0.029 (0.027)	0.066 (0.052)
Three month average of the 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

** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors by auction are provided. All regressions include firm-level fixed effects and 10 monthly dummy variables.

Table 4.4: Dispersion of Relative Bids

Variables	Base model	Asphalt vs. bridge	Asphalt items/ other items	Asphalt items/ fuel items
	(1)	(2)	(3)	(4)
Bids after policy enactment (β_1)	0.065** (0.015)	0.029** (0.015)	-0.073* (0.039)	-0.083** (0.051)
Bids from treatment group (β_2)	-0.056 (0.055)	-0.066** (0.026)		
Bids from treatment group after policy enactment (β_3)	-0.022 (0.019)	-0.053** (0.023)		
Number of bids submitted	-0.004 (0.004)	-0.003 (0.004)	-0.101 (0.135)	-0.009 (0.015)
Seasonally adjusted unemployment rate	0.024 (0.020)	0.027 (0.027)	-0.108 (0.180)	-0.009 (0.021)
Three month average of the real volume of projects	-0.002 (0.068)	-0.004 (0.008)	0.763 (0.489)	-0.010 (0.052)
Three month average of the number of building permits	-0.017 (0.096)	0.045 (0.038)	-0.015 (0.065)	-0.148* (0.082)
Number of observations	777	533	381	203
Adjusted R^2	0.144	0.139	0.021	0.077

** denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors by auction are provided. All regressions include firm-level fixed effects and 10 monthly dummy variables.

Table 4.5: 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	-0.007	-0.017	-0.015	-0.039**	-0.024*	-0.040**	-0.119**	-0.100**	-0.197**	-0.135**	-0.178**	-0.300**
enactment (β_1)	(0.012)	(0.010)	(0.019)	(0.014)	(0.013)	(0.019)	(0.021)	(0.024)	(0.040)	(0.033)	(0.043)	(0.076)
Bids from treatment	0.080**	0.060**	0.050**	0.061**	0.031**	-0.005						
group (β_2)	(0.010)	(0.009)	(0.016)	(0.013)	(0.013)	(0.019)						
Bids from treatment group	-0.037**	-0.040**	-0.047**	-0.084**	-0.092**	-0.113**						
after policy enactment (β_3)	(0.012)	(0.019)	(0.039)	(0.016)	(0.015)	(0.023)						
Number of Observations	6441	6441	6441	4239	4239	4239	3284	3284	3284	1956	1956	1956
Method: Fixed Effects Quantile Regression												
Bids after policy	-0.002	-0.013	-0.011	-0.026	-0.016	-0.013	-0.115**	-0.098**	-0.217**	-0.137**	-0.165**	-0.392**
enactment (β_1)	(0.015)	(0.013)	(0.020)	(0.017)	(0.014)	(0.021)	(0.027)	(0.024)	(0.036)	(0.054)	(0.052)	(0.095)
Bids from treatment	0.078**	0.062**	0.068	0.075**	0.033	0.020						
group (β_2)	(0.012)	(0.010)	(0.017)	(0.020)	(0.020)	(0.033)						
Bids from treatment group	-0.050**	-0.043**	-0.069**	-0.118**	-0.115**	-0.142**						
after policy enactment (β_3)	(0.014)	(0.012)	(0.020)	(0.017)	(0.014)	(0.023)						
Number of Observations	6441	6441	6441	4239	4239	4239	3284	3284	3284	1956	1956	1956

**denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Standard errors are calculated using bootstrap with 100 replications. All regressions include 10 monthly dummy variables.

Table 4.6: Alternative Specifications for Robustness Checks

Variables	Base model				Asphalt items vs other items			
	Relative bids				Relative bids		Ratio of relative bids	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bids after policy enactment (β_1)	0.096		-0.002	-0.005	-0.014		-0.186**	-0.191**
	(0.074)		(0.025)	(0.025)	(0.050)		(0.039)	(0.039)
Bids from treatment group (β_2)	0.032	-0.033	0.056**	0.055**	0.107**	0.184**		
	(0.029)	(0.031)	(0.020)	(0.020)	(0.031)	(0.056)		
Bids from treatment group after policy enactment (β_3)	-0.072**		-0.048**	-0.047*	-0.121*			
	(0.036)		(0.026)	(0.026)	(0.041)			
Time		-0.008				0.033		
		(0.009)				(0.024)		
Time*bids from treatment group		0.003*				-0.004		
		(0.002)				(0.004)		
Number of plan-holders			-0.014**				-0.022**	
			(0.004)				(0.005)	
Expected number of bids submitted				-0.022**				-0.043**
				(0.006)				(0.008)
Number of observations	904	2585	6441	6441	901	2530	3284	3284
Adjusted R^2	0.029	0.094	0.042	0.027	0.096	0.059	0.038	0.040

**denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. All regressions include 10 monthly dummy variables.

Table 4.7: Regressions of Project Relative Bids Using Proportions of Asphalt Items

Variables	Base model	Asphalt paving
	(1)	(2)
Bids after policy enactment (β_1)	0.001 (0.023)	-0.043 (0.042)
Proportion of eligible items	0.108** (0.045)	-0.037 (0.058)
Proportion of eligible items from projects after policy enactment	-0.128** (0.028)	-0.118** (0.052)
Capacity utilization rate	0.041 (0.033)	-0.011 (0.018)
Distance to project location	0.018** (0.004)	0.021** (0.005)
Number of bids submitted	-0.018** (0.003)	-0.007** (0.004)
Average rivals winning to plan-holding ratio	0.015 (0.227)	-0.151 (0.129)
Closest rival's distance to project location	-0.004 (0.009)	0.014** (0.005)
Rivals minimum backlog	0.002* (0.001)	0.002* (0.001)
Seasonally adjusted unemployment rate	-0.048** (0.015)	-0.055** (0.010)
Three month average of the real volume of projects	-0.006 (0.024)	-0.020 (0.021)
Three month average of the number of building permits issued	-0.017 (0.032)	-0.063 (0.039)
Number of observations	6441	1314
Adjusted R^2	0.042	0.223

**denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. Robust clustered standard errors by auction are provided. All regressions include firm-level fixed effects and 10 monthly dummy variables.

Table 4.8: RDD Fixed Effects of Project Relative Bids from Asphalt and Bridge Types

Bandwidth	Dependent variable: project relative bids from asphalt and bridge types	
	Asphalt paving	Bridge work
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. For asphalt projects, number of observations and adjusted R^2 for the three specifications are 157 (0.2130), 267 (0.1889), and 280 (0.1879); for bridge projects, number of observations and adjusted R^2 (in parenthesis) for the three specifications are 627 (0.0155), 871 (0.0360), and 1117 (0.0432).

Table 4.9: Fixed Effects Difference in Difference of Winning Itemized Bids

Variables	Eligible projects Relative bids Asphalt items vs. Other items (1)	Eligible projects with fuel items Relative bids Asphalt items vs. Fuel items (2)
Bids after policy enactment (β_1)	-0.066*(0.040)	0.033 (0.057)
Bids from treatment group (β_2)	0.205** (0.028)	-0.093** (0.038)
Bids from treatment group after policy enactment (β_3)	-0.117** (0.036)	-0.149** (0.049)
Capacity utilization rate	-0.012 (0.045)	-0.010 (0.065)
Distance to project location	0.003 (0.010)	-0.006 (0.013)
Number of bids submitted	-0.015** (0.007)	-0.034** (0.010)
Average rivals winning to plan holder ratio	-0.270 (0.245)	-0.010 (0.0386)
Closest rival's distance to project location	0.013 (0.008)	-0.000 (0.011)
Rivals minimum backlog	0.001 (0.002)	0.002 (0.003)
Seasonally adjusted unemployment rate	-0.043** (0.015)	-0.056** (0.023)
Three month average of the real volume of projects	-0.051 (0.035)	-0.045 (0.052)
Three month average of the number of building permits	-0.081* (0.049)	-0.026 (0.071)
Number of observations	2030	1164
Adjusted R^2	0.079	0.053

**denotes statistical significance at the 5% level and * denotes statistical significance at the 10% level. All regressions include firm-level fixed effects and 10 monthly dummy variables.

CHAPTER 5

On the Distributional Impact of Price Adjustment Policies:

Bidding Patterns and Survival in the Market

This essay continues to investigate the effects of asphalt price adjustment focusing on the asymmetric nature of letting participants.[11] Based on biddings records published by ODOT in the extended period between January 2002 and September 2010, we examine how contractors of different sizes and levels of experiences are impacted by the risk discounting policy in aspects of their bidding behaviors, participations patterns, and survival prospects.

5.1 Introduction

Chapter 4 described the increasing popularity of price indexation policies on volatile inputs. One of the incentives motivating transportation agencies to adopt such special provision is the escalation of highway construction cost index[12], noticeably steeper than consumer price index (CPI) and producer price index (PPI) in the past couple of decades. The National Highway Construction Cost Index (NHCCI), furnished by Federal Highway Administration (FHWA) since 2003, displayed an alarming 40% increase in mere three years from 2003 to 2006. At the regional level, several DOTs constructed their own cost indices, all of which exhibited similar trends. Washington DOT reported a formidable 92% spike in its own index from 1997 to 2006 and an 87%

[11] This chapter is based on a joint work with Georgia Kosmopoulou and Carlos Lamarche. I would like to express my gratitude of both for their great mentorship and patient help.
[12] That may lead to the decline of government purchasing power.

rise in its neighboring states; Caltran noted that price index based on selected construction items underwent a 120% jump within the same interval; TxDOT also documented comparable findings through time (Bohuslave 2006). The Bid-Price Index (BPI), another nationwide indicator published by FHWA, increased by 70% from the base value in 1997 to 2006. Price fluctuations in oil-based inputs, such as asphalt concrete, are believed to be the main culprit driving up the costs.

As highlighted above, careful evaluations of policy impacts will provide useful guidance for practices. Meanwhile, studying policy effects on firms in highway construction with potential asymmetry in mind can be especially important since bidder heterogeneity is a defining feature of this sector (Cho 1986). In an industry where economies of scale play a key role, market concentration is fairly skewed toward a small set of strong contenders. For instance, the ten largest firms in our database were awarded over half of all auctioned projects and more than 65% of the total contracted value. At the same time, the market displays an above average turnover rate. Compared with manufacturing, the percentage of failed new construction firms is considerably higher (Audretsch and Mahmood 1995). Both statistics suggest that many small and startup businesses compete as marginal players without ever making it to the short list of major contractors. High volatility in input prices reduces the survival chances of fringe firms on top of their limited scope and tenure. While large firms are generally better informed, possess more bargaining power and manage to share risk with their input suppliers, small ones are less able to do so and often have to build higher risk premium into their bids. The recent price volatility in oil-based materials reinforces unbalance among competitors.

Theory expects adjustment clauses to balance out some of this disparity. By reducing information rents and networking benefits enjoyed by large establishments, the policy lessens the comparative disadvantage caused by limited capacity and restores a more leveled playing field for entrants and small firm to facilitate competition. This chapter engages in producing empirical evidence for the theoretical argument. The remainder proceeds as follows: section 5.2 overviews theoretical discussions, section 5.3 presents summary statistics, Section 5.4 details empirical findings from three angles: distinguishing different kinds of firms, the policy's effects on bids, on bidding and winning patterns, and on survival perspective, and Section 5.5 concludes.

5.2 Theoretical Discussion

Before turning to data, it is helpful to set up a simple theoretical framework to guide the empirical analysis. This model is an extension of the one in section 4.3, with one dimension added: distinguishing participants with respect to individual levels of capital accumulation. To ease the reading, let me recap the basic framework and some critical assumptions. Again, consider a number of n bidders compete for a government contract in a low price sealed bid auction at time t. The project will be completed at time $t+1$. Bidders are risk neutral. A bidder has only an estimate, $c^e_{i,t+1}$ for the cost at the time of bidding. Assume that the true cost $c_{i,t+1} = c^e_{i,t} + d_{t+1}$ where d_{t+1} represents the difference between estimated and actual costs affected by market forces and exogenous shocks. The cost $c^e_{i,t}$ is drawn from a twice continuously differentiable distribution with a strictly positive density. Bidders of different sizes may have different liquidity constraints. Each bidder has some capital available at the time of bidding w_{it}, which also has a twice continuously differentiable distribution on its support. $c^e_{i,t}$ and w_{it} are assumed to be independent of each other, suggesting that larger firms are not necessarily more efficient. Bidders can finance future projects by borrowing at a cost which depends upon the amount of internal capital through function $R(c^e_{i,t} - w_{it})$, with $R'(c^e_{i,t} - w_{it}) > 0$. The cost of a project now becomes $c_{i,t+1} = c^e_{i,t} + d_{t+1} + R(c^e_{i,t} - w_{it})$.

The uncertainty in the price of volatile inputs, in this case asphalt mixture product, may cause the actual fulfillment cost of firms to deviate from $c^e_{i,t}$. Let $d_{t+1} = \bar{c}_{t+1} - \bar{c}_t$ where $\bar{c}_{t+1}$ and $\bar{c}_t$ are indices at the time of construction completion and letting respectively. $\bar{c}_{t+1}$ is a random variable with a know distribution ex ante. One can think of cost realizations in the following way: A firm receives a quote from a supplier at time t on the price of asphalt at *t+1* which is uncertain and depends on market forces beyond the control of local suppliers. The price index represents the average price across suppliers at a specific time period affected by exogenous shocks. The differences in the cost index through time capture potential fluctuations in the cost beyond the control of the supplier at time *t*. The bidder who bids b_{it} and is awarded the contract receives a utility of $u(b_{it}, c_{i,t+1}, w_{it}) = b_{it} - c^e_{i,t} - d_{t+1} - R(c^e_{i,t} - w_{it})$ with $-R'(\cdot) < 0$. Let $s_{it} = c^e_{i,t} + R(c^e_{i,t} - w_{it})$ be the privately observed component of the cost and y_{1t} denote the infimum of the remaining estimates of s_{it}. Under the assumption of logconcavity of distributions for both $c_{i,t}^{e}$ and w_{it}, the unique symmetric equilibrium bidding strategy for bidder i in the first price auction held at t is:

$$B(s_{it}) = E(y_{1t} \mid y_{1t} \geq s_{1t}) + E(d_{t+1}^{*} \mid s_t \geq s_{it}) \tag{5.1}$$

As mentioned in section 3.3, by providing contingent compensation, the adjustment clauses modify the difference between initial estimates and the realized costs to become:

$$d_{t+1}^{*} = \begin{cases} \overline{c}_{t+1} - \overline{c}_t & \text{if } -1 \leq \frac{\overline{c}_{t+1} - \overline{c}_t}{\lambda \overline{c}_t} \leq 1 \\ \lambda \overline{c}_t & \text{if } \frac{\overline{c}_{t+1} - \overline{c}_t}{\lambda \overline{c}_t} > 1 \\ -\lambda \overline{c}_t & \text{if } \frac{\overline{c}_{t+1} - \overline{c}_t}{\lambda \overline{c}_t} > -1 \end{cases}$$

where λ is the proportion of price adjustment specified by the indexing policy. Meanwhile, the cost of borrowing often depends upon capital accumulation and uncertainty. The policy makers control the level of uncertainty through the trigger value λ, which introduces an additional parameter to the cost of borrowing. Intuitively, financial costs rise with both the amount of loans and the level of uncertainty, i.e. $R_1(c_{i,t}^{e} - w_{it}, \lambda) > 0$ and $R_2(c_{i,t}^{e} - w_{it}, \lambda) > 0$. Consequently, the bidding strategy becomes:

$$B(s_{it} \mid \lambda) = E(y_{1t} \mid y_{1t} \geq s_{1t} \mid \lambda) + E(d_{t+1}^{*} \mid s_t \geq s_{it} \mid \lambda) \tag{5.2}$$

We have demonstrated in section 4.3 that due to the pressure of cost overruns, adjustment clauses can induce lower equilibrium bids (intensified competition) and less dispersion in bid distribution. Here the focus is placed on how the common uncertainty affects the behaviors and performances of firms having different access to and costs of external financing. In particular, we establish two hypotheses that will be empirically evaluated in the next section.

<u>The Effect of Capital Accumulation on the Variance of Bids</u>

Size is used to approximate firms' capital accumulation (w_{it}) in the empirical analysis, a typical proxy in the literature (e.g., Brito and Mello 1995, Hubbard 1998, and Persson 2004). On the one hand, empirical research in both business and consumer loan markets (Krainer 2004, Kaplin et al. 2009, Edelberg 2006, Hubbard 1998) shows that the interest rate spread between high-risk and low-risk borrowers' increases with credit risk. On the other hand, a number of papers (Ehermann 2000, Gertler and Gilchrist 1994, Martinelli 1997) have noted the asymmetric change in borrowing costs of firms to different scales when financial constraints become more binding. Although all firms are subject to tightened borrowing conditions, the adverse effects are greater for small firms, represented by a bigger jump in their loan interest rates. Therefore, costs of external financing are expected to increase more rapidly for the small relative to the large when general default risk is increasing. Conversely, when the enactment reduces common uncertainty all firms are faced with, small firms should have more to gain than big ones in terms of greater reduction and less variance in required interest rates, leading to lower and more centralized costs and bids.

The Effect of Capital Accumulation on the Survival

The greater liquidity constraints small firms are faced with have an impact on growth as well. Previous research on bidding asymmetries has established that, if borrowing costs are convex in wealth and an unconstrained bidder has the same willingness to pay as a constrained bidder, the bid of the constrained bidder will be more aggressive (see Proposition 3 in Quintero Jaramillio 2004). In the presence of high uncertainty unconstrained firms will survive longer. Rhodes-Kropf and

Viswanathan (2005) focus on debt finance and find that if bidders have asymmetric risk and liquidity constraints, any information rents they receive depend on valuations and their cash positions. Depending on the individual level of risk and liquidity, the interest rate may be too high for some constrained bidders to survive. Bidding aggressiveness becomes more pronounced if bidders are risk averse. Projecting from the work of Holt (1979), the reduction in uncertainty due to a price adjustment clause will increase expected utility significantly and lead to a decrease in expected bids, benefiting growth and survival in the market.

5.3 Measurement and Summary Statistics

The set of panel data used for this chapter encompasses all projects auctioned off from September 2003 through September 2010, collected via publicly accessible pages on the official site of ODOT. Records between January 2002 and August 2003 are utilized as history.

Upon its introduction in June 2006, the price indexing system extensively reduced contractors' concerns for the high price volatility of asphalt related items that all have to face. Special provision 109.12 amended to the standard specification states that, for applicable asphalt binder materials, if the current price index exceeds by more than 3% the base value, a lump-sum adjustment is transferred from ODOT to the contractor, with the amount dependent on the quantity of asphalt items and the extent of price deviation. The direction of payment is reversed if the current index declines from its base value by 3% or more. Eligible items cover a wide class of bituminous products of different mixtures and hardness, a complete list of which can be found at ODOT website. Out of 1883 projects contracted in the sample window, 1018 contain eligible asphalt items (54%). Between periods divided by the policy initiative, the proportion of asphalt projects appears to be fairly similar (52% and 56% of the total volume respectively). Hence, this presents an opportunity to evaluate firms' bidding strategies resulted from the policy change and examine related implications.

This chapter extends the literature of bidding asymmetry by examining the differential effects of asphalt adjustment policy on firms of various scales. However, how to define large firms apart from small firms is a frequently encountered empirical question. Number of employees is a common measure in the literature (Acs and Audretsch 1987). Unfortunately, such micro-level private-sector records are not available from public sources. Inspired by the close link between work load and number of employees, we tried two alternatives: maximum capacity and market share. Maximum capacity of a construction firm is its highest value in committed construction backlog through the period, a good measure of firms' operating scale. Market share, on the other hand, captures more directly contractors' success and competitiveness. The two variables are correlated with at degree 0.89, a justification for the immediate link between having more committed work and occupying a larger chunk of the market. In fact, regressions adopting both standards to define large and small firms produce similar results, confirming robustness of the choices. We also experimented with other calculations for both variables, such as going with a particular type instead of all projects and multiple cut-off points. In all cases, consistent findings prevail. Finally we decide to employ market share as a proxy for payroll size, where large firms consists of businesses that won more than 1% of the total awarded value in the sample, with the rest classified as small firms. Under such a division, slightly under one fifth (27 out of 157) of all participating firms are characterized as large, who jointly control 80% of the market.

Figure 5.1 presents probability density graphs of relative bids on asphalt and fuel items separately for small and large firms. Relative bid, calculated as the absolute bid normalized by state engineer's estimate, is used to facilitate comparisons across scales. Graphs to the left are based on itemized bids on adjustment eligible asphalt binder products, whereas those to the right depict itemized bids on adjustment ineligible fuel-related materials. Since asphalt and fuel are both by-products of the oil refining process, their market prices are inherently linked together. Indeed, the price indices of the two are highly correlated with a correlation coefficient of 0.79 from 2000 to 2010. Therefore, we would expect submitted bids, primarily built upon costs of asphalt and fuel items, to have a similar trajectory through time. With kernel estimates, however, we observe a substantial leftward shift in the period after the policy implementation in the bid distributions of asphalt items across firm sizes, unmatched by the panel to the right. If such pattern persists upon controlling for other covariates, it ought to be attributed to the impact of price adjustment provision.

Move on to comparisons in the size dimension. As previously mentioned, small contractors might be submitting higher bids due to stricter liquidity constraints or limited network. To discern differences in this dimension, we consider bids by small and large businesses separately. Top row of Figure 5.1 represents bids submitted by firms occupying 1% or more of the market; and bottom row displays bids by the others. Overall, firms of various sizes bid in highly comparable ways. This may not be surprising in the light of the fact that projects are awarded solely on the basis of low bids and the competitive feature of auction mechanism. Taking a closer look, the left shift in asphalt bids appears more pronounced for the subset of smaller bidders, and this point will be further explored in the next section. As far as fuel bids are concerned, both groups submitted higher bids in the second period, in agreement with the extensive volatility of the price of fuel since 2006. Table 5.1 summarizes descriptive statistics separately for bidders distinguished by size. The sample window naturally divides into before and after upon the introduction of adjustment clauses in June 2006. When all bids are considered, average bids on adjustment eligible asphalt are significantly lower after the adjustment policy was enacted across both groups, mirroring the impression in Figure 5.1. Meanwhile, bids based on fuel fail to display a comparable trend over time. When we restrict attention to winning bids only, the temporal shift for asphalt items carries through, while the difference in fuel items is either insignificant in magnitude or reversed in direction. Another interesting finding is note in the variable *Bid dummy*, which takes value 1 when a planholder participated in the actual letting and 0 otherwise. In the presence of adjustment clauses, small firms are more likely to actively participate upon acquiring plans. The probability of participation for large firms remains practically the same compared to the period before. In the next section, we formalize the investigation of whether clauses indexing asphalt prices have encouraged small businesses to participate more frequently.

5.4 Empirical Results

The section carries out a more rigorous and comprehensive study looking for the differential effects of policy change among public procurement contractors. We analyze three aspects of the adjustment clauses. First, we study bidding differences across time periods and firm sizes considering both location shift at the mean level and variation in the shape of distribution of bids. Second, we seek to detect any changes in bidding or winning frequencies caused by the initiative. Finally, accounting for impacts on bids and participation patterns, we consider how the policy has affected firms' duration in the market.

5.4.1 How Asymmetric Market of Construction Procurement Is

It is commonly acknowledged that in construction industries, scales economies are very important and there may be quite unbalanced market concentration among participants. A small portion of "top firms" may take up the majority of contracted values, while the rest of firms are competing on the fringe.

In the local ODOT market, the top 20 contractors combined won 70% of the total volume of projects. In contrast, 56% of all participating firms (those have purchased plans) never won a single contract between September 2003 and September 2010. When broken down by major work types[13], groups of asphalt paving, grading and draining, bridge work and traffic signals all display similar characteristics regarding market composition. Herfindahl indices for the segments are: 0.05, 0.05, 0.07, and 0.12

[13] The other types, concrete and clearance, are omitted due to limited number of projects within each category.

respectively, all regard unconcentrated market structures by definition. Moderate values of Herfindahl index shed light on the competitiveness of market outcomes, a strongly advocated virtue of auction mechanism. Meanwhile, the statistics indicate a somewhat unbalanced market with considerable asymmetries between major and fringe firms.

5.4.2 Distributional Effects of Adjustment Policy on Bidding

As described in the previous chapter, the official enactment of the asphalt price adjustment clause in June 2006 posits a natural dichotomy of the entire period, and the distinction between policy applicable asphalt items from policy ineligible fuel items enables the treated-control comparison based on ODOT data alone. Again, we utilize the difference-in-difference framework specified as follows:

$$y_{ijat} = \beta_1 T_{it} + \beta_2 A_t + \beta_3 (T_{it} \times A_t) + x_{iat}^{'}\gamma + z_{at}^{'}\delta + w_t^{'}\zeta + \alpha_i + d_j + m_t + \varepsilon_{iat} \qquad (5.2)$$

where each observation represents one bid submitted by firm i, for item j, in auction a, at time t. Relative bid y_{ijat}, ratio of the bid divided by its engineer's cost estimate, is employed as the primary dependent variable and is comparable among projects of various scales. Asphalt items, which are eligible for policy adjustment, serves as the treated group; while fuel items, which are intrinsically similar but unaffected by the policy, provide a good candidate as the controlled. T_{it}, the group dummy, is equal to 1 for asphalt items; A_t the time dummy, takes the value of 1 for bids submitted after June 2006. Right hand side control variables include covariates of three categories to account for observed heterogeneity across auctions and firms, namely bidder, rival, and general economic characteristics, denoted by x, z and w respectively. Detailed descriptions are provided in Table 3.2. Besides, we employ item, firm and time fixed effects (notations α, d and m) to absorb unobserved individual idiosyncrasies.

In chapter 4, we perform conditional mean regressions where β_3 is found to be negative as participants insulated from unbounded risks bid more aggressively. Here, the main concern is rather about how policy effects differ among asymmetric bidders with respect to network connections and leveraging abilities. We explore the question through quantile regression models applied to large and small firms separately. This way, $\beta_3(\tau)$ captures the distance between bidding distributions of the control and the treated at τ-th quantile, changes attributable to the enactment of asphalt adjustment clauses. Put into the setting of equation 5.2, it can be expressed as follows:

$\beta_3(\tau) = [Q_Y(\tau \mid T = 1, A = 1, x, z, w, \alpha, d, m) - Q_Y(\tau \mid T = 0, A = 1, x, z, w, \alpha, d, m)] -$

$[Q_Y(\tau \mid T = 1, A = 0, x, z, w, \alpha, d, m) - Q_Y(\tau \mid T = 0, A = 0, x, z, w, \alpha, d, m)]$. In Table 5.2 we report conditional and unconditional quantile regression results for both groups. While conditional quantiles (following the seminal work of Koenker and Bassett, 1978) are commonly applied in the empirical literature, unconditional quantiles introduced by Firpo, Fortin, and Lemieux (2009) relaxes the dependence of results on explanatory covariates by integrating them out and more closely resembles the theoretical framework laid out in section 5.2. Nonetheless, consistency between results of the two routes underline that relative bids on asphalt and fuel items are quite comparable in terms of independent variables: the characteristic of bidders, rivals, and business conditions. With all controls present, firms continue to react positively to adjustment clauses. At the first quartile, policy impacts on inducing more aggressive bids demonstrate statistical and economic significance for both large and small. For instance, an asphalt bid submitted after June 2006 is lowered by at least 8.6% provided other circumstances the same. However, discrepancy emerges as we move on to higher quantiles. For the group of small bidder, policy influences permeate through the entire distribution and gain in size as we move up. At the same time, the bid reducing effect of indexation clauses gradually diminishes for large firms, and eventually reduces to not statistically different from zero at the 90th quantile. Overall, both conditional and unconditional quantile regressions show that contractors bid more aggressively upon the implementation of adjustment provision, with small firms responding more favorably, especially in the upper quantiles of itemized bids.

Now direct attention to how the spread of itemized bids may change after adjustment clauses were introduced. Instead of making parametric assumptions and comparing variances directly, we propose to look for evidence in quantile regressions, which by definition convey a picture for the entire distribution of policy impacts. As described above, large firms' response to adjustment clauses grows insignificant moving up quantiles, but the trend is reversed for small contractors. Therefore, we would expect that the spread of bids on the treated asphalt items narrows down more conspicuously for small firms in the second period, driven by the intensified policy effects toward the high end. Figure 5.2 provides a visualization for distributions before and after separately for large and small. The upper panel displays probability densities, and the lower one shows corresponding cumulative densities. It must be noted that simulated rather than actual data are employed to produce the graphs. We plug in estimated coefficients of quantile regressions and mean values of all covariates except the treatment indicator. Specifically, solid lines are based on the expression $Q_Y(\tau \mid \cdot) = Q_Y(\tau \mid A \times T = 0, x = \bar{x}, z = \bar{z}, w = \bar{w}, \alpha = \bar{\alpha}, d = \bar{d}, m = \bar{m})$, and dashed lines are derived from $Q_Y(\tau \mid \cdot) = Q_Y(\tau \mid A \times T = 1, x = \bar{x}, z = \bar{z}, w = \bar{w}, \alpha = \bar{\alpha}, d = \bar{d}, m = \bar{m})$, where in both cases, $\tau \in \{0.10, 0.11, \ldots 0.90\}$, ranging from 10% to 90% with a 1% step size. Stark contrasts appear between graphs horizontally. For asphalt bids submitted by large firms, there is almost a pure location shift between periods. However, for small business, there seems to be two simultaneous changes: a left shift at the mean level and a collapse of bids to down the center of the distribution, suggesting a reduction in the variance. Same impressions are drawn by cumulative density graphs too.

As mentioned previously, literature has established a close connection between firms' borrowing constraints and their characteristics. In particular, firms of limited sizes tend to have limited access to external funds compared to large ones. Derivatives in Section 5.2 forecast that when financial constraints are relaxed, bids by small firms out to demonstrate lower average and reduced variation. Our findings illustrated above lend support to the theoretical prediction that more gains are to be derived by firms which used to face tighter borrowing conditions.

In the base line setting, we include fixed effects for item, firm and time intending to account for individual heterogeneity at these levels. As a robustness check for the parameter of interest, we repeat the same regressions excluding item type dummies. Table 5.3 reports regression coefficients under this setting. Consistent findings with Table 5.2 reassure that β_3, the unique change to bids in the treated group after policy, is not sensitive alternative specifications. Furthermore, concentrating on bids that have a direct impact on ODOT cost, Table 5.4 presents parameters based on the subsample of winning bids. In regard of fewer observations, we report results for quartiles only. In generally, winning contractors behave very comparably to other competitors. The key DID parameter is consistently above zero in all three columns. The gradual divergence of policy impacts between large and small firms moving up quantiles has diminished, suggesting that strong contenders bid more aggressively throughout the distribution when risk is alleviated.

5.4.3 Changes in Participation and Winning Patterns

In this section, we examine participation and winning frequencies contrasting firms of different sizes in the period preceding and following the indexation of asphalt prices. ODOT requires all firms interested in bidding to purchase plans in advance. Only 56% of planholders end up submitting bids. Hence, we obtain a measure of bidding frequencies by dividing the number of actual bids over the number of plans bought. The likelihood of winning given bidding is constructed following the same logic. Table 5.5 reports binary regression results examining the two patterns. We present estimates using both logistic and complementary log-log functions, where Pregibon test of goodness suggests the latter to be a more appropriate choice of functional form. The first two columns record the likelihood of participation conditional on acquiring plans. The same set of covariates is employed to control for observable heterogeneity. There are no noticeable changes in firms' participation mode after policy initiation, indicated by an insignificant β_1 for both groups. Besides, the negative β_2 suggests that large and small firms share a lower inclination toward bidding for asphalt projects than non-asphalt ones, other factors being equal. However, we observe a substantially higher tendency of small contractors bidding on asphalt projects after the special provision was enacted, not matched by the large counterparts. This finding parallels the unilateral increase of *Bid dummy* in the group of small bidders illustrated in Table 5.1. Columns (3) & (4) disclose the probability of winning a contract conditional upon submitting a bid. Neither large nor small firms register significant differences in the winning pattern after adjustment clauses. To sum up, Table 5.5 shows that when excessive risk is relieved by indexed prices of asphalt binder, small firms are incentivized to submit bids more frequently after qualifying as planhoders. In the mean time, winning pattern conditional on bidding stays roughly constant. Both results combined to put small firms in an improved position of winning contracts overall.

5.4.4 Post Entry Bidding, Participation and Winning of Entrants

Until this point asymmetric responses to indexation clauses have been examined along the dimension of operating sizes. New firms are treated the same as existing ones, i.e. divided into large or small pending the total value of awarded projects. However, due to shared characteristics such as short history and limited connections, entrants could be subject to certain policy asymmetry not captured by the above analysis distinguishing size only. For example, large entrants may be affected differently than large incumbents who have accumulated the benefits of learning. Likewise, small entrants could be even more curbed by price volatility than small incumbents who have been around and established a reputation. Therefore it might be interesting to isolate the group apart from other existing firms to study whether newcomers as a group respond to ODOT asphalt price indexation in a systematic way.

A firm is considered an entrant if it is observed to have submitted bids preceding August 2003 (in historical records), otherwise it falls into the class of incumbents in the analysis window starting in September of 2003. Table 5.6 presents the basic statistics of entrant group. The pattern between periods fairly resembles that of small firms revealed in Table 5.1, with an obvious shift in bids of adjustment eligible asphalt items and no discernable movements in bids of adjustment ineligible fuel items. Besides, in the presence of adjustment clauses, entrants are more likely to submit bids upon becoming plan holders. Next we move on to formally analyze the policy impact. As shown in Table 5.7, entrants are more responsive to adjustment clauses, and the difference between periods is statistically significant across quantiles. This is not surprising considering the adverse effect of excessive uncertainty for this group. Winning bids regressions using entrant sample are shown in Table 5.8. Compared to results based on the full sample, winning entrants firms adjust bids downward much more aggressively in the period after. However, the results must be taken cautiously in light of the much smaller sample.

As for participation patterns, literature has noted that entrants, as opposed to incumbents, are more conservative and thus less active in submitting bids after purchasing plans. To test if our sample agrees with the stylized fact, we contrast the three groups: entrants, small incumbents and large incumbents. Table 5.9 presents the regression coefficients of participation and winning patterns. As in the previous section, binary regressions using logistic and complementary log-log transformations are applied. The negative coefficients before bids by entrants confirm compliance with previous findings (large incumbents are the omitted group here). Meanwhile, they are more vigorous participants after the implementation of adjustment. Considering together the group dummy and the cross product (-0.500 and 0.487 respectively), it can be inferred that the clauses have almost fully countered the influences of excessive uncertainty and made new firms equally likely to participate as incumbents. Policy effects grow larger when the sample is restricted to eligible projects as shown in the last two columns, but essentially same conclusions hold. Turning to the bottom panel, we again observe no change to winning patterns of bidding firms.

In summary, this section complements Section 5.4.2 and 5.4.3 by investigating the sample of entrants, just to discover that they respond to the intervention similarly as small firms with a slightly larger magnitude. The findings agree with theoretical arguments that link capital accumulation and financial constraints to uncertainty coping abilities.

5.4.4 Survival Perspective of Entrants

So far we have analyzed the first two aspects set out at the beginning of this section. Empirical evidence underlines the hypothesis that firms of smaller sizes have more to benefit from indexation of prices, characterized by higher bidding aggressiveness and more active participation. In this section, we try to evaluate the policy impact on small firms via a more direct route: whether their survival prospects are improved. If small business could stay longer in the market, they help to restrain market power, enhance long-run competition and achieve better allocation of resources. We focus on small firms since they are the main victims of excessive uncertainty. To answer this question, we measure the duration of survival by the number of months firms stay active in ODOT procurement lettings held monthly.

Before producing empirical tests, we need to draw attention to two important facts associated with our data. First, 90 firms entered the local the procurement market during the observation window, 88 of which are small ones. We identify a contractor as a first time bidder if it didn't appear in the history records between January 2002 and August 2003. Since our interest lies in the post-entry performance of small firms, we consider only the pool of small sized entrants, i.e. 88 firms in total. Despite the limited number of observations, our current sample is suitably extensive considering the relative size of Oklahoma's heavy construction industry. According to the U.S. economic census, there are in total 194 operating establishments undertaking highway and bridge construction in the state in 2007, up from 117 establishments 5 years ago. Second, when quantifying the duration of survival, we recognize a firm entering the public procurement auctions when it submits a bid for the first time. Meanwhile, a firm is deemed to exit the industry if it has been inactive for 12 consecutive months. The 12 month cut-off is adopted based on the fact that over 95% of projects are completed within 360 days. Since most firms will be exhausting their workload and seeking new opportunities in one year's time, it is quite likely that companies that remain dormant for 12 month or longer continuously have retreated from the regional market. To account for firms who have been bidding within the last year of the sample period, we append records from October 2009 to September 2010 to extend the window for identifying market exitors. If, however, a firm is observed to submit bids in the extension period, it is coded as censored.

A natural starting point of survival evaluation would be to approximate the probability of a new firm bidding t months after initial entry, distinguishing between periods divided by the policy change. Table 5.9 presents results of standard nonparametric Kaplan-Meier estimator. Judging by the numbers, in the period after June 2006, the cumulative hazard rate for entrants declines less rapidly, indicating that they are observed longer as active competitors. For instance, while the probability of an average firm bidding 12 months into its entry is 57% before adjustments, it steps up to 85% after. The finding becomes more informative when we take apart new firms that have participated in asphalt projects which are subject to the policy influences from the others who have only participated in non-asphalt ones and were thus least affected by the intervention. The last four columns of Table 5.10 verify that the extended duration of active participation is statistically significant for entrants bidding on asphalt projects, who exhibit higher probability to being continuously present for 1 month, 3 months, and 12 month intervals. In contrast, for entrants participating in non-asphalt projects alone, the inter-period change is much less pronounced, and we fail to reject the null hypothesis of Wilcoxon test that survival probabilities are equal before and after the policy implementation.[14]

Being the least restricted econometric setting, nonparametric analysis above does not account for other factors potentially affecting the survival of entrants, such as firm size. To address this issue, we employ semi-parametric and fully parametric regressions to estimate how the indexation of asphalt prices impacts the instantaneous failure rate of new firms in the ODOT market while incorporating the control variables used previously.[15] Table 5.11 presents estimation results under three functional choices: Cox proportional hazard model, exponential function, and Weibull function. Consistent with the impression under Kaplan-Meier framework, entrants that have participated on asphalt projects (β_2) display a lower hazard rate, but not statistically different from zero after the inclusion of controls. Nonetheless, the group of entrants that came in after adjustment clause and bid on asphalt work (β_3) registers a significantly improved survival chance over entrants that came in after June 2006 but were confined to non-asphalt contracts, or entrants participating in asphalt projects but came in before the policy initiative. As for other independent variables omitted from the table, establishment size exerts positive impact on duration, agreeing with "the stylized fact" of the literature (Geroski 1995).

[14] It is worth noting that firms engaging in the two segments of projects displayed quite distinctive survival patterns even before the adjustments clauses kicked in. Many projects using asphalt binder are surfacing and pavement jobs, generally considered private costs and involving less uncertainty concerning the work to perform. On the other hand, more than 60% of ineligible projects are related to bridge constructions which typically contain a notable public cost component and thus are more uncertain. (See Hong and Shum, 2002 for similar classifications of projects.) Since it usually takes cumulative expertise to assess site conditions and evaluate work nature, the perspective of newly entering firms in this category can be more dismal.

[15] Some of them are time-independent, such as maximum capacity. On the other hand, to accommodate for those time-dependent variables, we put in base line status. For example, unemployment rate is taken to be the value from the initial time of entry; cohort heterogeneity is attended with the inclusion of yearly dummies based on the date of entry.

As a sensitivity check, we also utilize a continuous measure for participation in the risk discounted asphalt projects, as reported in Table 5.12. Compared with the discrete dummy of 0 or 1, the continuous variable counts how many times a firm bid for asphalt projects and provides a more accurate degree of its involvement with the policy change. If price indexation is the underlying difference maker in survival perspective, a firm that frequently competes for asphalt auctions is likely to be influenced more substantially than an occasional participant, and thus leads to different duration paths. Parametric regressions under the alternative specifications also yield β_3 to be negative and statistically different from 0, attesting to the supportive effects of policy change on small entrants' probability of survival.

Quiros and Timmermann (2004) have argued that firms with a size disadvantage are more vulnerable to worsening of economic conditions or higher borrowing standards. It is agreed by both theoretical and empirical research (Clementi and Hopenhayn 2002, Tsoukas2011 among others) that liquidity constraints play a key role in determining business failures: less stringent borrowing restrictions will facilitate the survival of firms, especially small and inexperienced ones. We provide evidence that the introduction of price adjustment policy when oil prices are uncertain and highly volatile has had a beneficial effect on new firms in highway construction. Upon the introduction of price adjustments for volatile asphalt binders, entering firms who have been struggling to finish projects now survive longer. The lower need for external financing (in cases of a cost overrun) has led to a substantially improved survival rate of newcomers and enhanced competition.

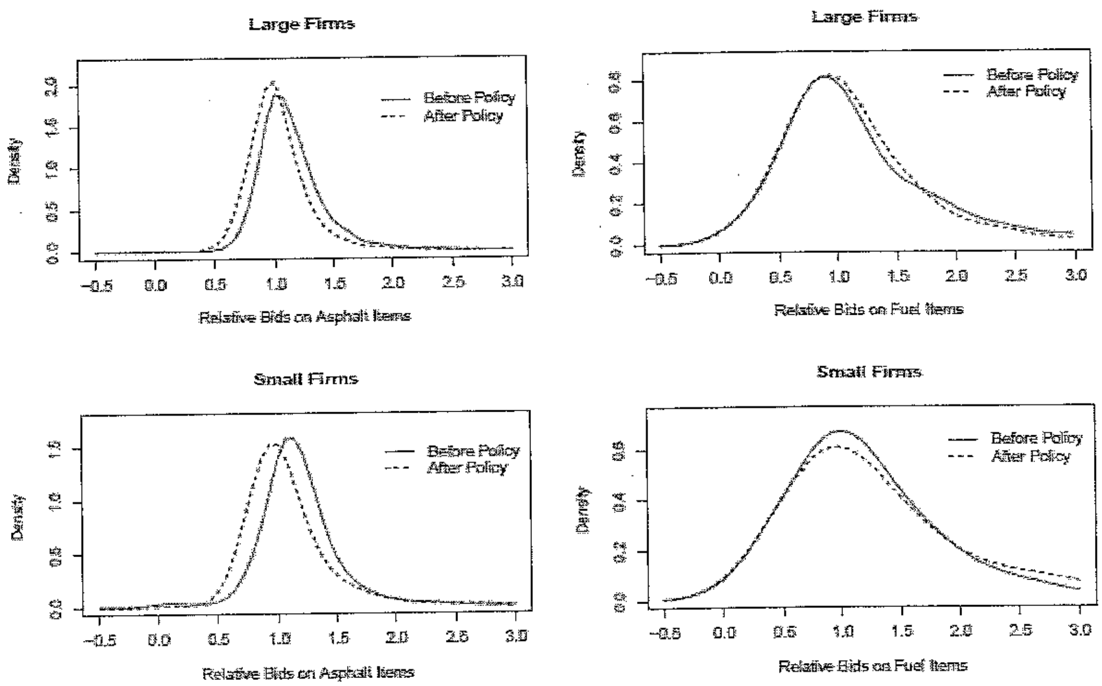
5.5 Conclusion

In June 2006, ODOT began to complement general construction specifications with a special provision of price adjustment for asphalt binder products. This paper studies the effect of the policy keeping in mind the different characteristic among participants in this market. Supporting theoretical arguments, our findings show an asymmetric impact of the policy, which have implications on bidding outcomes, survival and long run competition in procurement auctions.

The indexation of selected input prices has induced more aggressive bidding from all firms but especially small ones, lending new evidence for the common notion that they are generally faced with more adverse liquidity constraints and have more to gain when investment risks are reduced. Small firms also exhibit more competitive participation tendencies in the. post-policy period. The survival prospect of small entrants for has been significantly improved by policy implemented, and such positive changes are unique to entrants that have been bidding on policy eligible asphalt projects.[16]

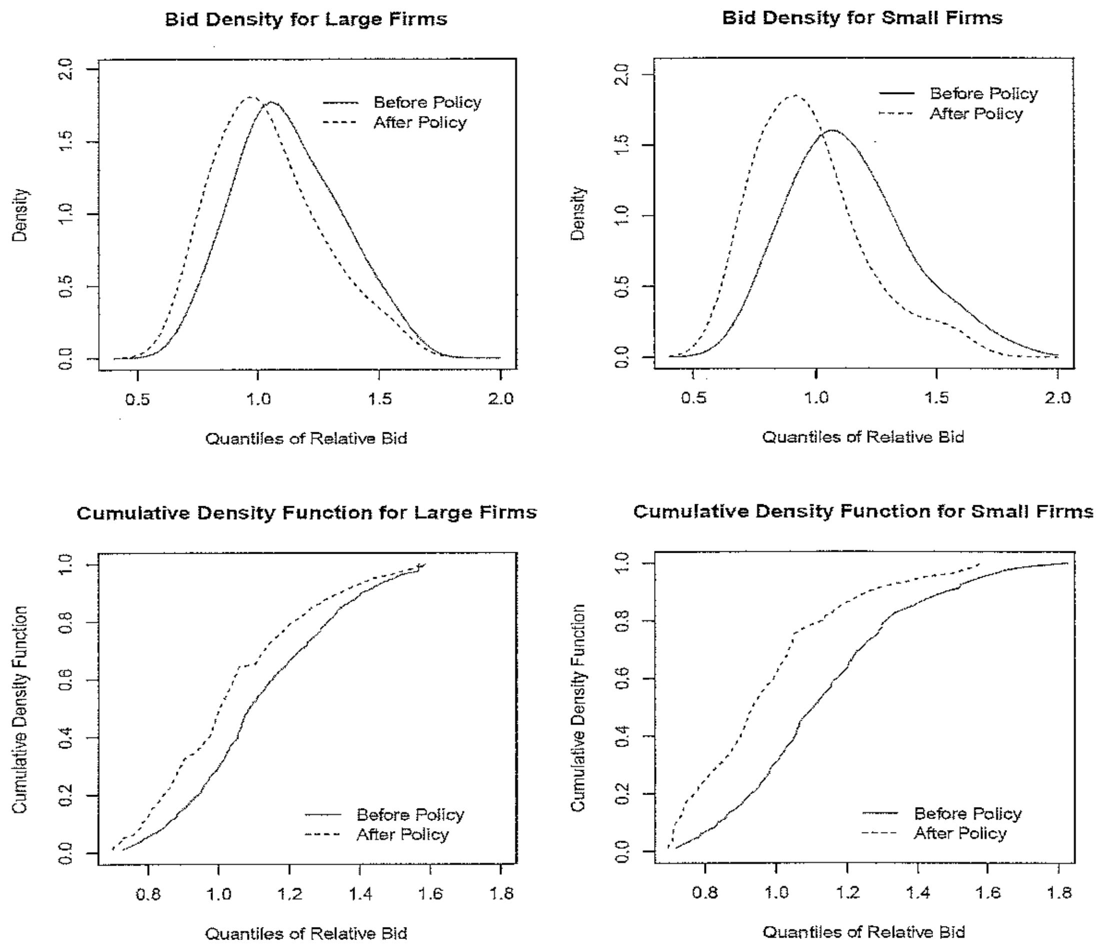
[16] A potential concern with findings from our main regressions is the self selection by bidders into asphalt projects (those subject to adjustment clauses and thus eligible for ex post transfers). Biases may arise if the pool of participants of asphalt projects has significantly changed between periods in terms of competitiveness or quality. For example, if some firms systematically choose to enter asphalt projects more frequently after policy enactment and bid more aggressively, failure to account for such differences may attribute spurious effects to the indexation policy. To address this issue, we have examined participation pattern carefully and shown that, on the one hand, there is no systematic difference in bidding frequencies of firms into asphalt projects in periods before and after; and on the other hand, contractors seem to base participation decisions on the nature of tasks rather than having asphalt items or not.

Figure 5.1: Kernel Densities for Relative Itemized Bids



The figure contrast relative bids by large and small firms on asphalt and fuel items before and after the policy implementation.

Figure 5.2: Density Graphs for Simulated Bids on Items



Data points are generated by employing estimated coefficients from quantile regressions and mean values of all covariates except for treatment status and period indicator, which take 0 or 1 depending on type of item and date respectively.

Table 5.1: Descriptive Statistics by Large and Small Firms

Variables	Large Firms		Small Firms	
	Before	After	Before	After
Relative bid on	1.169	1.042	1.196	1.090
asphalt items	(0.358)	(0.303)	(0.465)	(0.409)
Relative bid on	1.208	1.172	1.271	1.337
fuel items	(0.794)	(0.695)	(0.818)	(0.876)
Winning relative bid	1.126	0.998	1.171	1.051
on asphalt items	(0.274)	(0.263)	(0.563)	(0.412)
Winning relative bid	1.104	1.082	1.088	1.170
on fuel items	(0.681)	(0.702)	(0.723)	(0.806)
Bid dummy	0.598	0.590	0.506	0.539
	(0.490)	(0.481)	(0.500)	(0.498)
Average rivals' winning to	0.161	0.161	0.162	0.161
planholding ratio (ARWP)	(0.032)	(0.032)	(0.039)	(0.037)
Capacity utilization rate	0.225	0.283	0.122	0.128
	(0.247)	(0.252)	(0.230)	(0.230)
Past winning to	0.161	0.159	0.162	0.163
planholding ratio (WP)	(0.054)	(0.049)	(0.116)	(0.123)
Number of planholders	6.393	6.511	6.315	6.344
per auction	(2.876)	(2.901)	(2.846)	(2.833)
Number of bids	3.462	3.533	3.563	3.629
per auction	(1.512)	(1.753)	(1.534)	(1.690)
Expected number of bids	3.605	3.640	3.532	3.590
per auction	(1.660)	(1.677)	(1.584)	(1.607)
Seasonally adjusted	4.742	4.440	4.762	4.437
unemployment rate	(0.432)	(1.143)	(0.518)	(1.105)

Standard errors are in parenthesis

Table 5.2: Conditional and Unconditional Quantile Regressions for Large and Small Firms with Firm and Item Fixed Effects

	Quantiles				
Variables	0.1	0.25	0.5	0.75	0.9
Large Firms Conditional Quantile Regression					
Bids after policy enactment	-0.002	-0.012	-0.026‡	-0.090*	-0.359*
(β_1)	(0.016)	(0.013)	(0.014)	(0.020)	(0.033)
Bids on asphalt items	0.719*	0.770*	0.522*	0.027	-0.205
(β_2)	(0.073)	(0.099)	(0.178)	(0.150)	(0.161)
Bids on asphalt items after	-0.103*	-0.096*	-0.102*	-0.067*	0.103
policy enactment (β_3)	(0.014)	(0.012)	(0.012)	(0.018)	(0.310)
Large Firms Unconditional Quantile Regression					
Bids after policy enactment	0.030	0.042†	-0.031†	-0.077*	-0.278*
(β_1)	(0.026)	(0.017)	(0.014)	(0.025)	(0.069)
Bids on asphalt items	0.378	0.484‡	0.432‡	0.759‡	-0.123
(β_2)	(0.422)	(0.280)	(0.237)	(0.406)	(1.132)
Bids on asphalt items after	-0.052†	-0.109*	-0.137*	-0.082*	-0.029
policy enactment (β_3)	(0.024)	(0.016)	(0.013)	(0.023)	(0.163)
Number of Observations	8305	8305	8305	8305	8305
Small Firms Conditional Quantile Regression					
Bids after policy enactment	-0.043†	-0.059*	-0.005	-0.011	0.126*
(β_1)	(0.021)	(0.011)	(0.010)	(0.026)	(0.048)
Bids on asphalt items	0.930*	0.874*	0.974*	0.794*	0.774*
(β_2)	(0.056)	(0.045)	(0.069)	(0.111)	(0.142)
Bids on asphalt items after	-0.052*	-0.086*	-0.100*	-0.127*	-0.234*
policy enactment (β_3)	(0.018)	(0.010)	(0.009)	(0.024)	(0.046)
Small Firms Unconditional Quantile Regression					
Bids after policy enactment	-0.006	0.008	-0.010	-0.032	0.055
(β_1)	(0.037)	(0.027)	(0.026)	(0.043)	(0.119)
Bids on asphalt items	1.175†	0.676‡	0.224	0.328	0.636
(β_2)	(0.535)	(0.390)	(0.370)	(0.609)	(1.692)
Bids on asphalt items after	-0.023	-0.107*	-0.122*	-0.149†	-0.243†
policy enactment (β_3)	(0.034)	(0.025)	(0.023)	(0.038)	(0.107)
Number of Observations	4399	4399	4399	4399	4399
Controls	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes	Yes	Yes
Item Effects	Yes	Yes	Yes	Yes	Yes

The symbols ‡, †,* denote statistically different from zero at the 0.10, 0.05 and 0.01 level of significance.

Table 5.3: Robustness Check on the Parameter of Interest: Bids on Asphalt Items after Policy Enactment (β_3)

	Conditional Quantiles			Unconditional Quantiles		
Subsamples	0.1	0.5	0.9	0.1	0.5	0.9
Large Firms	-0.095†	-0.107*	0.086	-0.053†	-0.142*	-0.019
	(0.017)	(0.011)	(0.301)	(0.024)	(0.013)	(0.063)
Small Firms	-0.072*	-0.100*	-0.290*	-0.034	-0.124*	-0.237*
	(0.023)	(0.018)	(0.059)	(0.034)	(0.023)	(0.106)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Effects	Yes	Yes	Yes	Yes	Yes	Yes

The symbols ‡, †,* denote statistically different from zero at the 0.10, 0.05 and 0.01 level of significance.

Table 5.4: Quantile Regression Results for Winning Bids Only

	Quantiles		
Variables	0.25	0.5	0.75
Win by large firms			
Bids after policy enactment (β_1)	-0.035	-0.031	-0.020
	(0.030)	(0.022)	(0.032)
Bids on asphalt items (β_2)	-0.314	-0.311	-0.203
	(0.365)	(0.360)	(0.614)
Bids on asphalt items after	-0.087**	-0.080**	-0.107**
policy enactment (β_3)	(0.024)	(0.020)	(0.031)
Number of Observations	3160	3160	3160
Win by small firms			
Bids after policy enactment (β_1)	-0.075	-0.062	-0.064
	(0.040)	(0.063)	(0.050)
Bids on asphalt items (β_2)	0.665	0.422	0.484
	(0.332)	(0.351)	(0.406)
Bids on asphalt items after	-0.089**	-0.109**	-0.118**
policy enactment (β_3)	(0.032)	(0.036)	(0.046)
Number of Observations	1156	1156	1156

The symbols **,* denote statistically different from zero at the 0.10 and 0.05 level of significance.

Table 5.5: Participation and Winning Patterns of Large and Small Firms

Variables	Probability of Bidding Logit (1)	Probability of Bidding Clog-log (2)	Probability of Winning Logit (3)	Probability of Winning Clog-log (4)
Large Firms				
Bids after policy enactment	-0.004	0.006	0.035	0.038
(β_1)	(0.153)	(0.096)	(0.234)	(0.200)
Bids on asphalt projects	-0.129	-0.078	0.340	0.273
(β_2)	(0.113)	(0.071)	(0.242)	(0.203)
Bids on asphalt projects after	0.107	0.064	-0.229	-0.195
policy enactment (β_3)	(0.144)	(0.091)	(0.195)	(0.169)
Small Firms				
Bids after policy enactment	0.097	0.091	-0.172	-0.137
(β_1)	(0.107)	(0.077)	(0.148)	(0.143)
Bids on asphalt projects	-0.572*	-0.391*	0.002	0.013
(β_2)	(0.081)	(0.058)	(0.139)	(0.146)
Bids on asphalt projects after	0.213†	0.123‡	0.066	0.046
policy enactment (β_3)	(0.104)	(0.073)	(0.162)	(0.164)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes

Choices of functional forms are logistic for (1) & (3), and complementary log-log for (2) & (4). The symbols ‡, †,* denote statistically different from zero at the 0.10, 0.05 and 0.01 level of significance.

Table 5.6: Descriptive Statistics for Entrants

Variables	Entrants	
	Before	After
Relative bid on asphalt items	1.329	1.058
	(0.445)	(0.357)
Relative bid on fuel items	1.128	1.097
	(0.697)	(1.016)
Winning relative bid on asphalt items	1.262	1.014
	(0.166)	(0.307)
Winning relative bid on fuel items	0.746	0.978
	(0.165)	(0.557)
Bid dummy	0.458	0.538
	(0.499)	(0.499)
Average rivals' winning to plan holding ratio (ARWP)	0.161	0.162
	(0.037)	(0.035)
Capacity utilization rate	0.108	0.115
	(0.221)	(0.232)
Past winning to plan holding ratio (WP)	0.165	0.157
	(0.145)	(0.135)
Number of plan holders per auction	6.738	6.913
	(2.293)	(2.851)
Number of bids submitted per auction	3.774	4.185
	(1.527)	(1.672)
Expected number of bids submitted per auction	3.634	3.899
	(1.664)	(1.665)
Seasonally adjusted unemployment rate	4.727	4.428
	(0.475)	(1.090)

Standard errors are in parenthesis

Table 5.7: Unconditional Quantile Regression Results for Bids Submitted by Entrants

Variables	Quantiles				
	0.1	0.25	0.5	0.75	0.9
	Entrants				
Bids after policy enactment	-0.131**	-0.062	-0.052	-0.078	-0.408**
(β_1)	(0.052)	(0.037)	(0.044)	(0.055)	(0.080)
Bids on asphalt items	1.484**	1.248**	0.923**	0.818**	0.166
(β_2)	(0.283)	(0.200)	(0.239)	(0.296)	(0.439)
Bids on asphalt items after	-0.158**	-0.115**	-0.110**	-0.131**	0.190**
policy enactment (β_3)	(0.052)	(0.036)	(0.044)	(0.054)	(0.080)
Number of Observations	1498	1498	1498	1498	1498

The symbols **,* denote statistically different from zero at the 0.10 and 0.05 level of significance.

Table 5.8: Quantile Regression Results for Winning Bids Submitted by Entrants

Variables	Quantiles 0.25	0.5	0.75
Win by entrants			
Bids after policy enactment (β_1)	0.031	0.154	0.355**
	(0.066)	(0.090)	(0.159)
Bids on asphalt items (β_2)	0.620**	0.762**	1.878
	(0.207)	(0.282)	(0.500)
Bids on asphalt items after	-0.260**	-0.350**	-0.475**
policy enactment (β_3)	(0.103)	(0.155)	(0.201)
Number of Observations	446	446	446

The symbols **,* denote statistically different from zero at the 0.10 and 0.05 level of significance.

Table 5.9: Participation and Winning Patterns of All Firms Contrasting Pre and Post Policy Grouped by Size and Experience

	All projects		Eligible projects	
	Logistic	Complementary Log-Log	Logistic	Complementary Log-Log
	Probability of bidding			
Variables	(1)	(2)	(3)	(4)
Bids after policy enactment (β_1)	0.028	0.031	-0.079	-0.039
	(0.113)	(0.078)	(0.133)	(0.092)
Bids by entrants	-0.500**	-0.321**	-0.769**	-0.540**
	(0.207)	(0.151)	(0.244)	(0.186)
Bids by entrants after policy enactment	0.487**	0.326**	0.522**	0.370*
	(0.204)	(0.147)	(0.275)	(0.205)
Bids by small incumbents	-0.285*	-0.159	-0.651**	-0.433**
	(0.159)	(0.110)	(0.145)	(0.101)
Bids by small incumbents after policy enactment	0.131	0.087	0.197*	0.146*
	(0.130)	(0.080)	(0.126)	(0.090)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Number of Observations	11658	11658	6507	6507
Wald χ^2	243.01	251.98	391.40	411.24
	Probability of winning			
Variables	(5)	(6)	(7)	(8)
Bids after policy enactment (β_1)	0.006	0.003	-0.123	-0.103
	(0.132)	(0.107)	(0.143)	(0.116)
Bids by entrants	-0.116	-0.120	-0.682**	-0.587**
	(0.245)	(0.199)	(0.324)	(0.274)
Bids by entrants after policy enactment	-0.229	-0.187	0.244	0.196
	(0.230)	(0.187)	(0.344)	(0.294)
Bids by small incumbents	-0.134	-0.159	-0.444**	-0.362**
	(0.169)	(0.110)	(0.205)	(0.169)
Bids by small incumbents after policy enactment	-0.191	-0.135	0.131	0.108
	(0.150)	(0.125)	(0.178)	(0.150)
Controls	Yes	Yes	Yes	Yes
Time Effects	Yes	Yes	Yes	Yes
Number of Observations	6444	6444	3304	3304
Wald χ^2	312.80	351.48	175.73	199.47

The symbols **,* denote statistically different from zero at the 0.10 and 0.05 level of significance.

Table 5.10: Kaplan-Meier Estimates for Bidding Duration Probability

Time	Survival Function Estimates					
	All Entrants		Entrant Bidding on Asphalt Projects		Entrant Bidding on Non-asphalt Projects	
	Before	After	Before	After	Before	After
1 month	0.714	0.906	0.857	1.000	0.533	0.608
	(0.076)	(0.042)	(0.079)	-	(0.128)	(0.116)
3 months	0.685	0.882	0.786	1.000	0.458	0.517
	(0.079)	(0.046)	(0.076)	-	(0.131)	(0.143)
12 months	0.566	0.847	0.714	0.917	0.381	0.458
	(0.085)	(0.056)	(0.090)	(0.079)	(0.130)	(0.153)
Wilcoxon test (p-values)	0.007		0.004		0.416	

Standard errors are in parenthesis.

Table 5.11: Semi-parametric and Parametric Results for Hazard Rate Function

Variables	Hazard Models		
	COX PH	Exponential	Weibull
	(1)	(2)	(3)
Entrants after policy enactment	-0.346	0.406	0.029
(β_1)	(0.578)	(0.621)	(0.610)
Entrants bidding on	-0.385	-0.729	-0.591
asphalt projects (β_2)	(0.552)	(0.620)	(0.584)
Entrants after policy enactment	-2.411†	-3.016†	-2.718†
bidding asphalt projects (β_3)	(1.022)	(1.023)	(1.022)
Controls	Yes	Yes	Yes
Number of Observations	88	88	88

Column (1) presents results using Cox proportional hazard model, and (2) and (3) are based on Exponential and Weibull regression models respectively. Standard errors are in parenthesis. The symbols ‡, †, * denote statistically different from zero at the 0.10, 0.05 and 0.01 level of significance.

Table 5.12: Semi-parametric and Parametric Results for Hazard Rate Function – A Robustness Check

Variables	Hazard function estimates		
	COX PH	Exponential	Weibull
	(1)	(2)	(3)
Entrants after policy enactment	-0.466	-0.412	-0.060
(β_1)	(0.523)	(0.523)	(0.608)
Number of times entrants who participated	-0.104	-0.052	-0.068
in eligible projects (β_2)	(0.131)	(0.062)	(0.139)
Number of times entrants who came in after policy	-0.327*	-0.468**	-0.420**
enactment participated in eligible projects (β_3)	(0.194)	(0.221)	(0.212)
Controls	Yes	Yes	Yes
Number of Observations	88	88	88

Column (1) presents results using Cox proportional hazard model, and (2) and (3) are based on Exponential and Weibull regression models respectively. Standard errors are in parenthesis. **and* denote statistically different from zero at the 0.05 and 0.01 level of significance.

CHAPTER 6

SPEED INCENTIVES IN PUBLIC PROCUREMENT AUCTIONS

This essay deals with another instrument devised by state transportation agencies aiming to improve the efficiency of procurement and construction of highway contracts. Based on an extensive dataset of repair and reconstruction projects administered by ODOT between 2005 and 2010, we empirically evaluate whether the new auction designs, known as incentive/disincentive and A+B contracting, have achieved what they set out to do.

6.1 Background and Motivation

In the United States, sealed bid low price auction is the most widely used mechanism by Departments of Transportation to procure basic infrastructure work such as road paving, bridge approach and intersection modification. As advocated by many economists, open process and clearly formulated rules featured in competitive auctions are conducive to equal opportunities and inhibiting favoritism treatments, contributing to lower costs and higher efficiency for the public sector. However, if there are external effects that cannot be integrated into the system, externality may arise to cause significant efficiency loss.

In public procurement industry, one such example is the time taken to complete a project. In the traditional setting of low price sealed bid auctions, construction plans prepared by state engineers usually assign the maximum number of days for project completion in advance. Contractors are hardly involved in the process of plan drafting, and therefore have to take for granted the designated time when proposing a cost to undertake the work. Theoretically, since contractors are bounded only at the upper end, they may choose to complete at any time within the allocated time frame. In reality, they rarely, if ever, finish ahead of schedule. The time set by engineers is often a reasonable estimate of the duration needed; acceleration is possible but probably costly. Note that, according to the general specifications of many Departments of Transportation, there is a daily punitive fee charged to the contracting firm if it fails to complete and deliver on time. However, there is no matching remunerative bonus if the contractor achieves an early completion. As a result, contractors are given little incentive to speed up their work.

Meanwhile, social welfare clearly depends on the length of the period a construction project lasts. In addition to commuters' frustration and agony that are hard to measure, slower traffic flow, increased commuting time and serious safety concerns in the work zone may generate tremendous negative externalities for the society. For example, Interstate 35 is an important national highway going across the state of Oklahoma extending north to Kansas and south to Texas. According to ODOT daily traffic count records, one section between Oklahoma City and Norman carries over 100,000 vehicles an average day. Assume that a construction work on I-35 results in a delay of 30 minutes for every traveler on the route with time valued at $10 per hour, the total loss to social welfare is estimated be a daunting $500,000 a day.

In order to remedy inefficiency of the current system, Departments of

Transportation have experimented with creative contract designs aiming to encourage contractors to internalize the cost of delay and shorten construction duration. From the perspective of policy evaluation, it is economically sensible to internalize the negative externality if gains of faster completion outweigh costs.

There are in general two approaches government agencies have invented to reduce the negative externality: incentive/disincentive and A+B milestones. Incentive/disincentive bidding largely resembles the standard structure except that firms will be rewarded if they satisfactorily fulfill the contract before the calendar date prescribed in the plan. In case of an overdue completion, firms would be fined at a disincentive rate on top of the punitive fee which applies to all projects. Both rates are set by the state and provided in the plan. The other design, A+B bidding, is more sophisticated and delegates more freedom to the private sector participants. For projects auctioned through this mechanism, firms are required to submit a two-part offer: the A part is the dollar amount for completing the project, the same as the bid they would submit with an standard design; the B part, the innovative component, allows the firm to propose the number of days they need to complete the project (provided that it is within a reasonable range). Adding up part A (bid) and the product of part B (time) and a "value of time" assigned by the state leads to a single number, which is then used to select the low bidder/winner. The winning contractor may also be subject to incentive/disincentive payments according to the time it indicates in part B. This way, awarding decisions take into account both the direct cost of government procurement and welfare loss incurred by commuters, arriving at the a contractor who delivers the project at the lowest social cost. It should be clarified that since winning firms are not meant to be paid the B component, the cost to DOTs consists of part A alone. To distinguish between the different components of the bid, part A is sometimes referred to as "item bid" as it is the sum of cost associated with all construction items, part B as time bid, and the sum of A and B as total bid. The standard design where contractors do not weigh in on construction time may be called A-only bidding.

In this chapter, we implement an empirical assessment of speed incentive designs based on data collection in Oklahoma. Both incentive/disincentive and A+B have been practiced by ODOT in its monthly lettings. We are able to contrast contract time and bids under all three regimes (A only, incentive/disincentive and A+B). First, we would like to examine whether additional freedom and/or incentives offered by innovative designs have reduced project duration. Meanwhile, since it is usually costly for contractors to speed up, they may adjust bids upward to remain equally profitable, resulting in higher bids received by ODOT. We seek to provide quantitative evidence about how much it takes to achieve faster completion.

This essay relates directly to the emerging literature studying the speed incentive designs by transportation agencies. Caltran is the first Transportation Department to apply time incentive provisions in public procurement at large scale. As an area of high traffic volume and population density, California is believed to suffer severely from traffic delays[17] and thus ought to derive significant benefits from the new contracting methods. Bajari and Lewis (2011) are based on the usage of A+B contracts

[17] A temporary (2-day) lane closure in a section of I-405 was referred to as "Armageddon" by several mainstream news channels, underscoring the severe impacts it had on local traffic.

by California Department of Transportation between 2003 and 2008. With carefully constructed control group that consists of highly similar standard contracts, they find that on average, A+B contracts are completed much quicker, around 60% of the maximum time allowed. Meanwhile, the winning bid is noticeably higher, about $1.5 million more per project, compared to the average project worth of $15 million. However, it is substantially outweighed by the reduction in commuters' negative externality which is estimated to be $6.4 million per contract. Unfortunately, they excluded the less sophisticated incentive/disincentive design from consideration. Another study examining the effects of incorporating completion time into competitive bidding is the working paper by Gupta and Snir (2009). Based on a relatively small sample of A+B projects collected from Minnesota Department of Transportation (MnDOT), they concentrate on the actual cost realization rather than the winning offer out of the bidding process. Through a game theoretic model, they predict that in equilibrium, contractors have the incentive to propose unrealistically low completion time (B bid), finish late and pay a penalty. The outcome mainly results from a distortion in the value revelation process where the firm with low bid is not necessarily picked out as the winner. It suggests an interesting extension for this essay: to evaluate not only the direct effects of the regulation on bidding, but also how it is enforced and realized eventually.

This chapter also contributes to the effort in auction literature to assess the effectiveness of procurement mechanisms used and the impacts of various public policies. Based on auctioned contracts between 1997 and 2003 in Oklahoma and Texas, De Silva, Dunne and Kosmopoulou (2008) capitalize on the change of information releasing policy on state engineer's cost estimates and investigate its influences on bidding. Bidding preference toward certain groups, such as domestic suppliers or small disadvantaged businesses, has been the focus of several studies (Naegelen and Mougeot, 1998; Marion, 2007, 2009a; De Silva, Dunne, Kosmopoulou and Lamarche 2010). Thomas and Wilson (2002) and Bajari, McMillan and Tadelis (2009) investigate 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, Houghton and Tadelis (2009) find that even in standard procurement contracting, anticipated changes to initial plans after awarding of contracts can cause firms to significantly shade their offers with respect to expected adaptation costs.

6.2 Data

As mentioned in section 3.1, we obtain data from the publicly available files on ODOT website. This exhaustive sample includes all construction contracts procured between 2005 and 2010. We utilize this prorated period during which ODOT applied the special provisions with relatively stable frequencies. Besides using the standard A only mechanism, ODOT utilizes both incentive/disincentive and A+B innovative methods trying to achieve higher efficiency in public construction projects. During the period, 1754, 161 and 101 projects are successfully contracted under regimes A only, incentive/disincentive and A+B respectively. In terms of observations under alternative methods, our dataset is quite rich, especially compared to samples employed in similar studies.[18]

Among projects under the conventional method, the largest one is estimated to cost over $66.2 million by state engineers, the smallest $3800, and the mean of all around $1.52 million, demonstrating that the sample covers a wide range of project scales. Winning bids of A only auctions display a similar distribution with a mean of $1.41 million and a standard deviation of $2.8 million. The total projected cost (based on winning bids) to the state agency amounts to $2.48 billion. Regarding incentive/disincentive and A+B types respectively, the mean of winning bid is $2.46 million and $9.34 million, and the standard deviation is $5.70 million and $12.8 million. Apparently, both incentive/disincentive and A+B projects are worth considerably more than A only ones, and A+B contracts are significantly larger than incentive/disincentive ones as well.

Table 6.1 presents a summary of some important characteristics of auctions by contract design. The variation between types in number of days assigned by state engineers echoes that reflected by project values, where A+B requires a lot more days to complete than incentive/disincentive and incentive/disincentive than A only. On the other hand, the relative winning bid, the ratio of winning bid divided by estimate, does not show statistical difference between any two comparison groups. This finding suggests that, regardless of work scales or usage of time incentive, competitive outcomes tend to converge. Now consider the nature of work under the three designs.

[18] In Bajari and Lewis (2011) the dataset includes 79 A+B contacts, while the sample in Gupta and Snir (2009) contain only 25 projects of A+B design.

Among A+B projects, surfacing and bridge work each makes up approximately one third of the total number. However, an overwhelming 84.2% of incentive/disincentive contracts are road surfacing or resurfacing, and all A+B contracts except one involve tasks related to surfacing or bridge construction. There also seems to be a clustering effect regarding project locations. While both A only and incentive/disincentive are roughly evenly scattered among the eight geographic districts of Oklahoma[19], nearly 85% of A+B projects are located in District 3 (32%), District 4 (19%), or District 8 (34%).

6.3 Empirical Analysis

The stark differences in contract characteristics between three regimes suggest that applications of time incentive special provisions are not random. To learn about assigning criteria, we asked the engineers of ODOT whether there are any rules in determining when and where to apply the innovative designs. They replied that their primary assignment criteria concerns to project scales and population density of the area. So it should not be a surprise that A+B is used most frequently in Tulsa metro area (District 8), OKC metro area (District 4) and Moore/Norman metro area (District 3). In addition, both incentive/disincentive are mostly applicable to projects on the highway system but rarely used in project on other roads such as county roads or city streets. In fact, about 77% of A only projects are located on the highway system, while for incentive/disincentive and A+B the proportions are 98% and 99% respectively. When it comes to the selection between incentive/disincentive and A+B, it usually depends on project duration, and the rule-of-thumb cut-off point is at 120 days, although there may

[19] The division is available at: http://www.okladot.state.ok.us/flddiv.htm.

be some exceptions. This helps to explain the cost differentials between projects using the two innovative approaches.

To test the assignment guidelines, we estimate a probit regression for usage of incentive/disincentive and A+B designs separately. The right hand side covariates include cost estimate and days allocated by engineers, types of tasks involved, a dummy for the three metro areas, and a binary indicator for the urban freeway system (interstate, US route, and state highway). We have tried additional explanatory variables including other types of tasks, more specific location or highway type indicators, but neither are they significant nor having impacts on the rest of the controls. Regression results are reported in Table 6.2. Look at the incentive/disincentive column first. We see that the number of days and surfacing type are both positive and statistically different from zero. On the other hand, compared to conventionally let projects, incentive/disincentive projects are not necessarily worth more after controlling for other factors. Turning to A+B projects, all covariates are positive and significant. Larger scale, longer duration and being surfacing or bridging work all increase the probability of A+B assignment. Further, projects located in one of the three metro divisions are on average 36% more likely to be assigned the A+B design given the combination of value, day and nature of task. The results discussed above underscore the well-executed ODOT guidelines.

After confirming the non-random assignment of incentive/disincentive and A+B contracts, the difference observed in Table 6.1 may be attributed largely to the dissimilarity across contracts. Many projects included in the column A only are intrinsically inclined toward the standard auction mechanism and thus do not represent a quality comparison. Based on ODOT general guidelines, in Table 6.3 we choose a subsample of standard projects that could have been eligible for the new mechanism assignment ex ante, to form a more comparable control group. In particular, for incentive/disincentive, we select only standard freeway surfacing projects that are to be completed in 207 days or less (the 90th percentile of the day distribution for incentive/disincentive type). In regard to for A+B, we restrict the sample to include paving or bridge work on highways located in Division 3, 4 or 8 lasting 120 days and above. There are now 459 and 120 observations left in the refined control groups for incentive/disincentive and A+B respectively. Consistent with our expectation, the improved control and treatment pair are much better matched on most observables, assuring that we have informative comparison groups to proceed.

Now we turn to the central question brought up in the introduction section: do the new regimes successfully motivate contractors to strive for speedier project delivery? For the A+B structure, we are able to answer the question directly. State engineers set a maximum number of days allowed in the plan, but firms are free to choose any time before the deadline as their "customized" duration. Therefore, the ratio between the time bid of the winning contractor and the days designated by the state is a natural candidate to measure the relative completion speed. This ratio for A+B type is 81.5%. To put it into context, it is equivalent to a saving of 49.5 days for each project. A calculation similar to the one in Section 6.1 may lead to significant gains in eliminated negative externality. Meanwhile, due to the setting of incentive/disincentive bidding[20], we are unable to conduct a parallel analysis to A+B bidding. However, according to our discussion with department officials, incentive/disincentive design is mostly applied where slow completion may result in severe inconvenience to the public and hence speed is greatly appreciated.[21] It might be safe to assume that the maximum number of days allowed for incentive/disincentive should be at most as large as that of standard contracts and possibly smaller.

So far, our analysis suggests that the A+B design noticeably reduces the duration of projects while incentive/disincentive design is likely to lead to a faster completion. We would like to investigate what it has cost ODOT to achieve this socially more efficient outcome. This question can be answered by estimating the treatment effects of new designs on bids: a comparison between counterfactual winning bids that would have been realized had the projects were auctioned the conventional way and the actual bids received by ODOT. Relating to the literature of program evaluation, the objective estimator is the average treatment effect on the treated (Δ^{TT}).

Following the example in Bajari and Lewis (2011), a simple OLS model is carried out first trying to project the counterfactual winning bids on important project characteristics. In addition to contract design dummies, department's cost and duration estimates, we also include fixed effects for years, divisional level locations, freeways, and nature of work to account for unobserved heterogeneity. It is worth noting that both

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[20] Contractors are not able to propose their own schedules but rather work under the plan and earn a bonus when completing ahead of time.

[21] One example they gave is the resurfacing project on I-35 right before the OU-Texas game.

winning bids and engineers' estimates are expressed in logarithm as is the common practice in the literature.

Table 6.4 presents the coefficients of selected independent variables. In both cases, engineers' estimates for cost and duration are significant, consistent with previous findings. In fact, the magnitudes of both coefficients correspond quite well to the estimates reported in Bajari and Lewis (2011). Nevertheless, the variables of interest, namely the mechanism dummies, set apart out findings from theirs. The coefficient in front of the A+B dummy is -0.003, fairly small in size and negative in direction. The statistical insignificance means that the A+B contracting method does not significantly raise procurement costs for ODOT. Let's direct attention to the first column of incentive/disincentive treatment. The coefficient on the dummy variable is negative (-0.032, significant at 10% level), suggesting that the innovative structure actually leads to savings for ODOT, albeit limited in dollar amount. Both models report a very high R^2, largely attributable to the exceptional fit provided by engineers' cost estimates.

The second route we take is the non-parametric matching method. Since some of the matching observables are categorical (division, freeway type, nature of work and year) and the standard contracts in control groups are quite abundant, we are able to force exact matches with respect to those cells. In fact, the exact match rate is 67% of the time. Table 6.5 summarizes the results estimated via nearest neighbors matching. Consistent with our findings from log linear OLS, neither incentive/disincentive nor A+B increase the winning bids received by ODOT significantly. For the incentive/disincentive design, bids submitted by winning contractors are again lower compared to standard A only auctions. For A+B design, the bids tend to be higher than under standard mechanism, but the difference is not statistically different from zero. The results point to the favorable effects of time incentive contracting methods on social welfare.

6.4 Discussion and Future Extension

Our investigation thus far has demonstrated two aspects of the creative speed incentivized structures. On the one hand, they are likely to lead to shortened construction time, approximately by 18.5% in the case of A+B.[22] Since delayed traffic inflicts negative externality on commuters, this will contribute to improvement in social welfare. On the other hand, through both log linear OLS regressions and non-parametric matching approach, we show that the innovative designs do not necessarily increase the winning bids or consequently raise the payment made by ODOT to contractors.

Now let's contemplate the findings more carefully. First of all, the results may appear too good to be true. Commuters are strictly better off, the government is not worse off, and the society's construction amount of infrastructure projects has not been reduced. We don't have data to evaluate the profiting performance of individual firms. Nonetheless, because their decisions to bid and contract with the state are voluntary, we believe that their well beings shouldn't change dramatically between the standard and alternative regimes. Second, our results seem at first thought to posit a slight

[22] but unfortunately unable to be quantified for incentive/disincentive

contradiction with conclusions drawn by Bajari and Lewis (2011). They find that A+B design does raise the cost of Caltran by inducing higher winning bids, but it is more than offset by a much larger increase in commuters' welfare. Based on the trade-off between California Department of Transportation and resident travelers, they conclude a favorable evaluation of A+B special provision.

I propose a couple of explanations in an effort to reconcile the difference. First, recall the structure of ODOT special provision concerning time incentive designs. A "value of time" is assigned for each A+B contract, as the weight of speed relative to construction costs. Apparently, this value affects the part B bid submitted by firms. In Oklahoma, the average value of time is slightly over $9000, considerably smaller than the policy parameter chosen by Caltran at more than $15000. Lower values of time constitute smaller incentives for contractors to accelerate. In fact, the ratio of part B bid to maximum time allowed time ratio is a radical 59.5% in California but only a moderate 81.5% in Oklahoma. Meanwhile, given the typical convex form of the cost functions (with respect to the number of days for completion), it might take a much larger cost increment to reduce the duration from 81.5% to 59.5% than from 100% to 81.5%. As ODOT officials put it, if contractors are mainly driven by a weak incentive to "trim excess fat rather than seriously accelerate", their costs shouldn't be significantly changed (think about the flat region on the marginal cost curves). Figure 6.1, adapted from Figure 2 in Bajari and Lewis (2011), visualizes this relationship. The acceleration cost when the number of days allowed for completion is reduced from 160 to 120 (40 days difference), $C_{120} - C_{160}$, could be substantially larger than the cost when the number of days is reduced from 200 to 160 (again 40 days difference), $C_{160} - C_{200}$. The difference grows more pronounced as the cost curve becomes steeper. Second, Bajari and Lewis (2011) have cautioned the replicability of their results as they are considerably dependent on the policy parameters, such as the value of time set by the state departments. Our results may be better referenced in areas with lower population density such as midsize cities.

We conclude the essay with a few remarks regarding future improvements to this research. We have shown, based on bidding outcomes, that: incentive/disincentive and A+B initiatives lead to higher utility for commuters and lower costs for the state. But adjustments, negotiations and revisions to original plans may cause the final costs to deviate from the winning bids received. As a result, the study will be more robust with an evaluation of policy enforcement and eventual realizations. Besides, current analysis has been based on project level data. It could be interesting to utilize our special access to itemized bids (as described in section 3.2) and implement a closer assessment of variations in bidding strategy under the standard and new regimes. Moreover, an improvement in efficiency does not necessarily imply an optimal outcome. If modification in rules can further increase social welfare, possibly at the expense of a small bump in the procurement cost (like the situation encountered in Bajari and Lewis, 2011), it is an economically rational move. However, such counterfactual experiments would probably require more complicate structural modeling and computer programming.

Figure 6.1: Cost Function and Completion Time

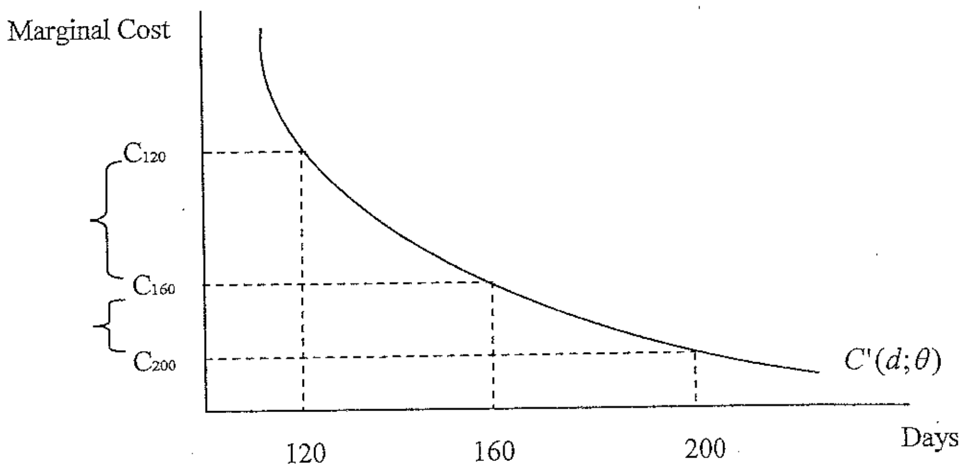

Table 6.1: Summary Statistics

Project Characteristics	Standard A only	Incentive/ disincentive	A+B
Engineer estimate (in millions of dollars)	1.523	2.464	9.340
	(3.045)	(5.702)	(12.816)
Winning bid (in millions of dollars)	1.412	2.230	8.450
	(2.807)	(5.017)	(10.905)
Relative winning bid (winning bid/estimate)	0.932	0.935	0.943
	(0.201)	(0.157)	(0.153)
Number of days assigned by engineer	120.4	149.4	266.6
	(91.1)	(126.1)	(169.4)
Number of bids submitted	3.064	2.950	3.118
	(1.897)	(1.400)	(1.478)
Nature of work: surfacing	0.333	0.842	0.504
	(0.472)	(0.375)	(0.491)
Nature of work: bridge	0.397	0.100	0.453
	(0.500)	(0.300)	(0.478)
Location: Division 3, 4 or 8	0.483	0.491	0.864
	(0.500	(0.501)	(0.347)
Number of observations	1754	161	101

Summary statistics including all projects auctioned between 2005 and 2010 by ODOT, split into 3 groups based on usage of time incentive provisions. Standard errors are reported in parenthesis.

Table 6.2: Probit Regressions of Special Provisions Assignment

Variables	Incentive/ disincentive	A+B
Engineer estimate (in millions of dollars)	-0.0015	0.0041***
	(0.0016)	(0.0013)
Number of days assigned by engineer	0.0021***	0.0024***
	(0.0006)	(0.0006)
Nature of work: surfacing	0.940***	0.346***
	(0.112)	(0.124)
Nature of work: bridge	-0.812***	0.376***
	(0.095)	(0.123**)
Location: Division 3, 4 or 8	0.050	0.951***
	(0.095)	(0.141)
Urban freeway system (Interstate, US route or state highway)	0.396	0.417***
	(0.196)	(0.127)
Number of observations	1915	1855

Statistical significance is denoted by *, ** and *** at 10%, 5% and 1% levels respectively. Standard errors are reported in parenthesis.

Table 6.3: Summary Statistics: Refined Samples

Project Characteristics	Standard A only	Incentive/ disincentive	Standard A only	A+B
	Control (1)	Treated (1)	Control (2)	Treated (2)
Engineer estimate	3.350	2.464	5.077	9.340
(in millions of dollars)	(4.426)	(5.702)	(6.700)	(12.816)
Winning bid (in millions of dollars)	3.132	2.230	4.796	8.450
	(4.344)	(5.017)	(6.327)	(10.905)
Relative winning bid	0.954	0.935	0.967	0.943
(winning bid/estimate)	(0.153)	(0.157)	(0.159)	(0.153)
Number of days assigned	151.1	149.4	257.5	266.8
by engineer	(120.5)	(126.1)	(93.6)	(169.4)
Number of bids submitted	3.146	2.950	3.150	3.118
	(1.718)	(1.400)	(1.851)	(1.478)
Number of observations	459	161	120	101

Summary statistics based on carefully selected sub samples of A only project to best resemble the treated groups. Specifically, for incentive/disincentive, control (1) is made up of standard freeway surfacing projects less than 207 days; for A+B, control (2) consists paving or bridge work on the freeway system in Division 3, 4 or 8 and lasting over 120 days. Standard errors are reported in parenthesis.

Table 6.4: OLS Regressions for Treatment Effects

Variables	Log of Winning Bid	
	Incentive/ disincentive	A+B
Log of engineer estimate	0.950***	0.948***
	(0.010)	(0.0024)
Log of number of days assigned by engineer	0.067***	0.084***
	(0.013)	(0.005)
Mechanism indicator	-0.032*	-0.003
	(0.016)	(0.027)
Number of observations	620	221

Statistical significance is denoted by *, ** and *** at 10%, 5% and 1% levels respectively. Standard errors are reported in parenthesis.

Table 6.5: Matching Technique for Treatment Effects

Variables	Incentive/ disincentive	A+B
Change in winning bids ODOT received (in millions of dollars)	0.937 (0.533)	-0.040 (0.112)

Matching is based on nearest neighbors, with exact match on categorical variables including district, nature of work, freeway type and year. Closest one match is used. Statistical significance is denoted by *, ** and *** at 10%, 5% and 1% levels respectively. Standard errors are reported in parenthesis.

CHAPTER 7

CONCLUSION

7.1 Summary of Findings

The objective of this thesis was to investigate how the industry of public construction procurement is affected by two innovative policy designs, both of which have been widely practiced by state Departments of Transportation in the United States. The problem is particularly interesting considering the immediate and dynamic interactions between private and public sectors in the industry. Auction theory has seen substantial progress in past several decades. However, theoretical research still manages to isolate one factor at a time. Faced with multiple real market complications, this project takes on primarily an empirical perspective, capitalizing on a current, rich and unique dataset collected in the state of Oklahoma in the period extending from January 2002 to December 2010.

The first essay, "Price Adjustment Policies in Procurement Contracting: An Analysis of Bidding Behavior," examined how bidding strategies are impacted by the introduction of price adjustment clauses on the input of asphalt binders. The study found that, consistent with the prediction from a simple theoretical model, firms bid more aggressively when excessive uncertainty is removed. When more refined comparisons are paired up, the policy effect is shown to gain significance both statistically and economically.

The second essay, "On the Distributional Impact of Price Adjustment Policies: Bidding Patterns and Survival in the Market," continues to evaluate the price indexation program of asphalt binder, with a concentration on the potential asymmetries among different players in the market. Based on the large dataset and modern econometric techniques, we have demonstrated that small firms respond more positively to the policy by disproportionally adjusting their bids downward. In addition, they are also found to be participating more frequently and display an improved survival prospect in the post policy period.

In the final essay, "Speed Incentives in Public Procurement Auctions," we analyzed another initiative introduced to maintain auctions of infrastructure projects: special provisions which internalize time consideration into standard contracting. The two designs, incentive/disincentive and A+B bidding, are assessed with respect to the standard structure in terms of completion time and procurement costs. Our findings suggest that the innovative structure could considerably shorten construction time without significantly increasing contract costs paid by government agencies, combined amounting to higher social welfare.

7.2 Extensions

I consider myself fortunate to have access to this extensive dataset for my dissertational research. As mentioned in section 3.1, there are more than 10000 observations in the sample at project level. The availability of itemized data makes the dataset even richer. At item level the number of observations easily reaches 150000, more than 10 times as many as project level. Thus more targeted research is enabled to study bidding strategies or changes equilibrium behaviors by analyzing itemized data. So far, the research into itemized data has paid off. Nonetheless, there is much more to be explored and discovered.

An interesting extension could be to consider a structural model that is rooted in the fundamental assumptions of economic theory. Structural framework also allows one to conduct counterfactual experiments more effectively and efficiently, which is of particularly value in program evaluations.

Withstanding the merits of data described just above, this project is solely based on evidence from Oklahoma. Obtaining data from other states could facilitate studies about how to set optimal policy parameters, such as trigger value λ in the case of price adjustment clauses.

7.3 Conclusions

To sum up, this project complements current literature in the fields of empirical industrial organization and public policy evaluation. We have shown that indexation of asphalt price implemented by Oklahoma Department of Transportation exert positive effects on construction lettings by eliciting more aggressive bids from all participants and elevating the performance and survival of small and new businesses, both contributing to intensified competition and more efficient resource allocation.

ODOT's another initiative known as speed incentivized contracting designs, is shown to positively affect the auction outcome: combination of reduced construction time and roughly unchanged procurement costs leads to higher level of social welfare.

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