Strategic Bidding and Contract Renegotiation

Hojin Jung[*], Georgia Kosmopoulou[†], Carlos Lamarche[‡] and Richard Sicotte[§]

Abstract

This paper studies how the anticipation of ex post contract renegotiation results in ex ante strategic bidding behavior, thereby increasing procurement costs. We estimate the incidence and magnitude of strategic bidding using recent data on road construction projects in Vermont. We show that firms bid less aggressively on items that are expected to have positive quantity adjustments and more aggressively on items that are expected to have either negative quantity adjustments or price adjustments. Our structural model allows firms to predict quantity adjustments based on their historical probabilities and their access to engineers' project plans. Our empirical analysis shows that the magnitude of estimated markups is systematically higher for projects with positive quantity adjustments than those without such renegotiations. The difference in markups across renegotiated and non renegotiated projects exceed the difference in relative project costs by 3.84% at the mean level. At the itemized level, bidders increase their markups and strategically adjust their bids upwards on items that have a high likelihood of positive renegotiation and lower their bids on items with no likelihood of renegotiation to maximize their potential surplus while maintaining a relatively high likelihood of submitting a winning bid.

[*]University of Oklahoma, 211 Hester Hall, 729 Elm Avenue, Norman, OK 73019. Email: hojin.jung-1@ou.edu

[†]University of Oklahoma, 203 Hester Hall, 729 Elm Avenue, Norman, OK 73019. Email: georgiak@ou.edu

[‡]University of Kentucky, 335A Gatton College of Business and Economics, Lexington, KY 40506. Email: clamarche@uky.edu

[§]University of Vermont, 336 Old Mill, 94 University Place, Burlington, VT 05405. Email: richard.sicotte@uvm.edu

1 Introduction

A perennial challenge in procurement contracting is that for complex projects engineers are unable to provide complete contract specifications. As a result, there are often discrepancies between the original and final contract specifications and payment estimates due to incomplete designs or unexpected changes in plans. Such discrepancies lead to extensive ex post renegotiations between state agencies and contractors. The Federal Acquisition Regulation (FAR) prohibits price renegotiations unless an item is added to the contract in the field or there is a relevant price adjustment clause. However, quantity adjustments are common, and firms that anticipate quantity renegotiation often modify their bidding strategies accordingly. In particular, contractors are able to increase their expected profits by submitting high unit prices on items expected to overrun in the future and by submitting lower unit prices on items whose actual quantity used is expected to decrease (Athey and Levin, 2001).

This study examines how ex post renegotiation in procurement contracting affects outlays on road construction contracts by the Vermont Agency of Transportation. First, we employ reduced form estimation to study bidding behavior under all forms of negotiation, while controlling for a variety of factors, including competition, local market power and firms' debt to asset ratios. A study of the relative size of adjustments at the project level can be used to assess the overall impact of strategic bid manipulation on markups, but the test may confound such effects with influences from other sources, such as coordination and dispute resolution costs.

To address these concerns, we isolate projects consisting of items that are renegotiated frequently, and employ a structural auction model to uncover contractors' costs and markup changes. We compare relative bidding strategies on items with high and low likelihood of renegotiation and assess the impact of renegotiation to the Agency's expenditure. We use nonparametric estimation methods similar to the ones developed by Guerre, Perrigne, and Vuong (2000) and Bajari, Houghton, and Tadelis (2011) to estimate the distribution of latent costs after controlling for project heterogeneity. Using itemized level bid information, we construct estimates of the markup of bids above costs and compare how they vary across auctions with and without renegotiation. Examining bidders' markups allows us to infer whether the anticipation of ex post renegotiation based on careful reading of the plans and historical probabilities of occurrence affects strategic bidding behavior.

Bidders who bid on each work item consider not only the costs to complete the project, but also take into account incomplete information on a project's characteristics and associated opportunities for strategic bidding on particular items. Rational bidders incorporate a high risk premium of uncertainty into the bid ex ante to reduce risk exposure. As such, bidders often increase their bids for higher valued or more complex projects. Bajari, Houghton, and Tadelis (2011) studied renegotiation and adaptation costs at the project level under the assumption that bidders have rational expectations. Bidders predict upcoming renegotiations and react to their prospect. We focus on strategic manipulation of bids and their contribution to submit unbalanced bids at the item level as well as submit a markup increase at a project level. To a large extent, bidders manipulate prices per unit based on the possibility of ex post renegotiation to cover adaptation costs and increase their expected profits without lowering the probability of winning the auction.

We consider highway construction projects let in the state of Vermont from 2004 to 2009. When controlling for project heterogeneity from observed bids including size and project types, our estimation results show that, there is little difference in costs between projects that were renegotiated and projects that were not. We find, however, that the magnitude of estimated markups is systematically higher for the project group experiencing renegotiation. Indeed, the difference in markups across renegotiated and non renegotiated projects exceed the difference in relative project costs by 3.84% at the mean level. Estimated markups should depend on contractors' adaptation costs and their strategic bidding behavior. At the itemized level, our results suggest that bidders increase their markups and strategically adjust their bids upwards on items that are renegotiated or have a high likelihood of renegotiation. At the same time and in the same projects they lower their bids and markups on items that are not renegotiated to maximize their potential surplus ex post, while maintaining the likelihood of a winning the contract. This behavior leads to an increase in the cost of contracting for the state and the public.

The rest of the paper proceeds as follows. We begin with a literature review in the next section. Section 3 provides an overview of the data. In Section 4, we present the model and our identification strategy and discuss structural empirical analysis. Section 5 offers concluding remarks.

2 Literature Review

Renegotiations are sometimes necessary to mitigate inefficiency caused by contractual incompleteness but they often distort contractors' ex ante incentives. Bidders would consider renegotiations as an opportunity to seek rents. Iossa, Spagnolo, and Vellez (2007) argue that renegotiations can have negative impact on ex ante efficiency because a bidder has weak incentives to reduce cost or to improve quality when the contractor expects possible future renegotiations. Furthermore, renegotiations generate additional transaction costs in contracting, which are found to be significant in Bajari, Houghton, and Tadelis (2011). Their findings imply that renegotiation generates an additional \$2.20 in costs for every dollar of a positive quantity adjustment in the California highway construction industry.

Bajari, Houghton, and Tadelis (2011) use a structural auction approach to uncover bidders' latent costs and calculate markups incurred by renegotiations. They obtain those estimates from a project level instead of an itemized level analysis which is the focus of our study. They argue that renegotiations generate significant adaptation costs that result in higher markups. Their sample of projects have a variety of renegotiations, such as positive and negative quantity adjustments, extra work and deductions. We also consider a wide range of negotiations in our reduced form analysis but turn into a subset of more homogeneous contracts with positive quantity adjustments to quantify via structural estimation the impact of positive renegotiation and compare our results to a baseline set of projects with no renegotiations.

Athey and Levin (2001) find that bidders strategically bid by using their private information in the timber industry in which payments are based on ex post harvested quantities. Theory suggests that the optimal bidding strategy for bidders would be to submit unbalanced bids with zero prices on items that are expected to have quantity deductions and high prices on items that are expected to overrun. Frequent rejections of unbalanced bids or bidders' attitudes toward risk are cited as the most important reasons for deviations from the optimal strategies on the field.

Gil and Oudot (2008) show that, in the defense procurement sector and the movie exhibition industry, the more competitive is the bidding award mechanism, the less frequent are ex post contract renegotiations. Regarding flexibility and renegotiation in the field, recent studies, Tadelis and Bajari (2006) and Chong, Staropoli, and Yvrande-Billon (2009), argue that renegotiation may improve upon efficiency as an award mechanism in procurement when projects are complex or when less potential competition is expected. In public procurement auction, the use of competitive auction mechanism is often preferred by the FAR regardless of its drawbacks because that award mechanism is known to promote competition and transparency. In that setting contractual incompleteness leaves room for bidders to strategically bid in the procurement auction.

The empirical auction literature has proposed a number of approaches to structurally recover the underlying distribution of latent values. The two step nonparametric estimation method in Guerre, Perrigne, and Vuong (2000) is recognized as an important breakthrough. They propose that in the first step, the sample of pseudo private values can be obtained from observed bids. Then from the pseudo sample, the distribution of bidders' private values is estimated using a nonparametric estimator. Our modeling environment is more clearly suited to an independent private value (IPV) model with asymmetric bidders. In this setting we are able to express each bidder's inverse bid function as a function of his rivals' bid distributions from the two-step approach. Alternative structural approaches are used in Bajari and Ye (2003) and Bajari, Houghton, and Tadelis (2011).

3 Data and summary statistics

3.1 An Overview of Change Orders on Vermont Transportation Contracts

Our dataset consists of 312 construction projects auctioned off between May 2004 and December 2009 by the Vermont Agency of Transportation (VTrans). We classify auctions by project type: asphalt projects, bridge projects and miscellaneous projects.[1] The auction takes place on a weekly basis and a sealed-bid format in which the lowest bid is awarded the contract. When advertising a project to the public, VTrans provides detailed engineer's plans and information on the work site,

[1]Miscellaneous projects include traffic signaling and lighting, grading and draining, parking lots and landscaping.

the required completion date and a brief description of the project.[2] The engineer's plans provide a list of quantities for each item in the project plan. All participants in the auctions are required to submit bids for each item level on the list. The auction data include information on the identities of plan-holders, the identities of all bidders, their bids, the winning bid and engineering cost estimate for a project. Furthermore, we have a dataset on change orders, which includes the proposed quantity and unit-price for each renegotiated item within a contract and a brief description of the reasons for that change. Change orders are widely used in fixed-price contracts and are filled only if changes of plans or specifications are significant relative to the original contracts.[3] They include ex post payments made by the Vtrans due to all types of adjustments, namely positive quantity and price adjustments as well as payments made to VTrans due to negative quantity adjustments. Hence, we have information on the actual quantity used in the field and the actual ex post payments in a contract.

Table 1 provides summary auction and change orders statistics for the period of analysis. On average, the number of bidders and the number of prequalified plan-holders are 3.349 and 5.026 per auction, respectively. The number of different items in the contract has been used as a proxy for project complexity. In our sample dataset, on average a project consists of 60 different items. Winning bids on renegotiated contracts are $1,805,793 with an engineering cost estimate of $1,910,227. The relative bid, calculated as the bid divided by the engineer's cost estimate, is used as a measure of bidding aggressiveness. Two hundred and fifty six contracts were supplemented by change orders making up 82.05% of construction projects auctioned off during our sample period. The average change order amount per contract is $173,582 representing a 8.15% of the average winning bid amounts. There is, on average, $ 221,207 paid to contractors due to price adjustments, $151,064 due to positive quantity adjustment and -$223,896 paid by the firms to the state due to negative quantity adjustments. Positive quantity adjustment is the most dominant type of renegotiation.

[2]Prequalification status is achieved by the successful completion of two procedures: (1) annual prequalification: the prequalification committee at VTrans annually assigns each firm certain limitations as to the value of projects and number contracts that they are allowed to undertake in Vermont; (2) contract prequalification: the process to obtain permission to submit a bid for a particular contract for a contractor who already obtained annual prequalification. See the Vermont Agency of Transportation Policies and Procedures on prequalification, bidding, and award of contracts for more details.

[3]For example, in the state of Vermont, a change order is recorded when it results in a cost increase of 5% or more on the item or causes an increase in the contract total pay amount.

For example, 70% of change orders include positive quantity adjustments during our sample period. On average firms bid 3.5% above the engineering cost estimate and win with bids that are 2.3% below the engineering cost estimate. The final relative payment amount resulting from the change order is 5.6% above the engineering cost estimate. In other words, winning bidders negotiate a 7.9% increase in payment relative to the winning bid.

Table 1: Descriptive Statistics

Variable	Observation	Mean	Standard Deviation	Min	Max
Bidders (per contract)	312	3.349	1.959	1.000	11.000
Plan-holder (per contract)	312	5.026	3.163	1.000	16.000
Complexity (Number of distinct items per contract)	312	60.228	35.346	2.000	245.000
Winning bid amount (in millions)	312	$1.806	$2.260	$0.025	$22.000
Engineering cost estimate of the winning contract (in millions)	312	$1.910	$2.432	$0.026	$24.600
Bidding amount (in millions)	775	$1.782	$2.361	$0.025	$29.500
Relative bid (before COs: (bid / engineering cost estimate)	775	1.035	0.199	0.500	1.500
CO amount (in thousands)	256	$173.582	$323.097	-$116.848	$2,331.255
Price Adjustment (in thousands)	41	$221.207	$240.114	$5822.320	$1,047.280
Positive Quantity Adjustment (in thousands)	181	$151.064	$224.815	$0.000	$1,259.335
Negative Quantity Adjustment (in thousands)	85	-$223.896	-$421.314	-$3,003.329	-$0.500
Relative winning bid (before COs)	256	0.977	0.190	0.436	1.564
Relative payment amount (after COs)	256	1.056	0.228	0.532	2.014

Figure 1 offers evidence on the difference between the distributions of relative winning bid in contracts before and after change orders are filed. The figure presents kernel density plots of relative winning bids of initial contracts against the final relative payment amounts. It illustrates one of the striking features of contracting: change orders tend to increase cost payments, and the increase tends to be more pronounced at the upper tail of the distribution.

In Table 2, we examine the behavior of the main firms in the highway construction industry in the state of Vermont during this period of time. We see evidence of market concentration with one firm undertaking 35.73% worth of contracts and eight firms having 74.50% of the market share. A key variable here is Money Left on the Table (MLT) which results from the difference between the winning bid and the bid of the second lowest bidder.[4] The weighted MLT is the average money

[4] We measure MLT as the proportional difference between the winning and the second lowest bid when there are multiple bidders. In the case of a single bidder, the money left of the table is constructed as the proportional

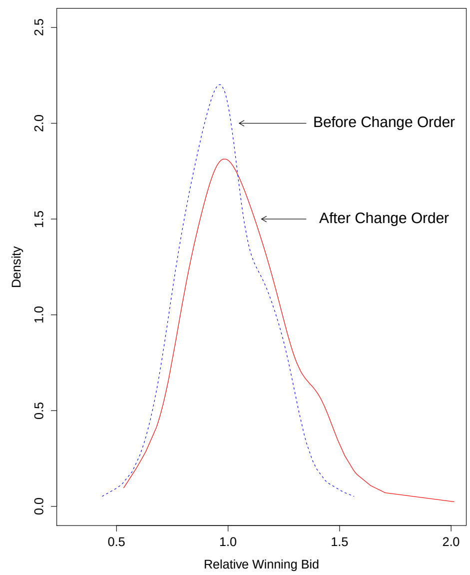

Figure 1: Kernel density plots of relative winning bids

left on the table per bidder weighted by the engineering cost estimate of each project won.

We want to investigate if larger or smaller weighted value of the MLT would be associated with higher tendency to submit change orders. A firm may bid aggressively to win a contract, leaving a large amount of surplus on the table, and then try to renegotiate to regain part of its lost surplus. We observe that the strongest competitors leave a small weighted MLT but still renegotiate large amounts, and vice versa. Change order amounts are often related to the size of the contract and other characteristics of the competitive environment. The empirical analysis that follows controls for those factors. The proportion of renegotiated value varies significantly across firms ranging from 3.62-11.95%.

Table 2 also shows that the most active firms in the construction market enjoy less competition. On average, the top two firms face 1.433 fewer competitors than other firms. For firms that won more than 10% of the total value procured, the average number of competitors is 2.531, which is still 1.283 fewer than the rest of the firms face per auction. We see that 91% of participants in these auctions are fringe firms during the sample period, winning an average of 1.83 projects.[5] Lastly, it

difference between the winning bid and the engineering cost estimate.

[5]We defined a fringe firm as one that won less than 2 % of total value procured during our sample period.

Table 2: Bidding and renegotiation activities of 92 firms

Firm ID	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)	(K)
1	$206,900,000	35.731	$2,913,862	71	2.211	4.463	18.097	69.000	60	65	8.981
2	$69,177,640	11.948	$2,096,292	33	2.788	8.199	82.433	68.576	28	30	11.947
3	$59,560,076	10.287	$6,617,786	9	4.111	9.111	30.144	116.000	8	8	4.771
4	$28,339,592	4.895	$3,542,449	8	3.375	7.006	75.082	67.250	4	6	10.238
5	$22,173,372	3.830	$2,463,708	9	4.111	4.201	31.236	90.000	9	9	3.830
6	$19,879,150	3.433	$2,484,894	8	3.000	6.069	32.139	74.750	6	7	6.069
7	$14,099,262	2.435	$1,174,939	12	5.917	6.962	34.582	66.333	9	10	9.512
8	$11,687,370	2.019	$1,460,921	8	3.500	8.316	23.830	78.625	6	8	3.617
Rest (84 Firms)	$147,600,000	25.500	$958,738	154	3.714	13.073	47.793	46.844	94	113	5.468

(A): Total Value of Winning Projects
(B): Value of Winning Projects/Value Procured
(C): Average Value of a Project Won
(D): Number of Wins
(E): Average Number of Competing Bids on Contracts Won
(F): Weighted MLT (%)
(G): Total Debt/Total Asset (%)
(H): Average Complexity of Contracts Won
(I): Number of Contracts with New Items Added
(J): Number of Contracts Renegotiated
(K): Final Change Order Value/Total Value of Projects (%)

should be noted that, for most of these firms, revenue from change orders constitutes over 5% of the payout on the contract, and in some cases significantly more. Firms with the largest number of projects tend to renegotiate more, and the change order amount is a larger proportion of their payments.

The table clearly suggests that the probability of renegotiation increases by the project size and complexity. Contractors awarded high value contracts with a large number of components tend to submit more change orders. Most change orders include some renegotiation about the use of unanticipated materials in the field. Our dataset also contains financial information on firms related to debts and assets. With the exception of firms 2 and 4 whose debt to asset ratio is high, fringe firms seem to be more financially constrained compared to other active dominant firms in the market. These two firms won a combined 16.84% of the total contract value awarded during the sample period. Their debt to asset ratios are significantly higher than that of the other firms, and their percentage of renegotiated value is twice as high. Excluding those two firms, fringe firms are financially more constrained compared to other active large firms in the market.

3.2 Reduced form estimation

This section presents a set of descriptive regressions to investigate the effect of renegotiation on bidding behavior. The basic model is as follows:

$$y_{iat} = X'_{at}\beta + W'_{it}\gamma + Z'_t\delta + m_t + \alpha_i + u_{iat},$$

where the unit of observation is a relative bid submitted by bidder i, in auction a, in month t. The variable y_{iat} denotes a relative bid in auction a. The independent variables include factors used to control for observed heterogeneity across bidders and projects. We include (1) auction specific characteristics (X), (2) bidder specific characteristics (W), and (3) variables measuring general economic conditions (Z). Table A.1 in the appendix provides a detailed definition on these independent variables. The model also includes monthly dummy variables m_t's, and firm specific effects α_i's. The error term u_{iat} is assumed to be the sum of an auction specific effect and a disturbance i.e., $u_{iat} = \mu_a + \epsilon_{iat}$.

As mentioned earlier, there are three different avenues for additional payments: price adjustment, positive quantity adjustment and negative quantity adjustment. Price adjustments are based on a price adjustment clause that has been enacted to reduce risks related to the fluctuation of the prices of basic inputs such as fuel and asphalt.[6] We use their proportional amounts to the engineer's cost estimate at the auction level as independent variables in this analysis. The vector X includes "expected number of bidders" and number of days to complete a project. The variable expected number of bidders controls for differences in competition by incorporating the probability that a plan-holder will participate in the auction letting.[7] The variable "calendar days" controls for size effects of different projects because projects requiring longer days to complete may be more prone to higher levels of uncertainty or complexity. The "project type" dummy to control for bidding behavior across different types of projects.

We include a number of variables to control for bidder and rival characteristics. Consistent with prior literature, we include bidder and rivals' distances to work sites and their backlogs. We also include, however, detailed financial information on each bidder such as assets, debt and revenue. We use for the first time in the empirical auction literature bidders' financial information. The information allows us to measure business strength and capacity more accurately, rather than resorting to constructions based on local workloads as a proxy of firm activity based on state-level data.[8] We construct a financial leverage ratio, the debt to asset ratio, in order to measure a firm's bidding reaction to financial constraints. Zhou, Kosmopoulou, and Lamarche (2012) show that price adjustment policy allows smaller (potentially more financially constrained) firms to bid more aggressively most likely due to lower risk exposure.

To account for heterogeneity in size and experience across bidders, we designate a bidder as a top firm if its annual revenue is greater than 20% of the total value of all firms' revenues each year during the sample period. In addition, to control for the possibility of systematic differences in

[6]The price adjustment amount depends upon the magnitude of deviation of the average fuel price from the index price during the project construction period and the quantities of the contract pay items subject to the price adjustment clauses. In this study all projects have positive price adjustments even though they could be positive or negative.

[7]In Vermont, plan-holders' identities are publicly available if the number of qualified plan-holders is larger than 3.

[8]We might keep in mind that Vermont is a smaller state and almost half of the headquarters of contractors are located outside the state. Without knowing their business activity out of state we will not be able to assess the effect of their capacity constraints on bidding.

the behavior of top firms in comparison to others, we use the interaction terms between the debt to asset ratio and the top firm dummy variable. We also allow for differential bidding behavior in local markets by incorporating in the model a measure of a bidder's local market power as an account of a firm's market share. A firm's local market power is defined as its working history at a county level: the proportion of all outstanding work in a county that is undertaken by a given firm. Larger values are associated with a firm having a dominant position in that county. It is also important to control for factors that affect the general economic conditions. In this analysis, we include three control variables such as the monthly gas price index, the number of building permits and the unemployment rate to capture business climate.

Table 3 presents the first set of regression results, consisting of two models aimed at explaining the variation in all bids submitted on all projects during the period of analysis. Our dependent variable is the relative bid. We estimate the models using ordinary least squares with robust standard errors. We then estimate a similar model including fixed effects to account for firms' different efficiency levels. The introduction of firm fixed effects controls for any additional idiosyncratic characteristic of individual bidders that drive bidding strategies. We report cluster-robust standard errors where clustering is at the auction level.

The variable on the proportion of ex post price adjustment amount is negative and statistically significant. Thus, considering the variable on price adjustment, firms bid more aggressively when there is a price adjustment mechanism in place. The evidence is consistent with Kosmopoulou and Zhou (2012) postulating that price adjustment clauses may produce direct cost benefits to state agencies. With no price adjustment in place, bidders are exposed to the risk of unanticipated changes in the cost of major inputs. As a result, they increase their bids to reduce risk exposure in long-term contracts. Bidding strategies, assuming rational expectations, eventually cause an increases in payments. A 2009 survey of contracting practices by state departments of transportation found that at least 40 states employed price adjustment clauses.[9]

The variable related to the proportion of ex post positive quantity adjustment amount is positive and statistically significant indicating that when bidders anticipate a larger proportion of positive

[9] For a discussion of this, see Kosmopoulou and Zhou (2012).

Table 3: Regression results for a model of relative bid.

Independent Variable:	OLS	Fixed Effect (Cluster)
Proportion of Price Adjustment	-1.137***	-1.366***
	(0.242)	(0.498)
Proportion of Positive Quantity Adjustment	0.350***	0.333***
	(0.133)	(0.014)
Proportion of Negative Quantity Adjustment	-0.469***	-0.460***
	(0.161)	(0.062)
New Item Amount	-0.246	-0.241**
	(0.190)	(0.104)
Debt to Asset Ratio	0.024	0.020
	(0.028)	(0.116)
Debt to Asset Ratio * Top Firm	-0.044	-0.197**
	(0.051)	(0.099)
Local Market Power	-0.101***	-0.074***
	(0.036)	(0.016)
Log of Calendar Days	0.010	0.017*
	(0.011)	(0.009)
Expected Number of Bidders	-0.011***	-0.014***
	(0.003)	(0.002)
Log of Firm's Backlog	0.001	0.001***
	(0.001)	(0.000)
Log of Rival's Minimum Backlog	-0.001	-0.003
	(0.001)	(0.004)
Gas Price Index	(0.001)	(0.004)
	(0.035)	(0.079)
Log of Number of Building Permits	-0.024**	-0.023***
	(0.012)	(0.005)
Log of Distance to the Project Location	-0.020**	-0.009
	(0.008)	(0.017)
Log of Rival's Minimum Distance	-0.004	-0.003
	(0.007)	(0.009)
Unemployment Rate	-0.045***	-0.046***
	(0.007)	(0.006)
Asphalt Project	0.001	-0.033
	(0.028)	(0.043)
Bridge Project	0.067**	-0.024
	(0.029)	(0.030)
Time Dummy	Yes	Yes
Fixed Effects (55)	No	Yes
Observations	775	775
R-squared	0.201	0.296

*** Denotes statistical significance at the 1% level, denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses.

quantity adjustment, they bid less aggressively. Meanwhile, the variable related to the proportion of ex post negative quantity adjustment is negative and statistically significant. The direction of these adjustments allows us to conclude that bidders are likely to manipulate their bids in anticipation of ex post quantity adjustments to increase their ex post payments. By doing that, bidders increase the probability of winning the project, and later they recover their forgone profits. This is consistent with theory (see Athey and Levin (2001)).

In the firm fixed effect specifications, the debt to asset ratio of top firms is statistically significant and negative. It implies that financially constrained top firms bid more aggressively. The backlog variable is positive and statistically significant indicating that capacity constrained firms bid less aggressively. The magnitude of this variable is small, perhaps showing that the commitment relative to their overall workload in Vermont could be small proportion of their budgets. The impact of the expected number of bidders is consistent with our expectation. Increased level of competition causes bidders to bid more aggressively.

We differentiate between change orders that add a completely new item in a project and change orders that add quantity to an existing item since the former indicates the incompleteness of project design and the later implies most likely uncertainty or engineering error. Contractual incompleteness may increase the likelihood of renegotiation, thereby encouraging more aggressive bidding behavior to acquire a contract. Firms with significant local market power bid more aggressively. In addition, among the variables controlling for the strength of an opponent, the variable on a rival's minimum backlog and distance to work site are not statistically significant across different specifications. Regarding general economic conditions, we found that bidders bid more aggressively when faced with a high unemployment rate, which indicates a decline in economic activity. Alternatively, we expect bidders to bid less aggressively as the number of building permits increases as there are more available outside opportunities particularly for concrete related work. This is not the case. Firms appear to bid more aggressively as the permits increases.

Table 4 provides the results when the unit of observation is an itemized bid. It offers the possibility to control for the items typically renegotiated. We use similar methodologies as those employed before, but now we include item fixed effects to capture different characteristics of tasks.

Table 4: Regression results for a model of relative itemized bid.

Independent Variable:	OLS	Fixed Effect (Cluster)
Likelihood of adjustment ×	0.545***	0.534***
item proportion (positive quantity adjustment)	(0.059)	(0.084)
Likelihood of adjustment ×	-1.479***	-1.287***
item proportion (negative quantity adjustment)	(0.258)	(0.472)
Likelihood of Positive Adjustment	-0.046	-
	(0.045)	-
Likelihood of Negative Adjustment	0.066	-
	(0.101)	-
Debt to Asset Ratio	0.010	0.013
	(0.010)	(0.036)
Debt to Asset Ratio × Top Firm	-0.107***	-0.298**
	(0.020)	(0.151)
Local Market Power	-0.000	-0.005
	(0.014)	(0.030)
Log of Calendar Days	-0.011***	-0.003
	(0.004)	(0.009)
Expected Number of Bidders	-0.010***	-0.007**
	(0.001)	(0.003)
Log of Firm's Backlog	0.002***	0.004***
	(0.000)	(0.001)
Log of Rival's Minimum Backlog	-0.002***	-0.002*
	(0.000)	(0.001)
Log of Distance to the Project Location	-0.002	0.001
	(0.003)	(0.008)
Log of Rival's Minimum Distance	-0.005*	-0.006
	(0.003)	(0.007)
Gas Price Index	-0.053***	-0.065**
	(0.013)	(0.031)
Log of Number of Building Permits	-0.011**	-0.010
	(0.004)	(0.011)
Unemployment Rate	-0.027***	-0.025***
	(0.003)	(0.007)
Asphalt Project	0.024**	0.010
	(0.012)	(0.030)
Bridge Project	0.066***	0.041
	(0.012)	(0.030)
Time Dummy	Yes	Yes
Firm Fixed Effects (55)	No	Yes
Item Fixed Effects (671)	No	Yes
Observations	38,937	38,937
R-squared	0.014	0.093

*** Denotes statistical significance at the 1% level, denotes significance at the 5% and * denotes significance at the 10% level. Robust standard errors are in parentheses.

We classify all items into three groups: items with ex post quantity overruns, items with ex post quantity under-runs, and items with no quantity changes ex post. There are 714 different items used during the sample period. Of those, 366 items never appear on a change order. In these regressions we use, in addition to the other relevant covariates, the interaction terms between the historical probability of a positive (negative) quantity adjustment on a particular item and its proportional adjustment amount to its engineering cost estimates.[10] The variable is taking into account the historical probabilities of renegotiation as well as the actual occurrence of such adjustments.

The itemized bid estimation shows that bidders submit higher bids on items that are expected to have a positive quantity adjustment, and lower bids on items that are expected to have a negative quantity adjustment in order to maximize expected profit without lowering significantly the probability of winning an auction. We also consider firm and rival characteristics. A larger expected number of bidders is associated with lower relative itemized bids. A greater backlog increases a firm's itemized bid. Bidders bid more aggressively when the unemployment rate is high. These findings are consistent with the results at the project level. An expected itemized positive quantity adjustments is statistically significant in any type of specification indicating that overall bidders bid less aggressively on items that are expected to experience positive quantity adjustments with non-zero historical probability. The significance of time-varying covariates is naturally not the same across the two specification as there is less variation now in the time dimension. This model specification does not allow us to study within-project variation in bidding behavior when there is only one type of adjustment taking place in a project, for example quantity adjustment, which is not with high frequencies in renegotiations.

4 Structural Estimation

The reduced form approach relies on linear regressions of the relative bids on a set of observable project, bidder characteristics and measures of economic fluctuation. A structural approach is currently used in the empirical auction literature as an alternative by assuming that the observed

[10]The average historical probability of positive quantity adjustments for an item is 4% with a standard deviation of 6% while that of negative quantity adjustments is 1% with a standard deviation of 3% during the sample period.

bids are the Bayesian Nash Equilibria of the theoretical model. This structural approach is used to recover the latent primitives of the auction model. Guerre, Perrigne, and Vuong (2000) prove that each private value can be shown as the distribution of observed bids and its density in bidder's optimization. In addition, they show that the inverse of bidding strategy is nonparametrically identified without computing the Bayesian-Nash Equilibrium strategy. We assume that bidders follow strictly monotonic and differentiable bidding strategies at the Bayesian-Nash Equilibrium.

4.1 Equilibrium Bidding Behavior

We use the structural auction model with asymmetric bidders, which is closely related to the previous literature such as Bajari and Ye (2003), Campo, Perrigne, and Vuong (2003), Bajari, Houghton, and Tadelis (2011). In the asymmetry case, the distributions of costs are no longer treated the same among bidders while symmetry assumes that private cost estimates are *iid*. The asymmetries may arise from different capacity constraints, distances to the work sites, financial status, cost efficiency level, or working experiences across firms.

We assume bidders are risk neutral having asymmetric IPVs. The bidding function is continuously differentiable and strictly increasing in cost. A project consists of a list of tasks, $t = 1, \ldots, T$. By letting b_t^i indicate bidder i' unit price on an item t, we define bid price vector as $b^i = (b_1^i, \ldots, b_T^i)$. The estimated quantity for each task t is q_t^e and its actual quantity used to complete the task is denoted as q_t^a. Therefore, estimated quantities and actual quantities in the project are the vectors of $q^e = (q_1^e, \ldots, q_T^e)$ and $q^a = (q_1^a, \ldots, q_T^a)$. In low price sealed bid auctions, a bidder i wins a contract if he/she submits a bid that is the lowest such as $b^i \cdot q^e < b^j \cdot q^e$ for all $\forall i \neq j$. Let $s^i = \sum_{t=1}^{T} b_t^i q_t^e = b^i \cdot q^e$ where the vector product of unit prices and estimated quantities. Then, if bidder i bids s^i, its probability of winning is defined as $H_j(s^i) \equiv \mathrm{pr}(b^i \cdot q^e < b^j \cdot q^e)$. Finally, $\prod_{j \neq i}(1 - H_j(s^i))$ is defined as the probability that bidder i wins the auction with s^i.

A breakdown of items by the probability of renegotiation, $k \in [0, 1]$, include two types of items: items that are not renegotiated (e.g., $k_t = 0$), and items that are renegotiated (e.g., $k_t > 0$). With probability k_t the specification about an item is incomplete or has an error and additional works are needed while with probability (1 - k_t) the original specification or plan accurately describes the task. We begin by deriving equilibrium bidding behavior from our simple theoretical model assuming that bidders have prior beliefs regarding the likelihood of renegotiations and then, we estimate the latent cost distributions using observed bids. Firm i's expected profit is $b_i - c_i$ if it is the winner and zero otherwise $\forall i \neq j$. We define bidder i's expected profit function as follows:

$$\pi_i(c_1, c_2, k_t) = \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right)\right] \times \left[\mathrm{pr}\left(\sum_{t=1}^{T} b_t^i q_t^e < \sum_{t=1}^{T} b_t^j q_t^e\right)\right] \quad (1)$$

$$\pi_i(c_1, c_2, k_t) = \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right)\right] \times \left[\prod_{j \neq i} (1 - H_j(s^i))\right] \quad (2)$$

Note that the profit function of the ith firm is equal to the expected markup times the probability that firm i is the lowest bidder. The FOC is equal to:

$$\begin{aligned}\frac{\partial \pi_i(c_1, c_2, k_t)}{\partial b_t^i} &= (k_t q_t^a + (1-k_t) q_t^e)\left[\prod_{j \neq i}(1 - H_j(s^i))\right] - \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right)\right] \\ &\times \left[q_t^e \sum_{k \neq i} h_k(s^i) \prod_{j \neq i,k} (1 - H_j(s^i))\right] = 0. \end{aligned} \quad (3)$$

Because $\left[q_t^e \sum_{k \neq i} h_k(s^i) \prod_{j \neq i,k} (1 - H_j(s^i))\right]$ is equal to $\frac{\partial s^i}{\partial b_t^i} \times \frac{\partial \left[\prod_{j \neq i}(1 - H_j(s^i))\right]}{\partial s^i}$ as shown in the Appendix, we write the first order condition as,

$$\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t) q_t^e\right) = \left(\frac{k_t q_t^a + (1-k_t) q_t^e}{q_t^e}\right) \times \left(\sum_{j \neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))}\right)^{-1}. \quad (4)$$

Equation 4 is expressing the FOC as a function of the probability that item t is renegotiated, k_t. If $k_t = 0$, then the FOC can be written as follows:

$$\sum_{t=1}^{T} (b_t^i - c_t^i) q_t^e = \left(\sum_{j \neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))}\right)^{-1}. \quad (5)$$

On the other hand, if $k_t > 0$, the equation is expressed as follows:

$$\sum_{t=1}^{T}(b_t^i - c_t^i)q_t^a = \left(\frac{k_t q_t^a + (1-k_t)q_t^e}{q_t^e}\right)\left(\sum_{j\neq i}\frac{h_j(s^i)}{(1-H_j(s^i))}\right)^{-1}. \tag{6}$$

4.2 Selected Sample Data

Our goal is to investigate whether ex post renegotiation affects firms' cost structures in a procurement auction with the IPV model. We calculate the contractor's markups with the estimated costs to infer its bidding strategies in auctions with and without renegotiations.[11] We restrict our attention to more homogeneous projects in road/highway contracts with 2 or 3 bidders.[12] Furthermore, we restricted the sample to projects with a project value between \$200,000 and \$5 million. The more homogeneous sample can be divided into two groups; one group consisting of projects with only positive quantity adjustments and the other group being projects in which there is no renegotiation at all. The descriptive statistics for these two groups are presented in Table 5. Notice that the size and number of tasks are notably different across projects in these samples in spite of our relative homogenization. As you can see from the table, the more complex a project is, the more likely it will be renegotiated. Intuitively, as a project takes more working days to complete or a project needs more work to be done, renegotiation occurs with higher probability.

This study analyzes the costs at the itemized level plagued by a dimensionality problem. For this reason, in our empirical analysis, we restrict attention to a project in which, at most, one item was renegotiated with the positive quantity adjustment. In particular, we pick four items[13] as shown in Table 6 for the analysis and focus on their cost estimates or their markups at the itemized

[11] The empirical auction literature studies the type of competition, bidding behavior, and the optimal auction format by recovering the distribution of bidder's valuations in Athey and Haile (2006).

[12] As De Silva, Dunne, Kankanamge, and Kosmopoulou (2008) discuss in detail, the individual bidder's efficiency level or its state of equipment is more critical to determine its cost in asphalt projects. We analyze the road/highway projects as the subsample for the IPV setting. The sample selection is justified by the fact that bidders more accurately estimate their costs for those projects than those for bridge projects which are typically studied with a common value setting. In road/highway projects, labor and material costs are mainly determined by a firm's internal specific characteristics. Therefore, we argue that those projects match the assumptions of the independent private value setting.

[13] Each pay item description is as follows; 406.25: Bituminous Concrete Pavement, 490.30: Superpave Bituminous Concrete Pavement, 621.90:Temporary Traffic Barrier and 630.15: Flaggers.

Table 5: Comparison of Summary Statistics across Projects

	Positive Quantity Adjustment					No Quantity Adjustment				
	Obs	Mean	Std	Min	Max	Obs	Mean	Std	Min	Max
Bid amounts (in $ million)	64	2.151	1.262	0.244	4.918	75	1.193	0.945	0.220	4.870
Engineer cost (in $ million)	64	2.198	1.343	0.254	4.754	75	1.219	0.993	0.214	4.908
Relative bid	64	1.039	0.238	0.627	1.676	75	1.029	0.210	0.729	1.723
Complexity	64	63.547	26.101	6.000	118.000	75	44.573	26.541	5.000	105.000
Calendar days	64	136.891	72.461	56.000	378.000	75	111.773	55.284	30.000	273.000
# of bidders	64	2.469	0.503	2.000	3.000	75	2.627	0.487	2.000	3.000

level. Those items renegotiated alone in a project are in the treatment group. Then, we select the same tasks in the contracts that do not experience renegotiations, and we put those items into the control group. Notice that the itemized bid prices are much more similar while the itemized bidding amounts are significantly different across items between two groups.

Table 6: Comparison of Summary Statistics for Pay Items

		Control Group					Treatment Group			
	Obs	Bid Price		Bid in $10000		Obs	Bid Price		Bid in $10000	
Pay Items		Mean (Std)	Min (Max)	Mean (Std)	Min (Max)		Mean (Std)	Min (Max)	Mean (Std)	Min (Max)
406.25	18	88.863	49.000	22.099	2.720	5	62.640	52.520	99.906	58.297
		(31.552)	(168.000)	(6.338)	(54.250)		(8.503)	(70.000)	(32.666)	(133.000)
490.30	28	72.593	44.500	80.089	27.000	15	76.718	42.000	135.073	25.336
		(19.527)	(110.000)	(47.614)	(187.395)		(36.067)	(165.000)	(77.165)	(313.425)
621.90	5	40.200	20.000	3.906	1.400	2	62.500	40.000	0.375	0.240
		(18.714)	(66.000)	(2.343)	(6.930)		(31.820)	(85.000)	(0.191)	(0.510)
630.15	73	22.216	10.000	3.069	0.050	5	30.590	22.500	6.718	3.375
		(9.779)	(63.000)	(3.671)	(17.550)		(14.492)	(56.450)	(4.359)	(14.113)

4.3 Estimation of bid distributions

Guerre, Perrigne, and Vuong (2000) (GPV hereafter) propose a two-step procedure to estimate a first-price sealed bid auction model. GPV estimate the distribution of observed bids and generate an estimate of a firm's cost by evaluating the first-order condition of its profit maximization in the theoretical model. Campo, Perrigne, and Vuong (2003) extend previous work by using the number of bidders to control for unobserved auction heterogeneity. Haile, Hong, and Shum (2006) (HHS hereafter) also develop an alternative method to control for auction-specific characteristics without increasing the sample size.[14] Bajari and Ye (2003) and Bajari, Houghton, and Tadelis (2011) employ a nonparametric approach that allows one to directly control for auction heterogeneity in the first step of the two-step process. The advantage of their methodology relative to HHS is that one does not need to estimate another conditional distribution to control for an unobservable auction heterogeneity.

We first run a reduced form regression controlling for auction specific characteristics, bidders specific characteristics, and general economic conditions such as

$$b_j^{(a)} q^{e(a)} = x_j^{(a)\prime} \mu + u^{(a)} + \varepsilon_j^{(a)}.$$

The dependent variable is the level of project bid amounts in auction (a). The vector x includes controls for ex post positive quantity adjustment and firm's financial information and its distance to the work site. $u^{(a)}$ controls for an auction specific fixed effect by including the number of bidders, calendar days and engineer's cost estimate. The cumulative distribution function of contractor j is obtained as follows:

$$H_j^{(a)}(s^i) \equiv Pr\left(b_j^{(a)} q^{e(a)} \leq s^i\right) = Pr\left(x_j^{(a)\prime} \mu + u^{(a)} + \varepsilon_j^{(a)} \leq s^i\right) \equiv G\left(\varepsilon_j^{(a)}\right).$$

Therefore, the residuals, $\widehat{\varepsilon}_j^{(a)}$, from the regression can be used to estimate the distribution of the error term, $G\left(\varepsilon_j\right)$, and then we use the estimated distribution for getting to the density, $\widehat{h}_j^{(a)}$, and CDF of the bid distributions, $\widehat{H}_j^{(a)}$. Note that, we use here a triweight kernel

$$K(u) = \frac{35}{32}(1-u^2)^3 1|u| \leq 1.$$

We use this triweight kernel to estimate density distribution functions. Furthermore, we select the bandwidth using the form $f_g = \kappa \hat{\sigma}(\widehat{\varepsilon}_j^{(a)})(nL_j)^{\frac{-1}{6}}$, where $\sigma(\widehat{\varepsilon}_j^{(a)})$ is defined as the standard deviation of $\widehat{\varepsilon}_j^{(a)}$, $\kappa = 2.9878 \times 1.06$, and L_j is the number of auctions in which a bidder j participated.

[14] De Silva, Dunne, Kosmopoulou, and Lamarche (2011) use the approach to control for many auction-specific characteristics and endogenous participation when they obtain bidding distributions and estimate pseudo costs with and without subcontracting goals.

The sources of markups over production costs could be the risk premium for project uncertainty and rents obtained by strategic bidding behaviors. Bajari (2001) shows that markups decrease as the number of bidders increases. Bajari and Ye (2003) find that estimated markups are consistently higher in the collusive models than in the competitive model, showing that they are around 3 to 4 % depending on the precise level of competition. Recently, Bajari, Houghton, and Tadelis (2011) report that the median markup above the cost estimate is 7.5 % for all bids and 17.7% for winning bids when considering adaptation costs. However, without accounting for ex post payments, the estimated markup drops to 3.6% for all bids and 12.5% for winning bids. The results imply that the previous literature might mis-specify markups because it fails to take into account the outcomes of renegotiations.

4.4 Estimation of project costs

Estimates of $H_j(s^i)$ are used to estimate a bidder i's probability of winning, $\prod_{j\neq i}(1 - H_j(s^i))$, and markups, $\left(\sum_{j\neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))}\right)^{-1}$, employing equations 5 and 6 to construct estimates of each project latent cost c^i. This sample of pseudo-values is then used to construct density functions. The remaining densities are obtained by a nonparametric model using the sample of pseudo-values, without any assumption regarding a specific functional form. In Table 7 we summarize our estimates of bidders' markups over estimated costs for projects with and without renegotiations after controlling for unobserved heterogeneity.[15] Here we report results at 20% through 80% rather than including the tails of the distributions in order to be cautious about the estimates at the tails. This result is

Table 7: Aggregate Markups

(%)	20(%)	30(%)	40(%)	50(%)	60(%)	70(%)	80(%)
With Renegotiation	5.300	7.860	10.420	14.390	18.360	23.965	29.570
Without Renegotiation	3.379	4.979	6.579	10.530	14.480	15.940	17.400

consistent with our reduced form estimates, which indicate that bidders behave strategically and achieve higher markups from projects in which they anticipate renegotiations. Furthermore, the

[15] Krasnokutskaya (2011) points out that the estimated average markups could be considerably higher when failing to control for unobserved heterogeneity.

estimated median markups are consistently higher than those reported in Bajari, Houghton, and Tadelis (2011).[16] The estimated median markups are 14.39% under ex post renegotiation, and they are substantially higher than those in contracts with no renegotiation.

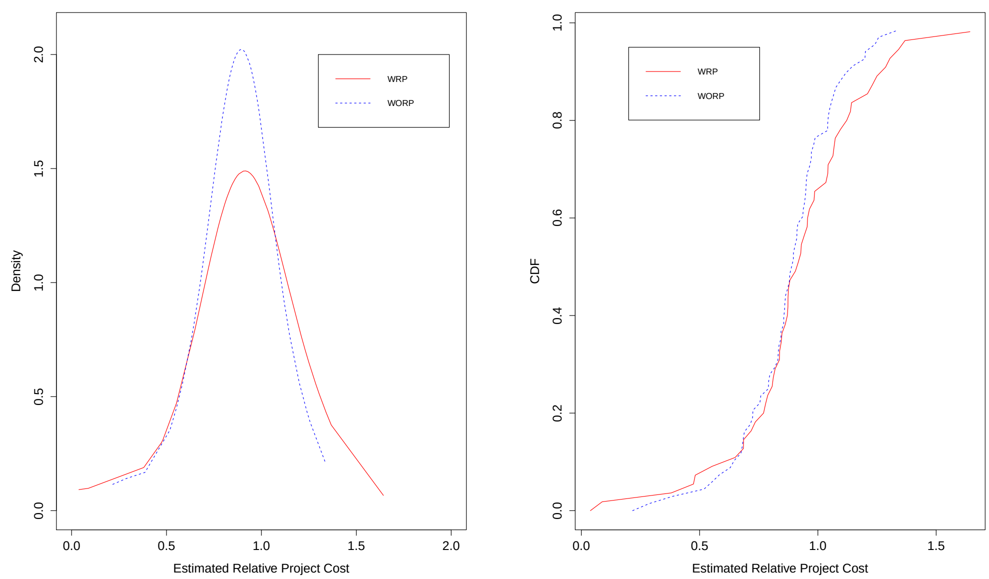

Figure 2: Relative Project Cost densities between with and without Renegotiation

Figure 2 shows the estimated relative project cost distributions for projects with and without renegotiations. The solid line indicates the project cost estimates of renegotiated projects while the dotted line is for not renegotiated projects. Note that the densities are obtained using the project pseudo costs divided by their corresponding engineering cost estimates to control for different project values. The figure to the left presents the estimated cost densities of projects while the right shows the empirical *cdf* for the costs.

4.5 Estimation of itemized costs

It is well known in the empirical auction literature that asymmetry among bidders within the IPV setting has no analytical solution due to an intractable system of first order conditions. Through the

[16]The possible reason could be that the road construction market is highly concentrated in the state of Vermont. For example, the top two firms won 1/3 of total projects during the sample period.

analysis, the maintained assumption is that the share of an item in a project's bid is proportional to the share of an item in a project's cost. For the simplicity of notation, the subscript 1 represents the project that is subject to renegotiation while the subscript 2 represents the project that experiences no renegotiations. Furthermore, the first m items are renegotiated in group 1 in our theoretical model. Equation 5 with the subscript can be expressed as follows:

$$TC_2^{i(e)} \equiv \sum_{t=1}^{T} c_{2,t}^i q_{2,t}^e = \sum_{t=1}^{T} b_{2,t}^i q_{2,t}^e - \left(\sum_{j \neq i} \frac{h_{2,j}(s_2^i)}{(1 - H_{2,j}(s_2^i))} \right)^{-1}. \tag{7}$$

If we separate items into two types (m and $T - m$) in the projects of the control group, we have

$$TC_2^{i(e)} \equiv \sum_{t=1}^{m} c_{2,t}^i q_{2,t}^e + \sum_{t=m+1}^{T} c_{2,t}^i q_{2,t}^e = \sum_{t=1}^{m} b_{2,t}^i q_{2,t}^e + \sum_{t=m+1}^{T} b_{2,t}^i q_{2,t}^e - \left(\sum_{j \neq i} \frac{h_{2,j}(s_2^i)}{(1 - H_{2,j}(s_2^i))} \right)^{-1}.$$

Also, equation 6 is equivalent to

$$\left[\sum_{t=1}^{m} (b_{1t}^i - c_{1t}^i) q_{1t}^a + \sum_{t=m+1}^{T} (b_{1t}^i - c_{1t}^i) q_{1t}^e \right] = \left(\frac{k_t q_t^a + (1 - k_t) q_t^e}{q_t^e} \right) \left(\sum_{j \neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))} \right)^{-1}.$$

After some algebra, it is possible to evaluate the total cost distribution for the group of renegotiated items as follows,

$$\begin{aligned} PTC_1^{i(a)} \equiv \sum_{t=1}^{m} c_{1,t}^i q_{1,t}^a = \sum_{t=1}^{m} b_{1,t}^i q_{1,t}^a &+ \left[\left(\sum_{j \neq i} \frac{h_{2,j}(s_2^i)}{(1 - H_{2,j}(s_2^i))} \right)^{-1} - \sum_{t=1}^{m} b_{2,t}^i q_{1,t}^e + \widehat{PTC}_2^{i(e)} \right] \\ &- \left[\left(\frac{k_t q_{1,t}^a + (1 - k_t) q_{1,t}^e}{q_{1,t}^e} \right) \left(\sum_{j \neq i} \frac{h_{1,j}(s_1^i)}{(1 - H_{1,j}(s_1^i))} \right)^{-1} \right]. \end{aligned} \tag{8}$$

Note that, $\widehat{PTC}_2^{i(e)}$ is constructed as the proportional amount of $\widehat{TC}_2^{i(e)}$ using the ratio of the itemized bid amount to the bid amounts in the control group. Those items experienced no renegotiations while they were renegotiated in the other contracts. We first estimate the left hand side of equation (7) and then we use these estimates to obtain the left hand side of equation (8). Because we are using a selected group of items that were both renegotiated and were not renegotiated in the period of analysis, we offer a comparison of latent costs that should not be affected by potential biases arising from latent item heterogeneity. Lastly, we are able to estimate the pseudo costs for the items that did not have renegotiations while some of other items are renegotiated in the same projects. We estimate them by subtracting aggregate markups from the project bids and by using the ratio of the itemized bid amount. The following figure is the estimated costs of the items on which this study focuses.

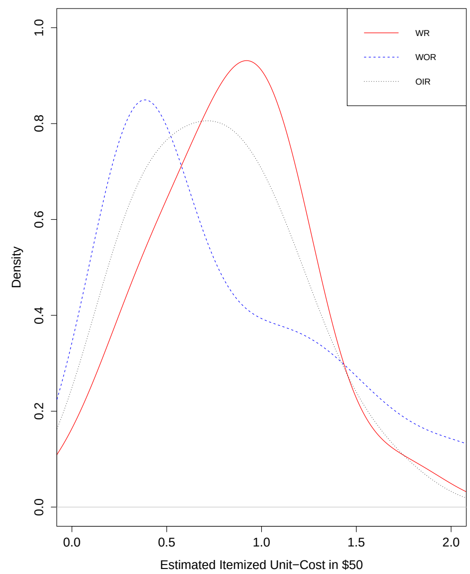

Figure 3: Itemized unit-cost densities: The curves represent items renegotiated (WR), items that were not renegotiated (WOR) and items that were not renegotiated while others were renegotiated in the same projects (OIR).

Figure 3 shows the itemized unit-cost estimates of different types of items. It shows that there are significant cost differences between types indicating the location shift to the right for the distribution of renegotiated items. The figure implies that renegotiation on an item could affect the entire project and bidders split adaptation costs across all items resulting from renegotiations in the same project. One possible explanation is that those items are frequently used in many projects. If there is a delay on those tasks, that could disrupt the flow of work and will increase the costs of the other tasks in the same project. The cost differences between WOR item and OIR item indicate the pure adaptation costs resulted from renegotiations in the same project.

Table 8: Estimated itemized Markups

(%)	20(%)	30(%)	40(%)	50(%)	60(%)	70(%)	80(%)
With Renegotiation	7.568	10.687	17.861	18.506	21.619	29.281	46.990
Without Renegotiation	2.872	5.206	6.357	8.848	11.334	18.050	23.361
Others Renegotiated	3.433	4.301	6.239	9.423	11.197	15.181	17.857

Table 8 shows bidders' strategic bidding behavior on the same items across cases when they are or are not renegotiated. We infer that bidders bid less aggressively on items with renegotiations while they bid more aggressively on items without renegotiations in the same projects. By doing so, they increase their expected profits without lowering the probability of winning. The mean markup for renegotiated items is about 18% which is much higher than that of bids. On the other hand, the mean markup for items that are not renegotiated is lower than that of bids because the responsiveness of itemized bids regarding renegotiations is much higher. These estimated markups imply that bidders are more likely to increase itemized bids on renegotiated items while they bid less aggressively on items that are not renegotiated in the same contract.

4.6 Testing the cost distribution invariance

We provide non-parametric tests for equality of two project cost distributions in Table 9. The column marked as (K-S) provides p-values corresponding to the Kolmogorov-Smirnov test.[17] This statistic is commonly used in literature to test for differences between two distributions, and we use it to evaluate if the cost distributions have same locations between projects with and without renegotiations. We fail to reject the null of equality of project cost distributions. Although, on average, the project relative pseudo cost with renegotiations is about 2% higher than that without renegotiations across projects, the difference is not statistically significant in both tests. However, the difference in estimated markups is much larger than the difference in estimated relative costs between renegotiated and no renegotiated projects, presenting 3.86% and 0.02% at the mean level, respectively. This evidence suggests that contractors extract high margins from renegotiated projects. At the itemized level, the testing result indicates that the difference in

[17] For the testing procedures, see De Silva, Dunne, Kosmopoulou, and Lamarche (2011)

itemized cost distributions between items with and without renegotiations is statistically significant at the 10% significance level. That is consistent with Figure 3 which shows that the location of cost distributions for those items are significantly different. The evidence lends support to the hypothesis that renegotiations of a particular item affect its cost.

Table 9: Tests for invariance of cost distributions to renegotiations

	With Renegotiation			Without Renegotiation			Tests
	Median	Mean	SD	Median	Mean	SD	(K-S)
Project level relative cost	0.905	0.905	0.286	0.885	0.873	0.209	0.637
Item level unit-cost (in \$50)	0.868	0.838	0.381	0.536	0.799	0.588	0.079

4.7 Counterfactuals

This subsection explains how we conduct the counterfactual exercise to estimate the cost changes as the renegotiations take place. We focus on renegotiated items only to compare their cost changes under different counterfactuals. We assume that there is a positive linear relationship between itemized bid amounts and the probability of renegotiation, implying that bidders use the information on historical probabilities for renegation of those items when submitting their itemized bids. The assumption directly implies that the itemized bid increases proportionally with its historical probability change. Using this assumption, we are able to adjust the observed itemized bids that would occur when the probability of renegotiations changes in the counterfactuals.

Figure 4 plots cost estimates under different counterfactual historical probabilities. The solid (red) line indicates the estimated itemized costs using the observed historical probability in our sample dataset. First, we assume that there are no renegotiations for those items. We estimate the itemized costs that would exist under this counterfactual scenario from equation 8, incorporating the adjusted itemized bids. The lowest cost distribution in the figure is obtained under that counterfactual. By construction, the estimated impacts on costs under the no renegotiation counterfactual are depicted as vertical distances between these two distributions. This itemized cost distribution under the counterfactual of no renegotiation could be the lower bound of the range of itemized costs for the renegotiated items if the decrease in the probability of renegotiation causes

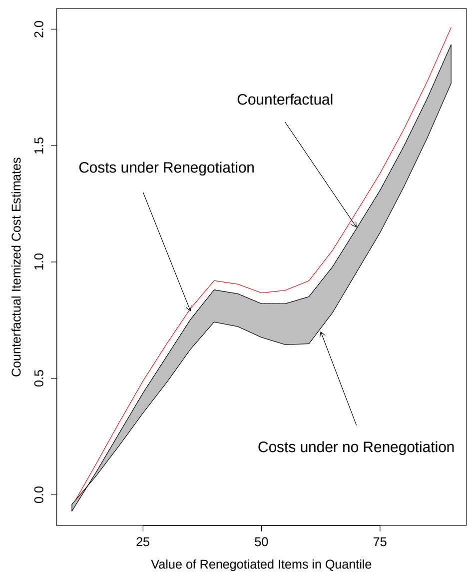

Figure 4: Counterfactual estimations for itemized costs

the itemized cost distribution to shift to the right. To test this, we show how the cost distribution shifts if a historical probability changes marginally. Under another counterfactual structure, we consider that the probability of renegotiation decreases by 6%.[18] The results of this second trial suggest that, as the probability of renegotiation changes, the cost distribution will also shift. It apparently shows that a slight decrease in probability of renegotiations causes the cost distribution to shift to the lower diagonal. From this conclusive evidence, we infer that once renegotiations take place, the itemized costs will increase. One possible explanation is that renegotiations will cause higher adaptation costs. Another possible reason is that high value projects are more uncertain.

5 Conclusion

This paper contributes to the empirical literature on auctions by providing an examination of how ex post renegotiation in procurement contracting affects outlays on road construction contracts. The analysis uses the nonparametric structural approach developed by Guerre, Perrigne, and Vuong (2000) and Bajari, Houghton, and Tadelis (2011) to estimate the distribution of latent costs after

[18]The average historical probability of renegotiation for the four renegotiated items is 24.67% during the sample period.

controlling for project heterogeneity. Our empirical results show a significant difference in the level of markups and the estimated itemized costs. The estimated markups are relatively higher than those reported in the literature because we utilize a sample of contracts with only positive quantity adjustments.

The itemized markups are even higher because firms realize that those items have a history of frequent renegotiation, and accordingly increase their bids on those items. The reduced form estimates of the itemized relative bid consistently show that bidders are more likely to bid less aggressively when they expect a particular item to overrun. Our estimates for itemized costs show that renegotiation on an item could affect the entire project and bidders split adaptation costs across all items in the same contract. Furthermore, our counterfactual exercise indicates that as the probability of renegotiation increases, the estimated itemized costs also increases due to contractor's adaptation costs and strategic bidding behavior. Finally, it is apparent that ex post renegotiation affects the cost paid by a state government.

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A Regression Variables

Dependent Variable	Descriptions and construction of the variable
Relative Bid	Bidding amount for each bidder on the original contract divided by engineer's cost estimate.cost estimate.
Relative Itemized Bid	Bids at item level divided by engineer's cost estimate of that item
Independent Variable	**Auction specific characteristics**
Proportion of Price Adjustment	Ex post total price adjustment amount divided by engineer's cost estimate in the project. The price adjustment amount is the reimbursed amount according to the price adjustment clauses for fuel and asphalt.
Proportion of Positive Quantity Adjustment	Ex post total positive quantity adjustment amount divided by engineer's cost estimate in the project.
Proportion of Negative Quantity Adjustment	Ex post total negative quantity adjustment amount divided by engineer's cost estimate in the project.
Proportion of Itemized Positive Quantity Adjustment	The dollar amount of ex post positive quantity adjustment divided by engineer's cost estimate at item level.
Proportion of Itemized Negative Quantity Adjustment	The dollar amount of ex post negative quantity adjustment divided by engineer's cost estimate at item level.
New Item Amount	The total value of new added items divided by bidding amount in the project.
Log of Calendar Days	The number of calendar days that are required to complete the project. The logarithm of the number of calendar days is used in the empirical analysis.
Expected Number of Bidders	It is calculated using past 12 month information for each bidder and plan holder list. We construct the probability of submitting bids conditional on being a plan holder. For an auction at time t, the expected number of bidders is the summation of the participation probabilities. Then, we multiply dummy variable to the expected number of bidders to identify an auction, in which the qualified plan holders are more than 3 on the plan holder list. The 3 qualified plan holders are the threshold to release the information on plan holders' identities.
Asphalt Project	The dummy variable that takes the value one if a project is the asphalt paving project.
Bridge Project	The dummy variable that takes the value one if a project is the bridge project.
	Bidder specific characteristics
Top Firm	A firm is assigned as a top firm if its annual revenue value is greater than 20% of the total value of all firms' revenues each year during the sample period.
Debt to Asset Ratio	A firm's total debt is the sum of current liabilities, long-term debt and other liabilities. We construct the ratio as a firm's total debt divided by its total asset every year.
Local Market Power	The total remaining value of a firm's ongoing projects in a county divided by the total remaining value of all firms' ongoing projects in that county at time t.
Log of Firm's Backlog	We assume that a project is completed in a uniform fashion over the length of the contract. A contract backlog is constructed by summing the remaining values of a firm's ongoing projects. However, if projects are completed, the backlog of the firm goes to zero. The logarithm of the amount of a bidder's current backlog is used in the empirical analysis.

Log of Rival's Minimum	The logarithm of the minimum of all rivals' backlog amounts in an auction Backlog
Log Distance to the Project Locations	The logarithm of distance between the firm's location and the location of work sites. If a project needs to perform statewide, we consider its location as the center of the state. Moreover, if a project has multiple sub-projects, we take the average of the distances to each work site.
Log Rival's Minimum Distance	The logarithm of the minimum of all rivals' distances between work sites and their locations in an auction
	Variables on general economic conditions
Gas Price Index	The three month moving average of the monthly posted gas price index in Vermont from the Vermont Agency of Transportation
Log of Number of Building Permits	The logarithm of the three month moving average of monthly building permits issued for Vermont from the Bureau of Economic Analysis.
Unemployment Rate	The monthly unemployment rate in Vermont from the Bureau of Labor Statistics (BLS)

B Derivations

We assume that there are 4 bidders such as i, j, k and l to show how we derived equation 4. Equation 2 can be written as,

$$\pi_i(c_1, c_2, k_t) = \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right)\right] \left[(1 - H_j(s^i))(1 - H_k(s^i))(1 - H_l(s^i))\right].$$

Note that $s^i = \sum_{t=1}^{T} b_t^i q_t^e$. After we take a derivative of a bidder's expected payoff function with respect to bidder i's unit price, we get

$$\begin{aligned}\frac{\partial \pi_i(c_1, c_2, k)}{\partial b_t^i} &= (k_t q_t^a + (1-k_t)q_t^e) \times \left[(1 - H_j(s^i)) \times (1 - H_k(s^i)) \times (1 - H_l(s^i))\right] + \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right)\right. \\ &\left. - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right)\right] \times \left[q_t^e \left[-h_j(s^i)(1 - H_k(s^i))(1 - H_l(s^i)) - h_k(s^i)(1 - H_j(s^i))(1 - H_l(s^i))\right.\right. \\ &\left.\left. - h_l(s^i)(1 - H_j(s^i))(1 - H_k(s^i))\right]\right] = 0. \end{aligned} \tag{B.1}$$

Simplifying we get equation 3.

$$\begin{aligned}\frac{\partial \pi_i(c_1, c_2, k)}{\partial b_t^i} &= (k_t q_t^a + (1-k_t)q_t^e) + \left[\prod_{j \neq i}(1 - H_j(s^i)\right] - \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right)\right] \\ &\times \left[q_t^e \sum_{k \neq i} h_k(s^i) \prod_{j \neq i,k} (1 - H_j(s^i))\right] = 0\end{aligned}$$

Now we divide equation B.1 above by $\left[(1 - H_j(s^i)) \times (1 - H_k(s^i)) \times (1 - H_l(s^i))\right]$.

$$(k_t q_t^a + (1-k_t)q_t^e) - \left[\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right)\right] \times \left[(q_{1t}^e) \sum_{j \neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))}\right] = 0$$

Simplifying we get equation 4.

$$\sum_{t=1}^{T} b_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right) - \sum_{t=1}^{T} c_t^i \left(k_t q_t^a + (1-k_t)q_t^e\right) = \left(\frac{k_t q_t^a + (1-k_t)q_t^e}{q_t^e}\right) \times \left(\sum_{j \neq i} \frac{h_j(s^i)}{(1 - H_j(s^i))}\right)^{-1}$$