Bidding for Incomplete Contracts: An Empirical Analysis of Adaptation Costs*

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Abstract

Public and private sector procurement contracts are often incomplete because the initial plans and specifications of the procured goods or services are changed and refined after the contract is awarded to the winning bidder. As a result, final costs differ from the winning bid and may include significant adaptation and renegotiation costs. We propose a stylized model of bidding for incomplete contracts and apply it to data from highway paving contracts. Reduced form regressions suggest that bidders respond strategically to contractual incompleteness and that adaptation costs, broadly defined, are an important determinant of the observed bids. We then estimate the costs of adaptation and bidder markups using a structural auction model. The estimates reinforce the reduced form analysis and suggest that adaptation costs, on average, account for about ten percent of the winning bid. The profit markups from private information and local market power, which are the focus on much of the literature on optimal procurement mechanisms, are much smaller by comparison. *JEL* classification D23, D82, H57, L14, L22, L74.

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1 Introduction

Procurement of goods and services is commonly performed using auctions of one type or another, the benefits of which are well known and vigorously advocated. Namely, competitive bidding will result in low prices and sets rules that limit the influence of favoritism and political ties. For standard goods, such as pencils, photocopy machines, and simple book-keeping software, it is rather straightforward to describe the item and proceed with a competitive auction.

Things are different for unique goods and services that are custom made to fit a buyer's needs. It is often quite costly for the buyer to translate his operational needs into well defined and communicable specifications that become the product's definition. Furthermore, as is often the case with custom ordered goods and services, during the production and delivery phase there will likely be glitches that require some adaptations and changes. These problems are often due to inadequate designs and specifications, to changes in the external environment, or more generally, to the incompleteness of the initial contract. In these events, the buyer and supplier will have to agree on the ways in which to adapt the original contract, both in terms of production specifications, and in terms of compensation. This may result in considerable discrepancies between the lowest winning bid and the actual costs that are incurred by the buyer.

To use a well known extreme example, consider the massive highway artery in Boston, referred to as the "Big Dig" by locals. On this project, 12,000 changes to more than 150 design and construction contracts have led to \$1.6 billion in cost overruns, many of which can be traced back to unsatisfactory design and site conditions that differed from expectations.[1]

As in the Big Dig, many construction projects involve a modification of the initial plans and specifications. These typically result in a cost increase that follows from two sources. The first are the direct costs of the additional work, which we refer to as *production costs*. The second, which we refer to as *adaptation costs*, are any costs that are incurred above and beyond the direct production costs of the project. For example, changing the contract disrupts the normal flow of work and thus increases the effort needed to coordinate workers, subcontractors and material suppliers, effort that could have been avoided

[1] According to the Boston Globe, "About \$1.1 billion of that can be traced back to deficiencies in the designs, records show: \$357 million because contractors found different conditions than appeared on the designs, and \$737 million for labor and materials costs associated with incomplete designs." Responsibility for these cost overruns is a subject of heated debate. See http://www.boston.com/news/specials/bechtel/part_1/. The inadequacies of this project received more recent coverage after the tragic death of a driver whose car was crushed by a collapsed ceiling.

with adequate planning in advance. Also, renegotiating the contract generates adaptation costs in the form of haggling, dispute resolution and opportunistic behavior. That said, in both the theoretical and empirical auctions literature, the issue of contractual incompleteness is ignored almost without exception.

In this paper we offer a first attempt to measure the economic costs of ex post adaptations that are due to incomplete contracts, and proceed to apply our framework to the procurement of highways in the state of California by Caltrans (California's Department of Transportation). We start with a simple theoretical framework motivated by the way highway improvement projects are often procured using *unit-price auctions*. These auctions are tailored to situations where there is little uncertainty about the measurable inputs needed for production, but there may be significant uncertainty about the actual quantities of each input that will ultimately be needed.

Procurement starts with a public engineer's estimate of the quantities of each work item that will be used (i.e., design and specification). Contractors then bid a per unit price for each item, and the contractor with the lowest estimated total bid, computed by multiplying the unit prices by the estimated quantities, is the winner. However, the total estimated bid is seldom equal to the final price paid by the buyer because ex ante *estimated* quantities and ex post *actual* quantities never perfectly agree. Also, there may be changes in scope when some fundamental design specifications of the project need to be altered. This often leads the parties to renegotiate compensation due to the required adaptations.

We develop a model in which contractors are experienced agents so that they rationally anticipate these changes and the associated adaptation costs that will be incurred as the project unfolds. That is, when observing the plans and specifications, and observing project and other buyer characteristics, the bidders will form rational expectations about the ways in which actual quantities will differ from estimated ones, as well as whether changes in scope will be required. Hence, these changes in payments and the resulting adaptation costs will be incorporated into the bids ex ante, and are passed through back to the Caltrans.[2]

We apply the empirical framework derived from our model to a unique panel data set of bids on highway contracts that we have collected from Caltrans. The data includes bidder identities, unit prices, cost estimates for each work item, and measures of cost advantages such as a bidder's distance to the project and its backlog. The data also contains detailed information on how the initial designs

[2]Haile (1991) explores timber auctions where forward looking rational bidders take into account the future possibility of resale to calculate their optimal bid.

were altered, which is not available in most studies of procurement. Unlike most auction procurement data available, our data includes *actual* quantities installed for all work items in the contract, as well as payments to the contractor from changes in scope.

In our empirical analysis, we first estimate a reduced form bid function. The theoretical model suggests that this regression should depend on project costs, the firm's market power and ex post changes to the contract. The strategy for identifying adaptation costs is based on the following implication of our theoretical model. Suppose that the contractors expect additional payments from Caltrans due to change orders made from altering the contract ex post. Controlling for project costs, auction theory predicts that for every additional dollar of profits, the contractors should lower their bid by one dollar. Thus, if the regression is correctly specified, the coefficient on ex post payments should be -1. In our data, we find that the coefficient for certain changes is 2. This coefficient implies that ex post changes on net generate more costs than revenue. This is even after using detailed cost controls in our bid function regressions. Our reduced form regressions imply that the additional costs from ex post changes are substantial and may account for about ten percent of the total bid.

While this may be surprising to many economists, this is not surprising when viewed in the context of the construction and engineering management literature (See, Hinze (1993), Clough and Sears (1994) , Ibbs et. al. (1986), Sweet (1994) and the overview in Bajari and Tadelis (2001)). as described earlier, changing the contract after it is awarded generates substantial extra costs for contractors for two reasons: First, there may be costs due to ex post bargaining, haggling and lawsuits over the payments made from changing the project specifications after the contract is awarded. Second, changing the contract disrupts the project work flow. The highway construction industry is quite competitive and the publicly traded firms in our sample report profit margins of less than 3 percent. Given the competitive nature of this business, contractors must attempt to anticipate these changes and include these additional costs in the bids. This is consistent with our reduced form findings.

Given the importance of ex post changes in our regression results, we check whether this finding is robust to alternative empirical specifications. Our regressions contain a highly detailed set of cost controls including an engineering cost estimate produced by Caltrans, a full set of firm fixed effects and firm specific distance to each project. Therefore, we have some confidence that our findings cannot be solely explained by omitted project costs.

To further push the robustness of our results we proceed to estimate a structural model that accounts for three potential sources of mark-ups over production costs. First, bidders markups are a function of private information and local market power. Second, we quantify the importance of incentives to submit "unbalanced" bids. As in Athey and Levin (2001), contractors can increase expected profits by increasing unit prices on items that are expected to overrun and decreasing unit prices on items that are expected to under-run. Third, we estimate the adaptation costs from changes to the initial specifications (estimated quantities) to uncover the non-production ex post costs of misspecified ex ante designs. Our structural estimates support our reduced form findings that these adaptation costs are larger than the other two distortions.

As a final check on our results, we search for an exogenous shifter of ex post payments to the contractor. As we explain in the paper, we use the identity of the Caltrans engineer assigned to the project as an instrument since individual engineers have discretion over ex post payment. We conclude our empirical analysis with a conservative bounding strategy to find upper and lower bounds on the adaptation costs. We continue to find large and significant estimates of adjustment costs under these two specifications, and conclude that our estimates are consistent with adaptation and changes being a major determinant of bids in this industry and an important potential source of inefficiency.

This paper is related to a recent literature on procurement when the original contract is subject to ex post changes. Several studies emphasize the importance of adaptation costs, including Williamson (1975, 1985), Crocker and Reynolds (1993), Bajari and Tadelis (2001), Corts and Singh (2004), Chakravarty and MacLeod (2004), and Bajari, McMillan and Tadelis (2006). Our paper also draws from the growing literature on structural estimation of auction models (See, e.g., Paarsch (1992), Donald and Paarsch (1993), Guerre, Perrigne and Vuong (2000), Campo et al. (2002), Pesendorfer and Jofre-Bonet (2003), and Athey, Levin and Seira (2004).[3]

Our analysis offers three contributions. First, we simultaneously estimate the effects of market power, incentives to submit unbalanced bids and adaptation costs on mark-ups over production costs in an auction model. The estimates imply that adaptation costs are significant—on average they are equal to about ten percent of the winning bid. Market power and unbalanced bidding, on the other hand, appear to be a fairly modest component of the markup. This finding

[3] Other researchers that have studied bidding for highway contracts include Porter and Zona (1993), Hong and Shum (2002), Krasnokutskaya (2004), Bajari and Ye (2003), Pesendorfer and Jofre-Bonet (2003) and Krasnokutskaya and Seim (2004).

is consistent with our reading of the literature on construction and engineering management that we surveyed in Bajari and Tadelis (2001). Previous empirical papers have not included the ex post payments used in our empirical analysis.

Second, our results suggest that profit mark-ups in standard models of bidding are often misspecified because they do not account for the significant discrepancies between initial bids and the final payments. Payments from changes to the contract can be substantial, implying that important parts of a contractor's revenues and costs are omitted in standard models. This in turn implies that policy geared towards reducing the amount of contractual incompleteness may have large benefits by reducing the costs of public procurement.

Third, our paper contributes to transaction costs economics by actually estimating adaptation costs. While transaction cost economics dates back to the original arguments laid out by Williamson (1975, 1985), to the best of our knowledge there are no empirical estimates of the *dollar value* of some of these costs. We demonstrate that standard methods for estimating auctions can be modified to yield an estimate of adaptation costs in procurement auctions.

2 Competitive Bidding for Highway Contracts

As described in Hinze (1993) and Clough and Sears (1994), procurements for highway construction, as well as many other procurements in the public sector, are often done through competitive bidding for unit-price contracts. For such contracts, civil engineers first prepare a list of items that describe the tasks and materials required for the job. For example, in the contracts we investigate, items include laying asphalt, installing new sidewalks and striping the highway. For each work item, the engineers provide an estimate of the quantity that they anticipate contractors will need in order to complete the job. For example, they might estimate 25,000 tons of asphalt, 10,000 square yards of sidewalk and 50 rumble strips. The itemized list is publicly advertised along with a detailed set of plans and specifications that describe how the project is to be completed.

A contractor that wishes to bid on the project will propose per unit prices for each of the work items on the engineer's list, so his bid is a vector of unit prices that specifies his price for each contract item. Table 1 shows the basic structure of a completed bid, which must be sealed and submitted prior to a set bid date. When the bids are opened, the contract is awarded to the contractor with the lowest estimated total bid, defined as the sum of the estimated individual line item bids (calculated by multiplying the estimated quantities of each item by the unit prices in the bid).[4]

Item	Description	Estimated Quantity	Per Unit Bid	Estimated Item Bid
1.	asphalt (tons)	25,000	$25.00	$625,000.00
2.	sidewalk (square yds)	10,000	$9.00	$90,000.00
3.	rumble strips	50	$5.00	$250.00
			Final Bid:	$715,250.00

Figure 1: Unit Price Contract–An Example.

As a rule of thumb, final quantities are never equal to the estimated quantities. For example, the engineers might estimate that it will take 25,000 tons of asphalt to resurface the stretch of highway listed in the plans but 26,752 tons are actually used. The difference, in fact, may be substantial if there are unexpected conditions or work has to be redone or eliminated. As a result, final payments made to the contractor are almost never equal to the original bid. The determination of the final payment can be rather complicated because in many cases is not the simple sum of actual item costs given the unit prices in the bid. Caltrans' *Standard Specifications* and its *Construction Manual* discuss the determination of the final payment at length. To a first approximation, there are three primary reasons for modifying the payments away from the simple vector product of unit prices and actual quantities.

First, if the difference between the estimated and actual quantities is small, then the contractor will indeed be paid the unit price times the actual quantity used. If the deviation is larger, however, or if it is thought to be due to negligence by one party, both sides will renegotiate an *adjustment of compensation*.[5] For illustration, consider the contract in Figure 1. If the asphalt ran over by 10,000 tons, Caltrans would hesitate to pay $250,000 more than they had anticipated. The parties might negotiate an adjustment of $(-\$20,000)$ to bring the total bill down. In our data, these adjustments are always recorded as a

[4] There are situations in which the Department of Transportation (DOT) can choose not to award the contract to the low bidder. The low bid can be rejected if the bidder is not appropriately bonded or does not have a sufficient amount of work awarded to disadvantaged business enterprises as subcontractors. Also, the DOT may reject bids judged to be highly unbalanced and therefore irregular.

[5] In the particular case of highway constrution procured by Caltrans, this type of adjustment is called for if the actual quantity of an item varies from the engineer's estimate by 25 percent or more. See the discussion of changes in the *Standard Specifications* and the *Construction Manual*.

lump sum reduction or increase, but one might also think of them as a way for parties to adjust the implied unit price on a particular item.

Second, in addition to changes in the estimated quantities, there may be a *change in scope* of the project. A change in scope is a change in the overall description and design of the project that needs to be completed. For instance, the original scope of the project might be to resurface 2 miles of highway. However, the engineers and contractor might discover that the subsurface is not stable and that certain sections need to be excavated and have gravel added, an activity that was not originally described. This would constitute a change in scope. In most cases, the contractor and Caltrans will negotiate a *change order* that amends the scope of the contract as well as the final payment. If negotiations break down, this may lead to arbitration or a lawsuit. Payments from changes will appear in two ways. First, to the extent that the change in scope affects pre-specified contract items, changes in the actual ex post quantities of those items will compensate the contractor for the direct production costs. Second, extra payments may reflect the use of unanticipated materials or other adjustment costs, and they are recorded as *extra work* in our data.

Finally, the payment may be altered because of *deductions*. If work is not completed on time or if it fails to meet specifications, Caltrans may deduct liquidated damages. Such deductions are often a source of disputes between Caltrans and the contractor. The contractor may argue that the source of the delay is poor planning or inadequate specifications provided by Caltrans, while Caltrans might argue that the contractor's negligence is the source of the problem. The final deductions imposed may be the outcome of heated negotiations or even lawsuits and arbitrations between contractors and Caltrans.

It is widely believed in the industry that some contractors attempt to strategically manipulate their bids in anticipation of changes to the payment. Contractors may strategically read the plans and specifications to forecast the likelihood and magnitude of changes to the contract. For instance, consider the example of Figure 1, in which the total bid is \$715,250. Suppose that after reading the plans and specifications, the contractor expects asphalt to overrun by 5,000 tons and sidewalk to under-run by 3,000 square feet. If he changes his bid on sidewalk to \$5.00 and his bid on asphalt to \$26.60 then his total bid will be unchanged. However, this will increase the contractors' expected total payment to \$833,750.00 ($26.6 \times 30,000 + 5 \times 7000 + 5 \times 50$) compared to \$813,750.00 when bids of \$25.00 and \$9.00 are entered. A profit maximizing contractor can therefore increase his total payment *without increasing his total bid* and thus will not lower his probability of winning the job. A bid is referred to as *unbalanced* if it has unusually large unit prices on items that are expected to overrun and unusually small unit prices on items expected to under-run.

Athey and Levin (2001) note that the optimal strategy for a risk neutral contractor is to submit a bid that has zero unit prices for some items that are overestimated, and put all the actual costs on items that are underestimated. This strategy will maximize the expected ex post payment while keeping the total bid unaltered. In the data, however, while zero unit price bids have been observed, they are very uncommon. Athey and Levin argue that risk aversion is one reason why this might occur, which in the absence of ex post changes seems like a plausible explanation for bidding behavior. After speaking with some highway contractors and reading industry sources we believe that for construction contracts other incentives are more important. Namely, Caltrans is not required to accept the low bid if it is deemed to be irregular (see Sweet (1994) for an in depth discussion of irregular bids). A highly unbalanced bid is a sufficient condition for a bid to be deemed irregular. As a result, a bid with a zero unit price is very likely, if not certain to be rejected. In our data, 4 percent of the contracts are not awarded to the low bidder, and according to industry sources the mostly likely reason is unbalanced bids.[6]

Also, the *Standard Specifications* and the *Construction Manual* indicate that unit prices on items that overrun by more than 25 percent are open to renegotiation. In these negotiations, Caltrans engineers will attempt to estimate a fair market value for a particular unit price based on bids submitted in previous auctions and other data sources. Caltrans may also insist on renegotiating unit prices even when the overrun is less than 25 percent if the unit prices differ markedly from estimates. This suggests that there are additional limitations on the benefits of submitting a highly unbalanced bid.

3 Bidding for Incompletely Specified Contracts

In this section we use the factual descriptions above to develop a simple variant of a standard private values auction model that will be the basis for our reduced form and structural empirical models.

3.1 Basic Setup

A project is characterized by a list of tasks, $t = 1, ..., T$ and a vector of estimated quantities that the buyer distributes to the potential contractors. The estimated

[6] Using blue book prices and previous bids, CalTrans is able to check whether bids for certain work items are unusually high or low.

quantity for each task is q_t^e, while the actual ex post quantity that will be needed to complete the task is q_t^a. Let $\mathbf{q}^e = (q_1^e, ..., q_T^e)$ and $\mathbf{q}^a = (q_1^a, ..., q_T^a)$ denote the vectors of estimated and actual quantities.

Since the focus of our study is on the potential adaptation costs from ex post changes and not on the rents that contractors receive due to their private information, we assume an extreme form of asymmetric information between the buyer and contractors. In particular, we assume that each contractor in the set of available bidders has perfect foresight about the actual quantities $\mathbf{q}^a$ while the buyer Caltrans is unaware of $\mathbf{q}^a$ and only considers $\mathbf{q}^e$. The perfect foresight of contractors can naively be interpreted as the contractors knowing the actual $\mathbf{q}^a$. Since we will assume that contractors are risk neutral, this specification can more convincingly be interpreted as contractors not having *exact* information about $\mathbf{q}^a$, but instead having *symmetric uncertainty* about the actual quantities, resulting in common rational expectations over actual quantities. This interpretation is useful for the empirical analysis because it generates a source of noise that is not specific to the contractor's information or the observable project characteristics.

Despite the fact that contractors have symmetric information about $\mathbf{q}^a$, they differ in their private information about their own costs of production. Let c_t^i denote firm i's per unit cost to complete task t and let $\mathbf{c}^i = (c_1^i, ..., c_T^i) \in \mathbb{R}_+^T$ denote the vector of i's unit costs. The total cost to i for installing the vector of quantities $\mathbf{q}^a$ will be $\mathbf{c}^i \cdot \mathbf{q}^a$, the vector product of the costs and the actual quantities. The costs (type) of contractor i are drawn from a well behaved joint density $f_i(\mathbf{c}^i)$ with support on a compact subset of $\mathbb{R}_+^T$. The distributions are common knowledge, but only contractor i knows $\mathbf{c}^i$. Also costs are independently distributed conditional on publicly observed information. We note that the private values assumption is commonly used when studying this industry (see Porter and Zona (1993), Krasnokutskaya (2004), Bajari and Ye (2003), and Pesendorfer and Jofre-Bonet (2003)). Testing for common values in this model with multiple units is much more complicated than in a single unit auction, and is beyond the scope of this research.

This specification, together with the symmetric information about $\mathbf{q}^a$, depicts a situation where contractors have rational expectations about what needs to be done to meet the contract (as in the most common type of procurement models) but they have private information about the costs of production.

Contractors bid by submitting a unit price vector $\mathbf{b}^i = (b_1^i, ..., b_T^i)$ where b_t^i is the unit price bid by contractor i on item t. Contractor i wins the auction and is awarded the contract if and only if $\mathbf{b}^i \cdot \mathbf{q}^e < \mathbf{b}^j \cdot \mathbf{q}^e$ for all $j \neq i$. That is, the contract is awarded to the lowest bidder, where the total bid is defined as the vector product of the contractor's unit price bids and the estimated quantities. Since the total bid is what matters to win the project, we define the the total bid, or *score* of bidder i as $s^i = \mathbf{b}^i \cdot \mathbf{q}^e$. This implies that our bidders participate in an auction with a simple linear scoring rule where each bid vector is transformed into a unidimensional score, the estimated price.[7]

If a risk neutral contractor has costs $\mathbf{c}^i$ and anticipates actual quantities to be $\mathbf{q}^a$ then we denote his total cost of production, which we refer to as his *type*, as given by $\theta^i \equiv \mathbf{c}^i \cdot \mathbf{q}^a$. Let $R(\mathbf{b}^i)$ be the gross revenue that a contractor expects to receive when he wins with a bid of $\mathbf{b}^i$. His expected profit from submitting a bid $\mathbf{b}^i$ is given by,

$$\pi_i(\mathbf{b}^i, \theta^i) = \left(R(\mathbf{b}^i) - \theta^i\right) \left(\Pr\left\{s^i < s^j \text{ for all } j \neq i\right\}\right)$$

where the interpretation is standard: the contractor receives the net payoff of revenue less production costs (calculated using the expected actual quantities) only in the event that all other bidders submit higher total bids (scores).

3.2 Revenues and adaptation costs

If the only source of revenue were the vector product of the unit prices with the actual quantities, then revenues would equal $\sum_{t=1}^{T} b_t^i q_t^a$. As discussed in the previous section, however, there are three other components that affect the gross revenue of the project: adjustments, extra work, and deductions. Following our assumptions that contractors are risk neutral and have symmetric rational expectations about the distribution of adjustment costs, we can introduce each of these three components as expected values, and include them additively into the contractors' profit function.[8] We denote the expected income (or loss) from adjustments as A, from extra work as X, and from deductions as D.

In the absence of adaptation costs, given actual quantities $\mathbf{q}^a$ the revenues to the winning bidder i would be

$$R(\mathbf{b}^i) = \sum_{t=1}^{T} b_t^i q_t^a + A + X + D.$$

[7] See Osband and Reichelstein (1985), Che (1993), and Bushnell and Oren (1994) for early work on scoring auctions, and a recent generalization by Asker and Cantillon (2006).

[8] As mentioned earlier, another simplistic way of interpreting this is that contractors have perfect foresight of these components. An alternative assumption would be that each contractor receives a signal of this common value, which would complicate the model beyond tractability.

In this case any payments captured by $A + X + D$ are just a transfer of funds from the buyer to the contractor. However, in the presence of adaptation costs every dollar that is transferred has less than its full impact on profits.

There are two possible types of adaptation costs. The first is the direct disruption to the planned production costs necessary to adapt to new site conditions and unanticipated work. Large highway repair projects require careful coordination between the general contractor, his workers, subcontractors, material suppliers and Caltrans engineers. Changes can disrupt the efficient rhythm of work on the job. It is not unusual for changes to cut in half the amount of asphalt laid by a contractor in a day. At this reduced rate, the project will take twice as long to complete and perhaps double the labor and capital costs.[9] To fix ideas, recall the scenario discussed in the introduction in which the contractor fails to deliver the proper density, which may not be his fault. In this case there will be disruption caused by delays to the continued work, and many expenses that are caused by the detection of low density. We denote these direct adaptation costs by τ_d.

A second source of adaptation costs are the resources devoted to contract renegotiation and dispute resolution. Estimates place the value of change orders at \$13 to \$26 billion per year, but researchers have noted that with the additional costs related to filing claims and legal disputes, the total cost of changes could reach \$50 billion annually (see Hanna and Gunduz (2004)). When a change is required, Caltrans may argue that failure to follow the original designs generated the need for change, while the contractor may argue that inadequate designs provided by Caltrans are to blame. The parties might therefore disagree about the compensation the contractor should receive from the change order. Moreover, they may similarly disagree over the best way to change the

[9] An example witnessed by one of the authors who worked on highway construction as a college student occurred while overlaying a concrete highway with asphalt. The concrete highway was approximately 30 years old and had innumerable cracks that had been patched with a dark, black "latex joint sealer". As paving began, the latex joint sealer came in contact with hot asphalt, which is typically 275 degrees. The now heated joint sealer would often (and sometimes dramatically!) explode through the freshly laid mat of asphalt. As a result, the latex joint sealer had to be removed from thousands of cracks by laborers using mostly hand tools before state engineers would allow the contractor to overlay the existing concrete road. This greatly slowed down the rate at which paving could occur, causing trucks to frequently stand in line for an hour before they could dump their asphalt into the paver. Not surprisingly, project costs skyrocketed. The contractor and the state engineers disagreed about the optimal method to deal with the latex crack sealer. The contractor preferred a method that would use less manpower and more machines to remove the crack sealer. Since the machines removed the crack sealer incompletely, the state preferred a method that had labors remove the sealer by hand. The contractor and the state engineers disagreed vehemently about the additional expense caused by the need to remove the crack sealer. Compensation for this change had to be renegotiated at length.

plans and specifications. The contractor might prefer an alteration that maximizes his profits from the change order, while Caltrans may desire an alternative alteration that minimizes the total cost. Disputes over changes may generate a breakdown in cooperation on the project site and possibly lawsuits. We denote these renegotiation costs by τ_r.[10]

In reality, the contractual incompleteness that leads to adjustments, extra work and deductions will be positively correlated with the direct costs from disrupting the normal flow of work and the indirect costs of renegotiation. We assume that these extra costs are proportional to the size of adjustments, extra work and deductions. For example, the imposed loss from extra work is given by $(\tau_d^X + \tau_r^X)X$.

Before completing the specification of the adaptation costs, it is useful to distinguish between positive and negative ex post adjustments to revenues. By definition, any extra work adds compensation to the contractor while any deduction is an ex post loss incurred by the contractor.[11] This implies that $X > 0$ and $D < 0$. The adjustments A, however, can be positive or negative. For this reason we separate them so that positive adjustments are labeled $A_+ > 0$ while negative ones are labeled $A_- < 0$. For positive ex post income, adaptation costs will cause some surplus to be dissipated and positive coefficients will be a measure of these losses. For negative ex post income, adaptation costs mean that the contractor will suffer a loss above and beyond the accounting contractual loss imposed by the adjustments or deductions. Therefore, the negative coefficients will measure these losses. Thus, using positive coefficients for the proportional adaptation costs τ_d and τ_r, we can write down the total ex post costs of adaptation as follows,

$$K = (\tau_d^{A+} + \tau_r^{A+})A_+ - (\tau_d^{A-} + \tau_r^{A-})A_- + (\tau_d^X + \tau_r^X)X - (\tau_d^D + \tau_r^D)D \quad (1)$$

and the total revenue as

$$R(\mathbf{b}^i) = \sum_{t=1}^{T} b_t^i q_t^a + A + X + D - K. \quad (2)$$

No adaptation costs imply the null hypothesis that $K = 0$. The more detailed coefficients on revenue adjustments capture a particular linear reduced

[10]There can be a second indirect source of costs if a contractor has to spend more resources on a current job due to changes. Jobs that are scheduled to start after the completion of the current job will suffer from higheer costs due to overtime of employees or the hiring of a larger workforce to make up for the extra work.

[11]Forced deductions are clearly a penalty. We are thus implicitly assuming that when changes in scope are agreed upon then the voluntary acceptance by the contractor implies that he is not losing money, by revealed preference.

form of the adaptation costs. As a first step, however, this simple specification is useful in that the lack of adaptation costs will be revealed by the data if the estimated coefficients are zero. If they are not, however, then this will indicate the presence of adaptation costs, the exact form of which can then be measured with more scrutiny. In our empirical analysis we tried several more flexible specifications, yet the simple linear specification seems to best fit the data.

To complete the specification of profits, we add a component that captures the loss from submitting irregular bids that are highly skewed. Given our risk neutrality assumption, if a bidder observes a difference between $\mathbf{q}^a$ and $\mathbf{q}^e$ then his incentive is to bid zero on items that are over-estimated and a high price on items that are underestimated. However, like in Athey and Levin (2001), such skewed bids are not observed. Athey and Levin argue that risk aversion may be one reason for a loss from skewed bids. After speaking with some highway contractors and reading industry sources such as Bartholomew (1998), Clough and Sears (1994), Hinze (1993) and Sweet (1994), it seems that other incentives may be more important to curtail skewed bidding, and we discussed these in the previous section (the fact that CalTrans is highly likely to reject unbalanced bids). In fact, in highway construction, as we will explain more in section 4, the blue-book prices for many of the tasks allow Caltrans to detect significant deviations from blue-book prices, and such bids are rejected as being irregular.

We impose a reduced form penalty that is increasing in the skewness of the bid. Clearly, the degree of skewness will depend on what "reasonable prices" would be. In practice, Caltrans engineers collect information from past bids and market prices to create an estimate $\overline{b}_t$ that represents the engineer's estimate for the unit cost of contract item t. Thus, given a vector of prices $\mathbf{b}^i$, a natural measure of skewness would be the distance from the blue-book prices $\overline{\mathbf{b}}$.

Let $P(\mathbf{b}^i|\overline{\mathbf{b}})$ denote the continuously differentiable penalty function of skewing bids. We impose four assumptions on $P(\mathbf{b}^i|\overline{\mathbf{b}})$. First, $P(\overline{\mathbf{b}}|\overline{\mathbf{b}}) = 0$, that is, there is no penalty from submitting a bid that matches the engineer's estimates. Second, $\frac{\partial P(\mathbf{b}^i|\overline{\mathbf{b}})}{\partial b_t^i}\Big|_{b_t^i=\overline{b}_t} = 0$, which implies that when the bids match the engineer's estimates, the first order costs of skewing are zero. These two assumptions seem natural ways to capture the costs of skewed bidding given the practices of Caltrans. Third, we assume that $P(\mathbf{b}^i|\overline{\mathbf{b}})$ is strictly convex, and finally, we assume that $\lim_{b_t^i\to 0} \frac{\partial P(\mathbf{b}^i|\overline{\mathbf{b}})}{\partial b_t^i}\Big| = \infty$. These last two assumptions guarantee an interior solution to the bidders' optimization problem in the choice of $\mathbf{b}^i$. For convenience we henceforth drop $\overline{\mathbf{b}}$ and use $P(\mathbf{b}^i)$.

This completes the specification of revenues as,

$$R(\mathbf{b}^i) = \sum_{t=1}^{T} b_t^i q_t^a + A + X + D - K - P(\mathbf{b}^i) \tag{3}$$

3.3 Equilibrium Bidding Behavior

Following standard auction theory, we will consider the Bayesian Nash Equilibrium of the static first-price sealed-bid auction as our solution concept. Our model is an independent private values setting that is similar to the multidimensional-type models of Che (1993) and is in many ways a simple special case of Asker and Cantillon (2006) where the project is fixed, and the principal's (buyer's) objective is trivially fixed given that the scoring rule is fixed. Similar to Che's "productive potential" and Asker and Cantillon's "pseudotype," our equilibrium behavior will be determined *as if* our bidders have a unidimensional type. The reason is that given the scoring rule, the choice of total bid, or *score* $s = \mathbf{b}^i \cdot \mathbf{q}^e$ is separable from the optimal choice of the actual bid vector $\mathbf{b}^i$.[12] As a result, the Bayesian game will have a unique pure strategy monotonic equilibrium.

It is useful to decompose bidder i's problem into two steps. First, given a score s, what is the optimal (skewed) bid that the bidder would like to have conditional on winning the auction. This would result in the bidding function $\mathbf{b}^i(s)$ (or $b_t^i(s),\ t = 1, ..., T$.) Then, given $\mathbf{b}^i(s)$, we can solve for the optimal score s that the bidder would like to submit.

The first problem of choosing the optimal bid function given a score s is given by

$$\begin{aligned} \max_{\mathbf{b}^i(\cdot)} \quad & \textstyle\sum_{t=1}^{T} b_t^i q_t^a - \theta^i + A + X + D - K - P(\mathbf{b}^i) \\ \text{s.t.} \quad & \textstyle\sum_{t=1}^{T} b_t^i q_t^e = s \end{aligned} \tag{4}$$

Solving this program yields $T + 1$ first order conditions (FOCs), the first T being,

$$q_t^a - \frac{\partial P(\mathbf{b}^i)}{\partial b_t^i} - \lambda q_t^e = 0 \text{ for all } t = 1, ..., T \tag{5}$$

and the last being the constraint.

Now that we have (implicitly) solved for $\mathbf{b}^i(s^i)$, we can complete the bidder's optimization problem of choosing his optimal score s^i. The probability that bidder i wins the auction with score s^i depends on the distribution of the scores of each of the other $j \neq i$ contractors. Let $H_j(\cdot)$ be the cumulative distribution

[12] That is, given the score (price) s, each bidder has an optimal choice of bids *conditional on winning*, $b_t^i(s)$, and given this optimal price policy, there is an optimal score $s(\theta^i)$ that is unidimensional. This is like Asker and Cantillon's *pseudotype*.

function of contractor j's score, s^j. The probability that contractor i with a score of s^i bids more than contractor j is $H_j(s^i)$. Thus, the probability that i wins the job with a score of s^i is $\prod_{j\neq i}\left(1-H_j(s^i)\right)$. Using this, as well as substituting for revenues with (3), yields the contractor's profit function,

$$\begin{aligned}\pi_i(s^i,\theta^i) &= \left[R(\mathbf{b}^i(s^i))-\theta^i\right]\times\left[\prod_{j\neq i}\left(1-H_j(\mathbf{b}^i\cdot\mathbf{q}^e)\right)\right] \qquad (6)\\ &= \left[\sum_{t=1}^{T} b_t^i(s^i)q_t^a-\theta^i+A+X+D-K-P(\mathbf{b}^i)\right]\times\left[\prod_{j\neq i}\left(1-H_j(\mathbf{b}^i\cdot\mathbf{q}^e)\right)\right]\end{aligned}$$

Substituting (3) for $R(\mathbf{b}^i)$, the FOC of this second stage of the problem is:

$$\begin{aligned}\tfrac{d\pi_i}{ds_t^i}= &\left[\sum_{t=1}^{T}\tfrac{db_t^i(s^i)}{ds^i}q_t^a-\sum_{t=1}^{T}\tfrac{\partial P(\mathbf{b}^i)}{\partial b_t^i}\tfrac{db_t^i(s^i)}{ds^i}\right]\times\left[\prod_{j\neq i}\left(1-H_j(\mathbf{b}^i\cdot\mathbf{q}^e)\right)\right]\\ &+\left[\sum_{t=1}^{T} b_t^i(s^i)q_t^a-\theta^i+A+X+D-K-P(\mathbf{b}^i)\right]\\ &\times\left[\sum_{k\neq i}(-h_k(s^i))\prod_{j\neq i,k}\left(1-H_j(s^i)\right)\right]=0\end{aligned}$$

and after some algebra, and recalling that $\theta_i=\sum_{t=1}^{T}c_t^iq_t^a$ we can express the FOC as follows,

$$\begin{aligned}\sum_{t=1}^{T}\left[b_t^i(s^i)-c_t^i\right]q_t^a= &\sum_{t=1}^{T}\tfrac{db_t^i(s^i)}{ds^i}\left[q_t^a-\tfrac{\partial P(\mathbf{b}^i)}{\partial b_t^i}\right]\left(\sum_{j\neq i}\tfrac{h_j(s^i)}{1-H_j(s^i)}\right)^{-1} \qquad (7)\\ &-A-X-D+K+P(\mathbf{b}^i)\end{aligned}$$

From our assumptions on the densities of types and on the penalty function, $H_j(\cdot)$ is differentiable with density $h_j(\cdot)$, and the first order conditions of the two stages of optimization are necessary and sufficient for describing optimal bidder behavior.

A Bayesian Nash Equilibrium is a collection of bid functions, $\mathbf{b}^i(\cdot)$ and scores s^i that simultaneously satisfies the system (5) and (7) for all bidders $i\in N$. As stated above, there is a unique monotonic equilibrium in pure strategies, and we will therefore use (7) as the basis for our empirical analysis.

The first order condition (7) provides some insight into a firm's optimal bidding strategy, and relates to the established literature of bidding without adaptation costs and changes. When $\mathbf{q}^e = \mathbf{q}^a$ and when there are no anticipated changes, the first order condition reduces to:

$$\mathbf{b}^i \cdot \mathbf{q}^e - \mathbf{c}^i \cdot \mathbf{q}^e = \left(\sum_{j \neq i} \frac{h_j(\mathbf{b}^i \cdot \mathbf{q}^e)}{1 - H_j(\mathbf{b}^i \cdot \mathbf{q}^e)} \right)^{-1} \tag{8}$$

This is the first order condition to the standard first price, asymmetric auction model with private values. It is easy to see that our model is a simple variant of the standard models of bidding for procurement contracts. (See, e.g., Guerre, Perrigne and Vuong (2000) and Athey and Haile (2006)). That is, the markups should reflect the contractors' cost advantage and informational rents as captured in the right hand side of (8).

For example, in our application markups should depend on whether or not contractor i's competitors are close or far from the project site, since this determines his relative advantage or disadvantage in the costs of hauling equipment and material. The markups should also depend on contractor i's uncertainty about his competitors' costs. Intuitively, we expect informational rents to increase as uncertainty about one's competitors' costs grows.

The innovation of the first order condition in (7) is the introduction of empirically measurable terms that are commonly ignored in previous studies. These include a term that reflects i's perceived penalty from unbalancing his bid so that his unit prices will not differ substantially from the norm (similar to the effects of risk aversion in Athey and Levin, 2001). Another set of terms included are the adaptation costs that are reflected in K. To see this, suppose that the contractor expects a deduction of \$1,000. The first order condition suggests that the contractor will raise his bid by $(1 + \tau_d^D + \tau_r^D)$ times \$1,000. Thus, the total costs of the deductions, as borne by the firm, are indirectly borne by the buyer, Caltrans.

Clearly, this model abstracts away from what are known to be fundamentally hard problems such as substituting the perfect foresight assumption on changes and actual quantities with a common values specification in which each bidder has signals of these variables. Despite these limitations, however, our first order conditions at a minimum generalize models previously imposed in both the theoretical and empirical literature, which implicitly impose the assumption that $\tau_l^m = 0$ for all $l \in \{d, r\}$ and $m \in \{A_+, A_-, X, D\}$. As we demonstrate shortly, this null hypothesis is strongly rejected by the data, and we will offer some evidence suggesting that adaptation costs of ex post changes may indeed be the reason.

4 Data

Our unit of observation is a paving contract procured by Caltrans during 1999 and 2000. We index the projects by $n = 1, ..., N$. Many of the variables in the theoretical section are directly measured in our data, and we use superscript (n) to index these variables for project n. For instance, $b_t^{i,(n)}$ denotes the unit price for the t^{th} item submitted by bidder i on project n. The sample includes $N = 414$ projects with a value of $369.2 million.[13] There were a total of 1,938 bids submitted by 271 general contractors located primarily in California.

In Table 1, we list the top 25 contractors in our data set and their market share. Over half of the participating contractors, 157 firms, never won a contract during the period. In fact, only 5 firms participated in more than 10 percent of the auctions. To account for some of this asymmetry in size and experience, we will sometimes distinguish between "top" firms and "fringe" firms, where fringe firms are defined as those who each won less than 1 percent of the value of contracts awarded. We let $FRINGE_i$ be a dummy variable equal to one if firm i is a fringe firm. Tables 1 and 2 summarize the identities and market shares of the top firms, and Table 3 compares bidding by the top and fringe firms.

For each project, we have collected detailed information from the publicly available bid summaries and final payment forms that include the project number, the bidding date, the location of the job site, the estimated working days required for completion, and other information about the nature of the job. They also contain the identities of the bidders and their itemized bids. Projects are broken down into an average of 33 items, although one project has 255 items. For each item, we have the unit prices for all bidders, along with the estimated quantity.

Additionally, the bid summaries report the engineer's estimate of the project's cost. This measure, provided to potential bidders before proposals are submitted, is intended to represent the "fair and reasonable price" the government expects to pay for the work to be performed.[14] This estimate can be thought

[13] The size of the market is defined as the value of the winning bids for the projects in our data set. As we discussed in Section 2, this could be different from the final payments made to the contractors. We focus on those contracts for which asphalt constituted at least one third of the project's monetary value. We also exclude contracts that were not awarded to the lowest bidder. This is usually due to irregularities in the lowest submitted bid, bid relief granted to a contractor who claimed mistakes were made in his proposal, or other reasons for which the bidder was found to be ineligible. Such contracts represent only about 5 percent of all paving projects under consideration.

[14] See the "Plans, Specifications, and Estimates Guide," published by the Caltrans' Division of Office Engineer for additional information about the formation of this estimate.

of as $\sum_t \bar{b}_t q_t^{e(n)}$, the dot product of "Blue Book" prices per item, $\bar{b}_t$, and the estimated quantities for project n. Caltrans measures $\bar{b}_t$ using the Blue Book prices contained in the Contract Item Cost Data Summaries, published by Caltrans' Division of Office Engineer.[15] We have merged this information into our data set. Thus, a unique feature of our data is that we directly measure all the tasks assigned to the firm, $\mathbf{q}^{e,(n)}$ and we have a cost estimate for every task $\bar{b}_t^{(n)}$. Such detailed cost information is rare in empirical Industrial Organization studies and it will allow us to incorporate a rather appealing set of controls in our regression analysis.

From the final payment forms, we collect data on the actual quantities, $q_t^{a(n)}$ used for each item. Additionally, the forms record the adjustments, extra work, and deductions that contribute to the total price of the project. These correspond to the variables $A^{(n)}$, $D^{(n)}$ and $X^{(n)}$ introduced in the previous section.

To account for the role that geographic proximity plays in determining a firm's transportation cost, we construct a measure of firm i's distance to the job site of project n, which we denote as $DISTANCE_i^{(n)}$. The contract provides information about the location of the project, often as detailed as the cross streets at which highway construction begins and ends.[16] We combine this with the street address of each bidding firm, and record mileage and travel time as calculated by Mapquest's geographic search engine. Contractors may have multiple locations or branch offices; when this is the case, the location closest to the job site is used. For those projects which cover multiple locations, we take the average of the distances and travel times to each location. Tables 4 and 5 summarize these calculated measures based on the ranking of bids. As expected, the contractors submitting the lowest bids also tend to have the shortest travel distances and times, reflecting their cost advantage.

It is clear that a firm's bidding behavior may be influenced by its production capacity and project backlog. In particular, firms that are working close to capacity may face a higher shadow price of free capacity when considering an additional job. Following the methods used by Porter and Zona (1993), we construct a measure of backlog from the record of winning bids, bidding dates,

[15] Not all items have values in this source. To circumvent this problem, we derive an estimate for the missing $\bar{b}_t$ using the mean of the unit prices bid in all the contracts that appear in our data. Our method of averaging submitted bids to construct engineering estimates is similar to how they are constructed by professional estimating companies. This had an R^2 of 0.69 when regressed on the estimates we received from the Caltrans Cost Data Book.

[16] Where the location information is less precise, we use the city's centroid or a best estimate based on the post mile markers and highway names included on every contract.

and project working days. We assume that work proceeds at a constant pace over the length of the project, and define the variable $BACKLOG_i^{(n)}$ to be the remaining dollar value of projects won but not yet completed at the time a new bid is submitted.[17] We then define $CAPACITY_i^{(n)}$ as the maximum backlog experienced for any day during the sample period, and the utilization rate $UTILIZE_i^{(n)}$ as the ratio of backlog to capacity. For those firms that never won a contract, the backlog, capacity, and utilization rate are all set to 0.[18]

Discussions with members of the industry have revealed that firms may take into account their competitors' positions when devising their own bids. For this reason, we will include measures of their closest rival's distance and utilization rate. That is, since we treat the distance from the construction site as a proxy for cost advantage, we define $RIVALDIST_i^{(n)}$ as the minimum distance to the job site among i's rival bidders on project n. Likewise, $RIVALUTIL_i^{(n)}$ is the minimum utilization rate among i's rival bidders on project n.

Summary statistics for the projects and the bids are provided in Tables 6, 7, and 8. There is noticeable heterogeneity in the size of projects awarded: the mean value of the winning bid is \$3.2 million with a standard deviation of \$7.4 million. The difference between the first and second lowest bids averages \$191,516, meaning that bidders leave some "money on the table." On average, the projects require just over four months to complete, and during this period, it is clear that several change orders are processed. The final price paid for the work exceeds the winning bid by an average of \$155,092, or about 5.2 percent of the estimate. As Table 9 shows, a significant component of this discrepancy can be attributed to overruns and under-runs on project items. Not only are there deviations in quantity, but large deviations also induce a correction to the item's total price, captured by the value of adjustments. In our sample, the mean adjustment is \$135,032. Compensation for extra work negotiated through after-contract change orders, as well as deductions, contribute to the difference, averaging \$207,476 and -\$9,715 respectively. Taken together, the size of these ex post changes suggests a sizeable degree of incompleteness in the

[17] The measure of backlog was constructed using the entire set of asphalt concrete contracts, even though a few of these were excluded from the analysis. Since we lack information from the previous year, the calculated backlog will underestimate the true activity of firms during the first few months of 1999; however, we believe the measure to be a good proxy.

[18] In Bajari and Ye (2003) we demonstrated that the shadow value of capacity enters into the first order conditions like a deterministic cost shifter. This assumption is valid if bidders are indifferent about which of their competitors wins a project so that there is no incentive to strategically manipulate the capacities of competitors. Including a complete dynamic analysis of capacity utilization along with incomplete contracting is beyond the scope of this paper. See Pesendorfer and Jofre-Bonet (2003) for an analysis of capacity constrained bidders.

original contracts.

Next, we present some evidence about whether contractors attempt to strategically skew their bids. As argued in Athey and Levin (2001), contractors can increase their profits, without lowering the probability that they win, by skewing their bids upwards on items that are expected to overrun and downwards on items that are expected to under-run. In Table 10, we investigate the incentives to skew bids by running a regression of the unit prices on the percent by which that particular item overran. The left hand side variable is the unit price divided by an engineer's estimate of the unit price. The coefficient on percent overrun is 0.027, which is statistically significant at the 1% level. That is, if a contractor expected a ten percent overrun on some item, he would shade his bid up by approximately one quarter of one percent, a modest amount. When we allow for heteroskedasticity within an item code by using fixed or random item effects, the coefficient on percent overrun is similar, although with 2450 types of items, these individual effects do not add much explanatory power to the regression. Overall, while all coefficients are significant, ex post overruns have little explanatory power for explaining the observed bids. This evidence suggests that incentives to skew are not a major determinant of the observed bids.[19]

5 Empirical Analysis: Reduced Form Estimates

5.1 Bid Regressions

We begin our analysis by performing some reduced form regressions in order to determine which covariates best explain the total bids. A typical bid regression in the empirical auctions literature is a reduced form approximation to equation (8). This equation implies that $\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)}$ should be determined by two sources: costs and measures of market power.

We control for firm i's costs using four terms. The first is the engineer's cost estimate, $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}$. A regression of $\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)}$, on the engineer's cost estimate, $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}$ yields an R^2 of 0.987 and a coefficient equal to 1.025. This implies that the engineer's cost estimate is a very good cost control since it explains almost all of the variation in the observed bids. Second, a firm's own distance to the project, $DISTANCE_i^{(n)}$ will influence costs. Asphalt is very

[19] We might be worried that the regression in Table 10 is misspecified because it does not account for the fact that the expected and actual values of the variables may differ. Following logic used in the estimation of Euler equations, we also estimated these equations using variables in the current information set as instruments. The results were nearly identical.

heavy and on most projects, tens of thousands of tons must be hauled from the asphalt plant to the highway, implying that distance to the plant will influence costs. Third, $UTILIZE_i^{(n)}$ will measure firm i's free capacity. As emphasized in Pesendorfer and Jofre-Bonet (2003), when a firm has little free capacity, its bid should increase because the opportunity cost of winning a job today may include not having enough free capacity to bid at upcoming lettings. Finally, recall that table 2 implies that the size distribution of firms in our industry is highly skewed. Therefore, it is desirable to allow the bids to differ by firm size and for this reason we include an indicator, $FRINGE_i^{(n)}$ for fringe firms as described above.

In equation (8), the term $\left(\sum_{j \neq i} \frac{h_j(\mathbf{b}^i \cdot \mathbf{q}^e)}{1-H_j(\mathbf{b}^i \cdot \mathbf{q}^e)}\right)^{-1}$ reflects firm i's market power. The term $\sum_{j \neq i} \frac{h_j(\mathbf{b}^i \cdot \mathbf{q}^e)}{1-H_j(\mathbf{b}^i \cdot \mathbf{q}^e)}$ is the derivative of the log of the probability that bidder i wins with a bid of $\mathbf{b}^i \cdot \mathbf{q}^e$. The distribution of j's bid, $H_j(\cdot)$, will depend on j's costs. We would expect j to bid more aggressively when it is closer to the project or when it has more free capacity. Equation (8) therefore suggests that i's markup over costs will vary positively with publicly observed information about the costs of his competitors. Empirically, we proxy for market power using three terms. The first is $RIVALDIST_i^{(n)}$, since if the closest competing firm to the project is farther away, then all else held fixed firm i will have more market power. The second is $RIVALUTIL_i^{(n)}$, since if i's rivals have high capacity utilization, then firm i will have more market power. Finally, $NUMBIDDERS_j^{(n)}$, the number of bidders in project n, is also a measure of market power.

It seems reasonable that the impact of our covariates on the bids will be proportional to the engineer's cost estimate $\left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right)$. For instance, one would expect increasing i's distance by 10 miles will raise the bid more on a contract with a \$5 million dollar estimate than a contract with a \$500,000 dollar estimate. This suggests using the following regression to approximate (8) in a reduced form:

$$\begin{aligned} \mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)} &= \alpha_0 + \alpha_1 \overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)} + \alpha_2 DISTANCE_i^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) \\ &+ \alpha_3 UTILIZE_i^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) + \alpha_4 FRINGE_i^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) \\ &+ \alpha_5 RDISTANCE_i^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) + \alpha_5 RIVALUTIL_i^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) \\ &+ NUMBIDDERS^{(n)} \cdot \left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right) + \varepsilon_{i,n} \end{aligned} \tag{9}$$

It is also natural to expect the variance of the error term to be proportional to $\left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right)$. A project with an a cost estimate of several million dollars will have a higher variance in the error terms than projects with a cost estimate of a few hundred thousand dollars. This suggest that the efficiency of our regression estimates would be improved by dividing our regression through by $\left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right)$ to control for heteroskedasticity. Therefore, we propose estimating the following equation:

$$
\begin{aligned}
\frac{\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}} &= \alpha_0 + \alpha_n + \alpha_i + \alpha_2 DISTANCE_i^{(n)} + \alpha_3 UTILIZE_i^{(n)} \qquad (10) \\
&+\alpha_4 FRINGE_i^{(n)} + \alpha_5 RDISTANCE_i^{(n)} + \alpha_5 RIVALUTIL_i^{(n)} \\
&+NUMBIDDERS^{(n)} + \varepsilon_{i,n}
\end{aligned}
$$

In addition to the covariates described above, we include α_n, a project n fixed effect and α_i, a firm fixed effect. The project fixed effect α_n allows us to control for information that is publicly observed by all the firms but not by us. This would include the impact of the engineer's cost estimate, but also could include the impact of ex post changes that are anticipated by the bidders. The firm i fixed effect, α_i, controls for omitted cost shifters of firm i that are persistent across auctions. As discussed above, the market shares of firms in this industry are highly skewed, suggesting that firms differ in their productivity or installed based of capital. Bid function regressions such as (10) are common in the literature. (See, e.g., Porter and Zona (2000)).

The results from the regression described in (10), and its variants, are displayed in Table 11. In all of our regressions, distance and fringe status are significant and have positive signs as expected. The average distance to the job site in our data is 72 miles. This "average" firm would bid approximately two percent more than a firm that is next to the project with a distance of zero. Fringe firms tend to bid 3 to 4 percent higher than more established competitors. The number of firms in a market has the expected sign on bids. Adding an additional bidder to the job lowers bids by about one percent. Rival distance and utilization are at best marginally significant in our regressions.

In the first two columns, however, the overall measure of goodness of fit is pretty low. In columns III and IV, we add project and firm fixed effects to the regression. The results suggest that both of these variables add considerably to goodness of fit, particularly project fixed effects. These effects capture characteristics of the job that are known to contractors but are unobserved in our data, such as the condition of the job site, the difficulty of the tasks, and anticipated changes.

5.2 Accounting for Changes and Adaptation Costs

While regressions such as those in Table 11 are common in the literature, equation (7) suggests that they are misspecified. Our theoretical analysis suggests that the regressions in Table 11 suffer from two sources of misspecification. First, the dependent variable is the total estimated bid, $\mathbf{b}^i \cdot \mathbf{q}^e$, instead of the (expected) total bid, $\mathbf{b}^i \cdot \mathbf{q}^a$. Second, the regressions above ignore the anticipated changes to payments due to adjustments, extras and deductions. Based on equation (7), we re-specify the reduced form regression as follows:

$$\frac{\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{a,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} = \alpha_n + \alpha_i + \alpha_2 DISTANCE_i^{(n)} + \alpha_3 UTILIZE_i^{(n)} + \alpha_4 FRINGE_i^{(n)} \tag{11}$$

$$+\alpha_5 RDISTANCE_i^{(n)} + \alpha_6 RIVALUTIL_i^{(n)} + \alpha_7 NUMBIDDERS^{(n)} + \varepsilon_{i,n} ,$$

where

$$\alpha_n = \beta_1 + \beta_2 A_+^{(n)} + \beta_3 A_-^{(n)} + \beta_4 X^{(n)} + \beta_5 D^{(n)} + \varepsilon_n .$$

The regression in (11) is similar to that in (10). However, we change the definition of the dependent variable to be consistent with (7). As in the previous reduced form bid regression, we correct for heteroskedasticity related to project size by dividing through by an estimate of that size, $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$.

In (11), we regress the fixed effects, α_n on the ex post changes in order to quantify their impacts on the observed bidding behavior. Equation (7) implies that the marginal impact of an extra dollar of change identifies the adaptation costs in our model. Recall that the total adaptation costs for, say, extra work X is given by the direct and indirect adaptation costs, previously denoted as $(\tau_d^X + \tau_r^X)X$. Our specification does not allow us to separate the direct and indirect adaptation costs, so we denote total adaptation costs from extra work as $\tau^X X$. Similarly, define $\tau^{A_+} A_+$, $\tau^{A_-} A_-$ and $\tau^D D$ as total adaptation costs for positive adjustments, negative adjustments and deductions. Following the logic of (7), our estimates of β_2 through β_5 offer estimates of the adaptation cost coefficients as follows[20]:

$$\begin{array}{ll} \beta_2 \equiv -(1 - \tau^{A_+}) & \beta_4 \equiv -(1 - \tau^X) \\ \beta_3 \equiv -(1 + \tau^{A_-}) & \beta_5 \equiv -(1 + \tau^D) \end{array}$$

[20]Recall that the RHS of (7) includes the payment X once as a payment, and then deducts $\tau^X X$ as the adaptation costs. Therefore the coefficient on X in (7) is $-(1 + \tau^X)X$, and since (11) regresses the bid on covariates instead of the cost, the signs are reversed and $\beta_4 = -(1 - \tau^X)$. A similar logic applies to the other ex post payment coefficients.

The above regression is estimated by least squares and in Table 12 we present the results of this re-specified reduced form regression. As columns I and II demonstrate, when we only include the firm's and its competitors' cost shifters as covariates, the results appear to be similar to Table 11. A firm's own distance and whether or not it is a fringe firm appear to be the most important predictors of the left hand side of (11), which uses actual ex post quantities. For a given project, fringe firms tend to bid slightly more than non-fringe firms. Project fixed effects also absorb a great deal of variation in the bids, again suggesting that there is some unobserved project-specific heterogeneity. Note, however, that the regression in Table 12, column II, is almost identical the to regression in Table 11, column III. However, the R^2 increases from 0.53 to 0.93 when we use the unit prices times the actual quantities as the dependent variable, as suggested by our first order conditions. We take this as evidence that using ex post information improves our ability to explain the observed bids considerably.

Next, we include the ex post changes. We use $DEDUCT^{(n)}$ and $EXTRA^{(n)}$ to denote the values of deductions and extra work, both normalized by dividing through by $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$. We denote the normalized positive adjustments and negative adjustments similarly, $PosADJUST^{(n)}$ and $NegADJUST^{(n)}$. The results of the regression without project fixed effects are shown in columns III and IV. It is worth noting that the coefficients on $DEDUCT^{(n)}$, $EXTRA^{(n)}$, $PosADJUST^{(n)}$ and $NegADJUST^{(n)}$ are almost identical with and without the fixed effects.

The results provide evidence that some form of frictions are imposed on the costs and revenues generated by ex post changes. For example, in column III of Table 12, the coefficient on $DEDUCT^{(n)}$ is -7.36 which implies for our model that $\tau^D = 6.36$. As we discussed in Section 3, if contractors were risk neutral and there were no adaptation costs, the coefficient on deductions should be -1. The fact that the coefficient is -7.36 is consistent with there being \$6.36 of adaptation costs for every dollar of deductions. This suggests that if contractors expect an extra dollar of deduction, they will raise their bid by \$6.36 *above and beyond* the expected loss of \$1, which is a way for them to compensate for the expected loss from the additional costs of adaptation and renegotiation. On a job with a \$6,118 deduction (the median deduction assessed in our sample), this implies an increased cost to the state of almost \$40,000. For the 414 jobs that we study, this implies that deductions add \$25,580,779 in adaptation costs to the final price paid by the state.

A similar interpretation may be given to the coefficient of -3.71 on negative adjustments, $NegADJUST^{(n)}$. When engineers underestimate the quantity of an item required to complete the job, the state will often negotiate a negative adjustment with a contractor who has bid that item at a high per unit price. Our regression results suggest that these negotiations carry with them a $2.71 adaptation cost for every dollar in adjustments. If bidders anticipate high downward adjustments of this sort, they tend to raise their bids, not only to recoup the expected loss, but also to recover the adaptation costs they must expend while haggling over price changes.[21]

If there were no adaptation costs and if contractors were risk-neutral, we would expect to find coefficients on positive adjustments equal to -1, implying that firms lower their bids by $1 when they expect to receive an additional $1 for work that has already been completed. The coefficient of 1.57 on positive adjustments implies that firms actually tend to *raise* their bids when they expect this additional compensation. One interpretation of this is that firms expect to spend $2.57 in adaptation costs for every dollar they obtain in adjustment compensation. Similarly, the coefficient of $0.96 on extra work implies that firms expect to spend $1.96 in adaptation costs for every dollar they obtain in adjustment compensation.[22]

It is worth noting that the adjustment costs implied from deductions are much higher than those implied by adjustments and extras. The natural interpretation through the lens of our model is that contractors require more up-front compensation when they expect funds to be deducted ex post, as opposed to adjustments and extras. This is in line with conventional wisdom in the industry. Deductions are imposed when the contractor is blamed for not performing according to expectations, which typically is accompanied by serious disputes that cause relationships to go sour, and this involves prohibitively high disruptions due to haggling, delays and rework.

In the final two columns of Table 12, we present instrumental variable esti-

[21] Our regressions also give us some evidence about the impacts of changes to the quantities on bids. Our model predicts that this could impact the bids through the skewing penalty. To account for expected quantity changes, we include two alternative measures that serve as proxies. $PCT^{(n)}$ is the average of the percent quantity overruns on each item t in a given project. Although this measure reflects upon the civil engineers' errors in estimation, it does not preserve the relative importance of contract items. A 10 percent overrun on a small item like milepost markers is quite different than a 10 percent overrun on a major item like asphalt concrete. To account for this we constructed another measure, $NOverrun^{(n)}$, which is defined as the sum of the dollar overrun on individual items, divided by the project estimate. This dollar overrun is computed by multiplying the difference in the actual and estimated quantity by the item cost estimate reported in the Contract Cost Data Book, $\bar{b}_t$. Since not all contract items are contained in the data book, $NOverrun^{(n)}$ should be thought of as a partial project overrun due to quantity changes in the more standard items.

[22] We note that our regressions imperfectly control for costs from extra work since these quantities associated with extra work are not directly observed by the econometrician. In our structural model, presented in the next section, we attempt to deal with this in two ways. First, we propose an IV strategy that exogenously shifts the payments from ex post changes. Also, we attempt to bound the potential bias from omitted costs.

mates. In column VI, we regress the project level fixed effects on measures of ex post changes to the project. These OLS results assume that ex post changes to the plans and specifications are exogenous. One might be concerned that ex post changes are more likely to be observed on projects that are more costly to complete for reasons due to factors that are unobserved to the econometrician even after controlling for a detailed cost estimate. As an instrument, we use the identity of the engineer that supervises the construction work for CalTrans. Recall that in highway construction, CalTrans is responsible for producing the project plans and specifications. The supervising engineer in practice has considerable discretion in what changes are made and the dollar amount paid for the changes. Some engineers are fairly liberal in making changes and adjusting contractor compensating, while others are more conservative. Thus, we use the identity of the engineer as an exogenous shifter of the ex post changes. The endogeneity problem, and our instrument, are discussed in detail in the next section. However, this straightforward instrumental variable regression is a useful baseline for comparing our estimates to the structural model of the next section. Notice that the estimated values using our instruments are remarkably similar to those from the OLS estimation.

In the rest of the paper, our goal will be to determine whether the results in Table 12, which imply large adjustment costs, are robust to changes in the method used to estimate these parameters. In particular, we will examine whether the results are robust to the four following forms of misspecification.

First, in our data, the bidders will be uncertain about the magnitude of ex post changes. Therefore, the first order conditions should include the expected values of $DEDUCT^{(n)}$, $EXTRA^{(n)}$, $PosADJUST^{(n)}$ and $NegADJUST^{(n)}$ instead of their actual values. The standard econometric analysis of measurement error suggests that our reduced form estimates of transactions costs will therefore be biased.

Second, our reduced form regressions imperfectly approximate the first order conditions. For instance, in the reduced form regressions we attempt to capture market power by including $RIVALDIST_i^{(n)}$ and $RIVALUTIL_i^{(n)}$ as regressors. However, the first order conditions imply that the probability of winning needs to be included in order to assess market power (e.g. the term $\left(\sum_{j\neq i}\frac{h_j(\mathbf{b}^i\cdot\mathbf{q}^e)}{1-H_j(\mathbf{b}^i\cdot\mathbf{q}^e)}\right)^{-1}$). Thus, the measurement of market power in the reduced form is misspecified and the interpretation of the regression coefficients is problematic as a result.

Third, the interpretation of the error term is not fleshed out in the above reduced form regressions, and the next section argues that the interpretation of the error term is subtle. Without a clear discussion of the error term, it is difficult to assess the plausibility of the instruments used for estimation. We propose instruments that allow for consistent estimation of the adaptation costs when there are two sources of endogeneity. The first are the expectational errors, discussed above. Second, we might worry that there are costs for completing the project that are observed to the firms and not to the economist, and that these costs are correlated with changes in ex post compensation. It is worth noting that our regression results above suggest that we have very good cost controls that explain much of the variation in the bids. However, to check the robustness of our results to unobserved costs, we will propose instruments, such as those used in the last two columns of Table 12.

Finally, we will describe a strategy to bound our estimates of transaction costs. An attractive feature of the bounding strategy is that it does not require the specification of instruments, and the idea behind our bounding strategy is simple. Suppose that there are unmeasured costs for completing the adjustments not captured in our cost estimate or other cost controls. As an upper bound, we suppose that there are one dollar of unmeasured costs of completing every dollar of extra work at one extreme, and zero dollars at another extreme.

In the next section, we shall discuss how to estimate the structural primitives of our model. Aside from addressing the four issues just discussed above, an advantage of the structural approach is that it will allow us to assess the relative magnitude of three potential distortions: (i) rents from private information and market power (ii) skewed bidding and (iii) adaptation costs. While the structural model will use somewhat different econometric methods, we shall find a great deal of consistency with our reduced form results.

6 Structural Estimation

In this section, we propose a method for structurally estimating the model discussed in Section 3. The estimation approach builds on the two-step nonparametric estimators discussed in Elyakime, Laffont, Loisel and Vuong (1994), Guerre, Perrigne, and Vuong (2000) and Campo, Guerre, Perrigne and Vuong (2002). In the first step, we estimate the density and CDF of the bid distributions for project n, denoted by $h_j^{(n)}(\mathbf{b}^i \cdot \mathbf{q}^e)$ and $H_j^{(n)}(\mathbf{b}^i \cdot \mathbf{q}^e)$ respectively. In the second step, we estimate the penalty from skewed bidding, σ, and the adjustment cost coefficients, τ^{A+}, τ^{A-}, τ^D and τ^X. We do this by using the first order conditions in (7) to form a GMM estimator.

6.1 Estimating Bid Distributions

Since we wish to include measures of firm specific distance and other controls for cross firm heterogeneity, nonparametric approaches would suffer from a curse of dimensionality. Hence, we will estimate $h_j^{(n)}(\mathbf{b}^i \cdot \mathbf{q}^e)$ and $H_j^{(n)}(\mathbf{b}^i \cdot \mathbf{q}^e)$ semiparametrically. We first run a regression similar to those in Table 11:

$$\frac{\mathbf{b}_j^{(n)} \cdot \mathbf{q}^{e,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^e} = x_j^{(n)\prime}\mu + u^{(n)} + \varepsilon_j^{(n)}$$

where as before the dependent variable is the normalized estimated bid, and $x_j^{(n)}$ includes the firm's distance and whether or not it is a fringe firm. We also include an auction-specific fixed effect, $u^{(n)}$, to control for project-specific characteristics that are observed by the bidders but not the econometrician.[23]

Let $\widehat{\mu}$ denote the estimated value of μ and let $\widehat{\varepsilon}_j^{(n)}$ denote the fitted residual. We will assume that the residuals to this regression are iid with distribution $G(\cdot)$. The iid assumption would be satisfied if the noise on total costs had a multiplicative structure, which we describe in detail in the next subsection. Under these assumptions, we observe that for project n:

$$\begin{aligned} H_j^{(n)}(b) &\equiv \Pr\left(\frac{\mathbf{b}_j^{(n)} \cdot \mathbf{q}^{e,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}} \leq \frac{b}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}}\right) \\ &= \Pr\left(x_j^{(n)\prime}\mu + u^{(n)} + \varepsilon_j^{(n)} \leq \frac{b}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}}\right) \\ &\equiv G\left(\frac{b}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}} - x_j^{(n)\prime}\mu - u^{(n)}\right). \end{aligned} \tag{12}$$

That is, the distribution of the residuals, $\varepsilon_j^{(n)}$ can be used to derive the distribution of the observed bids.[24] We estimate G using the distribution of the fitted residuals $\widehat{\varepsilon}_j^{(n)}$, and then recover an estimate of $H_j^{(n)}(b)$ by substituting in this distribution in place of G. An estimate of $h_j^{(n)}(b)$ can be formed using similar

[23] As Krasnokutskaya (2004) has emphasized, failure to account for this form of unobserved heterogeneity may lead to a considerable bias in the structural estimates. As a robustness check we also estimated a version of the model with random effects and found little quantitative change in our results.

[24] We include the fitted value of the fixed effect in order to control for omitted, auction specific heterogeneity. The fitted value of the fixed effect may be poorly estimated when the number of bidders is small and introduce bias into our estimates. However, the parameter estimates appeared to be more sensible than a model where they were not included.

logic. We note that both $H_j^{(n)}(b)$ and $h_j^{(n)}(b)$ will be estimated quite precisely because there are 1938 bids in our auction. Given the estimates $\widehat{H}_j^{(n)}$ and $\widehat{h}_j^{(n)}$ we generate an estimate for $\left(\sum_{j\neq i} \frac{\widehat{h}_j^{(n)}(\mathbf{b}_i\cdot\mathbf{q}^e)}{1-\widehat{H}_j^{(n)}(\mathbf{b}_i\cdot\mathbf{q}^e)}\right)^{-1}$.

6.2 Estimating Adaptation Costs

Next, we turn to the problem of estimating the adaptation costs. As demonstrated in section 5, the engineering cost estimate, $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$, is an excellent predictor of the bids. Therefore, we assume that a firm i's cost is a variant of the engineer's cost estimate with the following multiplicative structure:

$$\theta_i^{(n)} = \mathbf{c}_i^{(n)} \cdot \mathbf{q}^{a,(n)} \equiv \overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}(1+\widetilde{c}_i^{(n)}). \tag{13}$$

That is, *actual* total costs for firm i are a deviation from the engineer's cost estimate represented as a random variable $\widetilde{c}_i^{(n)}$ times the engineering estimate $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$. The assumption in (13) is similar to the multiplicative structure used in Krasnokutskaya (2004) and the location-scale models considered in Hong and Shum (2001) and Bajari and Hortacsu (2003). A similar assumption is also implicit in Hendricks, Pinkse and Porter (2003) where the authors normalize lots by tract size. We assume that $\widetilde{c}_i^{(n)}$ are iid.

By substituting (13) into (7), dividing by $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$, explicitly writing out K from (1) and rearranging terms we can write

$$\begin{aligned}\frac{\theta_i^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \quad = \quad & \frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}}\left(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{a,(n)} - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} q_t^{a,(n)} \left(\sum_{j\neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1-H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}\right)^{-1}\right) \\ & + \frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}}\left[(1-\tau^{A+})A_+^{(n)} + (1+\tau^{A-})A_-^{(n)} + (1-\tau^X)X^{(n)} + (1+\tau^D)D^{(n)}\right] \\ & - \frac{\sigma}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}}\left[P(\mathbf{b}^{i(n)}) - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} \frac{\partial P(\mathbf{b}^{i(n)})}{\partial b_t^i} \left(\sum_{j\neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1-H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}\right)^{-1}\right]\end{aligned} \tag{14}$$

Notice that aside from the adaptation costs parameters given by the τ's we introduce the coefficient σ for the part of the first order mark-up condition that includes the penalty from skewing.

To complete our structural empirical model we also include two additional sources of error in equation (14). The first is an expectational error which results from bidders not having perfect foresight about $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$. However, if bidders are risk neutral and have *rational expectations*, then the first order condition simply needs to be modified to include $EA_+^{(n)}, EA_-^{(n)}$, $EX^{(n)}$, and $ED^{(n)}$, the expected value of changes, instead of the actual values.

In our data, we do not directly observe bidders' expectations. However, we will use well known strategies from the estimation of Euler Equations (described below) to estimate the model. The expectational error is given by

$$\begin{aligned}\omega^{(n)} &= (1-\tau^{A_+})\left(A_+^{(n)} - EA_+^{(n)}\right) + (1+\tau^{A_-})\left(A_-^{(n)} - EA_-^{(n)}\right) \\ &\quad +(1-\tau^{X})\left(X^{(n)} - EX^{(n)}\right) + (1+\tau^{D})(D^{(n)} - ED^{(n)})\end{aligned}$$

A second source of error is that $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$ may be endogenous because there are omitted costs that are observed by the firms, but not accounted for in our cost estimate $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$. These costs may be correlated with $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$ since projects with large ex post changes are likely to be more complicated and more expensive to complete. To fix ideas imagine that for very complex projects there will be serious delays and difficulties that will increase the costs of production. If these delays are a source of deductions then the increased bids due to deductions may actually be a consequence of the increased production costs. We will denote these increased unobserved costs as $\xi^{(n)}$.

We will use an IV approach to correct for this possible endogeneity of $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$. To do this we need to find an exogenous variable that should affect the magnitude of ex post payment changes but not the unobserved project specific additional costs $\xi^{(n)}$. In our data we observe the identity of the Caltrans project engineer who supervised the project (i.e., the project manager). While Caltrans highway contracts have numerous clauses devoted to changes, contractual incompleteness implies that project engineers have considerable discretion over the scope of changes and deductions, and the process through which these changes are governed. It is well known in the industry that there is considerable heterogeneity in a given engineer's propensity to make changes to the contract or impose deductions. Like in many fields, some engineers are naturally adept at dealing with difficult situations and solving disputes while others are not. Some project engineers are harder to work with due to their propensity to impose deductions and adjustments, causing disruptions to the efficient flow of work and imposing undesirable renegotiation costs, and this is known to industry participants. Thus, the identity of the engineer will shift the distribution of ex post changes to the contract, *independent* of the specific contract characteristics.

In order for the identity of the engineer to be a valid instrument, it must satisfy two conditions: (i) first it must be correlated with our endogenous variables (changes to payments) and (ii) it must be uncorrelated with the error term. Condition (i) is fairly easy to verify. A regression of $A_{+}^{(n)}, A_{-}^{(n)}, X^{(n)}$ and $D^{(n)}$ on a full set of dummy variables for the engineer is highly significant, and the identities explain 30 to 40 percent of the variation in these variables. This is robust to changes in specification of the model, such as normalizing the changes by the engineer's cost estimate, including additional covariates and restricting attention to engineers who appear many times in our sample.

Condition (ii) is not possible to verify directly since it is an identifying assumption. However, it seems that to a first approximation it is plausible. Recall that a component of the error term is the set of expectational errors. By definition, expectational errors must be uncorrelated with the identity of the engineer if the engineer is known at time bidding occurs (which is typically the case). In fact, any variable known at the time of bidding is a valid instrument, as in rational expectations econometrics (see Hansen and Singleton (1982)). The intuition is simple: nothing known at the time of bidding can be correlated with the forecast error of payoff relevant variables.

In practice, the following sequence of events takes place. First, the CalTrans engineering staff draws a set of plans and specifications for a given highway project. Second, the project is publicly advertised and the plans, specifications and other bidding documents are made available to potential bidders. The plans and specifications will include the location of the project. The location of the project allows the contractor to determine the district office from which the engineer will be assigned. There are a handful of engineers at a given district office and they are matched to projects based upon their expertise and availability. The contractor will be able to form a reasonably accurate forecast about the identity of the engineer at this point. Third, the bids are submitted and finally, work begins and changes to the project are made based upon work progress and site conditions. We also estimated the model with additional instruments (e.g. contemporaneous cost shifters such as fuel prices at the time of bidding) with similar results.

Identification also requires that our instrument is mean independent of $\xi^{(n)}$. We argue that this assumption is reasonable for several reasons. First, one might be worried that project engineers predisposed to change the contract are assigned in a nonrandom way to more or less complicated projects. In our data, however, we find that the best predictor of the assignment of a project engineer to a contract is which of the 12 district offices the engineer works at. In the data, 98 percent of the engineers work in a single district. However, district dummies do not predict $A_{+}^{(n)}, A_{-}^{(n)}, X^{(n)}$ and $D^{(n)}$. All districts apparently have, on average, a similar share of projects that experience large changes. Since there is a scarce supply of engineers in any given district, and each engineer's capacity to take on projects is limited, this will generate some exogeneity in how engineers are assigned to projects with many changes.

Another (informal) test of nonrandom assignment is to regress measures of project engineer experience on ex post changes. In our data, we observe how many projects are assigned to a particular engineer, which we interpret as a proxy for experience or productivity. We regress this variable on $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$. Nonrandom assignment would imply that these more experienced engineers are assigned to projects with more changes. However, the R^2 this regression was less than 0.02.

Given these our two additional sources of error, $\xi^{(n)}$ and expectational errors, we can rewrite (14) as:

$$
\begin{aligned}
&\frac{\theta_i^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} - \frac{\xi^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} + \frac{\omega^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} = \qquad (15)\\
&\frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{a,(n)} - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} q_t^{a,(n)} \left(\sum_{j \neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1 - H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})} \right)^{-1} \right) \\
&+ \frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left[(1 - \tau^{A+}) A_+^{(n)} + (1 + \tau^{A-}) A_-^{(n)} + (1 - \tau^X) X^{(n)} + (1 + \tau^D) D^{(n)} \right] \\
&- \frac{\sigma}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left[P(\mathbf{b}^{i(n)}) - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} \frac{\partial P(\mathbf{b}^{i(n)})}{\partial b_t^i} \left(\sum_{j \neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1 - H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})} \right)^{-1} \right]
\end{aligned}
$$

Equation (15) is identical to (14) except that we have brought over two additional sources of error to the left hand side. We will define $\widetilde{e}_i^{(n)}$ as:

$$
\widetilde{e}_i^{(n)}(\sigma, \tau^{A+}, \tau^{A-}, \tau^D, \tau^X, h, H) \equiv \frac{\theta_i^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} - \frac{\xi^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} + \frac{\omega^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}}
$$

We will use (15) to form the moment condition below:[25]

$$
m_N(\sigma, \tau^{A+}, \tau^{A-}, \tau^D, \tau^X, h, H) = \frac{1}{N} \sum_n \sum_i \widetilde{e}_i^{(n)}(\sigma, \tau^{A+}, \tau^{A-}, \tau^D, \tau^X, h, H)(z_i^{(n)} - \overline{z}_i^{(n)})
$$

where $z_i^{(n)}$ is the value of the instrument for bidder i in auction n.[26] We will also include the engineer's cost estimate as an instrument since it is a natural shifter of the bidding strategies and thus correlated with the right hand side variables in (15). We index the moment condition by N to emphasize that the

[25] This follows from the moment condition that $\widetilde{e}_i^{(n)}$ and $z_i^{(n)}$ have a covariance of zero.

[26] Obviously, we can only use engineers who supervise more than one project as an instrument.

asymptotics of our problem depend on the number of auctions in our sample growing large.

Let $\widehat{h}$ and $\widehat{H}$ denote a first stage estimate of the bid densities and distributions. Let W be a positive semi-definite weight matrix. We use the following GMM estimator:

$$\left(\widehat{\sigma}, \widehat{\tau^{A+}}, \widehat{\tau^{A-}}, \widehat{\tau^{D}}, \widehat{\tau^{X}}\right) = \arg\min m_N(\sigma, \tau^{A+}, \tau^{A-}, \tau^{D}, \tau^{X}, \widehat{h}, \widehat{H})' W m_N(\sigma, \tau^{A+}, \tau^{A-}, \tau^{D}, \tau^{X}, \widehat{h}, \widehat{H})$$

Newey (1994) demonstrates that under suitable regularity conditions this estimator has normal asymptotics despite depending on a nonparametric first stage. Furthermore, the asymptotic variance surprisingly does not depend on how the nonparametric first stage is conducted, as long as it is consistent. The optimal weighting matrix can be calculated by using the inverse of the sample variance of $m_N(\sigma, \tau^{A+}, \tau^{A-}, \tau^{D}, \tau^{X}, \widehat{h}, \widehat{H})$ at a first stage estimate. In our application, the first stage estimates of $\widehat{h}$ and $\widehat{H}$ are quite precise given our regression coefficients since there are over 1900 individual bids. Therefore, it is quite unlikely that our first stage bid density and distribution estimates introduce significant bias into the estimates.[27]

Notice, however, that to estimate $\left(\widehat{\sigma}, \widehat{\tau^{A+}}, \widehat{\tau^{A-}}, \widehat{\tau^{D}}, \widehat{\tau^{X}}\right)$ we need to specify a skewing penalty function $P(\mathbf{b}^i)$. We use a particular functional form that is a convenient special case of the conditions we imposed on $P(\mathbf{b}^i)$ as follows,[28]

$$P(\mathbf{b}^i|\overline{\mathbf{b}}) = \sigma \sum_{t=1}^{T} \left(b_t^i - \overline{b}_t\right)^2 \left| \frac{q_t^e - q_t^a}{q_t^e} \right| \; . \tag{16}$$

The idea behind our choice is that the penalty increases for bids that are further away from the benchmark engineering estimate, and these get more weight if the actual quantity is further away from the estimated one. While in principal we could consider a more flexible penalty function for unbalancing, the number of observations will limit the number of parameters we can include in this term.

[27] Admittedly, we potentially introduce a bias into our estimates through the inclusion of auction specific fixed effects. The inclusion of the fixed effects may introduce a nuisance parameter problem into our estimates. However, the strategies proposed in the literature for dealing with unobserved heterogeneity (e.g. Krasnokutskaya (2004)) are not straightforward to apply to our more complicated framework. We found the estimates that controlled for unobserved heterogeneity lead to lower implied markups than estimates without fixed effects, consistent with the biases found in Krasnokutskaya (2004). Despite their limitations, we find the fixed effect estimates more plausible. We also found that random effects generated similar results.

[28] Strictly speaking, this does not guarantee that $\left.\frac{\partial P(\mathbf{b}^i|\overline{\mathbf{b}})}{\partial b_t^i}\right|_{b_t^i=0}$ is very large, but we still assume that an interior solution exists. The estimates act as a reasonable reality check.

This, together with our objective of keeping the structure of the model as close to the standard literature as possible, is why we introduce this fairly parsimonious specification.

Given estimates $\left(\widehat{\sigma}, \widehat{\tau^{A_+}}, \widehat{\tau^{A_-}}, \widehat{\tau^{D}}, \widehat{\tau^{X}}\right)$, we can recover an estimate of the contractors' implied markups. Using the functional form in (16) we estimate $\widehat{\theta}^i$, contractor i's total cost for installing the actual quantities by evaluating the empirical analogue of (7):

$$\begin{aligned}\left(\mathbf{b}^{i,(n)} - \widehat{\mathbf{c}}^{i,(n)}\right) \cdot \mathbf{q}^{a,(n)} = & \frac{q_t^{a,(n)} - 2\widehat{\sigma}\left(b_t^{i,(n)} - \overline{b}_t\right)\left|\frac{q_t^{a,(n)} - q_t^{e,(n)}}{q_t^{e,(n)}}\right|}{q_t^{e,(n)}} \left(\sum_{j \neq i} \frac{\hat{h}_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1 - \hat{H}_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}\right)^{-1} \\ & + \widehat{\sigma} \sum_t \left(b_t^{i,(n)} - \overline{b}_t\right)^2 \left|\frac{q_t^{a,(n)} - q_t^{e,(n)}}{q_t^{e,(n)}}\right| \\ & - (1 - \widehat{\tau^{A_+}}) A_+^{(n)} - (1 + \widehat{\tau^{A_-}}) A_-^{(n)} - (1 - \widehat{\tau^{X}}) X^{(n)} - (1 + \widehat{\tau^{D}}) D^{(n)}\end{aligned}$$

Using our estimates of $\widehat{H}$, $\widehat{h}$, $\widehat{\sigma}$, $\widehat{\tau^{A_+}}, \widehat{\tau^{A_-}}, \widehat{\tau^{X}}$ and $\widehat{\tau^{D}}$, it is possible to evaluate the right hand side of the above equation since all of the terms are either data or are parameters that we have already estimated.

6.3 Results

We summarize the structural estimates in Tables 13-16. Table 13 reports the parameter values from our semiparametric GMM estimator. The adaptation cost estimates are similar to the reduced form estimates discussed in Section 5. For instance, the second column of Table 13 implies that every dollar the contractor receives for a positive adjustment generates \$2.66 of adaptation costs. Recall that our results control for the quantities that were actually installed by the contractor, $\overline{\mathbf{b}} \cdot \mathbf{q}^a$. Moreover, as we described in the previous section, we have instrumented for the endogeneity of positive adjustments to account for a possible bias from omitted cost variables. Therefore, we argue that this estimate reflects adaptation costs instead of omitted costs $\xi^{(n)}$. It is worth noting that our reduced form estimate from Table 11 columns V and VI were \$2.72 and \$2.89 for this parameter, which is remarkably close.

Our other parameter estimates are also consistent with the presence of significant adaptation costs, and result in estimates that are similar to our initial reduced form estimates. A dollar of deductions generates \$8.71 in adaptation costs (\$6.36 in the reduced form) and a dollar of negative adjustments generates \$12.07 in adaptation costs. This last parameter is quite different from what we obtained in the reduced form estimates. That said, the average negative adjustments in our sample is only about \$3149 and the average negative deduction is \$9,714. Therefore, while the marginal effect of these variables are quite large, their total contribution to project costs is modest. The engineering staff at Caltrans would have an incentive to economize on negative adjustments and deductions if they believed these variables generate large adaptation costs as our estimates suggest.

The estimated value of the skewing parameter, σ is -2.2535E-06. This estimate is statistically significant and different from the sign predicted by our theoretical model. However, it is extremely small in monetary terms and has no appreciable impact on profits or overall costs. The result that there are small penalties from skewing is quite robust to alternative specifications for the functional form of the skewing penalty penalty. However, recall from Section 4 that positive and negative adjustments are essentially due to renegotiating unit prices. As an empirical matter, it may be difficult to separately identify a quadratic effect of overruns and under-runs, as captured in σ, from the linear effect captured in τ^{A_+} and τ^{A_-}.

In Tables 14a and 14b, we summarize our estimates of bidders markups. Our results suggest that the industry is quite competitive. The median profit margin is 3.6 percent for all bids and 11.9 percent for winning bids. We note that Granite Construction Inc. the largest bidder in our data is a publicly traded company and reports a net profit margin of 2.91 percent. The construction industry average according Standard and Poors is 1.9 percent. Profit margins based on SEC filings and our conception of profits differ in many respects. However, the available direct evidence on profit margins suggests that the construction industry is quite competitive and our results are consistent with this evidence.

As Tables 14a and 14b demonstrate, markups over direct costs $\left(\mathbf{b}^i - \mathbf{c}^i\right) \cdot \mathbf{q}^a$ are considerably higher than the profit margin. This is because our analysis distinguished between the *direct costs* of completing the project *without adaptation costs* and the added adaptation costs. The median markup over direct costs, $\left(\mathbf{b}^i - \mathbf{c}^i\right) \cdot \mathbf{q}^a$ is \$254,311 for all bids and \$491,083 for winning bids. The ratio of the markup over direct costs to the cost estimate for the median job is 18.1 percent for all bids and 29.2 percent for winning bids.

In Table 15, we compare the estimates in Table 14 with the estimated markups found using more standard methods that ignore the ex post changes to quantities and payments. Using our first stage estimates of $\hat{H}_j(\mathbf{b}_i \cdot \mathbf{q}^e)$ and $\hat{h}_j(\mathbf{b}_i \cdot \mathbf{q}^e)$, we evaluate the empirical analogue of equation (8), which is essentially the estimator discussed in Guerre, Perrigne and Vuong (2000). Equation (8) is a special case of our model in which we assume that $\mathbf{q}^a = \mathbf{q}^e$ and that that ex post changes can be excluded from the first order conditions. Previous empirical structural models of first price procurement auctions make these assumptions. These results, summarized in Table 15, look similar to the total markups reported in the last two columns of Table 14a and 14b. The median total markup is $224,788, or 12.1% of the estimate for winning bidders.

This is almost exactly the median profit margin estimated in Table 14. By comparing the first order conditions of the two models, this should not be surprising. The only difference in the *net profit margin* under the two approaches should come from the skewing penalty and the discrepancies between estimated and actual item quantities. Ex post changes will shift the bid, changing what we refer to as the direct markup, but do not alter the contractors' net profit margins. This is an important observation to the extent that it is a consequence of the "pass through" of costs: the profit margins over total costs are practically the same in both empirical models. However, our approach distinguishes the direct costs from the adaptation costs that follow from incompletely specified contracts. Our results therefore suggest that the standard first order condition used in previous empirical studies is misspecified because it does not account for ex post changes. In our application, failing to account for contract adaptations leads to estimates with a very different economic interpretation, and as discussed below, with very different policy implications.

7 Discussion

7.1 Lessons for Government Procurement

Our analysis offers some perhaps surprising lessons for the design of these highway procurement auctions. The first is that the existing system seems to do a good job of limiting rents and promoting competition in that the *total* markup is fairly modest. The median bidder in our sample of 1938 bids priced contract items so that, if he did win the project, he could expect a profit of $52,127, or 3.6% of the estimate. More interesting, though, is how firms make such a markup. Item-level reduced form regressions suggested that firms shade their bids upward slightly when they expect a particular item to run over. Yet, there is another reason for them to raise their unit price and overall bids when contracts are incomplete. Because they expect to be penalized with deductions and downward adjustments in compensation, and because adaptation costs erode more than any positive gains through change orders, they skew their bids upward to extract high rents on prespecified project items. Among winning bidders, the median value of this direct markup, $(\mathbf{b}_i - \mathbf{c}_i) \cdot \mathbf{q}^a$, is 29.2 percent of the project estimate.

Second, our estimates imply that adaptation costs are important. The implied adaptation costs on the different changes to final payment range from two dollars to over ten dollars for every dollar in change. When considering the amount of money awarded and deducted after the initial contract is signed, these costs are significant by any standard. Table 16 reports a lower and an upper bound for the adaptation costs on each project. These bounds are determined based on the possible margins that firms may collect on extra work through change orders. The lower bound is calculated as $2.6602A_+$ $+12.0712|A_-| + 1.5216X + 8.7111|D|$ and the upper bound is calculated as $2.6602A_+$ $+12.0712|A_-| + 2.5216X + 8.7111|D|$. The upper and lower bound differ by the coefficient on extra work, X. Suppose that the contractor was able to earn a profit margin from renegotiating changes as reflected in X. Our upper bound on profits from renegotiating the contract was \$1 for every \$1 of changes in scope. This implies that the adaptation costs of X were $2.5216X$ because firms receive an extra dollar of profits for every extra dollar in X.[29] The median estimate of adaptation costs is a significant component of costs by any standard. It has a lower bound of 14.6 (8.3, 20.9) percent of the estimate and an upper bound of 18.1 (12.4, 23.9) percent of the estimate. We conclude that adaptation costs account for a significant portion of total project costs.

These numbers might be surprising in the context of the existing economics literature which has emphasized private information and moral hazard as the main sources of departures from efficiency in procurement. However, this result is consistent with current thinking in Construction and Engineering Project Management. (See Bartholomew (1998), Clough and Sears (1994), Hinze (1993) and Sweet (1994). Also see Bajari and Tadelis (2001) for a more complete set of references and discussion of the literature). One of the central concerns emphasized in this literature are methods for minimizing the costs of disputes between contractors and buyers. The topic of controlling contractor margins by comparison receives relatively little emphasis in this literature.

Summing over all 414 projects in our data, the lower bound suggests that Caltrans spent \$189 million on adaptation costs in 1999 and 2000. The average

[29] Industry sources suggest that a twenty percent profit margin on change orders is most common. It is helpful to recall that our cost estimate controls for the quantities actually installed and that positive and negative adjustments are effectively changes to compensation from the unit prices. Hence, these are a pure transfer and do not involve additional costs that we have not controlled for in our cost estimate.

ratio of the adaptation costs to the winning bid is 0.1048. Even half of this number would be substantial. An implication of equation (7) is that Caltrans, and hence the taxpayer, is ultimately responsible for expected adaptation costs on the project as they are directly passed on from the bidders. Since the source of these costs is the incompleteness of project design and specifications, one policy implication is to consider increasing the costs and efforts put in to estimating and specifying projects before they are let out for bidding. Clearly, our estimates do not allow us to speculate on the costs and benefits of adding more engineering efforts ex ante. However, since the magnitude of our adaptation costs sizeable, there may be room to consider some experimentation with more careful and costly design efforts, and to carefully examine the results of any such added effort in ex ante engineering.

In Bajari, McMillan and Tadelis (2006), we study how private sector, non-residential building construction contracts are awarded in Northern California between 1995 and 2000. In the private sector, unlike the public sector, buyers can more easily use mechanisms other than competitive bidding to select a contractor. We find that open competitive bidding is only used in 18 percent of the contracts and that 44 percent of the contracts are negotiated. Also, Negotiated contracts are more commonly used for projects that ex ante appear to be the most complex and likely to change plans and specifications ex post.

A perceived advantage of negotiated contracts is that they allow the architect, buyer and contractor to discuss the project plans before construction begins. Thus, the contractor can point out pitfalls and suggest modifications to the project design before work begins. In negotiated contracts, some form of cost plus contracting is often used. As we discuss in Bajari and Tadelis (2001), cost plus contracts have poor incentives for contractors to control overall project costs. However, they are simpler to renegotiate since when changes occur, the contractor presents his receipts for the additional expenses and is reimbursed this amount. Thus, the often acrimonious process of writing change orders to the contract is avoided. Negotiated contracts may be less effective in selecting the lowest cost bidder compared to open competitive bidding. However, the results of this paper suggest that economizing on ex post transaction costs is an important potential source of cost savings and this may outweigh the benefits of competitive bidding in selecting the lowest cost contractor.

In the public sector, the use of negotiated contracts is problematic. Allowing for greater discretion in contractor selection increases the possibility for favoritism, kick backs and political corruption. The competitive bidding system is less prone to corruption since it allows for free entry by qualified bidders and there is an objective criteria for selecting the winning bidder. An important policy issue is whether it is possible to construct a mechanism that minimizes the ex post cost of making changes and the potential for corruption. To the best of our knowledge, this question has not been explored in the existing theoretical literature. Our research suggests that developing such a mechanism could improve efficiency in public sector procurement.

7.2 Concluding Remarks

Most of the existing literature on procurement is focused on designing a contract or auction that minimizes contractors' informational rents while giving appropriate incentives to minimize moral hazard. Taken literally, in this industry, our analysis suggests that a perhaps more important problem is to limit adaptation costs. These results are consistent with Bajari and Tadelis (2001) and Bajari, McMillan and Tadelis (2004) where we argued, heavily citing industry sources, that adaptation costs are a key determinant of contract form and award mechanism in private sector construction. We noted that in the private sector, open competitive bidding for fixed price contracts is only infrequently used because it is perceived to create large and inefficient levels of adaptation costs. We interpret our finding as further empirical evidence that adaptation costs are one of the leading disadvantages of the traditional competitive bidding system.

To the best of our knowledge, this is the first paper to use a structural model to recover estimates of adaptation costs, and our results suggest that these adaptation costs are an important determinant of observed bidding behavior. Therefore, structural models that fail to account for these costs might generate considerable biases in parameter estimates and estimated direct cost margins. Finally, our results suggest that commonly used reduced form bid functions are misspecified and thus biased when changes occur. The reduced form bid functions must control for ex post changes to the contract and the dependent variable should be the total bid using the actual quantities as weights.

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Table 1: Identities of Top 25 Firms

Firm ID	Firm Name	Market Share	Firm ID	Firm Name	Market Share
104	Granite Construction Company	27.2%	82	Excel Paving Company	1.5%
75	E L Yeager Construction Co Inc	10.4%	186	Pavex Construction	1.3%
135	Kiewit Pacific Co	6.6%	184	Parnum Paving Inc	1.2%
147	M C M Construction Inc	6.5%	23	Baldwin Contracting Company Inc	1.1%
125	J F Shea Co Inc	3.3%	162	Mercer Fraser Company	1.0%
244	Teichert Construction	3.3%	248	Tidewater Contractors Inc	1.0%
262	W Jaxon Baker Inc	2.9%	22	B E C Construction Co	0.9%
12	All American Asphalt	2.2%	126	J McLoughlin Engineering Co Inc	0.8%
251	Tullis And Heller Inc	2.1%	88	Ford Construction Co Inc	0.8%
237	Sully Miller Contracting Co	1.9%	96	George Reed Inc	0.7%
265	West Coast Bridge Inc	1.9%	87	FNF Construction	0.7%
25	Banshee Construction Co Inc	1.8%	253	Union Asphalt Inc	0.7%
107	Griffith Company	1.6%		**TOTAL**	**83.6%**

There were a total of 125 active bidders for asphalt concrete construction contracts in 1999. The firms listed above are the top 25 firms, ranked according to their market share, i.e. the share of total contract dollars awarded.

Table 2: Bidding Activities of Top 25 Firms

ID	No. of Wins	Total Bid for Contracts Awarded	Final Payments on Contracts Awarded	No. of Bids Entered	Participation Rate	Conditional on Bidding for a Contract			
						Average Bid	Average Engineer's Estimate	Average Distance (Miles)	Average Time to Job Site (Min)
104	76	343,987,526	378,629,804	244	58.9%	3,966,908	3,928,872	36.6	47.4
75	13	132,790,460	144,975,251	31	7.5%	8,607,538	8,610,249	61.0	70.6
135	5	112,057,627	92,031,048	30	7.2%	15,254,801	14,798,046	151.5	158.9
147	2	89,344,972	90,384,704	6	1.4%	21,952,372	22,397,538	72.6	77.8
125	9	43,030,861	46,506,051	40	9.7%	3,710,768	3,512,680	91.3	108.4
244	16	40,177,076	45,533,624	43	10.4%	3,104,075	2,915,690	40.6	52.3
262	13	37,702,631	40,808,024	65	15.7%	3,236,153	3,293,634	141.8	170.0
12	14	30,764,962	30,726,217	33	8.0%	2,425,688	2,429,789	24.0	29.7
251	10	27,809,535	28,651,380	16	3.9%	2,406,761	2,612,752	32.2	38.9
237	17	27,889,186	27,025,850	49	11.8%	2,389,932	2,386,667	54.4	59.9
265	4	26,786,493	26,426,965	9	2.2%	7,283,186	7,406,581	234.5	214.4
25	2	23,118,363	24,624,599	7	1.7%	5,448,318	5,467,099	40.4	43.3
107	8	21,981,980	22,706,554	26	6.3%	3,524,629	3,758,627	36.1	42.6
82	3	17,763,635	20,315,232	33	8.0%	2,045,813	1,907,715	24.2	28.7
186	7	17,160,757	18,050,388	22	5.3%	1,809,050	1,719,094	25.2	28.7
184	12	14,997,849	17,196,784	25	6.0%	1,780,978	1,869,706	84.6	106.9
23	5	14,178,601	15,726,516	21	5.1%	2,927,704	2,746,659	47.3	63.7
162	8	12,379,191	13,483,870	17	4.1%	1,557,772	1,570,402	37.0	47.5
248	3	11,256,234	13,258,546	3	0.7%	3,752,078	4,588,278	10.0	14.0
22	7	11,855,713	12,664,796	10	2.4%	2,333,166	2,215,831	98.7	128.1
126	2	11,258,867	11,390,486	18	4.3%	1,765,946	1,801,236	56.1	55.4
88	1	9,674,380	10,711,489	2	0.5%	8,567,932	8,500,931	87.5	102.5
96	6	9,244,215	10,290,260	18	4.3%	1,572,904	1,551,537	33.5	52.7
87	1	10,498,536	10,153,836	13	3.1%	12,431,695	12,434,916	388.2	380.9
253	6	9,042,273	9,394,612	12	2.9%	2,279,318	2,466,966	38.8	46.1

Table 3: Comparison Between Fringe Firms and Firms with Over 1% Market Share

	Fringe Firms	Non-Fringe Firms
Number of Firms	254	17
Number of Wins	198	216
Number of Bids Submitted	1238	700
Average Bid Submitted	$ 3,389,984.75	$ 5,404,392.50
Average Distance to Job Site (miles)	79.0	70.5
Average Travel Time to Job Site (minutes)	87.5	79.0
Average Capacity	$ 949,141.10	$ 33,243,336.00
Average Backlog at Time of Bid	$ 126,114.10	$ 7,725,654.00

The above averages were calculated by first calculating the average for each bidder, then averaging these means over the fringe and non-fringe firms, respectively.

Table 4: Distance to Job Site (in miles)

	Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
DIST1	47.47	60.19	0.27	413.18	DIST6	88.21	115.84	0.74	695.43
DIST2	73.55	100.38	0.19	679.14	DIST7	88.46	119.97	0.85	570.27
DIST3	75.47	95.56	0.13	594.16	DIST8	73.91	75.85	4.47	259.09
DIST4	84.38	89.87	1.45	494.08	DIST9	105.86	104.31	3.41	495.67
DIST5	76.12	86.33	1.25	513.31	DIST10	69.72	80.20	7.35	294.97

DIST1 is the distance of the lowest bidder, DIST2 is the distance of the second lowest bidder, and so on.

Table 5: Travel Time to Job Site (in minutes)

	Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
TIME1	56.95	64.28	1.00	411.00	TIME6	97.28	119.61	2.00	767.00
TIME2	82.51	97.51	1.00	614.00	TIME7	97.30	119.11	1.00	530.00
TIME3	85.86	97.44	0.00	580.00	TIME8	85.81	79.78	8.00	267.00
TIME4	94.04	89.82	4.00	449.00	TIME9	117.42	105.33	7.00	509.00
TIME5	85.92	85.39	5.00	458.00	TIME10	81.56	80.97	12.00	287.00

TIME1 is the distance of the lowest bidder, TIME2 is the distance of the second lowest bidder, and so on.

Table 6: Bid Concentration Among Contracts Awarded to Lowest Bidder

Number of Bidders	2	3	4	5	6	7	8	9	10	11+	Total
Contracts in 1999	21	47	36	30	11	8	4	2	3	0	162
Contracts in 2000	31	46	49	43	31	19	8	12	6	7	252

Table 7: Project Distribution throughout the Year

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Contracts in 1999	13	11	19	12	18	18	24	20	13	4	8	2
Contracts in 2000	12	14	23	36	16	26	10	39	25	22	20	9

Table 8: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Across Contracts Under Consideration					
Winning Bid	414	3,203,130	7,384,337	70,723	86,396,096
Markup: (Winning Bid-Estimate)/Estimate	414	-0.0617	0.1763	-0.6166	0.7851
Normalized Bid: Winning Bid/Estimate	414	0.9383	0.1763	0.3834	1.7851
Second Lowest Bid	414	3,394,646	7,793,310	84,572	92,395,000
Money on the Table: Second Bid-First Bid	414	191,516	477,578	68	5,998,904
Normalized Money on the Table: (Second Bid-First Bid)/Estimate	414	0.0679	0.0596	0.0002	0.3476
Number of Bidders	414	4.68	2.30	2	19
Distance of the Winning Bidder	414	47.47	60.19	0.27	413.18
Travel Time of the Winning Bidder	414	56.95	64.28	1.00	411.00
Utilization Rate of the Winning Bidder	414	0.1206	0.1951	0.0000	0.9457
Distance of the Second Lowest Bidder	414	73.55	100.38	0.19	679.14
Travel Time of the Second Lowest Bidder	414	82.51	97.51	1.00	614.00
Utilization Rate of the Second Lowest Bidder	414	0.1401	0.2337	0.000	0.9959
Across Bids Submitted					
Normalized Bid	1938	1.0474	0.2685	0.3834	7.8611
Distance to Job Site	1938	72.37	91.93	0.13	695.43
Travel Time to Job Site	1938	81.93	92.29	0.00	767.00
Backlog at Time of Bid	1938	5,453,880	16,433,078	0.00	1.503e+08
Capacity	1938	25,590,740	49,856,236	0.00	1.510e+08
Utilization (Backlog/Capacity)	1938	0.1221	0.2266	0.0000	0.9965
Minimal Distance Among Rivals	1938	26.70	36.60	0.13	618.62
Minimal Travel Time Among Rivals	1938	35.15	41.98	0.00	592.00
Minimal Utilization Among Rivals	1938	0.0226	0.0894	0.0000	0.9806

Table 9: Importance of Ex-Post Changes

	Obs	Mean	Std. Dev.	Min	Max
Adjustments	414	135,032	681,068	-178,183	12,142,414
Adjustments / Estimate	414	0.0242	0.0493	-0.2172	0.3962
Extra Work	414	207,476	706,372	0	12,271,703
Extra Work / Estimate	414	0.0628	0.0837	0	0.5960
Deductions	414	-9,715	47,933	-796,071	0
Deduction / Estimate	414	-0.0027	0.0093	-0.0698	0
CCDB Overrun = (ActQ-EstQ)*CCDB price	414	-67,040	502,017	-9,462,806	506,575
CCDB Overrun / Estimate	414	-0.0327	0.3186	-6.3401	0.1610
Final Payment-Winning Bid	414	155,092	1,503,604	-24,111,356	13,747,552
(Final Payment-Winning Bid) / Estimate	414	0.0523	0.1249	-0.6591	0.6530

The CCDB Overrun is meant to reflect the dollar overrun due to quantities that were misestimated during the procurement process. It is only a partial measure of the quantity-related overrun, since some of the nonstandard contract items do not have a corresponding price estimate from the Contract Cost Data Book (CCDB). The engineer's estimate was used to normalize this and the other measures.

Table 10: Skewed Bidding Regressions

Variable	OLS	Item Code Fixed Effects	Item Code Random Effects
Percent unit overrun	0.027 (3.79)	0.029 (5.52)	0.027 (5.37)
Constant	0.999 (161.2)	0.999 (157.1)	0.999 (160.1)
R^2	0.0004	0.0007	0.0004
Number of Obs.	65058	65058	65038

The dependent variable is the unit price bid on each contract item, normalized by the average unit bid. The percent unit overrun is the percent difference between the actual and estimated quantities reported for that item.

Table 11: Standard Bid Function Regressions

Variable	I.	II.	III.	IV.	V.
$DISTANCE_i^{(n)}$	0.0002	0.0002	0.0002	0.0001	0.0002
	(3.22)	(3.09)	(3.85)	(0.73)	(3.01)
$RIVALDIST_i^{(n)}$	-0.0002	-0.0002	-0.0003	-0.0001	-0.0002
	(-1.35)	(-1.78)	(1.99)	(-0.76)	(-1.10)
$UTILIZE_i^{(n)}$		0.036	0.041	0.071	0.038
		(1.31)	(1.61)	(2.51)	(1.52)
$RIVALUTIL_i^{(n)}$		-0.121	-0.032	-0.136	-0.043
		(-2.54)	(-0.64)	(-2.66)	(-0.58)
$FRINGE_i$		0.048	0.037		0.037
		(3.85)	(4.56)		(3.14)
$NUMBIDDERS^{(n)}$		-0.012		-0.013	
		(-6.99)		(5.47)	
Constant	1.04	1.08	1.01	1.11	1.02
	(111.47)	(70.93)	(94.20)	(63.11)	(68.23)
Fixed/Random Effects	No	No	Project FE	Firm FE	Project RE
R^2	0.004	0.022	0.53	0.198	0.007
Number of Obs.	1938	1938	1938	1938	1938

The dependent variable is the total bid divided by the engineer's estimate, where the total bid is the dot product of the estimated quantities and unit prices. Robust standard errors are used to compute t-Statistics, shown in parentheses.

Table 12: Bid Function Regressions Using Actual Quantities Instead of Estimates

Variable	I.	II.	III.	IV.	V.	VI.
$DISTANCE_i^{(n)}$	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002
	(1.52)	(3.00)	(1.67)	(1.11)	(4.19)	(4.19)
$RIVALDIST_i^{(n)}$	0.0006	-0.0004				
	(2.27)	(-2.45)				
$UTILIZE_i^{(n)}$	-0.0059	0.0362				
	(-0.11)	(1.99)				
$RIVALUTIL_i^{(n)}$	0.0888	-0.0459				
	(0.69)	(-0.82)				
$FRINGE_i$	-0.0047	0.031	-0.044	-0.034	0.02657	0.027
	(-0.19)	(3.93)	(-1.98)	(-1.54)	(3.43)	(3.43)
$NUMBIDDERS^{(n)}$	-0.0303					
	(-7.67)					
$PosADJUST^{(n)}$			1.57	1.78	1.72	1.89
			(6.41)	(7.93)	(5.40)	(6.29)
$NegADJUST^{(n)}$			-3.71	-3.76	-6.39	-6.29
			(-7.78)	(-7.74)	(-4.36)	(-4.36)
$EXTRA^{(n)}$			0.96	1.19	1.33	1.49
			(6.12)	(9.64)	(6.16)	(8.15)
$DEDUCT^{(n)}$			-7.36	-7.35	-9.93	-9.63
			(-9.11)	(-9.00)	(-6.48)	(-6.38)
$PCT^{(n)}$ (percent quantity overrun)			0.126		0.103	
			(3.44)		(1.77)	
$NOverrun^{(n)}$ (percent money overrun)				0.905		0.849
				(15.58)		(13.20)
Constant	1.147	0.976	0.892	0.898	0.969	0.969
	(36.51)	(107.1)	(39.1)	(40.5)	(160.4)	(160.4)
Fixed Effects	No	Project FE	No	No	Project FE	Project FE
Instruments					Resident Engineer	Resident Engineer
R^2	0.039	0.93	0.093	0.1357	0.9134	0.9134
Num. of Obs.	1938	1938	1938	1938	1938	1938

The dependent variable is the vector product of the unit price bids and the actual quantities, divided by the project estimate. Robust standard errors are used to compute t-Statistics, shown in parentheses. $NOverrun_{(n)}$ is a measure of the quantity-related overrun on standard contract items (those that have a CCDB unit price estimate). This overrun is calculated as the vector product of the CCDB prices (where available) and the difference between actual and estimated quantities. In the final two columns, the coefficients on $DEDUCT^{(n)}$, $EXTRA^{(n)}$, $PosADJUST^{(n)}$, $NegADJUST^{(n)}$, $PCT^{(n)}$, and $NOverrun^{(n)}$ are found by regressing the fixed effects onto these variables (which are constant within a project). The estimation was also performed using project random effects, but there was little difference in the estimates. Those results are not reported here.

Table 13: Structural Estimation

	Consistent GMM	Efficient GMM	Consistent GMM	Efficient GMM
Parameter Estimates				
PosADJUST$^{(n)}$	-2.88	-1.66	-3.91	-1.72
$(1-\beta_{+})$		(0.494)		(0.49)
NegADJUST$^{(n)}$	3.24	13.07	3.96	13.38
$(1+\beta_{-})$		(3.58)		(3.33)
EXTRA$^{(n)}$	-0.19	-1.52	-0.27	-1.88
$(1-\gamma)$		(0.407)		(0.397)
DEDUCT$^{(n)}$	11.1	9.71	11.97	9.61
$(1+\delta)$		(3.67)		(3.339)
Skewing Parameter				
Σ	-4.16E-06	-2.25E-06	-5.62E-06	-2.35E-06
		(8.01E-07)		(8.57E-07)
Implied Marginal Transaction Costs				
PosADJUST$^{(n)}$	3.88	2.66	4.91	2.72
		[1.69, 3.63]		[1.76, 3.68]
NegADJUST$^{(n)}$	2.24	12.07	2.96	12.38
		[5.05, 19.09]		[5.85, 18.91]
EXTRA$^{(n)}$ **	1.19	2.52	1.27	2.88
		[1.72, 3.32]		[2.10, 3.66]
DEDUCT$^{(n)}$	10.10	8.71	10.97	8.61
		[1.52, 15.90]		[2.07, 15.16]
Number of Obs	1938	1938	1938	1938
Instruments Used in Second Stage GMM	Resident Engineer	Resident Engineer	Resident Engineer, Engineer's Estimate	Resident Engineer, Engineer's Estimate

** These estimates represent an upper bound on transaction costs associated with changes in scope. They do not account for marginal costs associated with performing the extra work, which for a reasonable profit margin of 20 percent would lower our estimate by $0.80.

Consistent GMM estimates were computed using the identity matrix as the weighting matrix. In a second step, efficient GMM estimates were computed using the optimal weighting matrix derived from the variance of the sample moments in the first step. Standard errors were computed for the efficient estimator, and they appear in parentheses. These were also used to derive 95% confidence intervals (in brackets) for the implied transaction costs.

Table 14a: Markup Decomposition (All Bidders)

Percentile	Direct Markup $(b_i-c_i)q^a$	Direct Markup Estimate	Ex-Post Changes $A+X+D-TC(A_+,A_-,X,D)$	Ex-Post Changes Estimate	Skewing Penalty $\alpha \cdot \sum_t [(b_i-b)^2 \lvert\%Over_t\rvert]$	Skewing Penalty Estimate	Total Profit π	Total Profit Estimate
10	26,080	5.8%	-1,250,830	-40.6%	-135.16	-0.0088%	6,176	1.3%
20	54,117	9.1%	-647,812	-28.1%	-18.63	-0.0012%	11,392	1.8%
30	101,028	11.9%	-383,068	-20.7%	-6.24	-0.0003%	18,966	2.2%
40	175,646	14.1%	-230,172	-16.4%	-1.89	-0.0001%	31,073	2.8%
50	254,311	18.1%	-178,137	-11.4%	-0.60	0.0000%	52,127	3.6%
60	374,272	22.9%	-105,839	-9.6%	-0.21	0.0000%	82,845	4.6%
70	556,655	28.5%	-55,993	-7.4%	-0.08	0.0000%	131,306	6.0%
80	961,665	38.1%	-28,053	-4.6%	-0.02	0.0000%	227,667	8.7%
90	1,870,754	55.8%	-11,860	-2.2%	0.00	0.0000%	487,750	16.2%

Table 14b: Ex-Post Profit Decomposition (All Winning Bidders)

Percentile	Direct Markup $(b_i-c_i)q^a$	Direct Markup Estimate	Ex-Post Changes $A+X+D-TC(A_+,A_-,X,D)$	Ex-Post Changes Estimate	Skewing Penalty $\alpha \cdot \sum_t [(b_i-b)^2 \lvert\%Over_t\rvert]$	Skewing Penalty Estimate	Total Profit π	Total Profit Estimate
10	58,668	12.1%	-1,356,185	-41.5%	-128.89	-0.0068%	32,351	5.4%
20	126,980	15.7%	-771,265	-29.3%	-14.43	-0.0007%	61,427	6.4%
30	230,937	18.6%	-486,765	-21.7%	-4.98	-0.0002%	102,013	7.8%
40	338,568	23.6%	-284,847	-16.7%	-1.47	-0.0001%	154,834	9.8%
50	491,083	29.2%	-193,573	-11.6%	-0.59	0.0000%	225,931	11.9%
60	682,536	35.6%	-132,528	-9.6%	-0.20	0.0000%	295,515	14.8%
70	1,032,579	42.8%	-68,173	-7.2%	-0.09	0.0000%	425,906	20.4%
80	1,462,602	56.2%	-30,032	-4.6%	-0.03	0.0000%	711,475	27.1%
90	2,838,608	89.9%	-13,920	-2.4%	-0.01	0.0000%	1,259,569	50.7%

Table 15: Markups Implied by Standard Model
Without Transaction Costs or Ex-Post Changes

Percentile	All Bidders		Winning Bidders Only	
	Direct Markup $(b_i-c_i)q^a$	Direct Markup Estimate	Direct Markup $(b_i-c_i)q^a$	Direct Markup Estimate
10	6,001	1.3%	35,121	5.3%
20	11,547	1.8%	62,601	6.4%
30	19,067	2.2%	103,610	8.1%
40	30,829	2.8%	153,438	9.9%
50	51,167	3.6%	224,788	12.1%
60	82,976	4.4%	298,660	15.3%
70	132,191	5.9%	419,576	19.7%
80	224,722	8.8%	672,689	27.2%
90	464,602	15.8%	1,143,994	50.7%

Table 16: Transaction Costs

Lower Bound

Percentile	Total Transaction Costs	As a Fraction of the Estimate	As a Fraction of the Estimated Ex-Post Profit
10	13,952	2.5%	12.2%
	[6,624, 21,280]	[1.1%, 4.0%]	[6.0%, 18.3%]
20	32,011	5.3%	28.2%
	[16,076, 47,945]	[2.5%, 8.0%]	[16.0%, 40.5%]
30	74,297	8.1%	45.8%
	[46,029, 102,564]	[3.8%, 12.3%]	[24.5%, 67.1%]
40	142,054	10.6%	69.4%
	[54,049, 230,060]	[4.5%, 16.8%]	[34.1%, 104.7%]
50	215,862	14.6%	102.2%
	[118,958, 312,767]	[8.3%, 20.9%]	[48.5%, 155.8%]
60	348,860	18.7%	144.0%
	[211,132, 486,588]	[10.4%, 26.9%]	[74.2%, 213.9%]
70	589,379	25.3%	211.3%
	[251,585, 927,174]	[14.2%, 36.4%]	[119.6%, 303.1%]
80	919,457	33.0%	296.7%
	[440,170, 1,398,744]	[16.4%, 49.6%]	[140.9%, 452.5%]
90	1,597,358	46.5%	454.1%
	[810,019, 2,384,696]	[29.0%, 64.0%]	[230.3%, 677.9%]

Upper Bound

Percentile	Total Transaction Costs	As a Fraction of the Estimate	As a Fraction of the Estimated Ex-Post Profit
10	21,231	3.8%	18.8%
	[3,716, 38,745]	[2.6%, 5.1%]	[12.8%, 24.7%]
20	48,122	7.4%	37.8%
	[30,602, 65,641]	[5.1%, 9.8%]	[25.8%, 49.8%]
30	102,277	10.3%	66.2%
	[65,848, 138,706]	[6.8%, 13.7%]	[45.0%, 87.3%]
40	184,458	13.7%	92.1%
	[123,341, 245,575]	[9.3%, 18.0%]	[47.8%, 136.4%]
50	303,980	18.1%	138.5%
	[189,191, 418,768]	[12.4%, 23.9%]	[73.6%, 203.4%]
60	435,993	24.9%	184.0%
	[297,375, 574,612]	[16.2%, 33.5%]	[122.2%, 245.9%]
70	676,961	32.5%	266.4%
	[436,210, 917,711]	[14.9%, 50.0%]	[171.6%, 361.1%]
80	1,165,243	42.4%	387.3%
	[731,545, 1,598,940]	[27.1%, 57.6%]	[256.8%, 517.8%]
90	2,024,909	59.6%	587.0%
	[1,321,579, 2,728,239]	[38.2%, 81.1%]	[123.6%, 1050.4%]

The transaction cost is calculated as $2.6602\ (A_+) + 12.0712\ |A_-| + 1.5216\ (X) + 8.7111\ |D|$. We consider this to be a lower bound because it attributes much of the coefficient on extra work to marginal costs of production, rather than pure transaction costs. This amounts to an assumption that firms perform extra work at a zero percent profit margin. Each dollar awarded through a change in scope just covers the cost of performing that work. With $1 of marginal costs for every $1 of extra work, that leaves approximately $1.52 to be explained by transaction costs. The other extreme would be to assume a 100% profit margin on extra work, making it analogous to positive adjustments in compensation. This upper bound is calculated as $2.6602\ (A_+) + 12.0712\ |A_-| + 2.5216\ (X) + 8.7111\ |D|$. 95% confidence intervals, appearing in brackets, were calculated by taking the lower and upper confidence bounds of the parameter estimates and using them in the transaction cost equation instead of the point estimates.