Bidding for Incomplete Contracts: An Empirical Analysis of Adaptation Costs

April 6, 2010

Abstract

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 are an important determinant of their bids. This analysis is reinforced by a structural empirical model, in which we estimate adaptation costs and bidder markups. Our estimates suggest that adaptation costs account for 7-13.4 percent of the winning bid. Profit markups from private information and local market power, the focus in much of the procurement literature, are much smaller by comparison. Implications for government procurement are discussed *JEL* classifications: D23, D82, H57, L14, L22, L74.

Procurement of goods and services is commonly performed using auctions, the benefits of which are well known and vigorously advocated. Competitive bidding results in low prices and sets rules that limit the influence of favoritism. For standard goods, such as pencils, photocopy machines, and book-keeping software, it is straightforward to 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 costly for the buyer to translate operational needs into well defined and communicable specifications. Furthermore, during production 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.

Contractual incompleteness forces the buyer and supplier to agree on negotiated adaptations, both in terms of production specifications and compensation. This may result in considerable discrepancies between the winning bid and the final costs. A well known example is the massive highway artery in Boston, referred to as the "Big Dig". 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]

Adaptation typically results in cost increases of two sorts. First are the direct costs of the additional work. Second, are *adaptation costs*, which are any costs that are incurred above and beyond the direct production costs of the project. Changing the contract disrupts the normal flow of work and increases the effort needed to coordinate workers, subcontractors and material suppliers, effort that could have been avoided 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 contribute by offering 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 of unit-price auctions for highway improvement projects. 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 (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

[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." See http://www.boston.com/news/specials/bechtel/part_1/.

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.

In our model contractors are experienced agents who rationally anticipate these changes and the associated adaptation costs that will be incurred as the project unfolds. When observing the plans and specifications, 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, any changes in payments and the resulting adaptation costs will be incorporated into the bids ex ante, and are passed through back to Caltrans.[2]

We apply the empirical framework of our model to a panel data set of highway contract bids that we have collected from Caltrans. The data includes bidder identities, bids, detailed cost estimates, and measures of cost advantages. The data also contains detailed information on how the initial designs were altered, which is not available in most studies of procurement. In particular, our data includes both *estimated* and *actual* quantities for all work items in the contract, as well as payments to the contractor from changes in scope.

Our empirical analysis begins with reduced form estimates. The strategy for identifying adaptation costs is based on our theoretical model. Suppose that the contractors expect additional payments due to change orders made from altering the contract ex post. Controlling for costs, competition implies that for every extra dollar of profits, each contractor should lower its bid by one dollar. If the regression is correctly specified, the coefficient on ex post additional payments should be -1. We find that some coefficients are closer to $+1$, implying that ex post changes on net generate more costs than revenue. Additional costs from ex post changes are substantial and may account for almost eleven percent of the total bid, even after using detailed cost controls in our bid function regressions.

While this may surprise economists, these concerns are prevalent in the construction management literature (See Hinze (1993), Clough and Sears (1994), Ibbs et. al. (1986) and Sweet (1994)). As described earlier, changing the contract after it is awarded both disrupts the project work flow and adds costs due to ex post bargaining, haggling and lawsuits over the payments made from changing the project's specifications. 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.

To further push the robustness of our results we estimate a structural model that accounts for three sources of markups over production costs. First, markups are a function of private information and local market power. Second, we quantify the importance of

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

incentives to submit "unbalanced" bids. As in Athey and Levin (2001), contractors can increase expected profits by increasing (decreasing) unit prices on items that are expected to overrun (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 mark-up drivers.

As a final check on our results, we search for an exogenous shifter of ex post payments to the contractor. As we explain in sections 5.3 and 6.2, we use the identity of the Caltrans engineer assigned to the project as an instrument for changes since individual engineers have discretion over ex post adjustments. 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 adaptation 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 relates to the procurement literature that considers ex post changes to incomplete contracts. Following Williamson (1971), several studies emphasize the importance of adaptation costs including Crocker and Reynolds (1993), Bajari and Tadelis (2001) and Chakravarty and MacLeod (2009). Our paper also draws from the literature on structural estimation of auctions (See, e.g., Paarsch (1992), Donald and Paarsch (1993), Guerre, Perrigne and Vuong (2000) and Krasnokutskaya (2009).)[3]

Our analysis offers three contributions. First, to the best of our knowledge this is the first paper to recover estimates of adaptation costs. The estimates imply that these 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 components of the markup. This finding is consistent with our reading of the construction management literature 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 markups in standard bidding models are often misspecified because they do not account for the discrepancies between initial bids and final payments, omitting important parts of a contractor's revenues and costs. 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 estimating adaptation costs. While transaction cost economics dates back to the original arguments laid out by Williamson (1971), 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.

[3] Other studies of bidding for highway contracts include Porter and Zona (1993), Hong and Shum (2002), Bajari and Ye (2003), Pesendorfer and Jofre-Bonet (2003) and Krasnokutskaya and Seim (2009).

1 Competitive Bidding for Highway Contracts

Procurement for highway construction, as well as other projects in the public sector, is often done using bidding for unit-price contracts (Hinze (1993), Clough and Sears (1994).) For such contracts, 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 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 interested contractor will propose per unit prices for each work item on the engineer's list. Figure 1 shows an example of the structure of a completed bid, which must be sealed and submitted prior to a set 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 yards)	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 never equal the estimated quantities. Using our example, the estimate predicts that 25,000 tons of asphalt are needed to resurface the stretch of highway, but the actual quantity used will almost certainly be different. 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 it 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. To a first approximation, there are three primary reasons for modifying the payments away from the simple sum of actual unit costs.

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

[4] The lowest 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, bids judged to be highly unbalanced can be rejected, as discussed further below.

renegotiate an *adjustment of compensation*.[5] Using our example, 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, adjustments are recorded as a lump sum change, but one might also think of them as a way for parties to adjust the implied unit price on a particular item.

Second, there may be a *change in scope* of the project in the overall description and design that needs to be completed. For instance, the original scope 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 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 fixing his probability of winning. A bid is referred to as *unbalanced* if it has unusually high unit prices on items that are expected to overrun and unusually low unit prices on items expected to under-run.

Athey and Levin (2001) note that the optimal strategy for a risk neutral contractor is

[5] In the particular case of highway construstion 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.

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. In the data, however, while zero unit price bids have been observed, they are very uncommon. Athey and Levin suggest that risk aversion is one reason why this might occur. After speaking with some highway contractors and reading industry sources we believe that for construction contracts other considerations are more important. In particular, 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.[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.

2 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 empirical models.

2.1 Basic Setup

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

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

$\mathbf{q}^a$, 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.[7]

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

Contractors submit 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. 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.[8]

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*, 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).

[7] The private values assumption is commonly used for this industry (see Porter and Zona (1993), Krasnokutskaya (2009), Bajari and Ye (2003), and Pesendorfer and Jofre-Bonet (2003)). Testing for common values with multiple units is much more complicated than in a single unit auction, and is beyond the scope of this research.

[8] See Che (1993) and a recent generalization by Asker and Cantillon (2008).

2.2 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.[9] 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 $\mathbf{q}^a$ the revenues to the winning bidder i are

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

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 are *direct adaptation costs* due to disruption of the originally planned 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, and 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.[10] 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.

A second source of adaptation costs are *indirect adaptation costs* due to resources devoted to contract renegotiation and dispute resolution. Estimates place the value of change

[9] 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.

[10] An example witnessed by one of the authors occurred while overlaying a concrete highway with asphalt where innumerable cracks had been patched with a dark, black "latex joint sealer". As paving began, the latex came in contact with hot asphalt, and the heated joint sealer would often 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 vehemently about the additional expense caused by the need to remove the crack sealer. Compensation for this change had to be renegotiated at length.

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)). 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. Moreover, they may disagree over the best way to change the 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.[11]

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 (X) is given by $\tau^X X$.

Before completing the specification of 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 reduces the contractor's compensation.[12] This implies that $X > 0$ and $D < 0$. The adjustments A, however, can be positive or negative. We separate these so that positive (negative) adjustments are labeled $A_+ > 0$ ($A_- < 0$). 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, we can write down the total ex post costs of adaptation as follows,

$$K = \tau^{A_+} A_+ - \tau^{A_-} A_- + \tau^X X - \tau^D D \tag{1}$$

and the total revenue as

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

No adaptation costs imply the null hypothesis that $K = 0$. Our specification captures a particular linear reduced form of adaptation costs. As a first step, this specification is useful because the lack of adaptation costs will be revealed by the data if the estimated coefficients

[11] Another indirect source of adaptation costs are the extra resources spend due to changes. Jobs that are scheduled to start after the completion of the current job will incur higher costs due to overtime of employees or the hiring of a larger workforce to make up for the extra work.

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

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 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. As discussed in Section 2, however, contractors who submit bids that are too skewed risk having their bids rejected. Hence, skewing bids will impose a cost on the bidders.

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 $\bar{b}_t$ 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 satisfying the following assumptions: First, $P(\overline{\mathbf{b}}|\overline{\mathbf{b}}) = 0$ (no penalty from submitting a bid that matches the engineer's estimates). Second, $\left.\frac{\partial P(\mathbf{b}^i|\overline{\mathbf{b}})}{\partial b_t^i}\right|_{b_t^i=\bar{b}_t} = 0$ (when the bids match the engineer's estimates, the first order costs of skewing are zero). These two assumptions seem natural given the practices of Caltrans. Third, $P(\mathbf{b}^i|\overline{\mathbf{b}})$ is strictly convex, and finally, $\lim_{b_t^i \to 0} \left.\frac{\partial P(\mathbf{b}^i|\overline{\mathbf{b}})}{\partial b_t^i}\right| = \infty$. 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,

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

2.3 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 special case of Asker and Cantillon (2008) 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 $\mathbf{b}^i$.[13] As a result, the Bayesian game will

[13] 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*.

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 $b^i_t(s),\ t = 1, ..., T.$) 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

$$\begin{array}{cc} \max\limits_{\mathbf{b}^i(\cdot)} & \sum_{t=1}^T b^i_t q^a_t - \theta^i + A + X + D - K - P(\mathbf{b}^i) \\ & \text{s.t.} \qquad \sum_{t=1}^T b^i_t q^e_t = s \end{array} \tag{4}$$

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

$$q^a_t - \frac{\partial P(\mathbf{b}^i)}{\partial b^i_t} - \lambda q^e_t = 0 \text{ for all } t = 1, ..., T \tag{5}$$

and the last being the constraint.

After (implicitly) solving 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 each of the other $j \neq i$ scores. Let $H_j(\cdot)$ be the cumulative distribution 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 $\prod_{j\neq i} \left(1 - H_j(s^i)\right)$. The contractor's profit function is,

$$\pi_i(s^i, \theta^i) = \left[R(\mathbf{b}^i(s^i)) - \theta^i\right] \times \left[\prod_{j\neq i} \left(1 - H_j(\mathbf{b}^i \cdot \mathbf{q}^e)\right)\right].$$

Substituting for revenues with (3) and recalling that $\theta_i = \sum_{t=1}^T c^i_t q^a_t$ we can express the contractor's FOC as follows:

$$\begin{aligned} \sum_{t=1}^T \left[b^i_t(s^i) - c^i_t\right] q^a_t = & \sum_{t=1}^T \tfrac{db^i_t(s^i)}{ds^i} \left[q^a_t - \tfrac{\partial P(\mathbf{b}^i)}{\partial b^i_t}\right] \left(\sum_{j\neq i} \tfrac{h_j(s^i)}{1-H_j(s^i)}\right)^{-1} \\ & - A - X - D + K + P(\mathbf{b}^i) \end{aligned} \tag{6}$$

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 (6) for all bidders $i \in N$. As stated above, there is a unique monotonic equilibrium in pure strategies, and we will therefore use (6) as the basis for our empirical analysis.

The first order condition (6) 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 FOC (6) reduces to:

$$\mathbf{b}^i \cdot \mathbf{q}^e - \mathbf{c}^i \cdot \mathbf{q}^e = \left(\sum_{j \neq i} \frac{h_j(\mathbf{b}^i \cdot \mathbf{q}^e)}{1 - H_j(\mathbf{b}^i \cdot \mathbf{q}^e)} \right)^{-1} \tag{7}$$

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 (7).

The innovation in (6) is the introduction of empirically measurable terms that were ignored in previous procurement studies, most notably the adaptation costs 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 $(1+\tau^D) \times 1,000$. The total costs of the deductions, as borne by the firm, are indirectly borne by 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 $\tau^l = 0$ for all $l \in \{A_+, A_-, X, D\}$. As we demonstrate shortly, this null hypothesis is strongly rejected by the data, and we will offer evidence suggesting that adaptation costs of ex post changes may indeed be the reason.

3 Data

Our unit of observation is a paving contract procured by Caltrans from 1999 through 2005.[14] 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 item t submitted by bidder i on project n. The sample includes $N = 819$ projects with a total awarded value of \$2.21 billion.[15] There were a total of 3,661 bids submitted by 349 general contractors.

[14] Contract details from 2001 and the first half of 2003 are no longer accessible from Caltrans, so our sample does not include contracts from these two periods.

[15] Market size is defined as the value of the winning bids for the projects in our data set (not the final payments made to the contractors.) We focus on contracts for which asphalt is at least 1/3 of the project's monetary value. We exclude contracts that were not awarded to the lowest bidder (which represent only 4.6 percent of all projects.) We also exclude 31 contracts for which there was only one recorded bidder and 65 contracts for which there is no itemized record of the final payment or pages missing from record files.

In Table 1, we list the top 25 contractors in our data set and their market share. Over half of the participating contractors, 193 firms, never won an asphalt contract during the period and only 2 firms participated in more than 10 percent of the auctions. To account for some of this asymmetry in size and experience, we let $FRINGE_i$ be a dummy variable equal to one if firm i is a "fringe" firm, defined as a firm that won less than 1 percent of the value of contracts awarded. 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 collected information from the publicly available bid summaries and final payment forms that include the project number, the bidding date, the location of the job, other information about the nature of the job and bidder identities with their itemized bids. Projects have an average of 33 items, although one project has 326 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.[16] This estimate can be thought of as $\Sigma_{t=1}^{T}[\overline{b}_t q_t^{e(n)}]$, the dot product of "Blue Book" prices per item, $\overline{b}_t$, and the estimated quantities for project n. Caltrans measures $\overline{b}_t$ using the Blue Book prices published in the Contract Cost Data Book (CCDB), an item-level data summary prepared annually by Caltrans' Division of Office Engineer.[17] 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 $\overline{b}_t^{(n)}$. Such detailed cost information is rare in empirical Industrial Organization studies and it allows us to incorporate an 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 advantage of geographic proximity (transportation cost) we measure the distance of firm i from project n, denoted as $DIST_i^{(n)}$.[18] Table 4 summarizes these

Lastly, during this time period, there were 22 paving contracts that were structured as "A+B" contracts, where bidders submit a bid on the number of days to completion as well as unit bids on itemized tasks. These types of contracts only appear later in the sample and are excluded.

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

[17] Not all items have values in this source. For items with no CCDB value, we derive an estimate for $\overline{b}_t$ using the average of the low bidder's unit price on an item over all contracts in a given district and year. This averaging method is consistent with the method professional estimating companies use to create benchmark prices for the CCDB. This $\overline{b}_t$ had an R^2 of 0.66 when regressed on the estimates we received from the CCDB. Furthermore, when we regress a constructed measure of $\sum_t \overline{b}_t q_t^{e(n)}$ on the engineer's total estimate from our raw data, the R^2 is 0.985.

[18] The contract provides the location of the project, often as detailed as the cross streets at which highway construction begins and ends. Where the information is less precise we use the city's centroid or a best

calculated measures based on the ranking of bids. As expected, the contractors submitting the lowest bids also tend to have the shortest travel distances, reflecting their cost advantage.

A firm's bidding behavior may be influenced by its production capacity and project backlog. Firms that are working close to capacity face a higher shadow price of free capacity when considering an additional job. Following Porter and Zona (1993), we construct a measure of backlog from the record of winning bids, bidding dates, 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.[19] We then define $CAPACITY_i^{(n)}$ as the maximum backlog experienced for any day during the sample period, and the utilization rate $UTIL_i^{(n)}$ 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.[20]

Firms may take into account their competitors' positions when devising their own bids. We therefore include measures of their closest rival's distance and utilization rate. We define $RDIST_i^{(n)}$ as the minimum distance to the job site among i's rival bidders on project n. Likewise, $RUTIL_i^{(n)}$ 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 5, 6, 7, and 8. There is noticeable heterogeneity in the size of projects awarded: the mean value of the winning bid is \$2.7 million with a standard deviation of \$6.9 million. The difference between the first and second lowest bids averages \$181,340, meaning that bidders leave some "money on the table." On average, the projects require 108 working days to complete, and several change orders are processed. The final price paid for the work exceeds the winning bid by an average of \$190,376 (5.8 percent of the estimate). As Table 8 shows, a significant component of this discrepancy can be attributed to over and under-runs on project items. 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 \$142,035. Compensation for extra work negotiated after change orders, as well as deductions, contribute to the difference, averaging $\$176,256$ and $(-\$8,615)$ respectively. These ex post changes suggest a sizeable

estimate based on the post mile markers and highway names included in every contract. Using the street address of each bidder we record mileage as calculated by Mapquest. When a contractor has multiple locations or branch offices we use the location closest to the job site. For projects that cover multiple locations we take the average of the distances to each location. Using Mapquest's estimated travel time rather than distance produced quantitatively similar results.

[19] This measure 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.

[20] 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.

degree of incompleteness in the original contracts.

As shown in Athey and Levin (2001), contractors can increase their profits by skewing their bids upwards (downwards) on items that are expected to overrun (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 estimate of the CCDB unit costs.[21] The coefficient on percent overrun is 0.0465, which is statistically significant at the 5% level. That is, if a contractor expected a ten percent overrun on some item, he would shade his bid up by approximately one half 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 1519 types of items, these individual effects do not add much explanatory power to the regression. This evidence suggests that incentives to skew are not a major determinant of the observed bids.

4 Reduced Form Estimates

4.1 Bid Regressions

We begin our analysis by performing some common reduced form regressions to determine what best explains the total bids. A typical reduced form approximation to equation (7) implies that $\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)}$ should be determined by 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, making the engineer's cost estimate an excellent cost control. Second, a firm's own distance to the project, $DIST_i^{(n)}$ will influence transportation costs. Third, $UTIL_i^{(n)}$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 auctions. Finally, Table 2 implies that the size distribution of firms 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.

The right-hand side term in equation (7) reflects firm i's market power. This suggests that i's markup over costs will vary positively with publicly observed information about the costs of its competitors. Empirically, we proxy for market power using three terms. The first is $RDIST_i^{(n)}$, 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 $RUTIL_i^{(n)}$, since if i's rivals have high capacity utilization, then firm i will have more market power. Finally,

[21]The Contract Cost Data Book only contains estimates for the more common variations of the specific construction items used in projects in any given year; many items are not reported. Therefore, this regression only uses 92 percent of all the item-unit bids submitted.

$NBIDS^{(n)}$, the number of bidders in project n, is also a measure of market power.

The impact of our covariates on the bids will be proportional to the engineer's cost estimate $\left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right)$. 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 one with a \$500,000 dollar estimate. It is also natural to expect the variance of the error term to be proportional to $\left(\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}\right)$. 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:

$$\begin{aligned} \frac{\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{e,(n)}} &= \alpha_0 + \alpha_n + \alpha_i + \alpha_2 DIST_i^{(n)} + \alpha_3 UTIL_i^{(n)} \\ &\quad + \alpha_4 FRINGE_i^{(n)} + \alpha_5 RDIST_i^{(n)} + \alpha_6 RUTIL_i^{(n)} \\ &\quad + \alpha_7 NBIDS^{(n)} + \varepsilon_i^{(n)} \end{aligned} \tag{8}$$

We include α_n, a project n fixed effect and α_i, a firm fixed effect. The project fixed effect allows us to control for information that is publicly observed by all the firms but not by us. The firm fixed effect controls for omitted cost shifters of firm i that are persistent across auctions. Bid function regressions such as (8) are common in the literature. (See, e.g., Porter and Zona (1993)).

The results from the regression described in (8), and its variants, are displayed in Table 10. Fringe status is significant and has positive signs as expected; fringe firms bid 3.4 to 4.7% higher than more established competitors. Distance is positive and significant in all but one specification; a firm located 94 miles from the project (the sample average) would bid about 1% more than a firm that is adjacent to the project. The number of firms in a market has the expected sign; adding an additional bidder to the job lowers bids by about 1.5%. Increases in rival's distance allows a firm to increase its own bid by 2-3% for every 100 miles.

The goodness of fit in columns I and II is pretty low. In columns III and IV, we add project and firm fixed effects. 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.

4.2 Accounting for Changes and Adaptation Costs

While regressions such as those in Table 10 are common, equation (6) suggests that they are 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 payment, $\mathbf{b}^i \cdot \mathbf{q}^a$. Second, the regressions ignore the anticipated changes to payments due to adjustments, extras and deductions. Based on equation (6), we re-specify the reduced form regression as follows:

$$\frac{\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{a,(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} = \alpha_n + \alpha_i + \alpha_2 DIST_i^{(n)} + \alpha_3 UTIL_i^{(n)} + \alpha_4 FRINGE_i^{(n)} \\ + \alpha_5 RDIST_i^{(n)} + \alpha_6 RUTIL_i^{(n)} + \alpha_7 NBIDS^{(n)} + \varepsilon_i^{(n)} \ , \tag{9}$$

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 (9) is similar to that in (8). However, the dependent variable is now consistent with (6). As before, 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 (9), we regress the fixed effects, α_n on the ex post changes in order to quantify their impacts on the observed bidding behavior. Equation (6) implies that the marginal impact of an extra dollar of change identifies the adaptation costs in our model. Following the logic of (6), our estimates of β_2 through β_5 offer estimates of the adaptation cost coefficients as follows[22]:

$$\beta_2 \equiv -(1 - \tau^{A_+}) \qquad \beta_4 \equiv -(1 - \tau^X)$$
$$\beta_3 \equiv -(1 + \tau^{A_-}) \qquad \beta_5 \equiv -(1 + \tau^D)$$

These regressions are estimated by least squares and the results appear in Table 11. As columns I and II demonstrate, when we only include the cost shifters of the firm and its competitors as covariates, the results appear to be similar to Table 10. 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 11, column II, is almost identical the to regression in Table 10, column III, although the R^2 increases slightly 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 subtle evidence that using ex post information improves our ability to explain the observed bids.

Next, we include the ex post changes. We use $DED^{(n)}$ and $EX^{(n)}$ to denote the values of the coefficients for 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, $PosADJ^{(n)}$ and $NegADJ^{(n)}$. The results of the regression without project fixed effects are shown in columns III and IV. The coefficients on $DED^{(n)}$, $EX^{(n)}$, $PosADJ^{(n)}$ and $NegADJ^{(n)}$ are similar with and without the fixed effects, and are significant at the 1% level in almost every specification.

The results provide evidence that frictions are imposed on the costs and revenues generated by adaptation. For example, in column IV of Table 11, the coefficient on $DED^{(n)}$

[22] Recall that the the coefficient on X in (6) is $-(1 + \tau^X)X$, and since (9) 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.

is -1.18, which implies that $\tau^D = 0.18$. As discussed in Section 3, if contractors were risk neutral and there were no adaptation costs, the coefficient on deductions should be -1. A coefficient of -1.18 is consistent with \$0.18 of adaptation costs for every dollar of deductions. If contractors expect an extra dollar of deduction, they will raise their bid by \$0.18 *above and beyond* the expected loss of \$1 to compensate for the expected adaptation costs. On a job with a \$5,000 deduction (the median deduction assessed in our sample), this implies an increased cost to the state of \$900. For the 819 jobs that we study, this implies that deductions add \$1,270,033.70 in adaptation costs to the final price paid by the state.

A similar interpretation may be given to the coefficient of -1.78 on negative adjustments, $NegADJ^{(n)}$. Our results suggest that negotiations over negative adjustments carry with them a \$0.78 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.[23]

If there were no adaptation costs we would expect to find coefficients on positive adjustments equal to -1. The coefficient of 0.81 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 \$1.81 in adaptation costs for every dollar they obtain in adjustment compensation. Similarly, the coefficient of 0.16 on extra work implies that firms expect to spend \$1.16 in adaptation costs for every dollar they obtain in adjustment compensation.[24]

4.3 Accounting for Endogenous Cost Shocks

The OLS results presented in columns I-IV of Table 11 assumed that ex post changes are exogenous. One concern is that ex post changes are more likely to be observed on projects that are more costly to complete due to factors that are unobserved to the econometrician

[23] 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.

[24] Our regressions imperfectly control for costs from extra work. 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 bound the potential bias from omitted costs.

even after controlling for a detailed cost estimate. For instance, a project in a more mountainous area will impose higher costs of standard production, and will be more likely to run into unanticipated changes due to the more challenging terrain. As a result, projects with more changes just have higher costs not because of adaptation costs but because of production costs. Hence, we might worry that there are costs for completing the project that are observed to the firms and not to us, and that these costs are correlated with changes in ex post compensation.

As an instrument we use the identity of the engineer that supervises the project. The supervising engineer 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. Contractors have a reasonable expectation of the engineer's identity at the time of bidding, as one is often assigned on the project plans and is available to answer questions prior to bidding. 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 section 6.2. However, this straightforward instrumental variable regression is a useful baseline for comparing our estimates to the structural model of the next section.

In columns V and VI of Table 11 we present instrumental variable estimates. In column VI, we regress the project level fixed effects on measures of ex post changes to the project. Notice that the estimated values using our instruments are similar to those from the OLS estimation. In the rest of the paper, our goal will be to determine whether the results in Table 11, which imply significant adjustment costs, are robust to changes in the method used to estimate these parameters, as well as several forms of misspecification.

5 Structural Estimation

The reduced form analysis suffers from four forms of misspecification. First, the bidders will be uncertain about the magnitude of ex post changes. Therefore, the first order conditions should include the expected values of $DED^{(n)}$, $EX^{(n)}$, $PosADJ^{(n)}$ and $NegADJ^{(n)}$ instead of their actual values. The standard econometric analysis of measurement error suggests that our reduced form estimates of adaptation costs will therefore be biased.

Second, our reduced form regressions imperfectly approximate the first order conditions. For instance, we attempt to capture market power by including $RDIST_i^{(n)}$ and $RUTIL_i^{(n)}$ 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 right-hand side term in (7)). Thus, the measurement of market power in the reduced form is misspecified and the interpretation of the regression coefficients is unclear as a result.

Third, the interpretation of the error term is not fleshed out in the reduced form regressions, and we argue below that this interpretation 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. The second are the endogenous cost shocks discussed in section 5.3.

Finally, we will describe a simple strategy to bound our estimates of adaptation costs. An attractive feature of the bounding strategy is that it does not require the specification of instruments.

We now proceed to describe a method for structurally estimating the model discussed in Section 3. Aside from addressing the four sources of misspecification, 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 uses different econometric methods, we shall find a great deal of consistency with our reduced form results. 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 a particular form of the penalty from skewed bidding and the adjustment cost coefficients, τ^{A_+}, τ^{A_-}, τ^D and τ^X. We use the first order conditions in (6) to form a GMM estimator.

5.1 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 10:

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

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.[25]

Let $\widehat{\mu}$ denote the estimated value of μ and let $\widehat{\varepsilon}_j^{(n)}$ denote the fitted residual. We 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, for project n:

[25] 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.

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

That is, the distribution of the residuals, $\varepsilon_j^{(n)}$ can be used to derive the distribution of the observed bids.[26] 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 logic. We note that both $H_j^{(n)}(b)$ and $h_j^{(n)}(b)$ will be estimated quite precisely because there are 3661 bids in our auction. Given the estimates $\widehat{H}_j^{(n)}$ and $\widehat{h}_j^{(n)}$ we generate an estimate for $\left(\sum_{j \neq i} \frac{\widehat{h}_j^{(n)}(\mathbf{b}_i \cdot \mathbf{q}^e)}{1-\widehat{H}_j^{(n)}(\mathbf{b}_i \cdot \mathbf{q}^e)}\right)^{-1}$.

5.2 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 firm i's cost is a variant of the engineer's cost estimate with the following multiplicative structure:

$$
\theta_i^{(n)} = \mathbf{c}_i^{(n)} \cdot \mathbf{q}^{a,(n)} \equiv \overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}(1 + \widetilde{c}_i^{(n)}). \tag{10}
$$

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 (10) is similar to the multiplicative structure used in Krasnokutskaya (2009) and the location-scale models considered in Hong and Shum (2002) 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 (10) into (6), dividing by $\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}$, explicitly writing out K from (1)

[26] 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.

and rearranging terms we can write

$$\begin{aligned}\frac{\theta_i^{(n)}}{\overline{\mathbf{b}}^{(n)}\cdot\mathbf{q}^{a,(n)}} &= \frac{1}{\overline{\mathbf{b}}^{(n)}\cdot\mathbf{q}^{a,(n)}}\left(\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{a,(n)}-\sum_{t=1}^{T}\frac{db_t^i(s^i)}{ds^i}q_t^{a,(n)}\left(\sum_{j\neq i}\frac{h_j^{(n)}(\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{e,(n)})}{1-H_j^{(n)}(\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{e,(n)})}\right)^{-1}\right) \quad (11)\\ &+\frac{1}{\overline{\mathbf{b}}^{(n)}\cdot\mathbf{q}^{a,(n)}}\left[(1-\tau^{A_+})A_+^{(n)}+(1+\tau^{A_-})A_-^{(n)}+(1-\tau^X)X^{(n)}+(1+\tau^D)D^{(n)}\right]\\ &-\frac{1}{\overline{\mathbf{b}}^{(n)}\cdot\mathbf{q}^{a,(n)}}\left[P(\mathbf{b}^{i(n)})-\sum_{t=1}^{T}\frac{db_t^i(s^i)}{ds^i}\frac{\partial P(\mathbf{b}^{i(n)})}{\partial b_t^i}\left(\sum_{j\neq i}\frac{h_j^{(n)}(\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{e,(n)})}{1-H_j^{(n)}(\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{e,(n)})}\right)^{-1}\right]\end{aligned}$$

To complete our structural empirical model we also include two additional sources of error in equation (11). 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 $\omega^{(n)} = (1-\tau^{A_+})\left(A_+^{(n)} - EA_+^{(n)}\right) + (1+\tau^{A_-})\left(A_-^{(n)} - EA_-^{(n)}\right) + (1-\tau^X)\left(X^{(n)} - EX^{(n)}\right) + (1+\tau^D)(D^{(n)} - ED^{(n)})$

A second source of error is that $A_+^{(n)}$, $A_-^{(n)}$, $X^{(n)}$ and $D^{(n)}$ may be endogenous because there may be some 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 $\xi^{(n)}$. In practice, these omitted costs will be minor relative to the costs we do observe. Recall that we observe the actual quantities used for each itemized component of the contract, and for 92% of these items, we have excellent cost data from the CCDB. If delays are accompanied by higher costs of production, much of this will be captured by higher actual quantities used of specified contract items. These are controlled for by $\overline{\mathbf{b}}^{(n)}\cdot\mathbf{q}^{a,(n)}$. Note that in a simple univariate regression this measure explains 97.4% of the variation in the ex post bid, $\mathbf{b}^{i,(n)}\cdot\mathbf{q}^{a,(n)}$.

To the extent that any additional unobserved costs remain, we will use an IV approach to correct for any 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.

For the identity of the engineer to be a valid instrument it must satisfy two conditions: (i) 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 engineer dummy variables is highly significant, and the identities explain 30 to 40 percent of the variation.

Condition (ii) is not possible to verify directly since it is an identifying assumption. However, it seems that to a first approximation it is very 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 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. Moreover, in many cases the engineer is assigned early and noted on the project plans for bidders to contact with questions about certain specifications. 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 the unobserved costs $\xi^{(n)}$. This assumption is reasonable for several reasons. First, one might worry that project engineers predisposed to change the contract are assigned in a nonrandom way to more or less complicated projects. We find, instead, 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: 96% of the engineers work in a single district. However, district dummies alone 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, each with a limited capacity to take on projects, 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. 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 implies that more experienced engineers are assigned to projects with more changes. However, the R^2 this regression was less than 0.01 and none of the coefficients on ex-post change variables were significant.

Given these our two additional sources of error, $\xi^{(n)}$ and expectational errors, we can rewrite (11) as:

$$\begin{aligned}
&\frac{\theta_i^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} - \frac{\xi^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} + \frac{\omega^{(n)}}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} = \\
&\frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{a,(n)} - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} q_t^{a,(n)} \left(\sum_{j \neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1 - H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})} \right)^{-1} \right) \\
&+ \frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left[(1 - \tau^{A_+}) A_+^{(n)} + (1 + \tau^{A_-}) A_-^{(n)} + (1 - \tau^X) X^{(n)} + (1 + \tau^D) D^{(n)} \right] \\
&- \frac{1}{\overline{\mathbf{b}}^{(n)} \cdot \mathbf{q}^{a,(n)}} \left[P(\mathbf{b}^{i(n)}) - \sum_{t=1}^{T} \frac{db_t^i(s^i)}{ds^i} \frac{\partial P(\mathbf{b}^{i(n)})}{\partial b_t^i} \left(\sum_{j \neq i} \frac{h_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})}{1 - H_j^{(n)}(\mathbf{b}^{i,(n)} \cdot \mathbf{q}^{e,(n)})} \right)^{-1} \right]
\end{aligned} \tag{12}$$

Equation (12) is identical to (11) except that we have brought over two additional sources of error to the left hand side. Notice, however, that 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,[27]

$$P(\mathbf{b}^i|\overline{\mathbf{b}}) = \sigma \sum_{t=1}^{T} \left(b_t^i - \overline{b}_t \right)^2 \left| \frac{q_t^e - q_t^a}{q_t^e} \right| . \tag{13}$$

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

[27] 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.

of parameters we can include in this term. 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.

We will define $\widetilde{e}_i^{(n)}$ as the left-hand side of (12):

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

Letting $z_i^{(n)}$ denote the value of the instrument for bidder i in auction n, we will use (12) to form the moment condition below:[28]

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

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 (12). We index the moment condition by N to emphasize that the 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 $m_N(\cdot)$ at a first stage estimate. The first stage estimates of $\widehat{h}$ and $\widehat{H}$ are quite precise given our regression coefficients since there are over 3600 individual bids. Therefore, it is quite unlikely that our first stage bid density and distribution estimates introduce significant bias into the estimates.[29]

Given the 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 (13) we estimate $\widehat{\theta}^{i}$, contractor i's total cost for installing the actual quantities by evaluating the empirical analogue of (6):

[28] This follows from the moment condition that $\widetilde{e}_i^{(n)}$ and $z_i^{(n)}$ have a covariance of zero. Obviously, we can only use engineers who supervise more than one project as an instrument.

[29] 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.

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

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 this equation.

5.3 Results

We summarize the structural estimates in Tables 12-15. Table 12 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 first column of Table 12 implies that every dollar of positive adjustment generates an additional \$2.17 of adaptation costs, while a negative adjustment generates an additional \$0.70 in such 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 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 estimates from Table 12 Column VI were slightly smaller but very close, at \$1.90 and \$0.59 for positive and negative adjustments respectively.

Our other parameter estimates are also similar to our initial reduced form estimates. A dollar of extra work generates up to \$1.12 in adaptation costs, which is similar to the \$1.23 estimated in the reduced form specification. Deductions may generate the largest adaptation costs, at \$2.87 for every dollar of deduction;[30] however, the coefficient is not statistically significant at standard levels. The lack of significance is most likely a result of the small variation in this type of ex-post change. Deductions only affect 209 of the 819 contracts (compared to 752 contracts with extra work and 536 contracts with positive or negative price adjustments), and much of the variance is driven by a single contract with a particularly large deduction of almost \$2.5 million.[31]

[30] We would not be surprised to find large adaptation costs related to deductions. 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.

[31] This contract was assessed \$2.38 million in liquidated damages for completing the project 119 days late, with the other deductions coming from quality and compliance penalties. Dropping this one contract does

The estimated value of the skewing parameter, σ is -1.203E-05. Although the negative sign is inconsistent with the predictions of our theoretical model, this estimate is not statistically significant at standard levels. It is also extremely small in monetary terms and has no appreciable impact on profits or overall costs. The result that there are no large penalties from skewing is quite robust to alternative specifications for the functional form of the skewing 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 13a and 13b, we summarize our estimates of bidders' markups. Our results suggest that the industry is quite competitive. The median profit margin is 3.8 percent for all bids and 12.8 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 to 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 13a and 13b 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 \$85,394 for all bids and \$238,461 for winning bids. The ratio of the markup over direct costs to the cost estimate for the median job is 7.5 percent for all bids and 17.7 percent for winning bids.

In Table 14, we compare the estimates in Table 13 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 (7), which is essentially the estimator discussed in Guerre, Perrigne and Vuong (2000). Equation (7) 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 14, look similar to the total markups reported in the last two columns of Table 13a and 13b. The median total markup is \$180,716, or 12.5% of the estimate for winning bidders.

This is almost exactly the median profit margin estimated in Table 13. 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

not substantially affect the results.

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.

6 Implications for Government Procurement

Our analysis offers some lessons for the design of 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 3661 bids priced contract items so that, if he did win the project, he could expect a profit of \$46,871, or 3.8% 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 17.7 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 70 cents to almost three dollars for every dollar in change. When considering the amount of money awarded and deducted after the initial contract is signed, these costs are sizable. Table 15 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 $2.17A_+ + 0.70|A_-| + 0.12X + 2.87|D|$ and the upper bound is calculated as $2.17A_+ + 0.70|A_-| + 1.12X + 2.87|D|$. 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 $1.12X$ because firms receive an extra dollar of profits for every extra dollar in X.[32] The median estimate of adaptation costs is a sizable

[32] 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

component of costs by any standard. It has a lower bound of 2.8 $(-0.1, 7.1)$ percent of the estimate and an upper bound of 8.0 $(4.3, 12.7)$ percent of the estimate. Hence, 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 819 projects in our data, our bounds suggest that Caltrans spent \$298 million to \$442 million on adaptation costs during our five and a half year sample period. The average ratio of the adaptation costs to the winning bid is 0.07-0.13. Even half of our lower bound would be substantial. An implication of equation (6) 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 is 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.

Bajari, McMillan and Tadelis (2009) 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. They 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

transfer and do not involve additional costs that we have not controlled for in our cost estimate.

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 adaptation 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.

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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	25.8%	338	Tullis Inc	1.2%
75	E L Yeager Construction Co	8.5%	410	Brosamer-Granite Joint Venture	1.2%
244	Teichert Construction	5.3%	199	R J Noble Company	1.1%
135	Kiewit Pacific Co	4.4%	234	Steve Manning Construction Inc	1.1%
12	All American Asphalt	3.6%	251	Tullis and Heller Inc	1.0%
262	W Jaxon Baker Inc	3.1%	96	George Reed Inc	1.0%
125	J F Shea Co Inc	3.0%	265	West Coast Bridge Inc	1.0%
147	M C M Construction Inc	1.9%	253	Union Asphalt Inc	1.0%
107	Griffith Company	1.8%	126	J McLoughlin Engineering Co	0.9%
23	Baldwin Contracting Company	1.8%	220	Security Paving Company	0.8%
162	Mercer Fraser Company	1.5%	25	Banshee Construction Company	0.8%
237	Sully Miller Contrac	1.3%	141	Lee's Paving	0.8%
186	Pavex Construction Division	1.2%		**TOTAL**	**75.3%**

There were a total of 349 active bidders for asphalt concrete construction contracts in our sample between 1999 and 2005. The firms listed above are the top 25 firms from our sample, 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)
104	179	621,600,000	668,900,000	542	58.2%	3,596,173	3,527,907	142.7
12	38	101,400,000	91,234,932	81	8.7%	3,206,513	3,082,469	31.9
262	29	85,545,453	82,081,219	118	12.7%	2,725,529	2,764,843	234.1
244	26	100,900,000	106,900,000	83	8.9%	4,285,574	4,019,036	60.4
237	22	31,916,930	31,053,539	84	9.0%	2,024,833	1,994,349	72.7
107	21	43,852,728	45,655,279	63	6.8%	4,090,919	3,698,395	56.6
186	20	60,147,332	59,570,065	64	6.9%	4,993,729	2,394,017	54.9
125	20	84,306,326	87,432,502	84	9.0%	3,213,128	2,952,142	80.7
23	18	50,349,018	54,314,369	72	7.7%	3,145,562	2,907,771	69.3
162	18	24,032,381	25,948,440	43	4.6%	1,332,335	1,420,838	77.9
75	15	233,200,000	267,200,000	43	4.6%	10,400,000	10,645,505	82.1
141	15	24,368,346	25,056,056	69	7.4%	2,511,144	2,434,596	59.6
178	12	34,351,922	35,217,056	32	3.4%	3,462,455	3,874,640	35.3
22	10	23,672,378	25,281,196	20	2.1%	2,552,561	2,452,782	125.9
251	10	27,809,535	28,651,380	16	1.7%	2,406,761	2,612,752	32.2
135	10	177,600,000	158,100,000	66	7.1%	16,900,000	13,465,323	527.2
126	9	42,562,276	38,125,924	50	5.4%	2,236,437	1,990,010	66.2
234	6	24,883,692	27,841,209	28	3.0%	1,960,130	1,797,009	164.9
83	5	136,400,000	85,959,098	15	1.6%	29,200,000	28,371,400	116.1
265	4	26,786,493	26,426,965	9	1.0%	7,283,186	7,406,581	234.5
25	3	39,437,722	40,445,359	15	1.6%	6,390,842	5,753,646	42.4
9	3	25,953,398	25,663,971	33	3.5%	3,635,809	3,373,363	57.3
147	2	89,344,972	94,562,150	6	0.6%	22,000,000	22,397,538	72.6
57	2	53,728,000	46,654,800	5	0.5%	16,300,000	11,812,031	82.8
410	1	33,092,725	36,268,057	1	0.1%	33,100,000	28,181,000	141.0

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

	Fringe Firms	Non-Fringe Firms
Number of Firms	331	18
Number of Wins	440	379
Number of Bids Submitted	2396	1265
Average Bid Submitted	$ 3,181,687	$ 7,694,909
Average Distance to Job Site (miles)	98.03	100.1
Average Capacity	$ 1,907,413	$ 39,780149
Average Backlog at Time of Bid	$ 122,490	$ 6,702,847

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	36.19	41.26	0.10	378.00	DIST6	143.44	154.18	9.38	1100.00
DIST2	81.05	92.59	2.40	618.62	DIST7	167.20	146.08	12.78	977.00
DIST3	109.23	141.82	2.90	2497.00	DIST8	194.93	181.83	13.19	1084.00
DIST4	134.04	149.15	6.92	1171.00	DIST9	203.38	138.20	15.04	617.00
DIST5	143.71	203.02	8.44	2857.00	DIST10	215.56	150.08	16.34	479.27

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

Table 5: 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	30	45	49	43	30	21	6	12	6	7	249
Contracts in 2002	13	13	12	24	14	21	5	4	2	2	110
Contracts in 2003	2	9	6	5	2	1	1	0	0	1	27
Contracts in 2004	21	32	31	19	9	7	4	2	2	0	127
Contracts in 2005	46	38	34	7	8	6	5	0	0	0	144

Table 6: 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	24	21	20	8
Contracts in 2002	4	8	11	19	24	11	7	2	14	3	7	0
Contracts in 2003	0	0	0	0	0	0	2	8	5	4	2	6
Contracts in 2004	2	8	15	29	33	6	6	10	7	7	3	1
Contracts in 2005	4	10	24	26	23	17	5	6	9.8	10	5	4

Table 7: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Across Contracts Under Consideration					
Winning Bid	819	2,697,385	6859444	51,625.5	99600000
Markup: (Winning Bid-Estimate)/Estimate	819	-0.0545	0.1982	-0.6166	1.188
Normalized Bid: Winning Bid/Estimate	819	0.9455	0.1982	0.3834	2.188
Second Lowest Bid	819	2,878,726	7273552	60,764.5	1.07E+08
Money on the Table: Second Bid-First Bid	819	181,340.7	474494.5	67.5	7,389,144
Normalized Money on the Table: (Second Bid-First Bid)/Estimate	819	0.0763	0.0758	0.0002	0.7486
Number of Bidders	819	4.47	2.15	2	19
Distance of the Winning Bidder	819	82.37	114.50	0.1	1066
Utilization Rate of the Winning Bidder	819	0.1068	0.2023	0	1.0000
Distance of the Second Lowest Bidder	819	95.74	119.65	0.1	996
Utilization Rate of the Second Lowest Bidder	819	0.1144	0.2175	0	1.0000
Across Bids Submitted					
Normalized Bid	3661	1.044	0.2362	0.3834	3.1051
Distance to Job Site	3661	94.19	129.90	0.1	2857
Backlog at Time of Bid	3661	4,660,287	14,276,387	0.00	150,411,535
Capacity	3661	29,803,023	50,676,136	0.00	150,411,535
Utilization (Backlog/Capacity)	3661	0.1026	0.2189	0	1
Minimal Distance Among Rivals	3661	38.64	53.55	0.1	618.62
Minimal Utilization Among Rivals	3661	0.0168	0.0751	0.00	1

Table 8: Importance of Ex-Post Changes

	Obs	Mean	Std. Dev.	Min	Max
Adjustments	819	142,035	832,908	-195,727	15,450,334
Adjustments / Estimate	819	0.0210	0.0489	-0.2172	0.3962
Extra Work	819	176,256	657,249	0	14,697,661
Extra Work / Estimate	819	0.0608	0.0829	0	0.8455
Deductions	819	-8,615	94,642	-2,530,053	0
Deduction / Estimate	819	-0.0021	0.0095	-0.1928	0
CCDB Overrun = $(\mathbf{q}^a - \mathbf{q}^e)$*(CCDB price)	819	-62,204	486982	-9,462,806	1,699,937
CCDB Overrun / Estimate	819	-0.0222	0.2366	-6.3400	0.2859
Final Payment – Winning Bid	819	190,376	1,436,883	-24,111,355	21,190,429
(Final Payment – Winning Bid) / Estimate	819	0.0577	0.1187	-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 9: Skewed Bidding Regressions

Variable	OLS	Item Code Fixed Effects	Item Code Random Effects
Percent unit overrun	0.0465 (2.57)	0.0535 (2.47)	0.0465 (1.93)
Constant	1.7829 (29.14)	1.7826 (30.05)	1.7829 (59.13)
R^2	0.0000	0.0403	0.0000
Number of Obs.	109,624	109,624	109624

The dependent variable is the unit price bid on each contract item, normalized by the Contract Cost Data Book (CCDB) value. The percent unit overrun is the percent difference between the actual and estimated quantities reported for that item. Standard errors clustered by contract are used to compute t-Statistics, shown in parentheses.

Table 10: Standard Bid Function Regressions

Variable	I.	II.	III.	IV.	V.
$DIST_i^{(n)}$	0.0067 (2.13)	0.0094 (2.78)	0.0077 (3.43)	0.0037 (1.12)	0.0093 (4.11)
$RDIST_i^{(n)}$	0.0332 (3.77)	0.0201 (2.25)	-0.0072 (-0.80)	0.0233 (2.71)	0.0031 (0.43)
$UTIL_i^{(n)}$		0.013 (0.70)	0.0101 (0.65)	0.0478 (2.82)	0.0046 (0.36)
$RUTIL_i^{(n)}$		-0.1386 (-2.68)	0.0378 (0.79)	-0.1315 (-2.17)	-0.0305 (-0.64)
$FRINGE_i$		0.0472 (5.59)	0.0345 (6.54)		0.0369 (6.51)
$NBIDS^{(n)}$		-0.0148 (-10.2)		-0.0169 (-10.3)	-0.0157 (-4.53)
Constant	1.0253 (188)	1.0795 (92.5)	1.0156 (168)	1.122 (112)	1.0966 (57.7)
Fixed/Random Effects	No	No	Project FE	Firm FE	Project RE
R^2	0.008	0.035	0. 733	0.217	0.009
Number of Obs.	3661	3661	3661	3661	3661

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. Distances are measured in 100 miles. Robust standard errors are used to compute t-Statistics, shown in parentheses.

Table 11: Bid Function Regressions Using Actual Quantities Instead of Estimates

Variable	I.	II.	III.	IV.	V.	VI.
$DIST_i^{(n)}$	0.0231 (6.25)	0.0090 (3.62)	0.0262 (6.82)	0.0255 (6.90)	0.0093 (4.06)	0.0093 (4.06)
$RDIST_i^{(n)}$	0.0346 (4.35)	-0.0031 (-0.36)				
$UTIL_i^{(n)}$	0.0447 (2.16)	0.0155 (0.88)				
$RUTIL_i^{(n)}$	0.0987 (1.92)	0.0411 (0.89)				
$FRINGE_i$	0.0108 (1.21)	0.0317 (5.87)	0.0061 (0.70)	0.0102 (1.20)	0.0305 (5.77)	0.0305 (5.77)
$NBIDS^{(n)}$	0.00517 (2.54)		0.0018 (0.94)	0.0036 (1.89)	0.0015 (0.98)	0.0034 (2.17)
$PosAdj^{(n)}$			0.1800 (3.72)	0.8057 (9.97)	0.1044 (4.54)	0.9048 (8.88)
$NegAdj^{(n)}$			-1.4832 (-3.36)	-1.7783 (-3.95)	-1.2379 (-3.06)	-1.5921 (-3.58)
$EX^{(n)}$			0.1631 (3.61)	0.1640 (3.83)	0.2217 (3.61)	0.2252 (3.81)
$DED^{(n)}$			-1.3960 (-2.65)	-1.1765 (-2.47)	-3.3156 (-4.43)	-2.5115 (-3.36)
$PCT^{(n)}$			-0.0041 (-0.22)		-0.0138 (-0.43)	
$NOverrun^{(n)}$				0.0057 (8.07)		0.0068 (8.59)
Constant	0.9325 (69.3)	0.9791 (159)	0.9482 (77.5)	0.9207 (75.3)	-0.0351 (-3.47)	-0.0649 (-6.16)
Fixed Effects	No	Project FE	No	No	Project FE	Project FE
Instruments					Resident Engineer	Resident Engineer
R^2	0.0258	0.7617	0.0452	0.0692	0.7616	0.7616
Num. of Obs.	3661	3661	3661	3661	3661	3661

The dependent variable is the vector product of the unit price bids and the actual quantities, divided by a measure of the project size ($q^{act} \cdot \bar{b}$). 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 NDED(n), NEX(n), NPosAdj(n), NNegAdj(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 12: Structural Estimation

	I.	II.	III.
Implied Marginal Transaction Costs			
Positive Adjustments (τ^{A+})	2.167 (0.386)	2.174 (0.347)	1.793 (0.357)
Negative Adjustments (τ^{A-})	0.695 (2.96)	4.801 (4.086)	1.108 (3.616)
Extra Work (τ^{X}) **	1.124 (0.144)	1.298 (0.188)	1.249 (0.202)
Deductions (τ^{D})	2.866 (4.666)	3.529 (3.842)	4.606 (5.575)
	Skewing Parameter		
Penalty (σ)	-1.203E-05 (9.641E-06)	-1.230E-05 (8.908E-06)	-9.870E-06 (7.460E-06)
Number of Obs	3661	3661	3661
Instruments Used in Second Stage GMM	Resident Engineer, Engineer's Estimate	Resident Engineer, Engineer's Estimate, Month and District Dummies	Resident Engineer, Engineer's Estimate, Dollar Overrun on Contracted Items (**CCDB·** (**q**^{a} **-q**^{e}))

* 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. The results of the efficient GMM estimations are reported here. Standard errors appear in parentheses.

** 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.

Table 13a: Markup Decomposition (All Bidders)

Percentile	Direct Markup	Direct Markup Estimate	Ex-Post Changes	Ex-Post Changes Estimate	Skewing Penalty	Skewing Penalty Estimate	Total Profit	Total Profit Estimate
10	11,140	2.5%	-374,713	-10.5%	-151.46	-0.0101%	7,035	1.4%
20	20,957	3.6%	-159,751	-6.3%	-25.64	-0.0013%	12,172	1.9%
30	33,373	4.8%	-78,893	-4.6%	-6.47	-0.0005%	18,848	2.4%
40	51,128	6.0%	-39,812	-3.2%	-2.21	-0.0002%	29,554	3.0%
50	85,394	7.5%	-21,434	-2.3%	-0.83	-0.0001%	46,871	3.8%
60	138,759	9.5%	-12,167	-1.5%	-0.30	0.0000%	69,453	4.7%
70	224,663	12.0%	-5,145	-0.8%	-0.10	0.0000%	112,543	6.4%
80	392,926	16.6%	-1,716	-0.3%	-0.03	0.0000%	193,564	9.4%
90	859,543	28.0%	-528	-0.1%	0.00	0.0000%	408,554	17.4%

Table 13b: Ex-Post Profit Decomposition (All Winning Bidders)

Percentile	Direct Markup	Direct Markup Estimate	Ex-Post Changes	Ex-Post Changes Estimate	Skewing Penalty	Skewing Penalty Estimate	Total Profit	Total Profit Estimate
10	40,503	7.3%	-386,111	-11.2%	-64.78	-0.0032%	31,365	5.2%
20	67,792	9.5%	-168,661	-6.9%	-7.33	-0.0005%	55,075	6.7%
30	102,624	12.0%	-92,745	-5.1%	-2.26	-0.0001%	78,198	8.0%
40	157,254	14.3%	-48,590	-3.5%	-0.74	-0.0001%	114,876	10.6%
50	238,461	17.7%	-25,987	-2.4%	-0.29	0.0000%	176,799	12.8%
60	345,230	21.2%	-14,665	-1.6%	-0.12	0.0000%	249,149	16.0%
70	502,948	27.6%	-5,804	-0.8%	-0.05	0.0000%	378,575	21.0%
80	847,461	39.3%	-1,933	-0.4%	-0.01	0.0000%	603,817	31.1%
90	1,676,429	63.6%	-556	-0.1%	0.00	0.0000%	1,156,066	55.4%

Table 14: 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	7,019	1.4%	32,593	5.4%
20	12,169	1.9%	55,756	6.7%
30	18,855	2.3%	79,688	8.2%
40	29,472	2.9%	119,833	10.4%
50	46,133	3.6%	180,716	12.5%
60	69,487	4.6%	248,674	15.7%
70	111,532	6.2%	364,014	20.6%
80	193,172	9.1%	607,608	32.0%
90	397,009	16.7%	1,107,054	54.9%

Table 15: Transaction Costs

Lower Bound

Percentile	Total Transaction Costs	As a Fraction of Contract's Estimate	As a Fraction of Contract's Estimated Ex-Post Profit
10	556	0.1%	0.4%
	[-80,140, 1,821]	[-6.7%, 0.4%]	[-47.7%, 1.5%]
20	1,925	0.4%	1.9%
	[-24,107, 6,301]	[-2.7%, 1.2%]	[-16.7%, 6.4%]
30	5,452	0.7%	4.6%
	[-8,005, 17,864]	[-1.0%, 2.7%]	[-6.9%, 14.0%]
40	14,374	1.7%	8.5%
	[-2,191, 44,068]	[-0.4%, 4.8%]	[-2.5%, 26.1%]
50	30,672	2.8%	16.8%
	[-656, 77,926]	[-0.1%, 7.1%]	[-0.6%, 44.5%]
60	56,984	4.3%	29.9%
	[122, 142,011]	[0.0%, 9.9%]	[0.0%, 77.2%]
70	108,417	6.5%	54.5%
	[23,366, 263,111]	[1.6%, 14.0%]	[9.1%, 115.4%]
80	244,061	9.9%	88.7%
	[80,634, 475,695]	[3.8%, 19.9%]	[29.3%, 173.8%]
90	660,521	16.1%	155.2%
	[279,815, 1,016,771]	[7.3%, 30.9%]	[74.0%, 289.3%]

Upper Bound

Percentile	Total Transaction Costs	As a Fraction of Contract's Estimate	As a Fraction of Contract's Estimated Ex-Post Profit
10	4,201	0.8%	2.5%
	[-11,988, 5,940]	[-1.7%, 1.2%]	[-8.1%, 4.1%]
20	12,014	2.3%	9.6%
	[1,411, 183,56]	[0.3%, 3.4%]	[0.6%, 14.6%]
30	25,479	3.8%	20.7%
	[7,226, 421,23]	[1.4%, 5.9%]	[5.8%, 33.4%]
40	52,088	5.8%	34.3%
	[17,513, 83,192]	[2.5%, 8.7%]	[15.0%, 54.4%]
50	93,571	8.0%	53.9%
	[39,272, 140,530]	[4.3%, 12.7%]	[25.7%, 83.7%]
60	151,880	11.3%	80.7%
	[76,612, 232,469]	[6.1%, 16.8%]	[43.7%, 123.6%]
70	247,594	14.7%	120.9%
	[144,510, 416,230]	[8.8%, 22.8%]	[69.6%, 175.1%]
80	476,899	20.2%	178.6%
	[266,134, 692,475]	[12.9%, 30.9%]	[109.9%, 274.4%]
90	1,058,373	30.2%	294.2%
	[703,143, 1,473,841]	[19.1%, 44.2%]	[198.8%, 433.5%]

The adaptation cost is calculated as $2.17\,(A_+) + 0.70\,|A_-| + 0.12\,(X) + 2.87|D|$. 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.