Online Appendix for "Cost and Efficiency in Government Outsourcing: Evidence from the Dredging Industry"

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B Data and Estimation

B.1 Sample Construction

The original sample consists of 2487 contracted-out projects and 1945 projects completed by the Corps. Any projects that were missing bid information, project size, start date, or the number of working days were removed. There are three Corps districts that contract out dredging work on the Great Lakes: Chicago, Buffalo, and Detroit. These contracts were also removed, as there are no Corps-owned dredges that are active in the Great Lakes region. Lastly, extremely large projects (expected contract price exceeding $20M) were removed, as projects of this size are never observed to be taken by Corps dredges and they often require multiple large dredges working on the project at once, which is not something the Corps is equipped to accommodate. 77 Corps projects that had overlapping dates in the same district were combined. Additionally, 29 projects involving emergency dredging after the Deepwater Horizon oil spill in the Gulf region were removed. This leaves a final sample of 3,722 observations across 31 districts.

Table 6 gives a list of USACE districts and provides a breakdown of how many of the total projects in each district are Corps projects and how many are contracted out. It also lists the average volume of dredged material for projects in each district. Table 7 lists the total dredging projects each year and indicates how many were Corps projects and how many were contracted out.

Table 6: USACE Districts

District	**Total Projects**	**Corps Projects**	**Contracted Projects**	**Mean Project Size** (cu. yds. in thousands)
Alaska	51	2	49	401
Baltimore	112	39	73	537
Buffalo	78	0	78	206
Charleston	79	25	54	1,099
Chicago	33	0	33	95
Detroit	232	0	232	54
Galveston	215	0	215	1,747
Honolulu	8	2	6	94
Huntington	31	0	31	86
Jacksonville	189	17	172	624
Kansas City	2	2	0	47
Little Rock	4	0	4	1,251
Los Angeles	48	12	36	827
Louisville	16	1	15	945
Memphis	24	17	7	6,555
Mobile	127	16	111	1,296
New England	96	62	34	114
New Orleans	562	235	327	1,763
New York	138	26	112	524
Norfolk	203	80	123	270
Philadelphia	270	152	118	433
Pittsburgh	14	0	14	10
Portland	380	310	70	414
Rock Island	18	11	7	269
Sacramento	8	0	8	258
San Francisco	104	67	37	454
Savannah	43	0	43	2,798
Seattle	72	28	44	491
St. Louis	190	186	4	273
St. Paul	66	46	20	312
Tulsa	1	0	1	530
Vicksburg	86	68	18	765
Walla Walla	1	0	1	11
Wilmington	654	541	113	240

Table 7: Projects by Year

Fiscal Year	Total Projects	Corps Projects	Contracted Projects
1999	251	125	126
2000	232	114	118
2001	232	99	133
2002	263	141	122
2003	323	177	146
2004	275	145	130
2005	236	124	112
2006	248	156	92
2007	216	115	101
2008	218	118	100
2009	220	109	111
2010	283	132	151
2011	259	158	101
2012	251	145	106
2013	192	86	106

B.2 Estimation and Results

This section provides additional details on the estimation of the model.

B.2.1 Expected Contract Price

Expected winning bids are estimated directly from the data non-parametrically. First, the distribution over the number of bidders is estimated. This is done non-parametrically by counting the number of observations with each number of bidders after smoothing over contract characteristics. The maximum number of bidders in each district k is $\overline{N}_k$. This is estimated by taking the maximum number of bidders observed in the market over the sample period. Let $\eta_{kn}(x_t)$ be the probability that n bidders are observed in an auction with project characteristics x_t. Next the expected winning bid conditional on the number of bidders is with a Nadaraya-Watson estimator. Let $\mathcal{A}_n$ denote the set of auctions in which there are n bidders. Then the expected winning bid for an auction with characteristics x in market k is given by averaging over the expected winning bid for each number of bidders:

$$\hat{R}(x, \widehat{\overline{N}_{k_t}}) = \sum_{n=1}^{\widehat{\overline{N}_{k_t}}} \hat{\eta}_{kn}(x_t) \left(\frac{\sum_{t \in \mathcal{A}_n} K\left(\frac{x - x_t}{h_x}\right) b_t}{\sum_{t \in \mathcal{A}_n} K\left(\frac{(x - x_t)}{h_x}\right)} \right).$$

The kernel function K is a multiplicative normal kernel, and the bandwidth parameter h_x is obtained using Silverman's rule of thumb.

B.2.2 Government Cost Distribution

The government cost distribution is estimated from periods in which the available project is located in the same district as the assigned government dredge and the next available project in the dredge's region will begin after the current project has ended. There are 1086 such observations in the data.

Estimation of the parameters in (α, ρ) takes place by linking the observed choices for the static periods to the conditional distribution function of government costs. The each government choice observation is a draw from a Bernoulli distribution with probability parameter given by the distribution of government costs evaluated at the expected contract price. Recalling that G denotes the cdf of C_{gt}, we have that

$$\Pr(d_t = 0 | z_t) = G(R(x_t, \overline{N}_{k_t})).$$

We obtain the estimator for (α, ρ) by gathering all static observations and maximizing the joint two-step likelihood after plugging in the first-stage estimates for $R(z_t)$ obtained in the previous section. More formally, let $\mathcal{T}$ represent the set of periods in which the future value components of utility cancel. Then the estimator is

$$(\hat{\alpha}, \hat{\rho}) = \arg\max_{\alpha, \rho} \prod_{\tau \in \mathcal{T}} G(\hat{R}(x_t, \widehat{\overline{N}}_{k_t}); \alpha, \rho)^{1-d_t} \times [1 - G(\hat{R}(x_t, \widehat{\overline{N}}_{k_t}); \alpha, \rho)]^{d_t} \qquad (17)$$

With the estimate for the government cost distribution we can proceed to the estimation of the dynamic model and recover the distance cost parameter.

B.2.3 Distance Parameter θ

In the data, several districts have multiple dredges that perform projects in the district. This complicates dynamic considerations, as the availability of both dredges must be accounted for when considering the future value component. For these regions, I consider all dredges that are linked by the overlapping district(s) simultaneously; this results in a state variable consisting of distances and locations for each of the dredges in that set of districts. In such cases I assume that an in-house decision to send the closest available dredge to the project. This assumption is empirically motivated: for over 97% of in-house projects the closest available dredge is selected to complete it.[36] This result of this grouping is a set of five non-overlapping regions $I_1, ..., I_5$, in which no vessel operating in any one of the regions takes projects in any of the others, that operate in parallel. There are also fifteen fiscal years Y spanning 1999-2013. Hence, the value function is generated via backwards induction for each region-year pair, and estimates are obtained by maximizing the likelihood across all such region-year pairs. For notational simplicity I drop the dependence on the regions I and fiscal year Y in much of what follows.

The last step in the estimation of the model primitives relating to government cost is to use the results of the first two stages to write an expression for the value function that allows for estimation of the distance cost parameter θ. Specifically, the estimator for θ will be a two-stage maximum likelihood estimator in which the first-stage estimates are plugged into the likelihood function for government decisions. Construction of the value function is done through backwards induction; beginning in the last period T we have that the probability that the project is kept in-house

[36]This can be understood by thinking of the network of districts as approximately linear, with most regions consisting of locations along the coast or within the inland waterway system. For these networks there is no distance reduction from sending any vessel that isn't already the closest to the project.

$p_{0T}(z_t)$ is

$$\begin{aligned} p_{0T}(z_T) &= \mathbb{1}_{\{y_T=0\}}\Pr(C_{gT}+\theta\delta_T < R(x_T,\overline{N}_{k_T})) \\ &= \mathbb{1}_{\{y_T=0\}}G(R(x_T,\overline{N}_{k_T})-\theta\delta_T \mid x_T) \end{aligned}$$

and $p_{1T}(z_T)=1-p_{0T}(z_T)$. Then the ex-ante value function in period T and state z_T is

$$\overline{V}_T(z_T)=p_{0T}(z_T)\mathbb{E}[\pi_0(z_T)|d_T=0]+p_{1T}(z_T)\pi_1(z_T)$$

which can be expressed as

$$\overline{V}_T(z_T)=p_{0T}(z_T)\left[\theta\delta_T+\frac{\int_0^{R(x_T,\overline{N}_{k_t})-\theta\delta_T}u\hat{g}(u)du}{\hat{G}(R(x_T,\overline{N}_{k_T})-\theta\delta_T)}\right]+p_{1T}(z_T)R(x_T,\overline{N}_{k_T}).$$

For $t=1,...,T-1$ we have that

$$\begin{aligned} p_{1t}(z_t) \quad &= \quad \mathbb{1}_{\{y_t=0\}}\Pr\Bigg(C_{gt}+\theta\delta_t+\beta_t\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{0t}(z_{t+1}|z_t) < R(x_t,\overline{N}_{k_t}) \\ &\quad +\beta_t\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{1t}(z_{t+1}|z_t)\Bigg). \end{aligned}$$

Recalling that

$$\begin{aligned} v_{0t}(z_t) &= \theta\delta_t+\beta_t\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{0t}(z_{t+1}|z_t), \\ v_{1t}(z_t) &= R(x_t,\overline{N}_{k_t})+\beta_t\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{1t}(z_{t+1}|z_t). \end{aligned}$$

then the ex-ante value function in period t and state z_t is

$$\overline{V}_t(z_t)=p_{0t}(z_t)\left[v_{0t}(z_t)+\frac{\int_0^{v_{0t}(z_t)-v_{1t}(z_t)}u\hat{g}(u)du}{\hat{G}(v_{0t}(z_t)-v_{1t}(z_t))}\right]+p_{1t}(z_t)v_{1t}(z_t).$$

Then we can express the conditional choice probability of keeping a project in-house as

$$\hat{p}_{0t}(z_t) = \hat{G}(v_{0t}(z_t) - v_{1t}(z_t)).$$

Recalling that there are five non-overlapping regions I and fifteen fiscal years Y, this gives the estimator for θ as

$$\hat{\theta} = \arg\max_{\theta} \prod_{I=1}^{5} \prod_{Y=1}^{15} \prod_{t \in T_{IY}} (\hat{p}_{1t})^{d_t} \times (1 - \hat{p}_{1t})^{1-d_t}. \tag{18}$$

where T_{IY} is the set of projects in region I during fiscal year Y. Since the estimates from the first stage are consistent estimates for the estimated winning bid and the distribution of government costs, (18) yields a consistent estimate for θ.

Finally, the estimate for θ is robust to both different choices for the annual discount parameter $\tilde{\beta}$ as well as different specifications for time discounting. The first three rows of Table 8 shows the value for θ when different values of $\tilde{\beta}$ are used in estimation. The last row shows the estimate obtained when all periods are assumed to have the same discount factor: $\beta_t = \tilde{\beta}^{1/T}$ for all t, where T is the total number of projects. This corresponds to the assumption that the USACE treats all periods as if they have the same duration in calendar time, or that project start dates are approximately evenly distributed throughout the year. The results are similar across specifications, suggesting that the results are robust to different assumptions on time discounting by the USACE.

Table 8: Estimates of θ for varying time discount factors

$\tilde{\beta}$	$\hat{\theta}$
0.90	0.0212
0.94	0.0222
0.99	0.0207

B.2.4 Entry Cost Distribution

Estimation of the entry cost parameters proceeds in two steps. First estimates for the equilibrium entry cutoff values $\hat{e}_k^*(x)$ are generated from equation (10) using the empirical distributions over the number of bidders $\hat{\eta}_{kn}$. Then for each λ, $\zeta(\hat{e}_k^*(x))$ gives the probability for an individual bidder's entry into an auction in market k with project characteristics x. The estimate $\hat{\lambda}$ is generated by maximizing the likelihood of the observed number of bidders in each auction.

B.2.5 Firm Cost Distribution

The winning bid distribution is estimated parametrically, with the parameterization given by

$$b_{it} \sim \text{Log-normal}(\mu_t, \gamma_t),$$

where

$$\log(\mu_t) = \mu_{0t} + \mu_{1t}x_{1t} + \mu_{2t}x_{2t} + \mu_3 N_t, \quad \log(\gamma_t) = \gamma_0 + \gamma_1 x_{1t} + \gamma_2 x_{2t} + \gamma_3 N_t.$$

Once estimates of the winning bid distribution parameters have been obtained, firm costs can be expressed as

$$\hat{c} = b - \frac{N[1 - \hat{W}(b)]}{(N-1)\hat{w}(b)}. \tag{19}$$

where b is a submitted bid. Hence for any bid, the associated cost can be found by applying (19) using the estimated winning bid distribution. To generate the cost distributions, bids are randomly sampled from the bid distribution obtained via the order statistic transformation $\hat{H}(b) = 1 - [1 - \hat{W}(b)]^{1/N}$ and these sampled bid values are used to generate firm costs $\hat{c}$.

B.2.6 Discussion of Results

This section provides additional discussion of the results and compares the Corps cost estimates to available cost accounting data from the USACE and Government Accountability Office (GAO). There are two main sources of data. The first is the USACE Continuing Dredging Cost database, which contains information on cost-per-cubic yard measures for Corps and industry dredging. The second is a GAO report that conducts a cost audit of a particular USACE dredge, the *Wheeler*, that overlaps with the early years of the sample. Additional cost estimates are obtained from a 2005 USACE Report to Congress (United States Army Corps of Engineers (2005), Table 11) that contains cost-per-day estimates for Corps and industry dredges.

Table 9 contains the cost-per-cubic yard (in 2013 US dollars) and cost per working day estimates supplied by the USACE. Primarily the table indicates that Corps dredges are estimated to have lower cost per cubic yard measures but higher cost per working day measures when compared to industry dredges. As discussed in the text, these cost measures match my estimates on a qualitative basis, as they imply that Corps dredges should take projects that have a high ratio of cubic yards to working days. This feature is present in the data and is reflected in my estimates.

However, other data sources suggest that the cost measures reported by the USACE may under-report the total costs of dredge operation. In particular, they may reflect only a limited set of variable costs, such as those associated with labor and fuel, and do not factor in maintenance, repairs, and other costs. I demonstrate this issue using the costs associated with the Corps dredge *Wheeler* over the early years of my sample, as there are multiple sources on costs over this time period for this particular vessel. In addition to the cost per cubic yard measure reported by the Corps, from which total costs can be constructed from the total cubic yards reported to be dredged by the vessel, a GAO report, GAO-03-382, performed an audit of the operational costs of the *Wheeler* from 1994-2001.

Table 9: Cost comparison between USACE and industry dredging

Cost per cubic yard:

	Cost per cu. yd.			Cost per cu. yd.	
Year	**Corps**	**Industry**	**Year**	**Corps**	**Industry**
2000	2.66	4.12	2009	3.37	6.30
2001	2.62	4.55	2010	3.78	8.08
2002	2.99	5.13	2011	2.87	7.06
2003	3.32	5.07	2012	3.16	5.69
2004	3.35	4.15	2013	3.35	5.74
2005	2.86	4.77	2014	4.32	6.74
2006	3.02	6.09	2015	5.11	7.09
2007	2.85	5.93	2016	4.08	6.23
2008	2.82	5.46	2017	4.51	5.40

Corps average:	\$3.39/cu. yd.
Industry average:	\$5.76/cu. yd.

Cost per working day:	
Corps cost per working day:	\$47,000 - \$87,000
Industry cost per working day:	\$34,905 - \$65,700

Sources: USACE Dredging Continuing Cost database (USACE Institute for Water Resources (2018)) and Table 11 (page 18) of 2005 USACE Report to Congress (United States Army Corps of Engineers (2005)).

Table 10 shows results of the GAO audit of total average costs for operation of the Wheeler separated into two time periods. The table is taken from Table 1 of Government Accountability Office GAO-03-382, which tracked how total costs changed with different utilization levels of this dredge. The average total annual cost for the years 1998 through 2001 was \$13,631,862, while the total costs associated with payroll and fuel was \$4,390,390. For the years that overlap with my data, 1999-2001, the Corps reports for the average annual total costs associated with projects completed by the Wheeler as \$4,926,817. This strongly suggests that Corps cost estimates are under-reporting the average total cost of completed projects, and may

Table 10: Cost summary for Corps dredge *Wheeler*, 1994-2001

Cost Component	**1994-1997**	**1998 - 2001**	**Percentage Change**
Average days worked	183	83	-55%
Average cubic yards	11,847,040	5,245,606	-56%
Crew size	54	42	-21%
Average annual cost	$17,136,028	$13,631,862	-20%
Payroll costs	$3,635,146	$3,557,938	-2%
Fuel costs	$1,206,578	$832,452	-31%
Other costs	$12,294,304	$9,241,472	-25%

Source: Table 1 (page 13) of GAO-03-382 (Government Accountability Office (2003)).

instead reflect only the costs associated with labor and fuel. This may not be important if these labor and fuel costs represented all or most of the variable costs associated with project completion. However, this is not the case, as variation in the utilization of the *Wheeler* over the years covered in the report had significant effects on costs not associated with fuel or labor. Table 10 shows that "Other costs" declined by over $3 million, or 25%, when the utilization of the dredge declined by 55%. While many of the expenses in the "Other costs" category are likely fixed, the variation present with changes in utilization indicates substantial variable costs associated with dredge operation.

As a back-of-the-envelope calculation to assess total variable costs, suppose that "Other costs" OC is linear in working days WD with a fixed costs component FC, or $OC = FC + \delta \times WD$. Applying this specification to the two columns in Table 10 gives the fixed costs as $FC = \$6,707,621$ and the per-day variable costs not associated with labor and fuel as $\delta = \$30,528$. Combining this with the variable costs of fuel and labor implies a total per-day cost of $83,425 for the period 1998-2001. The estimates from my model imply a per-day cost of $75,801 (in 2003 dollars, the year of the report's publication). While this comparison is extremely narrow in scope, covering only one vessel for a subset of the years in my data, it is suggestive evidence that my estimates are broadly of an appropriate magnitude for the Corps' marginal costs.

This variation in marginal costs of Corps dredge operation also suggests that a substantial portion of the Corps' dredging costs are associated with additional dredge utilization, and fixed costs do not make up an overwhelming component of expenses. As discussed in Section 5.2, if the Corps faces extremely high fixed costs but low variable costs, then it may not have a total cost advantage for small projects but instead only a marginal cost advantage. While the available cost data does not allow for direct comparison of fixed costs between Corps and private sector dredges, the GAO audit of the *Wheeler* does indicate that variable costs are a substantial component of operational expenses. Additionally, if the Corps had a low marginal cost relative to private sector dredges, one might expect to see overall utilization at high and stable rates, as idle dredging resources would be wasting the fixed cost investment. However, as indicated in Table 15 of Section B.4.2 there is high variation in the utilization of dredges over time.

B.3 Testing for selection in auction entry

The model used for entry of potential bidders into the auction is that of Levin and Smith (1994) (henceforth LS), which assumes that bidders have no knowledge of their private costs until after they make an entry decision. A recent empirical literature has investigated whether there might be the possibility of selective entry: bidders receive a noisy signal as to their private valuations prior to making an entry decision, and choose to enter based on the information contained in this signal.[37] Such an entry process will attract bidders that will typically have lower-than-average costs into the auction, as in general only those potential bidders that have received signals indicating a high probability of low project costs will choose to pay the entry cost to participate in the auction.

To examine whether selective entry is a factor in this market, I use the non-

[37] Papers that empirically investigate the possibility of selective entry include Li and Zheng (2009) and Roberts and Sweeting (2013).

parametric test of Marmer, Shneyerov, and Xu (2013).[38] The intuition behind the test is that when the number of potential bidders changes this should change the observed bid distribution differently when there is selection versus when there is not. That is, when there is selective entry then the bidders that choose to enter in auctions with high numbers of potential bidders should have lower costs, and therefore lower bids, than in auctions with lower numbers of bidders. In the LS model, because bidders have no knowledge of costs prior to entry there should be no difference in bids across auctions with different numbers of potential bidders, conditional on the same number of active bidders. They propose a test based on the test statistic $T(x) = \sup_{\tau \in \Gamma} T(\tau, x)$ where

$$T(\tau, x) = \sqrt{Lh^{d+1}} \sum_{N=\underline{N}}^{\overline{N}-1} \sum_{N'=N+1}^{\overline{N}} \frac{|\hat{\Delta}(\tau, N, N', x)|}{\hat{\sigma}(\tau, N, N', x)},$$

the difference between quantiles of bidders' valuations for each quantile value $\tau \in \Gamma$ is

$$\hat{\Delta}(\tau, N, N', x) = \hat{Q}(\tau|N', x) - \hat{Q}(\tau|N, x),$$

the conditional quantile function of the distribution of active bidders' costs is

$$\hat{Q}(\tau|N, x) = \hat{\xi}(\hat{q}(\tau|N, x)|N, x),$$

and the inverse bidding strategy $\xi(\cdot)$ is given by

$$\xi(b|N, x) = b - \left(\frac{1}{N-1}\right)\left[\frac{1-p(N, x)}{g(b|N, x)p(N, x)} + \frac{1-G(b|N, x)}{g(b|N, x)}\right].$$

Here $p(N, x)$ is the probability of that an individual bidder submits a bid with N potential bidders in an auction with characteristics x, $G(b|N, x)$ is the distribution of observed bids in an auction with N potential bidders with characteristics x, and

[38] The notation used to decribe the components of the test statistic comes directly from their paper.

$g(b|N,x)$ is the associated density. The dimension of the auction characteristic space $\mathcal{X}$ is d. These are estimated non-parametrically from the data,[39] with the additional of a transformation of the winning bid distribution $G_w(b|N,x)$ as winning bids are the only bids observed in my sample:

$$1 - G_w(b|N,x) = \frac{(1 - p(N,x) + p(N,x)[1 - G(b|N,x)])^N - (1 - p(N,x))^N}{1 - (1 - p(N,x))^N}$$

Finally, $\sigma^2(\tau, N, N', x)$ is the asymptotic variance of the test statistic:

$$\sigma^2(\tau, N, N', x) = \left(\int K(u)^2 du\right)^{d+1} \frac{(1 - p(N,x)(1-\tau))^2}{(N-1)^2 N p^3(N,x) g^3(q(\tau|N,x)|N,x)\pi(N|x)\psi(x)}$$

and $\pi(N|x)$ is the distribution of the number of potential bidders conditional on x.

I use the set of auctions in my sample with at least four potential bidders and two active bidders to construct the test statistic and critical values. Critical values are obtained via bootstrap, where for each bootstrap iteration m the test statistic is $T_m^*(x) = \sup_{\tau \in \Gamma} T_m^*(\tau, x)$ and

$$T_m^*(\tau, x) = \sqrt{Lh^{d+1}} \sum_{N=\underline{N}}^{\overline{N}-1} \sum_{N'=N+1}^{\overline{N}} \frac{|\hat{\Delta}_m(\tau, N, N', x) - \hat{\Delta}(\tau, N, N', x)|}{\hat{\sigma}_m(\tau, N, N', x)}$$

Details of the test results are in Table 11 where critical values are based on 1000 bootstrap samples. High values of the test statistic would indicate the presence of a selection effect. The LS model cannot be rejected at the 10%, 5%, or 1% confidence levels, suggesting that the selection effect is not a large factor in this market and the LS model is a reasonable representation of bidder entry behavior.

[39] Specifically, these objects are estimated non-parametrically using two auction characteristics, working days and project volume, using normal kernels with bandwidth parameters chosen by Silverman's rule of thumb.

Table 11: Test results for selective entry

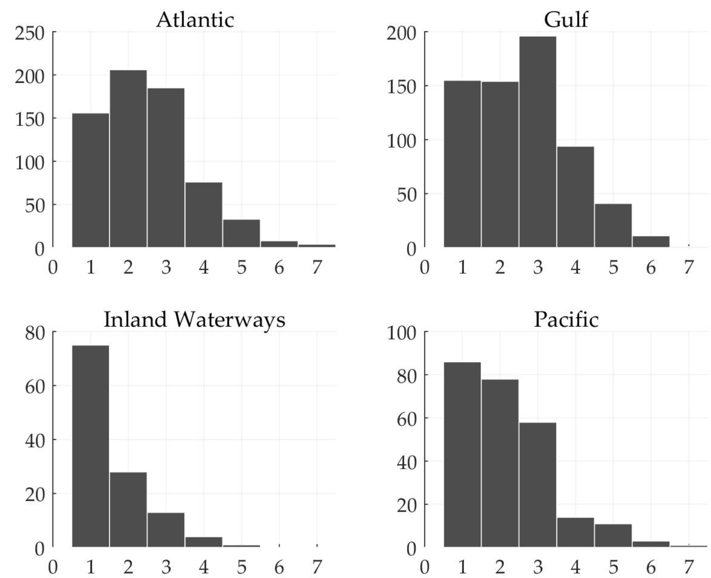
Test statistic	10% critical value	5% critical value	1% critical value
3,615.9	7,783.1	9,895.6	41,440

B.4 Other Figures and Tables

This section gives additional figures and tables, split into three subsections. The first subsection provides additional details on the auctions, including bidder participation, cost distributions by number of bidders, auction model fit, and regressions of winning bids on availability of USACE dredges, number of recently issued private dredging permits, and other variables. The second subsection provides additional details of government dredging activity and also provides supporting evidence that costs are similar across districts by comparing the average costs per cubic yard of dredged material. The last section presents evidence that the contracted price is a good estimate for the final ex-post price after all adjustments have been made, suggesting that holdup and ex-post renegotiation are not large factors in this market.

B.4.1 Auction

Figure 5: Histogram of Auction Participants by Region



Note: Histogram of the number of bidders in project auctions separated by region. Districts located on the Atlantic and Gulf coasts have comparatively higher numbers of bidders, while the Inland Waterways and Pacific regions have lower competition overall and a greater chance of having a single bidder.

Table 12: Regressions of variables on number of bidders

	(1)	(2)
Working Days	0.007**	0.005
	(0.002)	(0.002)
Project Volume (cu. yds.)	-0.034	-0.135***
	(0.028)	(0.039)
# Ongoing USACE projects	-0.036	-0.033
	(0.020)	(0.020)
USACE eng. estimate		0.194***
		(0.054)
Constant	3.164***	1.603**
	(0.328)	(0.553)
District	Yes	Yes
Year	Yes	Yes
Observations	1,777	1,777

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table contains regression results for the effect of observable characteristics on the number of bidders. The variable "Ongoing Projects" represents the number of projects underway in the district at the time the current project is set to begin. That this variable has a statistically insignificant effect on the number of bidders in the auction, suggesting that the number of currently ongoing projects does not impact bidder participation in auctions.

Table 13: Effects of USACE dredge availability, distance, and current ongoing projects on winning bid levels

	(1)	(2)	(3)	(4)
USACE dredge available	0.011	-0.022		
	(0.067)	(0.031)		
Working Days	0.014***	0.001	0.016***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
Project Volume (cu. yds.)	0.523***	0.042***	0.524***	0.042***
	(0.020)	(0.009)	(0.021)	(0.010)
# Ongoing USACE projects	-0.017	-0.002	-0.011	-0.001
	(0.010)	(0.004)	(0.010)	(0.005)
USACE eng. estimate		0.929***		0.929***
		(0.013)		(0.014)
Distance			-0.004	-0.003
			(0.004)	(0.002)
Constant	1.228***	-6.246***	1.244***	-6.199***
	(0.221)	(0.125)	(0.246)	(0.139)
District	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	1,777	1,777	1,599	1,599

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table contains regression results for the effect of observable characteristics on the winning bid. The variable “Ongoing Projects” represents the number of projects underway in the district at the time the current project is set to begin. The availability of a USACE dredge is captured by the indicator “USACE dredge available”, which is equal to one if a Corps dredge that serves the district is available and is zero otherwise. The variable “Minimum USACE dredge distance” measures the minimum distance from the project to any available USACE dredge.

Private dredging permits statistics:

B.4.2 USACE

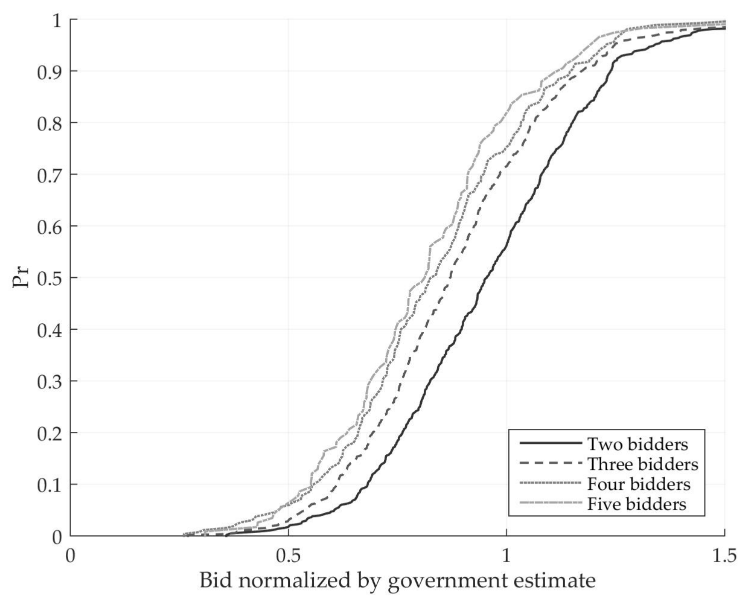
Table 14: Effects of private dredging activity on winning bid levels

	Winning bid				Number of bidders	
	(1)	(2)	(3)	(4)	(5)	(6)
Working Days	0.014***	-0.001	0.014***	-0.001	0.014*	0.014*
	(0.003)	(0.001)	(0.003)	(0.001)	(0.007)	(0.007)
Project Volume (cu. yds.)	0.521***	0.070**	0.521***	0.070**	-0.462***	-0.461***
	(0.037)	(0.021)	(0.037)	(0.021)	(0.100)	(0.100)
# Ongoing USACE projects	-0.026	-0.016	-0.026	-0.016	-0.063	-0.062
	(0.025)	(0.012)	(0.025)	(0.012)	(0.053)	(0.053)
# Dredging permits issued (past 4 weeks)	-0.004	-0.002			0.002	
	(0.003)	(0.001)			(0.007)	
# Dredging permits issued (past 8 weeks)			-0.001	-0.001		0.002
			(0.001)	(0.001)		(0.004)
USACE eng. estimate		0.893***		0.895***	0.304*	0.303*
		(0.025)		(0.025)	(0.123)	(0.123)
Constant	0.926*	-6.155***	0.903*	-6.167***	2.197	2.177
	(0.390)	(0.249)	(0.391)	(0.249)	(1.434)	(1.434)
District	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	430	430	430	430	430	430

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. This table contains regression results that include data on private dredging permits issued from 2010-2013. The dependent variable is the log of the winning bid or the number of bidders for each project contracted out. The variables "# Dredging permits issued (past X weeks)" indicate the number of dredging permits issued by the USACE for dredging projects not overseen by the Corps and in the same district as the auctioned project. These variables serve as a measure of private (and non-USACE public) dredging activity currently underway in the district at the time the auction takes place.

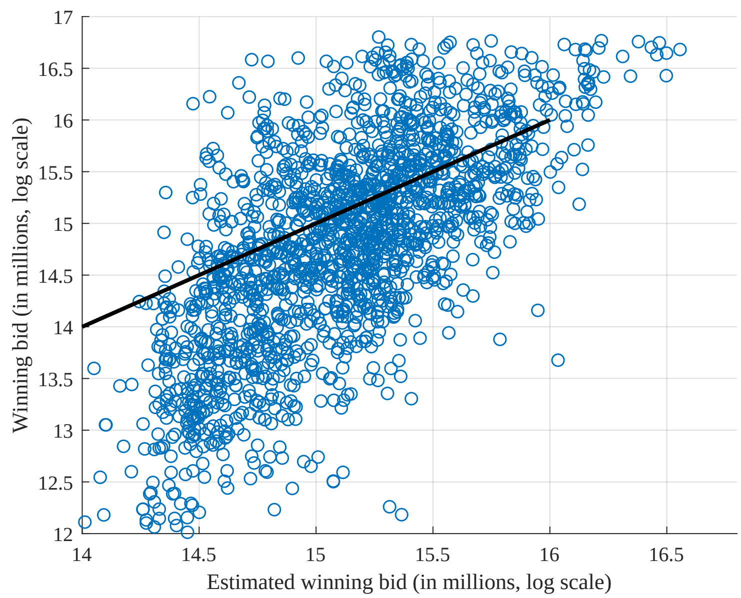
Variable	Mean	Std. Dev.	Min	Max
# Dredging permits issued (past 4 weeks)	11.28	15.81	0	117
# Dredging permits issued (past 8 weeks)	22.13	30.14	0	228

Figure 6: CDF of winning bids by number of bidders



Note: This figure shows the CDF of winning bids separated by the number of bidders. The bids have been normalized by the auction reserve, e.g. $\tilde{b} = b/r$ where r is the auction reserve.

Figure 7: Model fit for winning bids



Note: This figure plots the realized winning bid for each auction against the model prediction (i.e. the expected winning bid for the auction). Both the x-axis and y-axis are displayed on a log scale, and the solid black line represents the 45-degree line.

Table 15: Utilization of USACE dredges

	Working Days				Number of
Vessel name	Mean	Std. Dev.	Min	Max	districts
Hurley	136.5	33.8	89	215	1
Wheeler	87.3	39.0	25	162	3
McFarland	133.5	43.3	60	192	8
Essayons	179.6	41.1	38	216	5
Yaquina	180.5	15.6	131	197	4
Potter	129.8	53.9	10	213	4
Thompson	116.6	35.3	65	152	1
Jadwin	124.9	31.9	75	188	4
Currituck	329.6	33.7	259	365	7
Fry	287.4	68.2	114	363	4
Merrit	284.9	60.5	135	361	4
Schweizer	131.0	0	131	131	1
Goetz	147.3	58.6	20	211	3
Murden	107.3	132.3	6	257	2

Note: Annual working days and the number of USACE districts visited of each dredge in the USACE fleet over the years 1999-2013. The USACE operates a maximum of 12 dredges each year: the dredge Schweizer only operated for a single year in 1999 before being retired. The Goetz replaced the Thompson in 2005. The vessel Murden was added in 2012.

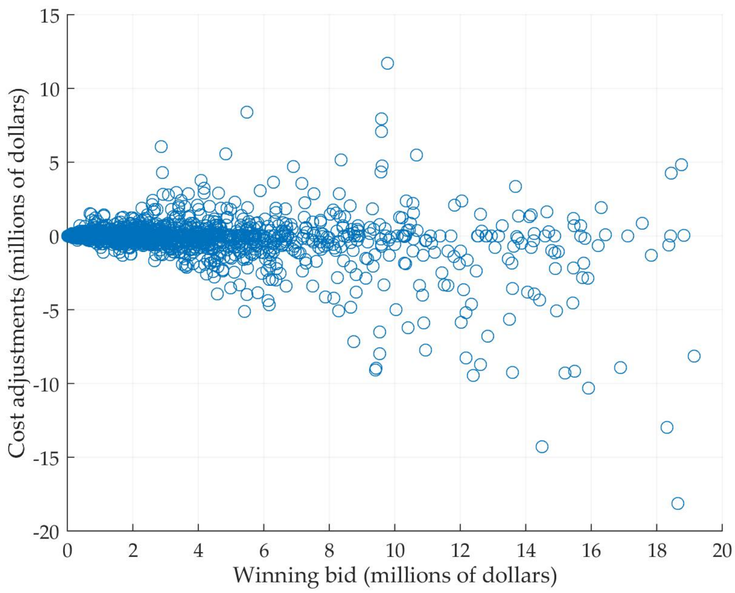
Table 16: Test of Cost per Cubic Yard Differences Against Sample Average by District

District	p-value
Alaska	0.7039
Baltimore	0.9237
Charleston	0.5519
Galveston	0.2417
Honolulu	0.0032
Huntington	0.7583
Jacksonville	0.6456
Little Rock	0.8468
Los Angeles	0.9860
Louisville	0.7424
Memphis	0.7854
Mobile	0.0109
New England	0.0001
New Orleans	0.0988
New York	0.4402
Norfolk	0.5437
Philadelphia	0.6128
Pittsburgh	0.2349
Portland	0.9422
Rock Island	0.8852
Sacramento	0.9068
San Francisco	0.9601
Savannah	0.5712
Seattle	0.7509
St. Louis	0.8420
St. Paul	0.8599
Tulsa	0.9248
Vicksburg	0.6804
Walla Walla	0.9083
Wilmington	0.4380

Note: This table reports the p-value of a difference in means test for cost per cubic yard of dredged material in each district versus the entire sample average. Before adjusting for testing multiple hypotheses there are three districts that have p-values significant at the 5% level: Honolulu, Mobile, and New England. Collectively, these projects in these districts account for 5.91% of all projects. After applying the Bonferroni correction for multiple comparisons, only one district, New England, has a mean cost per cubic yard that is significantly different from the sample average at the 5% level.

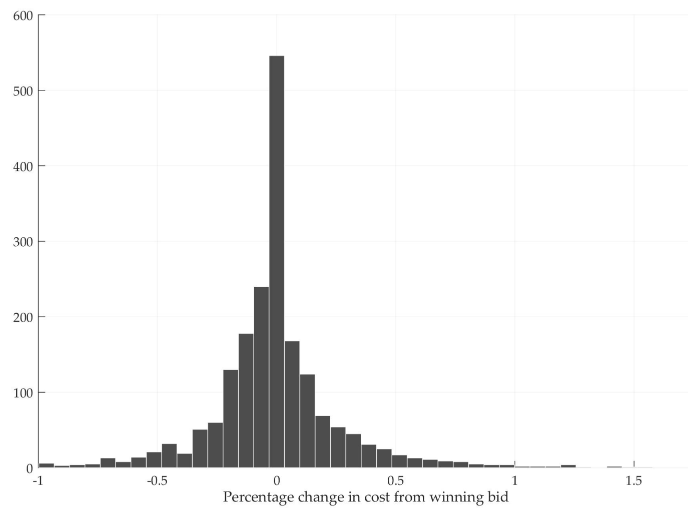
B.4.3 Ex-post payment changes

Figure 8: Winning Bids against Ex-post Payment Changes



Note: Plot of winning bids against the ex-post changes in payment to the contracted firm. There is no readily observable pattern that suggests cost adjustments correlate more strongly with smaller or larger projects; if anything, very large projects are more likely to have reductions made to the initial bid.

Figure 9: Histogram of Changes to Winning Bid



Note: This figure is a histogram of ex-post changes to contract price as a percentage of the winning auction bid. While nearly all contracts feature changes to the winning bid, the mean change is almost exactly zero.