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"COST AND EFFICIENCY IN DYNAMIC GOVERNMENT OUTSOURCING: EVIDENCE FROM THE DREDGING INDUSTRY"

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Cost and Efficiency in Dynamic Government Outsourcing: Evidence from the Dredging Industry

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Abstract

This dissertation contains essays on government outsourcing and identification of dynamic binary choice models. The first essay, titled "Mixed-Delivery of a Public Good: An Empirical Case Study of the Dredging Industry," provides a descriptive analysis of the United States dredging industry. The industry has several features that make it an interesting area to study delivery of public goods; most notably, provision of dredging services in the US are split between in-house provision by the US Army Corps of Engineers and contracting out to private sector dredging companies. Patterns of in-house government project selection suggest that government prefers to complete smaller projects and also indicates the presence of complementarities across projects arising from travel distance between project sites.

In the second essay, "Semi-parametric Identification of Dynamic Binary Choice Models," I give conditions under which both the per-period payoffs for each state and the distribution of the random, unobserved component of agent utility are identified. Most previous work in dynamic discrete choice models has used the assumption that the distribution of choice-specific utility shocks are known. I show that two conditions suffice to identify this distribution: first, that there is a period in which there is no future value component for agents. This can arise due to either non-stationary state transitions or a finite time horizon. Second, I assume that there is a state variable that enters into the utility for one of the choices through a known function. This allows for identification of the distribution of the unobserved utility component through variation in this state variable in the static periods.

Finally the last essay, titled "Cost and Efficiency in Government Outsourcing," builds a dynamic binary-choice model of government outsourcing decisions and applies the model to the dredging industry described in the first essay. I investigate the effect of government outsourcing on total expenditures and efficiency by considering how outsourcing decisions are determined along two dimensions: (i) cost differences between private firms and government suppliers of public goods and (ii) dynamics arising from cost complementarities and capacity constraints. Identification of the model uses the identification results from the second chapter, and allows for identification of the full distribution of government project costs. Model estimates indicate substantial cost savings due to outsourcing but also that government presence in the market is important for cost reduction. A counterfactual policy experiment featuring direct competition between government and private sector firms finds a total expenditure reduction of 17.1%.

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Chapter 1

Mixed-Delivery of a Public Good: An Empirical Case Study of the Dredging Industry

1.1 Introduction

When government decides how a public good or service will be delivered, it often considers a dichotomous choice between keeping all provision in-house or privatization of the entire industry or service. However, in many cases the government has the option to split provision between in-house resources and contracting out to private sector firms. This type of "mixed delivery" setting offers the government the opportunity to identify specific projects or tasks that lend themselves well to in-house completion, or would prove costly to outsource to private sector firms due to factors such as monitoring costs, as well as use the benefits of competition for other projects in order to bring the total cost of service provision down.

In this paper I examine mixed-delivery of public infrastructure projects in the United States dredging market. Dredging involved the excavation of underwater material, and its chief purpose is to keep waterways navigable for the passage of commercial vessels. Projects are completed by large vessels called dredges, which have all physical capital resources required for dredging projects built into the vessel itself. A US government agency, the United States Army Corps of Engineers, is responsible for maintaining all navigable waterways in the US and oversees all dredging projects that occur in these waters. A notable feature of this industry is that the Corps of Engineers splits completion of these projects across its own dredging vessels as well as outsourcing to private sector firms. The Corps of Engineers maintains a fleet of 12 dredges that complete projects at the Corps' behest, and any projects not assigned to Corps of Engineers dredges are contracted out to private sector firms through the use of procurement auctions.

The dredging industry features a small number of firms in each market, high entry costs due to the large cost associated with purchasing new dredging equipment, and geographic separation of markets in which firms largely compete only in local markets. These factors combine to keep the number of bidders in each auction low, and so the presence of the government in the market adds noticeably to the overall level of competition in the market.

I examine data on dredging projects occurring over a 15 year period from 1999-2013. The Corps of Engineers oversees the completion of several hundred dredging projects per year, with approximately half of these being completed in-house by Corps owned-and-operated dredges. The remainder of the projects are contracted out to private sector dredging companies using a first-price sealed-bid auction. The total awards from the auctions range between $700 million and $1.1 billion annually.

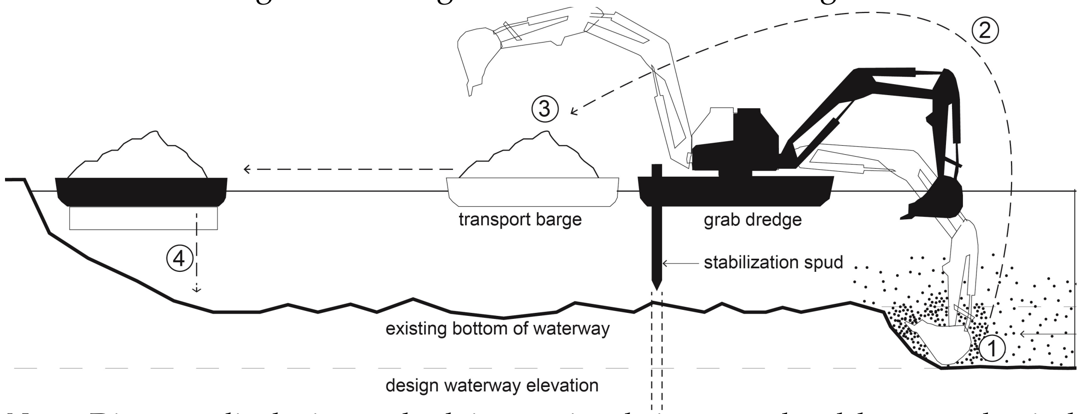
Using data on project allocation decisions and project characteristics, I document patterns in the US Army Corps of Engineers outsourcing decisions. I find evidence that smaller projects, as measured by the volume of material to be dredged as well as the number of working days required for project completion, are more likely to be kept in-house while larger projects are more likely to be contracted out. Additionally, projects that are farther away from the government's closest available vessel are more likely to be contracted out, suggesting that travel distance is costly for the Corps of Engineers. This suggests the following two features may be important in this market: variation in project completion cost between Corps of Engineers dredges and private sector companies, with government having a relative cost advantage for smaller projects and the opposite for larger projects, and dynamic effects arising from the travel distance to project locations. This second point is reinforced by regression results that indicate government decisions are sensitive to how current allocation decisions will affect future travel distances.

1.2 Dredging Projects in the US

Dredging is the act of excavating underwater material and moving it elsewhere. The primary purpose of these projects is to maintain navigable waterways for the passage of vessels. Dredging projects are completed by vessels called dredges, which are large ships which typically have all equipment and capital resources required for dredging built into the vessel itself. Figure (1.1) shows the operations of a mechanical dredge; there are many other types of dredges, with possibly the most common being the trailing suction dredge in which material is excavated by means of a pipe that trails behind the vessel and uses suction combined with a drill to break up and pull to the surface underwater material. Many types of dredges are in use, both across private sector firms as well as within government operations.

In addition to different types of dredges, there are many different types of dredging projects.

Figure 1.1: Diagram of a Mechanical Dredge



Note: Diagram displaying a dredging project being completed by a mechanical dredge. Material is excavated from the waterway floor by the dredge and is then loaded onto barges to be transported to a designated dumping site. Other types of dredges contain a container on board to hold dredged material for later transport.

As stated earlier, the most important function of dredging is to clear waterways for the passage of vessels; however, even this function can take many forms. The specifics of each project will depend on the type of waterway (river, harbor, open water, etc.), depth and gradient of the underwater material to be dredged, material type, and many other factors. In addition to this, there are other types of dredging projects, including projects aimed at maintaining levees, nourishing beaches, and dredging completely new waterways and passages.

In most cases a dredging project will require, in addition to the dredge used, a barge that contains quarters for the dredge crew, surveying equipment/barges, and a vessel to transport dredged material to a designated disposal site if this task is not completed by the dredge itself. The set-up for each project necessitates a "mobilization" period in which the crew, materials, and dredges and additional vessels required for the project are transported to the work site and constructed. Consequently, there is also a demobilization period in which the work site is dismantled and gear and equipment are moved from the site. The mobilization and demobilization phases of each project are often extremely costly, sometimes over one third of the total project costs.

The main costs of dredging operations, in addition to the costs associated with mobilization and demobilization, come from labor costs and fuel for the operation of the dredging equipment. The number of crewmembers on a dredge typically numbers between 15 and 35, although some vessels have as many as 50. In the case of private sector dredging companies, most workers are hired on a part-time, as-needed basis and the number of hours they work will often vary over the course of a project. In the case of projects completed by the Corps of Engineers, works are full-time Corps employees and all workers assigned to the dredge remain on the project site throughout the course of the project. The dredges themselves are require substantial fuel resources to run; dredge equipment often exceeds 10,000 hp, and operation of this equipment consumes large quantities of fuel.

1.2.1 Importance of dredging projects

Dredging is an important service for many sectors of the economy. Chiefly among these is the movement of goods and commodities along the nation's waterways, both for domestic as well as international trade. Other uses of dredging include beach nourishment/replenishment, levee repair and flood control, and for issues of national security. These important uses lead the Corps of Engineers to spend around $1.5 billion each year on dredging projects in the United States.

Waterway maintenance comprises the bulk of projects supervised by the Army Corps of Engineers. Previously dredged channels will accumulate silt, sand, and other sediment in regions that would impede the passage of commercial vessels if not removed. The purpose of these maintenance projects is to remove the build-up of material on the waterway floor to keep these passages clear. The waterways serve a vital role to the US economy, especially for exports of coal, petroleum, and wheat. Over 22% of all coal and petroleum shipped in the United States and over 60% of grain transported in the US are moved along these waterways. Much of this grain is moved down the Mississippi River to ports in New Orleans for export. Overall, water-borne transportation accounts for the majority of all US international trade by weight[1], and nearly all of this occurs using waterways and ports maintained by the Corps of Engineers. Waterway maintenance is important for domestic trade as well; the Corps of Engineers estimates that 22% of all commodities moved domestically are done using waterway transportation.

In addition to maintaining waterways, dredging serves other important functions. Among these are beach nourishment and national defense. Many of the nation's beaches rely on dredged material in order to maintain the appearance and gradient of the beach. Beaches can be shaped either using material from nearby the beach area or from suitable material dredged from another project. As an example, dredging operations were vital to the recovery efforts along the New Jersey coast after hurricane Sandy decimated much of the oceanfront property, including many of the state's beaches. Finally, national defense also serves as an important function of dredging operations. The Corps of Engineers is a military organization and, while many of its projects fall under the "Civil Works" category of operations, it has important strategic goals to consider. One of these strategic considerations is how military operations may disrupt waterways in ways that make it difficult for US naval vessels to move freely, and to alleviate any impediments to these movements. As such, the Corps of Engineers keeps bases near all active combat zones, as well as many other active US military bases abroad.

[1] In 2001, waterborne trade accounted for 78.7% of all trade by weight. Source: US International Trade and Freight Transportation Trends, BTS 2003.

1.3 The United State Dredging Industry

The dredging industry in the United States is noteworthy in that it features a government agency, the US Army Corps of Engineers, which oversees projects and allocates projects between in-house completion by Corps-owned-and-operated dredges and outsourcing to private sector dredging companies. The private market is characterized by low levels of competition, high entry costs, and firms that compete in local geographic markets. The Corps of Engineers oversees and monitors all projects and maintains its own dredging fleet that complete projects at the Corps' behest. The vessels often cover larger geographic areas than would be typical of private sector firms. The Corps of Engineers typically completes approximately the same number of projects as those outsourced to private sector firms, but these projects tend to be much smaller in terms of both volume of dredged material as well as number of working days required to complete the project.

1.3.1 History of Dredging in the United States

The US Army Corps of Engineers has long performed dredging operations in the United States. Under the Rivers and Harbors act – which was introduced in 1824 and expanded through various pieces of legislation throughout the 19th and early 20th centuries– the Corps of Engineers was tasked by Congress with maintaining all navigable waterways in the US, including all rivers, harbors, and ports. The Corps of Engineers kept a fleet of dredging vessels to complete these tasks, and until the late 20th century was the only party to engage in dredging operations in federal waters.

In 1972 Congress passed the Minimum Fleet Act (Public Law 95-269), which tasked the Corps of Engineers with reducing the federal dredging fleet to the minimum level so long as the private sector demonstrated "the capability to do such work and it can be done at reasonable prices and in a timely manner." This effectively gave the Corps of Engineers the dual directive to outsource as much work as possible while insuring that prices stayed within "reasonable" levels. At this time, the Corps of Engineers began selling many of its dredges to private sector dredging companies and actively soliciting these companies to bid in procurement auctions held for dredging projects. The next decade saw a substantial reduction in the volume of dredging work completed by the Corps of Engineers and a corresponding increase in the amount of work completed by private sector firms. The Corps eventually settled for a permanent fleet of 12 dredges and has operated at approximately the same capacity for several decades.

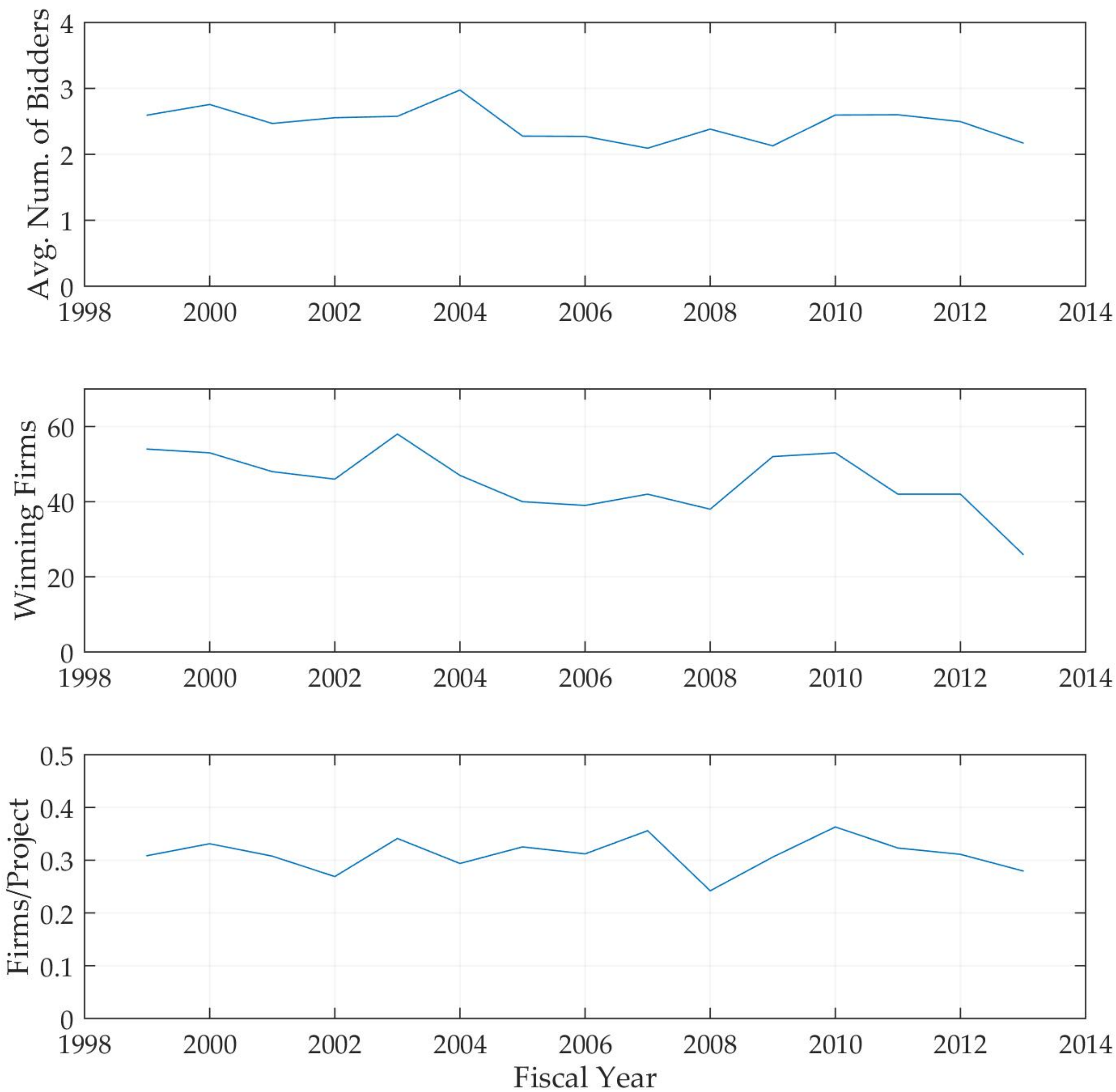
Over this time period, the private sector dredging industry stabilized, with the level of competition staying approximately constant over the last 15 years. Figure (1.2) shows three measures of the level of competition in the national dredging market from 1999-2013. The graphs suggest that the number of firms active in the market for dredging is relatively stable over time, especially after controlling for the number of projects outsourced to the private sector. This indicates that, after a period of growth following the Minimum Fleet Act in 1978, the private sector dredging industry leveled off and remained fairly flat thereafter. This is in large part due to the substantial fixed costs associated with starting a dredging company, as new dredges can cost many millions of dollars.[2]

The convergence of both the Army Corps of Engineers dredging fleet to a constant level and the industry to a stable level of competition have led to a balance in the work completed by the Corps of Engineers and that outsourced to private firms. Approximately half of all projects

[2]As an example, a new dredge purchased by the Army Corps of Engineers in 2011 to replace an aging dredge had a total price tag of nearly $25 million.

are completed in-house by the Corps, and the rest are outsourced to private sector firms using first-price sealed-bid auctions.

Figure 1.2: Dredging Procurement Competition Over Time



Note: These three figures display indicators of the level of competition in the dredging industry over 1999-2013. The top figure shows the average number of bidders in auctions for dredging contracts. The second figure displays the number of firms that won a contract within a given fiscal year. The bottom figure displays the number of winning firms per project in each year.

1.4 Empirical Setting and Data

The data analyzed in this paper come from dredging projects overseen by the United States Army Corps of Engineers (USACE). Dredging consists of excavation and transportation of underwater material. Dredging projects are carried out by large vessels known as dredges; a typical dredge has built-in machinery that excavates material from beneath the water as well as a storage container that will hold the dredged material until a disposal area is reached. The primary purpose of most dredging projects is the maintenance of shipping lanes and harbors to insure the safe passage of commercial vessels. Proper care of these passages is crucial to the United States economy as much of US international trade involves transport of goods along these waterways, and each year the USACE receives over $2 billion dollars from Congress to carry out these navigation projects. Each dredging project occurs in one of 34 USACE districts, which are located along the coasts and inland waterways of the United States.

The dredging industry is ideal for assessing project level dynamic government outsourcing for several reasons. First, the USACE maintains its own fleet of 12 dredges that complete dredging projects at the Corps' behest. In addition, many dredging projects are contracted out by the USACE to private sector dredging companies via first price sealed bid auctions. This allows for a direct comparison of which projects are kept in-house versus contracted out, and the procurement auction results give a direct indication of firm revenues and competition for projects. Another key feature of the market is that the Corps publishes activity for each of its dredges, including location and dredging activity, for every day of the fiscal year. This allows for tracking distance traveled and project availability for each vessel in the USACE fleet.

The market operates as follows. Prior to the start of each fiscal year the Corps publishes the schedule of projects to be completed over the next fiscal year. This schedule includes all projects across all districts. The schedule of projects is made on a yearly basis because (i) the sites that will require dredging work are typically not known years in advance and (ii) the navigation budget issued to the Corps is decided each year by Congress, and so the total budget available for dredging projects is not known until several months before the start of the fiscal year.[3] The district overseeing each project holds a first price sealed bid auction to contract out the project to a private firm or arranges for the Corps dredge charged with overseeing that district to complete it. Auctions occur on a rolling basis, with the bid opening date typically falling about two months prior to the start of the project while the contract is awarded about three to four weeks prior to the scheduled start date for the project. When a project is allocated to a government dredge, the vessel moves to the district in which the project is located and completes the project.

1.4.1 Data

The main source of data comes from the United States Army Corps of Engineers Navigation Data Center and includes information on all projects contracted out to private dredging companies and daily activities for all dredges operated by the USACE from 1999-2013. Data is collected at the district level and then published on a yearly basis on the Navigation Data Center webpage. I supplement this data set with between-port distances obtained from the National Oceanic and Atmosphere Administration (NOAA).

The Corps splits the project level data into projects contracted out and those kept in-house. In-house projects are assigned to one of the Corps dredges. Each dredge has a district tasked with operation of the dredge, and each dredge completes projects in the districts surrounding

[3] Additionally, emergency dredging work is rare. For example, in 2014 emergency dredging accounted for less than 1% of all dredged material.

its “home” district. Several government dredges are replaced over the 1999-2013 time period but the total number of operating vessels is kept constant throughout the sample period. Data for the in-house projects consists of the identity of the vessel completing the project, project characteristics such as volume and number of working days, and the district in which the project is completed.

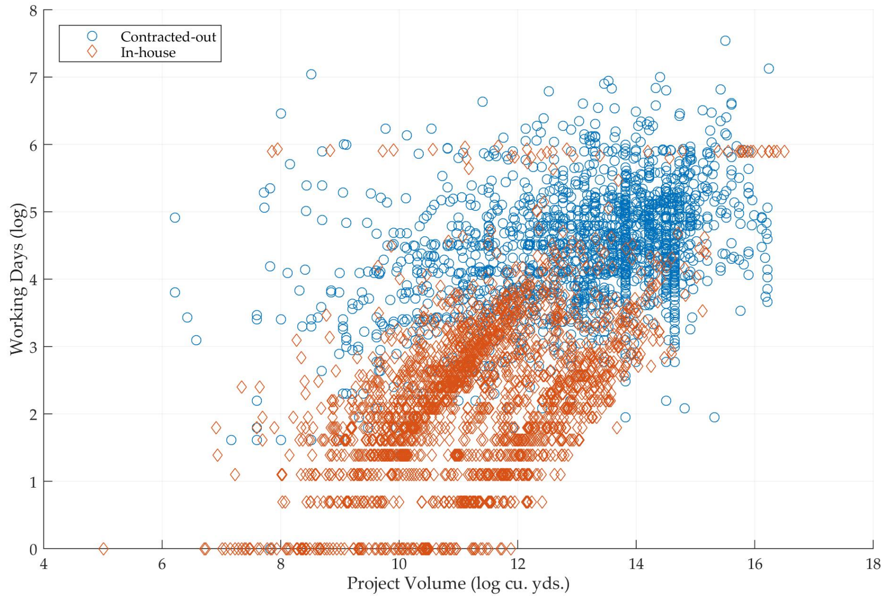
Outsourced projects are allocated by first price sealed bid auctions. Auction data consists of the winning bid and identity of the winning bidder, district where work was performed, number of bidders, and project characteristics such as date, volume of material to be excavated. Data for USACE projects consists of volume of excavated material, estimated number of working days, and the district where the project was completed.

Table 1.1: Summary Statistics

	Mean	Std. Deviation	Min	Max
Outsourced Projects				
Number of Projects/year	118.5	22.5	77	160
Cubic yds/proj (thousands)	1,177	1,575	0.500	11,300
Working Days	125.8	136.0	1	1887
Cost/project (millions)	4.03	3.83	0.0153	19.8
Number of Bidders	2.46	1.32	1	11
In-house Projects				
Number of Projects/year	123.2	28.2	57	172
Cubic yds/proj (thousands)	273.7	939.5	.150	14,721
Working Days	17.9	38.7	1	365
Average Distance (miles)	136.7	314.6	0	4007
Firm Statistics				
Projects	10.4	29.1	1	218
Districts	2.06	2.41	1	19
Mean Bid (millions)	2.59	2.34	0.062	15.77

There were 2178 projects awarded to private firms and 1940 projects taken by USACE dredges over the 15 year period in the data. After removing observations for which key data was missing,

Figure 1.3: Project Attributes and Make-or-buy Decision

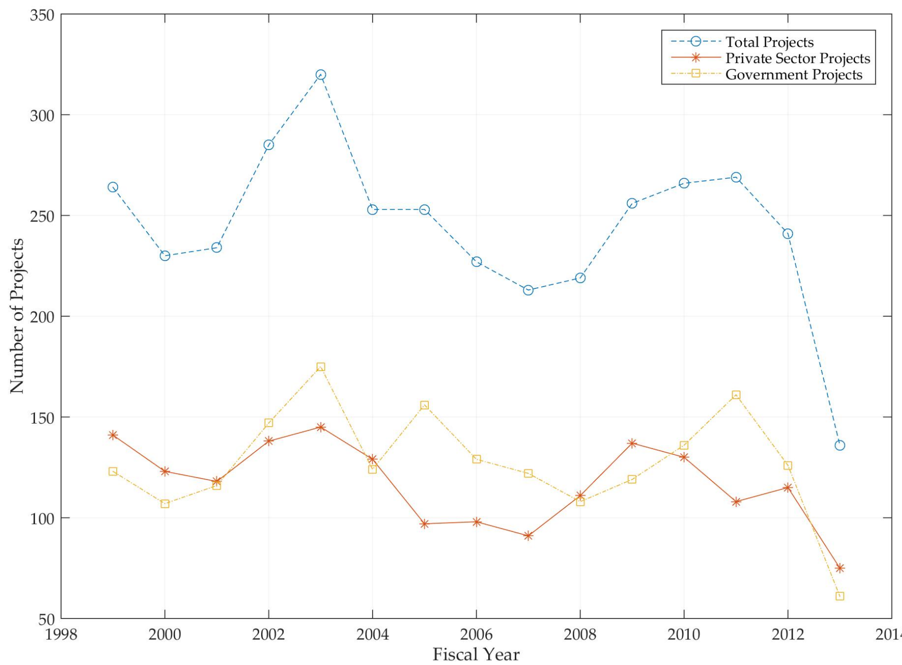


Note: Comparison of the project volume and number of working days required for in-house and contracted-out projects. While in-house projects completed by the government appear generally to be both lower volume and shorter, there are still many in-house projects that are comparable with the largest outsourced projects.

outlier projects, and projects from districts in which Corps dredges don't operate, the final sample consists of 3,625 observations. Additional information on the data and sample construction can be found in the Appendix. Table 1.1 contains summary statistics for the projects contained in the sample. There were $477 million dollars worth of contracts issued to private firms each year on average. Although the number of projects completed by the USACE is comparable to the number of projects outsourced, the USACE projects tend to be much smaller; the mean USACE project excavates less than 25% of the material excavated by the mean project completed by a private firm.

Overall there were 177 unique firms awarded contracts. Most firms are active in a small number of areas: the mean number of districts in which a firm is active is about two, while the median is one. This suggests that most firms confine their dredging operations to a small geo-

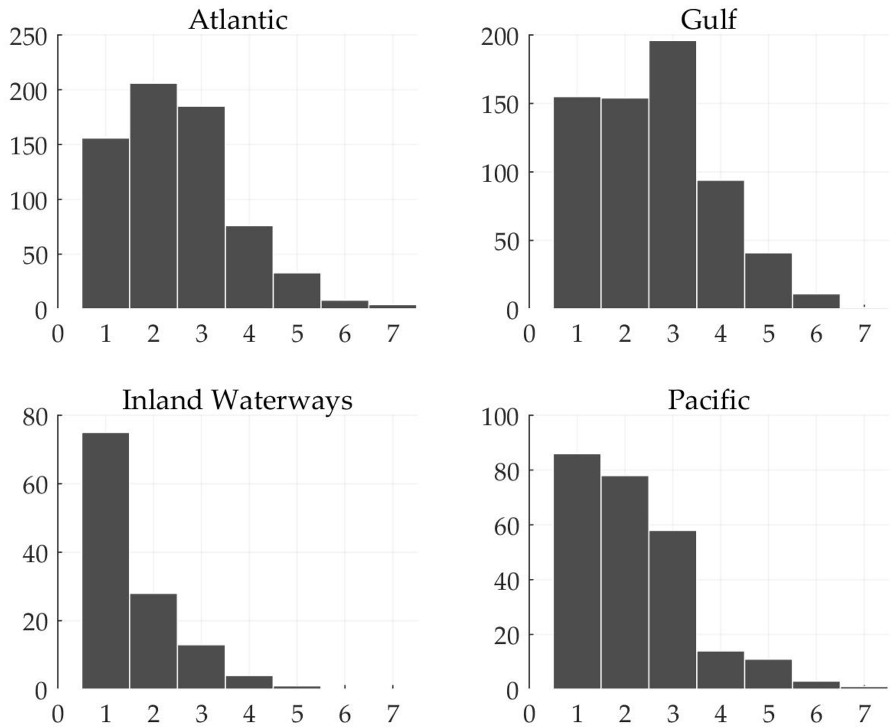
Figure 1.4: Number of Projects per Year Comparison



Note: Graph displaying the variation in the number of projects completed per year, including the total number of projects as well as in-house and outsourced projects.

graphic area. Additionally, private sector dredging capacity far outstrips government dredging resources, with an average of six dredging companies per district. Descriptive evidence suggests that capacity is not a limiting factor in auction participation: regression results (which can be found in the Appendix) indicate no statistically significant effect of the number of currently ongoing projects in a district on auction participation. Competition in the auctions is low, with a mean of 2.46 bidders per auction and a median of 3. Auctions with greater that four bidders are rare, while single-bidder auctions are not uncommon. The level of competition varies across districts. This can be seen graphically in Figure 1.5, which shows a histogram of the number of bidders in an auction grouped by region. Figure 1.6 shows the distribution of winning bids separated by the number of participating bidders. Predictably, additional bidders present in an auction is associated with lower winning bids.

Figure 1.5: Histogram of Auction Participants by Region



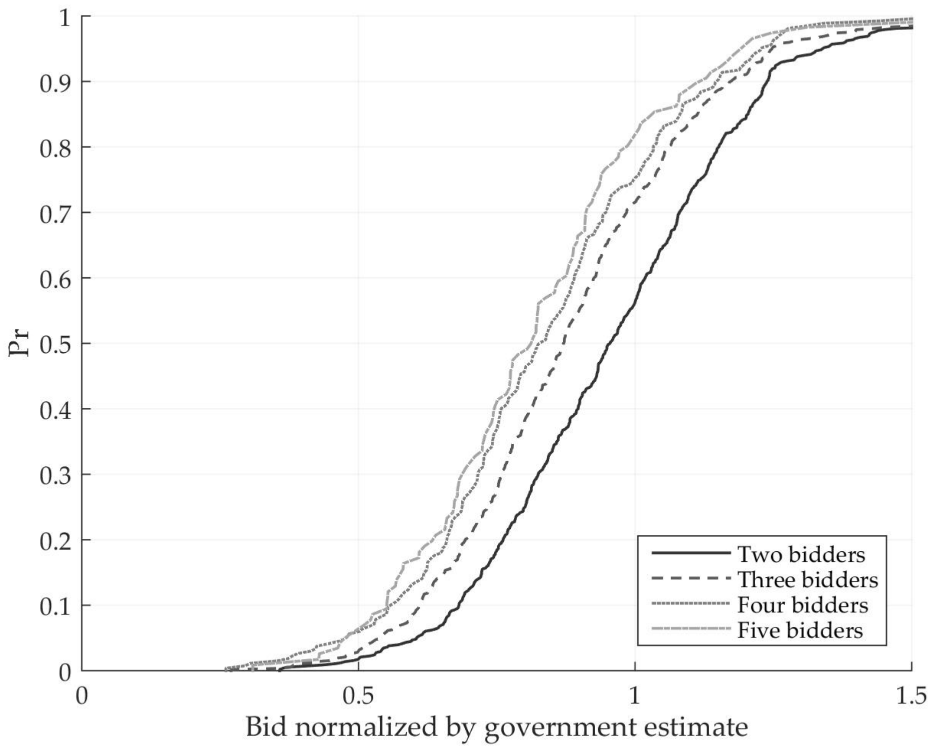
Note: Histogram of the number of bidders in project auctions separated by region. Districts located on the Atlantic and Gulf coasts have comparatively higher numbers of bidders, while the Inland Waterways and Pacific regions have lower competition overall and a greater chance of having a single bidder.

Another feature of the industry is that the expected total costs paid to contracted firms is very similar to the initial winning bid. This is in contrast to other construction industries in which changes to total project costs are a substantial component of overall payments and bidders can strategically respond to expected cost adjustments.[4] These cost increase could affect the government's decision to contract out a project or not, as it may be put in a disadvantageous negotiating position if circumstances necessitate changes to project design while a firm has already partially completed the project. However, for dredging contracts the winning auction bid is a very good estimate for the final contract price.[5]

[4]Bajari, Houghton, and Tadelis (2014) study this in the context of highway procurement auctions and find that bidders respond strategically to anticipated cost adjustments.

[5]Cost adjustment data is available for 78% of outsourced projects, and the average percentage change to the

Figure 1.6: Empirical CDFs of bid distributions by number of bidders



Note: Empirical bid distributions separated by number of bidders present in the auction and normalized by the government's estimated project cost.

1.5 Government Make-or-Buy Decisions

In order to examine the importance of project locations and distance traveled on the outsourcing decision, I regress the government's make-or-buy decision on observable project variables and distance measures. Table 1.2 gives coefficient estimates for a linear probability model of in-house government completion. "Project Volume" measures the amount of dredged material for a project in cubic yards, "Working Days" gives the number of days required to complete the project, and "Distance" gives the distance to project district in nautical miles. The variable "$t+1$ Distance Saved" gives the reduction in distance to the project in period $t+1$ should the

winning bid is almost exactly zero. A graphical representation of these changes can be found in the Appendix.

current project be taken; that is, it measures how much closer or farther the vessel will be to the next period's project if the current project is kept in-house. The estimates are consistent with the summary statistics in that government dredges are less likely to take larger volume projects and those that require more days to complete. Additionally, greater distance to a project decreases the chance that the project is kept in-house while additional distance saved to the next project will increase it. Taken together, these results suggest that travel distance incurs costs to government dredges and that the government is forward-looking with regard to total travel distance.

Table 1.2: Government Project Selection Probability (LPM)

Variable		**Coefficient**	
Dependent variable: in-house project		*(Std. Err.)*	
	(i)	(ii)	(iii)
log(Cubic Yds.)	-0.095***	-0.095***	-0.096***
	(0.006)	*(0.006)*	*(0.006)*
log(Working Days)	-0.011***	-0.011***	-0.011***
	(0.001)	*(0.001)*	*(0.001)*
Distance	-0.015***	-0.016***	-0.016***
	(0.002)	*(0.002)*	*(0.002)*
$t + 1$ Distance Saved	0.002**	0.002*	0.002**
	(0.001)	*(0.001)*	*(0.001)*
Constant	0.671***	0.597***	1.026***
	(0.062)	*(0.065)*	*(0.043)*
District	Yes	Yes	Yes
Season	No	Yes	Yes
Year	No	No	Yes
N	3625	3625	3625

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Linear probability model results for the probability that a project is kept in-house. Larger projects and those located farther away from a government dredge's current location are more likely to be outsourced. However, if taking a project will bring a government dredge closer to a subsequent project (represented by the variable "$t + 1$ Distance Saved"), then that project is more likely to me kept in-house.

Table 1.3: Government Project Selection Probability (Logit)

Variable	**Coefficient**		
Dependent variable: in-house project	*(Std. Err.)*		
	(i)	(ii)	(iii)
log(Cubid Yds.)	-0.266**	-0.277***	-0.283***
	(0.084)	*(0.083)*	*(0.084)*
log(Working Days)	-0.521***	-0.518***	-0.522***
	(0.071)	*(0.070)*	*(0.071)*
Distance	-0.107***	-0.117***	-0.121***
	(0.020)	*(0.021)*	*(0.021)*
$t+1$ Distance Saved	0.014*	0.013*	0.013*
	(0.006)	*(0.006)*	*(0.006)*
Constant	-0.329	-1.125	2.714
	(0.884)	*(0.925)*	*(12.354)*
District	Yes	Yes	Yes
Season	No	Yes	Yes
Year	No	No	Yes
N	3318.000	3318.000	3316.000

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Logit results for the probability that a project is kept in-house. Results are largely similar to the linear probability model results; in particular, projects with larger volume, larger number of working days, and farther distance are less likely to be kept in-house.

1.6 Conclusion

The dredging industry differs from many other examples of outsourcing in that it represents an example of mixed-delivery of a public good in which projects are completed by both government as well as private sector firms. This stands in contrast to other industries in which an outsourcing decision will focus on whether or not provision of the entire good or service should fully privatized or kept entirely in-house.

The data on dredging industry project allocation displays several attributes that make it attractive for analyzing dynamic government outsourcing decisions. The government maintains a sizable market presence in the form of 12 dredges that perform approximately half of all dredging projects. Completing projects requires transportation of the vessel and crew to the project location, with descriptive evidence suggesting that government vessels are averse to traveling large distances. Because dredges are discrete capital units and projects are often lengthy, dredge availability further drives dynamic considerations for the government The contracting process itself is a standard first price sealed bid auction in which cost adjustments are not a major factor in the overall expected costs. Furthermore, competition heterogeneity across districts leads to different patterns of outsourcing depending on the expected level of competition.

Chapter 2

Non-parametric Identification of Non-stationary Dynamic Binary Choice Models

2.1 Introduction

Dynamic discrete choice models have emerged as an important methodological tool in the analysis of many economic situations. These models have been used for applications in labor economics (Miller (1984), Keane and Wolpin (1997)), industrial organization (Ryan (2012)), patents and innovation (Pakes (1986)), and many other areas. The use of these models in empirical settings allows for the econometrician to gauge the impact of counterfactual policies and thereby pin down more precisely the effects of these policies than is typically possible using so-called "reduced form" methods alone.

From the earliest versions of these models, starting with the seminal papers of Miller (1984), Wolpin (1984), Pakes (1986), and Rust (1987), and continuing to the present day, these models have relied on the general structure and assumptions of the McFadden (1978) random utility framework. In particular, per-period agent utility for each choice consists of a deterministic component and a random choice-specific shock, where the shocks are typically assumed to be iid across choices and periods. In most settings, the distribution of the random utility shocks is assumed to be known. As shown in Rust (1994), this assumption, as well as fixing the time discount factor, is required to identify the utilities associated with each choice and state. The most common choice for this distribution is Type I Extreme Value, which leads to the familiar logit structure for the conditional choice probabilities.

While this assumption leads to a tractable formulation for the estimation problem and makes it easy to compute estimates in practice, the restriction to a known distribution on the choice-specific utility shocks is nevertheless quite restrictive. The goal of this paper is to explore scenarios in which both the choice-specific utilites and the distribution of utility shocks can be identified. To do this I focus on settings in which non-stationarity provides additional identifying power. In particular, when deterministic utilities do not vary across time for each state but either (i) state transitions vary across periods or (ii) there is a finite time horizon, it is possible to identify the distribution of choice-specific utility shocks when combined with a suitable normalization and an exclusion restriction.

2.1.1 Related Literature

2.2 Baseline Model

In this section I describe the basic framework for dynamic binary choice models and highlight the under-identification in the standard stationary case. The environment consists of a set of choices $\{0,1\}$ and states $\mathcal{Z}$. Time is discrete, with horizon $T \leq \infty$. Each period an agent makes a choice $j \in \{0,1\}$ and receives a period t payoff of $u_j(z_t) + \epsilon_{jt}$, where z_t is the state in period t and ϵ_{jt} is the choice-specific utility shock for choice j in period t. Additive separability of the u_j and choice shocks is a standard assumption in the dynamic discrete choice literature. The shocks are i.i.d. across choices and periods, and drawn from a common distribution G.

State transitions are governed by a Markov process in which $f_{jt}(z'|z)$ denotes the probability of reaching state z' next period after choosing choice j in period t conditional on current state z. An additional assumption is that of conditional independence: the evolution of the state variable z depends only on choices and the current state (and on the time period in the non-stationary case) but does not depend on the realization of the random utility shocks $\epsilon_t = (\epsilon_{0t}, \epsilon_{1t})$. Formally, this assumption is

$$f_{jt}(z'|z, \epsilon_t) = f_{jt}(z'|z).$$

Finally, the agent discounts future payoffs at a rate $\beta \in (0,1)$.

2.2.1 The agent's problem

Given the framework developed above, we can express the agent's optimization problem as a maximization of expected future utility flows. Specifically, let $d_j \in \{0,1\}$ represent the agent's choice, with $d_{jt} = 1$ representing that the agent has chosen choice j in period t and $d_{0t} + d_{1t} = 1$. The agent chooses a decision rule $\mathbf{d}$ to maximize expected discounted utility:

$$\mathbf{d}^* = \arg\max_{\mathbf{d}} \mathbb{E}\left[\sum_{t=1}^{T}\sum_{j=0}^{1} \beta^t d_{jt}(u_{jt}(z_t) + \epsilon_{jt}) \mid z_1, \epsilon_1\right]$$

The discount stream of payoffs received by the agent can also be expressed in a value function formulation:

$$V_\tau(z_\tau) = \max_{\mathbf{d}} \ \mathbb{E}\left[\sum_{t=\tau}^{T}\sum_{j=0}^{1} \beta^{T-t} d_{jt}(u_{jt}(z_t) + \epsilon_{jt}|z_\tau, \epsilon_\tau\right].$$

This has the following recursive formulation:

$$V(z_t) = \max_{d_t} \sum_{j=0}^{1} d_{jt}(u_{jt}(z_t) + \epsilon_{jt}) + \beta \mathbb{E}\left[V_{t+1}(z_{t+1})|d_t, z_t\right].$$

Since the choice-specific utility shocks ϵ_t are unobserved to the econometrician, it is useful to define the *ex-ante* value function; that is, the expectation of the value function before the shocks are revealed at the start of the period. This is given by

$$\overline{V}_t(z_t) = \int_\epsilon V(z_t) g(\epsilon_t) d\epsilon_t.$$

Using the recursive formulation, and recalling that states evolve according to the Markov transitions $f_{jt}(z_{t+1}|z_t)$, the *ex-ante* value function can be expressed as

$$\overline{V}_t(z_t) = \sum_{j=0}^{1} \int d^*_{jt}(z_t, \epsilon_t) \left[u_{jt}(z_t) + \epsilon_{jt} + \beta \int \overline{V}_{t+1}(z_{t+1}) f_{jt}(z_{t+1}|z_t) dz_{t+1}\right] g(\epsilon_t) d\epsilon_t$$

where $d^*_{jt}(z_t, \epsilon_t) = 1$ represents the decision rule that chooses choice j in period t given state z_t

and choice-specific utility shocks ϵ_t.

With an expression for the *ex-ante* value function we can now define the conditional value function, which will be the full value function without the choice specific utility shocks in the current period:

$$v_{jt}(z_t) \equiv u_{jt}(z_t) + \beta \int \overline{V}_{t+1}(z_{t+1}) f_{jt}(z_{t+1}|z_t) dx_{t+1}.$$

The choice-specific conditional value function $v_{jt}(x_t)$ will be the main component to expressing the decision problem of the agent. Specifically, agent's choose a decision rule d^* that satisfies

$$d_t^*(x_t, \epsilon_t) = \arg\max_j v_{jt}(x_t) + \epsilon_{jt}.$$

We can then use this framework to describe the probability that the agent chooses choice j in period t conditional on the state z_t; this is called the Conditional Choice Probability and is represented by

$$p_{jt}(z_t) = \int \mathbb{1}\{v_{jt}(z_t) + \epsilon_{jt} \geq v_{kt}(z_t) + \epsilon_{kt} \forall k\} g(\epsilon_t) d\epsilon_t$$

In the binary choice framework we have developed so far, this is equivalent to the following:

$$p_{1t}(z_t) = \Pr(v_{1t}(z_t) + \epsilon_{1t} \geq v_{0t}(z_t) + \epsilon_{0t}).$$

with $p_{0t}(z_t) = 1 - p_{1t}(z_t)$.

The primitives of the model are the utilities associated with each choice and state for each time period $u_{jt}(z_t)$, the time discount factor β, and the distribution of choice-specific utility shocks G. The problem of the econometrician is to identify these primitives from data on the choices made in each period d_{jt} and states z_t. In most settings, identification of the full system is impossible.

The case most commonly seen in the literature, in which utilities and state transitions are both stationary, is under-identified, and assumptions must be made on the distribution of shocks G, the time discount factor β, and a normalization of utilities for one choice in each state in order for the remaining utility terms to be identified.[1] First I will demonstrate that when assumptions are made on the discount factor β and distribution of choice shocks G that the utility parameters can be recovered (up to a normalization). I will then show the under-identification for the general case, and give conditions under which this under-identification issue can be resolved.

Identification in the case in which G and β are assumed known is constructed using arguments from Magnac and Thesmar (2002) and Arcidiacono and Miller (2011). In particular, from Arcidiacono and Miller (2011) we know that there exists an inversion function $\psi : [0, 1] \to \mathbb{R}$ that maps conditional choice probabilities into differenced conditional value functions:

$$\psi_j(p_{jt}(z_t)) = \overline{V}_t(z_t) - v_{jt}(z_t). \tag{2.1}$$

Define by $\kappa_{t+\rho}(z|z_t, \delta_t)$ the distribution over states reached ρ periods ahead of the current period, conditional on being in state x_t in period t and choosing choice δ_t. Specifically, κ has a recursive definition given by

$$\kappa_\tau(z_{\tau+1}|z_t, \delta_t = j) = \begin{cases} f_{jt+1}(z_{t+1}|z_t) & \text{if } \tau = t \\ \sum_{k=0}^{1} \sum_{z \in \mathcal{Z}} \mathbb{1}_{\{d'_{k\tau}=1\}} f_{k\tau}(z_{\tau+1}|z_\tau)\kappa_{\tau-1}(z_\tau|z_t, \delta_t = j) & \text{if } \tau > t. \end{cases}$$

Then after normalizing $u_{0t}(z_t) = 0$ for all $z_t \in \mathcal{X}$, we can use the inversion theorem and definition of κ to represent $u_{1t}(z_t)$ in terms of only the state transitions, conditional choice probabilities,

[1] Other settings have been explored in which the stationarity has been relaxed and the assumptions of a known β and normalized utility values can be relaxed; see for example Bajari, Chu, Nekipelov, and Park (2013).

inversion function ψ, and discount factor β:

$$u_{1t}(z_t) = \psi_0(p_t(z_t)) - \psi_1(p_t(z_t)) + \sum_{\tau=t+1}^{T} \sum_{z_\tau \in \mathcal{Z}} \beta^{\tau-t}\psi_0(p_\tau(z_\tau))\left[\kappa_{\tau-1}(z_\tau|z_t,\delta_t=0) - \kappa_{\tau-1}(z_\tau|z_t,\delta_t=j)\right] \tag{2.2}$$

Identification follows due to recovery of the conditional choice probabilities for each state from observed choices in the data and recovery of state transitions from the observed state transitions in the data.[2] Note that this gives exact identification of $u_{1t}(z_t)$; this means that relaxing the assumptions that G or β are known will lead to under-identification. To see this, consider the set of primitives (u, f, G, β) and now replace β and G with $\tilde{\beta}$ and $\tilde{G}$. With the same observed conditional choice probabilities $p_t(x_t)$, we can construct a new function $\tilde{\psi}_j(p_t(z_t))$ for each choice j and hence a new value for utility $\tilde{u}_{1t}(z_t)$ using equation (2.2). Because these two utilities $u_{1t}(z_t)$ and $\tilde{u}_{1t}(z_t)$ induce the same conditional choice probabilities, they are observationally equivalent.

2.3 Identification with Non-stationary State Transitions

This section describes the identification of the model primitives, which are the government cost distribution G, distance costs $\omega(\delta)$, entry cost distribution ζ, and firm cost distribution F, from the observables z_t, d_t, n_t, and the winning auction bids.

Identification of the government cost primitives uses an extension of the finite dependence methods of Arcidiacono and Miller (2011) and Arcidiacono and Miller (2016) to isolate "temporarily static" periods in which all future value terms cancel. This removes the primary obstacle to identification of the distribution of choice shocks in dynamic models, as the future value

[2] Note that this also requires the assumption of rational expectations, or that agents' beliefs over future states are consistent with the true probabilities of reaching those states.

terms themselves depend on the distribution. I then combine these static periods with an exclusion restriction that government costs are independent of the number of active firms within a district. The full distribution of government costs is traced out by variation in the number of active firms using an exclusion restriction in a similar manner to static non-parametric identification of binary choice models (e.g. Lewbel (2000)).

Specifically, I consider a reformulation of the dynamic discrete choice problem in which there exists another state variable ν_t taking values in $\mathbb{R}$ which affects the payoff for choice $j = 0$ but not $j = 1$. I will assume that ν enters the payoff linearly, but the results hold for any (known) monotonic function.[3] Additionally, I allow for the distribution of the choice specific utility shocks to depend on the state variable z_t so that the distribution function for ϵ_{jt} is $F(\cdot|z_t)$ and I define $\eta_t \equiv \epsilon_1 - \epsilon_0$. The distribution function of ν_t is denoted $H(\cdot|z_t)$. This is similar to the normalization of utilities required for identification: since only the difference between the choice-specific error terms appears in the agent's optimization problem, only the difference can be identified. Formally, after maintaining the normalization that $u_{0t}(z_t) = 0$ for all z_t and adding the new state variable ν_t, we have per-period payoffs given by

$$\nu_t \quad \text{if } j = 0 \tag{2.3}$$

$$u_{1t}(z_t) + \eta_t \quad \text{if } j = 1 \tag{2.4}$$

The non-stationarity aids in the identification of the distribution of η_t by creating situations in which all future value terms cancel. In Arcidiacono and Miller (2016) this occurs over the course of a finite (but positive) number of periods, called finite dependence. Specifically, there

[3] In Chapter 3 of this dissertation I apply this method to a scenario in which this state variable enters the payoff function non-linearly through the results of an auction process.

exists a sequence of choices such that after a finite number of periods the distribution over state variables is the same regardless of the choice made in the initial period. In my setting, I will assume that this resetting property of the state variable distribution happens immediately. That is, regardless of the choice made in the current period, the distribution of state variables next period is unchanged. This allows for immediate cancelation of all future value components, and the choice problem becomes static. This temporarily static feature is a property of (i) the state transition probabilities for that period and (ii) the current state. Since these temporarily static periods are a subset of all period-state combinations, the problem remains dynamic in nature with isolated incidences in which the future value components drop out.

Formally, the assumption of the existence of temporarily static periods is that there exists some set $\mathcal{T}$ and states z_t such that for all $t \in \mathcal{T}$, $f_{0t}(z'|z_t) = f_{1t}(z'|z_t)$. In this situation it is straightforward to demonstrate that all future value components cancel:

$$\begin{aligned} p_{1t}(z_t, \nu_t) &= \Pr(v_{1t}(z_t, \nu_t) + \eta_t \geq v_{0t}(z_t, \eta_t)) \\ &= \Pr\left(u_{1t}(z_t) + \eta_t \geq \nu_t + \beta \sum_{z_{t+1} \in \mathcal{Z}} \overline{V}_{t+1} \left[f_{0t}(z_{t+1}|z_t) - f_{1t}(z_{t+1}|z_t)\right]\right) \\ &= \Pr(\eta_t \geq \nu_t - u_{1t}(z_t)) \end{aligned} \tag{2.5}$$

If all states in $\mathcal{Z}$ are represented by the set of periods $\mathcal{T}$, then all primitives of the model are identified from the above equation and use of the full dynamic problem is not necessary. When not all z_t are present in the set of periods $\mathcal{T}$, a two step approach must be used, in which the first step entails identification of the distribution of η_t using the temporarily static periods and then in the second step this distribution is used in the dynamic problem to identify the remaining utility parameters $u_{1t}(z_t)$. This is formalized in the following theorem:

Theorem 2.3.1 *Assume that*

1. *The discount factor β is known.*

2. *Per-period payoffs take the form (2.3) and (2.4).*

3. *ν_t evolves exogenously and has support over $\mathbb{R}$.*

4. *η has a symmetric distribution with $\mathbb{E}[\eta] = 0$.*

4. *There exists a set of periods $\mathcal{T}$ such that for all $t \in \mathcal{T}$, $f_{1t}(z'|z) = f_{0t}(z'|z)$.*

5. *$H(\cdot)$ is strictly increasing and continuous.*

Then $H(\eta)$ and $u_{1t}(z)$ are identified. Furthermore, if the distribution of η is symmetric and $\{z_\tau : \tau \in \mathcal{T}\} = \mathcal{Z}$, H and $u_{1t}(z)$ are identified directly from the set of periods $\mathcal{T}$.

Proof. First suppose that all states z_t are represented in the periods $\mathcal{T}$. Then because ν takes values in $\mathbb{R}$, there exists some $\overline{\nu}$ such that $p_{1t}(z_t, \overline{\nu})$ =Pr$(\eta_t \geq \overline{\nu} - u_{1t}(z_t)) = 0.5$. If the distribution of η is symmetric with zero mean, this means that $u_{1t}(z_t) = \overline{\nu}$. Since all z_t are present in the set of periods $\mathcal{T}$, we can find such a $\overline{\nu}$ for each $z \in \mathcal{Z}$, and hence each $u_{1t}(z)$ is identified.

For the distribution of η, note that for any z once the value for $u_{1t}(z)$ is known then the distribution of η is traced out by variation in ν:

$$H(\nu - u_{1t}(z)|z) = p_{1t}(z, \nu)$$

and so quantiles of the distribution of η are recovered from the observed conditional choice probabilities, keeping the state z fixed and varying ν.

When not all states are present in the set of temporarily static periods $\mathcal{T}$, the distribution of η is recovered in the first step using the periods in $\mathcal{T}$ and then this distribution is used in standard representation arguments to recover the utility parameters. Using the same argument as above, one value of $u_{1t}(z_t)$ is identified by some $\overline{\nu}$. Then the distribution of η is traced out as before through variation in ν. Using this identified distribution in the dynamic problem yields that

$$\begin{aligned} p_{1t}(z_t, \nu_t) &= \Pr(v_{1t}(z_t, \nu_t) + \eta \geq v_{0t}(z_t, \nu_t)) \\ &= \Pr(\eta \geq v_{0t}(z_t, \nu_t) - v_{1t}(z_t, \nu_t)) \\ &= 1 - H(v_{0t}(z_t) - v_{1t}(z_t)) \end{aligned}$$

Then define the inversion function given by

$$\psi_1(p_{1t}(z_t, \nu_t)) \equiv H^{-1}(1 - p_{1t}(z_t, \nu_t)) = v_{0t}(z_t, \nu_t) - v_{1t}(z_t, \nu_t). \tag{2.6}$$

This gives the expression for $v_{0t}(z_t, \nu_t) - v_{1t}(z_t, \nu_t)$ required to express $u_{1t}(z_t)$ in terms of observables for all $z_t \in \mathcal{Z}$ using equation (2.2). ∎

2.4 Identification with Finite Time Horizon

In this section I detail identification in the case that the time horizon is finite in the presence of the same exclusion restriction used in the previous section. The result operates in much the same way: in the last period, there are no future value components and so variation in the exclusion restriction variable allows the distribution of the unobserved utility component to be traced out.

The set-up is the same as the previous section: per-period payoffs take the form given by

(2.3) and (2.4), with $\eta_t \equiv \epsilon_1 - \epsilon_0$ having CDF $H(\cdot)$. The main difference is the assumption that $T < \infty$, so that in the final period there are no discounted future values to consider for the agent. Additionally, state transitions are no longer required to be non-stationary; I will assume that state transitions are given by $f_j(z'|z)$ for all t for ease of notation, although indexing by t doesn't change any results.

The argument for identification then follows similarly to the previous case. In the last period, using the wide support and symmetry assumptions allows for identification of $u_1(z_T)$ for some z_T. Then variation in ν_T traces out the distribution of η, and then the identified distribution H is used to recover utilities for any states that are not represented in the final period. This is formalized in the following theorem.

Theorem 2.4.1 *Assume the following:*

1. *The discount factor β is known.*

2. *Per-period payoffs take the form (2.3) and (2.4).*

3. *ν_t evolves exogenously and has wide support.*

4. *η has a symmetric distribution with $\mathbb{E}[\eta] = 0$.*

5. *The time horizon is finite: $T < \infty$.*

Then $H(\cdot)$ is identified and $u_1(z_t)$ is identified for each $z_t \in \mathcal{Z}$.

As indicated above, the proof follows the same argument as the proof for the temporarily static case, except that the static periods arise through the finite time horizon assumption rather that through the non-stationarity of state transitions.

2.5 Conclusion

This chapter has provided conditions under which it is possible to relax the assumption that the distribution of the unobserved component of agent utility in dynamic binary choice models is known. Nearly all prior papers in the literature on identifying and estimating dynamic discrete choice models has assumed that the distribution of the unobserved choice-specific utility shocks is known, with the most common assumption being a Type 1 Extreme Value distribution for tractability in estimation. In contrast, I demonstrate conditions under which it is possible to non-parametrically identify both the deterministic utility parameters associated with agents' choices and the distribution of the differenced unobserved choice shock distribution in binary choice models.

There are two main conditions that allow for this identification result. First, non-stationarity that results in cancellation of the future value terms for a subset of periods is required. I supply two such scenarios: one in which "temporarily static" periods arise within the course of a potentially infinite dynamic decision problem due to time-dependent state transitions which do not depend on the choice made for a subset of periods, and the finite time horizon case in which the last period has no dynamic component for the agent. The second condition required is the presence of a state variable that enters the utility function in a known way and affects the payoff for only one of the two choices available to the agent. Under these conditions, the distribution of the unobserved component of agent utility is identified using the conditional choice probabilities in the static periods by variation in this second state variable. Once this distribution is identified, utilities associated with each state can be identified using standard representation arguments.

While this paper focuses on single-agent binary-choice dynamic models, it would be interesting to explore extentions of these results beyond this basic case. Additional assumptions may be required to give the same identification result for multi-choice models. Additionally, dynamic games already suffer from a larger degree of under-identification than single-agent dynamic decision problems, and so the difficulties with bringing these results to bear on dynamic games seem larger. Nonetheless, due to the wider applicability of these scenarios exploration into relaxing the assumptions on the distributions of unobserved utility components could be a promising area for future research.

Chapter 3

Cost an Efficiency in Government Outsourcing

3.1 Introduction

When a government provides a public good, it has two methods for its delivery: outsourcing to the private sector and in-house public sector provision. These methods are not mutually exclusive and are often used in combination. Public good delivery may require a sequence of tasks or projects to be completed, and government agencies decide which are to be contracted out and which are to be completed in-house. Examples of this type of mixed-delivery setting include maintenance, legal services, regulatory compliance, and construction.

Given the widespread nature of such outsourcing, assessing its costs and benefits is important in evaluating the functions of government. Contracting projects out to the private sector may benefit government agencies through the awarding of projects to more efficient private sector firms. Additionally, a multitude of projects to be allocated can lead to substantial dynamic effects due to capacity restrictions or cost synergies.[1] However, there is little empirical evidence on the effects of mixed-delivery public good provision on expenditures and even less pertaining to the role of dynamics in determining outsourcing outcomes. The focus of this paper is to address these issues by providing a direct comparison of private sector and in-house government costs of public good provision and by quantifying the impact of dynamics on outsourcing outcomes. I then investigate how changes to the procurement mechanism that increase direct competition between government and private firms can lead to improvements in total expenditures and efficient project allocation.

The empirical setting used to analyze these questions is the United State dredging industry, from which I use data on project-level outsourcing decisions made between 1999 and 2013. Each year the United States Army Corps of Engineers oversees the completion of several hundred dredging projects, which are maritime construction projects that help keep waterways navigable. Approximately half of these projects are assigned to government owned and operated dredges. The remainder are contracted out to private firms via procurement auctions whose awards total between \$700 million and \$1.1 billion annually. The government faces two factors that lead to future cost considerations for each decision. First, projects may be hundreds of miles apart, and transporting large dredging vessels and other equipment necessary to complete the projects is costly. Second, project dates routinely overlap and dredges themselves must remain on the project site until the work is completed; as such, assignment of a government dredge to work on one project may preclude keeping a future project in-house. I then specify and estimate a dynamic binary choice model of government outsourcing decisions that accounts for both cost differences between private firms and the government that varies with project characteristics

[1]For example, a municipality deciding whether to renew a contract for emergency medical services may consider an upcoming contract renewal decision for fire prevention and suppression in its decision, as fixed costs of establishing an in-house ambulatory service might be shared with that of a fire department.

and dynamic effects arising from travel distance costs and capacity.

The model features one project to be completed in each period, and periods that proceed in two stages. The second stage is the auction stage, and is only reached conditional on the government choosing to outsource the project. Firms draw entry costs and enter the procurement auction if their entry cost is lower than the expected profit from entering. Bidders then receive independent cost draws from a shared cost distribution and bid in a first-price sealed-bid auction for the contract. In the first stage, the government observes project characteristics, learns its cost, and makes a binary outsourcing decision. The decision is driven by comparison of their cost with the expected winning auction bid after accounting for the possibility that future costs are likely to be affected by the decision of whether or not to keep the project in-house. Future costs are affected by the outsourcing decision through two channels: an in-house project in a location far from future projects incurs additional travel costs compared with keeping the dredge in its current location, and in-house project completion may render a dredge unavailable to be assigned to future projects, necessitating outsourcing of those projects.

Results from the structural model indicate substantial cost differences between private firm and government provision, with a government cost advantage for smaller projects while larger projects favor private firms. I estimate that average private firm costs are 23% lower than government costs for outsourced projects. However, in-house provision remains cost-efficient for approximately half of all projects, and government presence in the market remains an important cost reducing force. In order to better gauge the importance of government project completion, I perform a series counterfactual simulations in which I sequentially reduce the number of vessels in the government's dredging fleet. I find that a capacity reduction of up to one sixth would have little impact on total expenditures, but that further reductions cause increases in costs. This suggests that while government may be slightly over-invested in dredging capacity, large reductions to the government's fleet would increase government cost burden for dredging projects.

The estimation results also indicate that dynamics are an important component of government outsourcing decisions. Using the model estimates I simulate a myopic government decision maker by setting the discount factor to zero. The simulation results indicate that a government decision maker that is not taking dynamic effects into account would keep 7.6% fewer projects in-house and face overall cost increases of 3.1%.

Using the model estimates I perform a counterfactual policy experiment featuring direct competition between government and private sector firms. As the decision to outsource a project is made before the result of the procurement auction is known, projects for which outsourcing is optimal ex-ante may be better suited for in-house provision ex-post (or vice-versa). To alleviate this I consider the following changes to the government's procurement mechanism: the government holds a procurement auction for every project and directly participates in the auction by setting a reserve price determined by its own project costs. The reserve price is dynamically optimal in the sense that it accounts for the impact of current outsourcing decisions on future costs. I find that total expenditures would be reduced by 17.1% through such a policy, indicating that there is scope for the government to further leverage its own resources in the procurement process to improve outsourcing outcomes.

This paper makes two main contributions. First, I provide direct cost comparisons between government and private sector project completion that enable an assessment of the effects that outsourcing has on total government expenditures and allocative efficiency. Many reasons have been posited as to why private firms may have cost advantages over government agencies for certain tasks, such as use of high-powered incentives, reduction of inefficient bureaucratic policies, and more flexible labor practices. Conversely, a full-time staff of skilled in-house employees may mitigate fixed costs associated with projects.[2] Despite the large literature on when projects or tasks are best suited for the public or private sector (e.g. Williamson (1999)), little empirical attention has been devoted to measuring and quantifying differences in costs between government and private sector production.

Secondly, this paper captures dynamic effects in government outsourcing decisions. Most of the empirical literature on make-or-buy decisions has abstracted from these effects to focus on a static environment. However, repeated decisions can give rise to many features that would impact future costs, such as repeated bargaining games, relational contracting, or cost synergies across projects or tasks. The empirical results of this paper suggest that dynamic effects are an important consideration in outsourcing decisions for the dredging market.

Identification of the distribution of government costs is complicated by two factors: government observations are a binary decision variable which yield no direct indication of government project costs, and outsourcing decision outcomes themselves depend on the distribution of government costs through the future value terms associated with each choice. I use a two-step procedure to overcome these hurdles to identification. In the first step, I exploit the non-stationarity of the state transitions to identify periods in which the choice problem becomes temporarily static; in my setting, this occurs when government is considering outsourcing for a project that (i) will not require a change of location and (ii) will be completed before the next project is scheduled to begin. In such cases both factors that affect future costs are not changed by the government decision of whether or not to outsource, and so future value terms cancel for these periods. Next, I make use of heterogeneity in competition across dredging markets that generates variation in

[2]Detailed knowledge of project designs in particular is an area where the USACE may have a fixed cost advantage, as government engineers must familiarize themselves with construction plans and techniques whether those plans are issued in a contract or implemented during in-house completion.

the expected winning bid while holding other project characteristics fixed. Quantiles of the government cost distribution are then identified through binary choice observations for each of the markets observed in the data. This distribution is then used in the dynamic problem, allowing for identification of travel costs through variation in distance to project locations. The distribution of private firm costs are identified by applying the results of auction theory to the cases in which only the winning bid and number of bidders are observed. Lastly, the entry costs of bidders are identified through variation in participation decisions across markets.

The rest of the paper is structured as follows: in the remainder of this section I discuss related literature. In Section 2 I discuss the empirical setting and data. Section 3 describes the structural model of government outsourcing decisions. Sections 4 and 5 discuss identification and estimation, respectively. Section 6 presents the estimates of the structural model. Section 7 gives the results of counterfactual simulations. Section 8 concludes.

3.1.1 Related Literature

This paper is related to four literatures: the theory of the firm and firm boundaries, government scope and government outsourcing, procurement and procurement auctions, and structural estimation of dynamic discrete choice models.

There is a vast literature on the boundaries of the firm, starting with Coase (1937). Previous approaches to characterizing which projects are completed in-house and which are contracted out include the principal-agent moral hazard model of Holmstrom and Milgrom (1994), the transaction cost framework introduced in Williamson (1975) and Williamson (1979), and the property rights model of Hart and Moore (1990). Holmstrøm and Roberts (1998) provide a theoretical overview and Lafontaine and Slade (2007) survey empirical work on these models. While my model is agnostic as to the source of cost differences between government in-house work and contracted firms, the model of varying employee incentives of Holmstrom and Milgrom (1994) may help explain lower private sector costs for some projects. The ex-post renegotiation and hold-up problems common to models of transaction costs do not appear significant in the dredging industry, as the data indicate that the winning auction bid serves as a very good estimate for the final costs of project completion. Additionally, asset specificity is low, as the types of dredges are similar across the public and private sectors and dredges can be used for many different projects.[3] Instead, my model focuses on dynamic effects and differences in costs between the government and private sector firms.

Related to the work on firm boundaries are papers that deal specifically with the scope of government. Tiebout (1956) first recognized the potential benefits of public provision of services when institutional rigidities are important. Hart, Shleifer, and Vishny (1997) discuss incomplete contracting, costs, and quality in private sector provision of public goods, and Hart (2003) summarizes developments in the theoretical literature on government outsourcing. In order to focus on productivity differences across the public and private sectors I abstract from quality differences in this paper.[4] Empirical papers relating to government outsourcing include Levin and Tadelis (2010), who examine local governments' choices over which services to keep in-house and which are to be contracted out using a transaction costs model, Warner and Hebdon (2001), in which the effect of political affiliation and unionization on local government restructuring is studied, and Bel and Rosell (2016), who estimate a cost function for bus service in a mixed-delivery system in which both government and private firms provide bus services. The main

[3] Indeed, many of the dredges owned by private sector firms were once owned and operated by the USACE.

[4] Empirical wok on quality differences for outsourced projects is unclear, e.g. Cabral, Lazzarini, and de Azevedo (2010) who find no difference in quality for government-supervised private sector prisons when compared to public sector alternatives.

contribution of this paper relative to this literature is to separately estimate and compare government costs against private firm costs, in contrast to the aforementioned studies which focus on either assessing probability of government outsourcing without directly estimating costs or assume a common production function for government and private sector provision.

This paper contributes to a large and growing literature on government procurement and the use of auctions to contract with private firms. The most similar to this paper is Jeziorski and Krasnokutskaya (2013); they study a highway procurement market in which firms have the option to subcontract portions of the project out to other firms. The primary difference between this work and theirs is that I consider the case of discrete projects in which a binary outsourcing decision must be made for each project, while in their model projects are awarded to primary contractors who then choose a fraction of the project to contract out. Kang and Miller (2015), Krasnokutskaya and Seim (2011), and Li and Zheng (2009) empirically study bidder participation in procurement auctions under different government procurement practices.

This paper contributes to the literature on dynamic discrete choice models by identifying and estimating a dynamic binary-choice model which doesn't rely on distributional assumptions on the unobserved component of agents' utility. Norets and Tang (2013) is the only other paper of which I am aware that considers relaxing the assumption of known distributions in the estimation of dynamic models. They provide methods for non-parametric inference in dynamic binary-choice models which demonstrate that estimated parameters may be very sensitive to assumptions on the distribution of error terms. Rust (1994) first noted that dynamic discrete choice models are under-identified unless restrictions are made on the discount factor and distribution of choice-specific utility shocks, and Magnac and Thesmar (2002) provided general conditions under which normalized flow utilities are identified after fixing the discount rate and choice shock distribution. Buchholz, Shum, and Xu (2016) establish semi-parametric identification of the random component of agent payoffs for stationary dynamic discrete choice models featuring linear flow payoffs. This paper builds on the identification results relating to non-stationary models in Arcidiacono and Miller (2011) and Arcidiacono and Miller (2016) by using a specific application of the finite dependence procedure to eliminate future period value functions in some periods. The identification also draws on techniques used in non-parametric estimation of binary choice models in static settings, as in Lewbel (2000) and Matzkin (1992).

3.2 Empirical Setting and Data

The empirical setting used is the United States dredging industry, detailed in Chapter 1 of this dissertation. The dredging industry has several features that lend it to study of government outsourcing decisions. Chief among these is the presence of in-house government project completion resources in the form of 12 Corps of Engineers owned-and-operated dredges. In addition, many projects are outsourced to private sector firms through first-price sealed bid procurement auctions.

Table (3.1) contains summary statistics. Projects completed in-house by the Corps of Engineers are smaller, as measured by volume of dredged material, and shorter, in terms of working days required, than projects outsourced to private sector firms. Additionally, distance traveled to projects taken by Corps dredges is shorter than the unconditional distance to a project. These two features suggest that the Corps of Engineers may have different relative cost advantages for completing projects than private sector firms and that distance to project locations is a notable cost consideration for the Corps.

Another notable feature of the industry is that while travel distance and restriction in dredg-

Table 3.1: Summary Statistics

	Govt Projects	**Outsourced**
Projects per Year	123.2	118.5
	(28.2)	*(22.5)*
Cubic Yards per Project	273.7	1177.0
	(939.5)	*(1575)*
Working Days per Project	17.9	125.8
	(38.7)	*(136.0)*
Distance (in-house projects)	136.7	
	(314.6)	
Distance (all projects)	214.5	
	(382.7)	
Cost per project ($, millions)		4.03
		(3.83)
Number of Bidders		2.46
		(1.32)

Note: Table lists mean values, with standard deviations in parentheses

ing capacity due to a limited number of vessels are both factors that restrict Corps of Engineers dredging capabilities, neither of these appear to be large factors for private dredging companies. The average number of districts in which a private firm competes is just two, suggesting that firms do not have a traveling-salesman-like problem of minimizing distance, as is faced by the government, as the scope of operations of the firms is limited to a fairly small geographic area. Furthermore, firms do not appear to be capacity constrained: the appendix contains the results of a regression that indicate that the number of bidders in an auction is not lowered when the number of ongoing projects in that district is high, so that even a large amount of dredging resources already committed within a district does not decrease the expected number of competitors in a subsequent auction.

The market operates one fiscal year at a time. Near the start of each fiscal year, the Corps of

Engineers releases the schedule of projects to be completed that year. Auctions for outsourced projects are held on a rolling basis, with the award date typically falling three to six weeks prior to the start date for the project.

3.3 Model

Motivated by the empirical facts presented in the previous section, in this section I consider a model of sequential project allocation in which the government makes outsourcing decisions in each period in order to minimize the expected cost of completing a known schedule of projects.[5] When making the outsourcing decision, the government considers the expected winning bid in the case that the project is contracted out and its own cost for the project, which it learns at the beginning of each period. Additionally, because vessels must be moved between project sites in order to complete projects and this travel is costly, the government considers the impact that vessels locations will have on future travel distances. Lastly, availability of vessels to complete projects is also factored into the government's decision, as current project allocation decisions may affect the ability to complete future projects in-house. If the project is contracted out, a first-price sealed-bid auction is held in which firms make entry decisions prior to bidding and the contract is awarded to the lowest-bidding firm.

[5]Other models of government preferences assume budget-maximizing objectives (e.g. Niskanen (1968), Niskanen (1971)), in which a "Sponsor" allocates the budget and has an inferior bargaining position relative to the bureau due to an informational disadvantage regarding the social value of the bureau's projects. In my setting, I assume that the "Sponsor" can compare costs of dredging for Corps dredges and private sector dredging and prefers the lower-cost option, even if the total number of dredging projects exceeds the social optimum.

3.3.1 Model Set-up

A risk-neutral government decision maker must complete a known sequence of projects over the course of one year. There are K districts in which projects must be completed. Time is discrete with a finite horizon T. Each period consists of one project to be either assigned to a government dredge or outsourced via a procurement auction. The state variables are denoted $z_t \equiv (\delta_t, x_t, y_t, \overline{N}_{k_t})$, where δ_t represents the distance from the government dredge to the current project district, x_t is a vector of project characteristics (e.g. project size), and $\overline{N}_{k_t}$ is the number of firms active in district k_t. The state variable y_t indicates the availability of the government vessel, with $y_t = 0$ indicates that the vessel is currently available at the start of period t and $y_t = c$ for $c \in \mathbb{N}$ indicating that there are c periods until the vessel is available to take another project.

The timing of the model is as follows: at the start of each period, the government learns its cost for completing the project in that period. It then forms expectations about the winning bid if the project were to be contracted out and makes the outsourcing decision. If the project is kept in-house, the government vessel allocated to the project moves to the project's district and begins the project. If the project is outsourced, a first-price sealed-bid auction is held to determine which firm is awarded the contract. Note that each period corresponds to the allocation of a project while project completion times themselves may span multiple periods.

In describing the model I work backwards from the auction stage, first obtaining the expected winning bid in the auction conditional on a project being outsourced and then writing the government's payoffs and value function given expectations over the expected winning bids derived in the first section.

3.3.2 Auction Stage

When the government has made the decision to outsource the project a first price auction is held to determine to whom the contract is awarded. Firms active in the district in which the project is located then have the opportunity to bid for the project's contract. I assume that firm bidding behavior is myopic: given that many firms are active in only one or two districts and that the number of ongoing projects does not affect bidder participation, the main two factors driving dynamics in the government decision (i.e. distance to project sites and availability of dredges) are unlikely to be a strong factor in firm bidding decisions. As such, participating firms compete in a standard first-price sealed bid auction for the contract. Once a procurement auction is held, the government cannot renege and assign the project to a government dredge instead.[6]

Auction Entry

In this section I detail a model of bidder entry into auctions. The setup is the following: prior to learning their private costs for completing the project, bidders receive independent entry cost draws e from a common distribution ζ with support $[\underline{e}, \overline{e}]$. Each potential bidder is aware of his/her own entry costs but not the entry costs of other potential bidders. Additionally, entry costs are independent of project completion costs. After learning their entry costs, bidders make entry decisions based on the expected payoff from entering the auction. Bidders that choose to enter the auction then receive their private cost draw from the cost distribution and learn the number of other bidders competing in the auction.

[6] Evidence suggests that the government chooses to keep a project in-house after holding an auction very rarely: in a report to Congress, the US Army Corps of Engineers cites only one instance of this occurring over the two year period discussed in the report. Additionally, government proximity to and availability for projects has no detectable impact on bid levels, suggesting that firms do not reduce their bids to ensure that government does not decide to keep the project in-house ex-post.

Formally, suppose there are $\overline{N}$ potential bidders. Let e_i indicate the private entry cost drawn from ζ for bidder i,and let $\mathbf{e}_{-i}$ represent the entry costs of the other potential bidders. A pure strategy for player i is defined as a function $\sigma : [\underline{e}, \overline{e}] \to \{0, 1\}$ that maps each entry cost to an entry decision. Let $\mathbb{E}[u_i|N]$ represent the expected profit for bidder i upon entering an auction with N total bidders. Then there exists a threshold cost level e^* given by

$$e^* = \sum_{n=1}^{\overline{N}} \Pr(N = n \mid e^*)\mathbb{E}[u_i|N = n]$$

where any $e_i < e^*$ leads to entry and $e_i > e^*$ means that bidder i does not enter the auction. This can be re-expressed using the distribution of entry costs as

$$e^* = \sum_{n=1}^{\overline{N}} \binom{\overline{N}}{n} \zeta(e^*)^n (1 - \zeta(e^*))^{\overline{N}-n} \mathbb{E}[u_i|N = n] \tag{3.1}$$

Since the left side of (3.1) is increasing in e^* and the right side is decreasing in e^*, as higher entry costs leads to lower entry probabilities, the equilibrium cutoff point e^* exists and is unique.

Bidding

After bidders have made their entry decisions they draw costs and submit bids in a first-price sealed bid auction. I make the following set of assumptions regarding the auction model for auctions that have at least two bidders:

1. The number of bidders in the auction n is known.

2. Each bidder i receives an i.i.d. project cost draw c_{fi} from a common conditional distribution with cdf $F(c_f|x)$ with positive support on $[\underline{c}_f, \overline{c}_f]$.

3. There is no binding reserve price.[7]

4. Bidders play a symmetric Bayesian Nash equilibrium with bids that are increasing in costs.

For ease of notation, I suppress the conditioning on project characteristics x and the time subscript in what follows. Given the above assumptions the bid function can be written as

$$b^*(c_i) = \max_b \Pr(b \leq b_j \; \forall j \neq i) \times (b - c_i).$$

This has first order condition given by the differential equation

$$b'(c) = (b(c) - c)(n-1)\frac{f(c)}{1 - F(c)}$$

which has a closed-form expression given by

$$b(c_{fi}) = c_{fi} + \int_{c_{fi}}^{\infty} \frac{(1 - F(u))^{n-1}}{(1 - F(c_{fi}))^{n-1}} du. \tag{3.2}$$

For auctions that feature only one bidder, I follow Li and Zheng (2009) and assume that such bidders compete against the government in the auction. In such cases the government draws a bid from a distribution $\Phi : [\underline{c}_f, \overline{c}_f] \to [0, 1]$; bids that fall below the government's bid are accepted and those above are rejected.

The expected lowest bid is the main auction characteristic determining government outsourcing decisions. For a given number of bidders $N \geq 2$, define $m(c_{fi})$ to be the expected payment received by bidder i. Then $\mathbb{E}[m(c_{fi})|N = n]$ is the ex-ante expected payment received by each

[7] While the USACE issues an estimate for project costs and states that no bid may exceed 125% of the government estimate, this rule is frequently violated in the data. As such, I follow the existing literature on procurement auctions and assume no reserve price.

bidder when there are n bidders in the auction.

Because N is unknown to the government at the time the outsourcing decision is made the government takes the expectation of $\mathbb{E}[m(c_{fi})|N = n]$ over the number of bidders when assessing the expected winning bid. Each district k has $\overline{N}_k$ potential bidders. The probability distribution over the number of bidders is given by η_k, with η_{kn} the probability that there are n bidders in the auction. Defining R to be the expected ex-ante winning bid, we have

$$R = \sum_{n=1}^{\overline{N}_k} \eta_{kn} \cdot n\mathbb{E}[m(c_f)|N = n].$$

3.3.3 Outsourcing Decision

At the beginning of each period the government learns its cost for completing the project, which is drawn from a distribution that has conditional cdf $G(c_g|x_t)$. The distance cost associated with traveling to the project district is given by $\omega(\delta_t)$ and is assumed to be additively separable from the project completion cost. Define $d_t \in \{0, 1\}$ to be the decision variable in period t, where $d_t = 0$ represents that the project has been kept in-house and $d_t = 1$ indicates that the project has been contracted out. Letting $\pi_j(z_t)$ denote the per-period payoff for state z_t when $d_t = j$, the per-period payoffs have a simple expression of the form

$$\pi_0(z_t) = -\omega(\delta_t) - c_{gt} \tag{3.3}$$

$$\pi_1(z_t) = -R(x_t, \overline{N}_{k_t}) \tag{3.4}$$

where $R(z_t)$ is the expected winning auction bid. It is important to note here that the only random component of the government's payoffs enters through the government's cost draw c_{gt};

hence, this cost should be interpreted as the cost of completing the project relative to the cost of contracting the project out.[8]

The schedule of projects is known for each year, meaning that the project characteristics x_t and district-level competition $\overline{N}_{k_t}$ are known in advance for each project. Distance to future projects is determined by the current location of the government's work crews; when the government sends a vessel to a project location the distance to the subsequent project will be know with certainty. Hence, all state transitions are deterministic, with transitions for two of the states (project characteristics and district characteristics) determined exogenously while the transitions for distance and vessel availability are determined by the government's outsourcing decision and the schedule of projects. Note that while state transitions are deterministic, they are non-stationary as they are determined by the schedule of projects to be completed in subsequent periods. Define $q_{jt}(z_{t+1}|z_t)$ to be the state transitions after making choice j in period t and let Q_{jt} be the associated degenerate distribution. If we consider the schedule of projects to be a list, ordered by project start date and containing all the information relevant to each project, the state transitions can be thought of as crossing one project off of the list and moving to the next one, updating the locations and availabilities of the government vessels each period.

Current choices affect future states through the dependence of the state variables y_t, δ_t on the current period choice. A project that is far away from the remaining projects on the schedule for the fiscal year and has a long completion time will affect future payoffs by both (i) increasing the distance necessary to complete future projects and (ii) potentially rendering the vessel unavailable for the subsequent projects, taking away the potential for the government to save costs by keeping the project in-house.

[8]As any pair of choice specific utility shocks that lead to the same differenced distribution are observationally equivalent, normalizing one of the utility shocks to zero is necessary for identification.

With these factors in mind, the value function for choice j in period t can be written

$$V_{jt}(z_t) = \pi_j(z_t) + \sum_{\tau=t+1}^{T} \beta^{\tau-t}\mathbb{E}[\pi_{j^*_\tau}(z_\tau)], \tag{3.5}$$

where j^*_τ is the optimal choice in period j^*_τ. The ex-ante value function is given by

$$\overline{V}(z_t) = p_{0t}(z_t)\mathbb{E}[V_{0t}(z_t)] + p_{1t}(z_t)\mathbb{E}[V_{1t}(z_t)] \tag{3.6}$$

with $p_{0t}(z_t) = \Pr(V_{0t}(z_t) > V_{1t}(z_t))$. Now define $v_{jt}(z_t)$ to be the value functions conditional on choice j without the random cost c_{gt}; note that removal of this term affects only the in-house payoff. These conditional value functions can be expressed

$$\begin{aligned} v_{0t}(z_t) &= -\omega(\delta_t) + \beta\sum_{z\in\mathcal{Z}} \overline{V}_{t+1} q_{0t}(z|z_t) & (3.7)\\ v_{1t}(z_t) &= -R(x_t, \overline{N}_{k_t}) + \beta\sum_{z\in\mathcal{Z}} \overline{V}_{t+1}(z) q_{1t}(z|z_t). & (3.8)\end{aligned}$$

This allows for expression of the conditional choice probability of in-house provision as

$$p_{0t}(z_t) = \Pr(c_{gt} < v_{1t}(z_t) - v_{0t}(z_t)). \tag{3.9}$$

Note that capacity affects payoffs through the elimination of the in-house decision option when no dredges are available. In particular, this means that the value function is

$$V_t(z_t) = \begin{cases} \max\limits_{j\in\{0,1\}} \pi_j(z_t) + \beta \sum\limits_{z_{t+1}=1}^{Z} \overline{V}_{t+1}(z_{t+1}) q_{jt}(z_{t+1}|z_t) & \text{if } y_t = 0, \\ \pi_1(z_t) + \beta \sum\limits_{z_{t+1}=1}^{Z} \overline{V}_{t+1}(z_{t+1}) q_{1t}(z_{t+1}|z_t) & \text{otherwise.} \end{cases}$$

For a more concrete illustration of this, consider the following alternate representation. Let $\{d'_\tau\}_{\tau=t+1}^{T}$ be a sequence of decisions that starts with d_t and let $\kappa_\tau(z_{\tau+1}|z_t, d_t)$ be the state reached in period $t+1$ conditional on choice d_t and state z_t in period t following the decision rule $\{d'_\tau\}_{\tau=t+1}^{T}$. Formally, κ is defined as

$$\kappa_\tau(z_{\tau+1}|z_t, d_t) = \begin{cases} q_{d_t t+1}(z_{t+1}|z_t) & \text{if } \tau = t \\ \sum_{j=0}^{1} \sum_{z \in \mathcal{Z}} \mathbb{1}_{\{d'_{j\tau}=1\}} q_{j\tau}(z_{\tau+1}|z_\tau)\kappa_{\tau-1}(z_\tau|z_t, d_t) & \text{if } \tau > t. \end{cases}$$

Consider a project that will render a government dredge unavailable for the next $\bar{t}$ periods. Then the conditional value function of keeping the project in house is

$$V_{0t}(z_t) = \pi_{0t}(z_t) + \sum_{\tau=t+1}^{\bar{t}} \beta^\tau \pi_1(z_\tau) + \beta^{\bar{t}+1} \sum_{z_{\bar{t}+1}=1}^{Z} \overline{V}_{\bar{t}+1}(z_{\bar{t}+1})\kappa_{\bar{t}}(z_{\bar{t}+1}|z_t, d_t)$$

while the conditional value function of outsourcing is unchanged:

$$V_{0t} = \pi_0(z_t) + \beta \sum_{z_{t+1} \in \mathcal{Z}} \overline{V}_{t+1}(z_{t+1}) q_{0t}(z_{t+1}|z_t).$$

Hence, the government must trade off potential gains from keeping the project in-house in the current period with the expected losses that would be incurred through the inability to keep projects in-house for the next $\bar{t}$ periods.

3.4 Identification

Identification of private sector firm costs uses results from the auction literature for auctions with only winning bids known, for example in Athey and Haile (2002). Firm costs are then used to identify the expected bidder profit conditional on the number of bidders. Combining this with the empirical distribution over the number of bidders in the auction gives the expected auction profit conditional on entry. This generates an equilibrium cutoff condition for each number of potential bidders $\overline{N}$. Hence, quantiles of the entry cost distribution are identified through variation in the number of potential bidders.

3.4.1 Government Cost Distribution G and Distance Costs $\omega(\delta)$

Identification of G is established in two steps. The first step is to eliminate the future value component of government choices, as this is the main barrier to identification of the unobserved component of payoffs. This is done by extending the finite-dependence methods in Arcidiacono and Miller (2011) and Arcidiacono and Miller (2016). They demonstrate that in cases in which the distribution over state variables is the same after a finite number of periods, the future value components cancel for all remaining periods. In my setting I identify periods in which the equivalence of future state distributions is immediate; that is, the following period's state variables are unaffected by the current period decision. For these periods, the future value components cancel immediately, leading to a "temporarily static" period in which the agent makes choices that will have no impact on future value components.

In this setting, such a situation arises when an available dredge is located in the same location as the period t project and the project will conclude before the period $t+1$ project is set to begin. Then regardless of the choice to take the project or not the two factors affecting the future value function, distance to project and availability, are unaffected: the vessel remains in the original district and is available in both cases. As an example, consider a project in period t located in district k. There is also an available government vessel located in district k at the start of period

t; further, suppose that the period t project will conclude prior to the start of the project in period $t+1$. Then the state is $z_t \equiv (\delta_t, x_t, \overline{N}_{k_t}, y_t) = (0, x_t, \overline{N}_{k_t}, 0)$ and the current decision will not affect availability for the next period project. The project characteristics x and market competition $\overline{N}$ have exogenous transitions that are due to the schedule of projects and hence are unaffected by the choice of the government. The distance to the next project δ_{t+1} will remain fixed regardless of the outsourcing decision, as the vessel has not changed districts. Then the state variables at the start of period $t+1$ are $(\delta_{t+1}, x_{t+1}, \overline{N}_{t+1}, 0)$ whether the previous period's project was kept in-house or not.

It is straightforward to demonstrate that these circumstances result in static decisions:

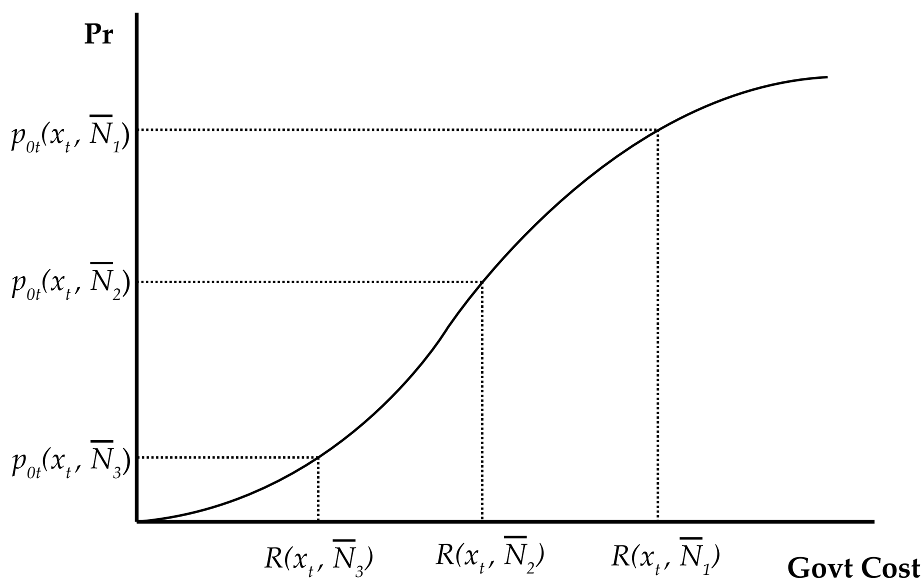
$$\begin{aligned} v_{1t}(z_t) - v_{0t}(z_t) &= \pi_1(z_t) - \pi_0(z_t) + \beta \sum_{z \in \mathcal{Z}} \left(\overline{V}_{t+1}(z) q_{1t}(z|z_t) - \overline{V}_{t+1}(z) q_{0t}(z|z_t) \right) \\ &= \pi_1(z_t) - \pi_0(z_t), \end{aligned}$$

since $q_{1t}(z|z_t) = q_{0t}(z|z_t)$. Hence, when the state transitions are the same for both choices, the ex-ante value function terms for the next period cancel and the differenced conditional value function can be expressed solely in terms of the current period flow utilities.

After obtaining a set of temporarily static observations using the method above, the distribution of G is identified using an exclusion restriction. Specifically, I assume that $\overline{N}$ affects the expected winning bid, and hence the probability of the outcome variable d, but is independent of C_g after conditioning on characteristics x. This allows variation in $\overline{N}$ to change the probability that $d_t = 1$ in a way that traces out the distribution of C_g.

To demonstrate the intuition, consider the following special case. Hold project characteristics x fixed across multiple projects; this yields the same distribution of government project costs for all projects. In this setting, the government's conditional choice probability of taking the project corresponds exactly to the probability that government costs are below the expected contract cost. As the distribution of firm costs is the same across all projects (due to x being fixed), variation in expected price is due only to variation in the market competition $\overline{N}$. This means that each value of $\overline{N}$ maps an expected winning bid into the probability that the government takes a project, generating a quantile of the government cost distribution for each value of $\overline{N}$. This is represented graphically in Figure 3.1.

Figure 3.1: Identification of Government Cost Distribution



Note: Holding the contract characteristics x_t fixed, the distribution function of government costs evaluated at the expected contract price for each level of competition n maps exactly to the conditional choice probability for that state.

After identification of G is complete, identifying $\omega(\delta)$ follows from the representation results of Arcidiacono and Miller (2011) after a normalization of $\omega(\delta)$ for one value of the state δ. These results are formalized in the proposition below.

Proposition 3.4.1 *Suppose the following assumptions hold:*

1. *$G(c|x,\overline{N}) = G(c|x)$ for all $x \in \mathcal{X}$.*

2. *There exists a set of periods $\mathcal{T}$ such that for each $\tau \in \mathcal{T}$ there exists a subset $Z_\tau \subset \mathcal{Z}$ for which the state transitions do not depend on the government's choice: $q_{1,\tau}(z_{\tau+1}|z_\tau) = q_{0,\tau}(z_{\tau+1}|z_\tau)$ for all $\tau \in \mathcal{T}$ and $z_\tau \in Z_\tau$.*

3. *$G(c|x)$ is strictly increasing for all $x \in \mathcal{X}$.*

4. *$R^{-1}(x,c) : \mathcal{X} \times [\underline{c}, \overline{c}] \to \mathcal{H}$ exists.*

5. *$\omega(\delta_0) = 0$ for some $\delta_0 \in \Delta$ and the discount factor β is known.*

Then $G(c \mid x)$ and $\omega(\delta)$ are identified for all $x \in \mathcal{X}$ and $\delta \in \Delta$.

Assumption 1 is the exclusion restriction which allows for variation in $\overline{N}$ to trace out quantiles of the government cost distribution. Assumption 2 is the assumption that ensures a set of periods and states for which all future value terms cancel. Assumption 3 is required to apply the inversion theorem of Hotz and Miller (1993). Assumption 4 guarantees a one-to-one mapping between pairs $(x, \overline{N})$ and expected winning bids. Finally, Assumption 5 is a normalization that enables identification of $\omega(\delta)$ for all $\delta \neq \delta_0$.

3.4.2 Auction Game

Firm costs

Identification for the distribution of firm costs follows the arguments of Guerre, Perrigne, and Vuong (2000) and Athey and Haile (2002) applied to auctions in which bidders have independent private costs and only the winning bid is observed. The number of bidders n is known. Let $H(\cdot)$

and $W(\cdot)$ denote the distribution of all bids and winning bids, respectively. In a symmetric Bayesian Nash equilibrium, the bidding function solves

$$b^*(c_f) = \max_b [1 - H(b)]^{n-1} \times (b - c_f)$$

which has solution that can be written as

$$c_f = b - \frac{[1 - H(b)]^{n-1}}{(n-1)[1 - H(b)]^{n-2} h(b)},$$

where $h(\cdot)$ is the density associated with the distribution function H. After applying an order statistic transformation we have

$$c_f = b - \frac{n[1 - W(b)]}{(n-1)w(b)},$$

where again $w(\cdot)$ is the density associated with the distribution $W(\cdot)$. This gives the distribution of winning costs $F_W(c_f)$, and using the transformation $1 - F_W(c_f) = [1 - F(c_f)]^n$ the full distribution of firm costs can be recovered.

Entry Costs

Identification of the entry cost distribution follows a similar argument to that of the identification of the government cost distribution. For a fixed vector of project characteristics x in market k with the number of potential bidders denoted $\overline{N}_k$, the entry cutoff e^* can be obtained by using the observed participation decisions for the probability distribution over the number of bidders in (3.1):

$$e^*_k(x) = \sum_{j=1}^{\overline{N}_k} \eta_{jk}(x) \mathbb{E}[u_i | n = j, x] \tag{3.10}$$

where $\eta_{jk}(x)$ is the observed probability of j bidders in an auction with characteristics x in market k. Variation in the number of potential bidders across districts generates different values for $e^*(x)$[9]. This means that

$$\sum_{j=1}^{\overline{N}_k} \zeta(e_k^*(x))^j (1 - \zeta(e_k^*(x))^{\overline{N}_k - j} \mathbb{E}[u_i \mid n = j, x] = e_k^*(x) \tag{3.11}$$

holds for each market $k \in \mathcal{K}$. Then the quantiles of the distribution ζ associated with each value of $e_k^*(x)$ are identified from (3.11).

3.5 Estimation

Estimation of the model primitives proceeds in three stages. In the first stage, non-parametric estimators for the number of potential bidders in each district and the expected auction price are obtained. These are then used to estimate the government cost distribution and distance costs. Finally, the observed distribution over the number of bidders is used with the estimated number of potential bidders to estimate the entry cost distribution, and firm costs are estimated from the auction data. While the identification results from the previous section are non-parametric, in practice the number of state variables and realized states make non-parametric estimation impractical. Hence, I make the following parametric assumptions in estimation:

- Government costs: $c_{gt} \sim$ Weibull(α_t, ρ_t),

  $$\alpha_t = \alpha_0 + \alpha_1 x_{1t} + \alpha_2 x_{2t}, \quad \rho_t = \rho_0 + \rho_1 x_{1t} + \rho_2 x_{2t}.$$

- Distance costs: $\omega(\delta_t) = \theta \delta_t$.

[9]Specifically, a lower number of potential bidders increases the expected profit and raises the equilibrium entry cutoff, while a higher number of potential bidders has the opposite effect.

- Entry costs: $e_t \sim \text{Exponential}(\lambda_t)$

$$\log(\lambda_t) = \lambda_0 + \lambda_1 x_{1t} + \lambda_2 x_{2t}.$$

- Winning bids: $b_t \sim \text{Log-normal}(\mu_t, \gamma_t)$

$$\log(\mu_t) = \mu_0 + \mu_1 x_{1t} + \mu_2 x_{2t} + \mu_3 n_t, \quad \log(\gamma_t) = \gamma_0 + \gamma_1 x_{1t} + \gamma_2 x_{2t} + \gamma_3 n_t.$$

Additionally, I fix the yearly discount factor $\beta = 0.94$.

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.[10] 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.

[10]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.

3.5.1 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.

3.5.2 Government Cost Distribution

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

$$(\hat{\alpha}, \hat{\rho}) = \arg\max_{\alpha,\rho} \prod_{\tau \in \mathcal{T}} G(\hat{R}(x_t, \widehat{\overline{N}}_{k_t}); \alpha, \rho)^{1-d_t} \times [1 - G(\hat{R}(x_t, \widehat{\overline{N}}_{k_t}); \alpha, \rho)]^{d_t} \tag{3.12}$$

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

3.5.3 Distance Parameter θ

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. The per-period discount factor is $\beta^{1/T_{IY}}$ where T_{IY} is the number of projects in region I for fiscal year Y. 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 $p_{0T}(z_t)$ is

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

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

$$p_{1t}(z_t) = \mathbb{1}_{\{y_t=0\}}\text{Pr}\left(C_{gt} + \theta\delta_t + \beta\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{0t}(z_{t+1}|z_t) < R(x_t,\overline{N}_{k_t}) + \beta\sum_{z_{t+1}\in\mathcal{Z}}\overline{V}_{t+1}(z_{t+1})q_{1t}(z_{t+1}|z_t)\right).$$

Recalling that

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

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

$$\hat{\theta} = \arg\max_{\theta} \prod_{I=1}^{5} \prod_{Y=1}^{15} \prod_{t \in T_{IY}} (\hat{p}_{1t})^{d_t} \times (1 - \hat{p}_{1t})^{1-d_t}. \tag{3.13}$$

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, (3.13) yields a consistent estimate for θ.

3.5.4 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 (3.10) 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.

3.5.5 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

$$\hat{c} = b - \frac{N[1 - \hat{W}(b)]}{(N-1)\hat{w}(b)}. \tag{3.14}$$

where b is a submitted bid. Hence for any bid, the associated cost can be found by applying (3.14) 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 $\hat{c}$.

3.6 Results

In this section I present the results of the structural estimation, assess the fit of the model, and explore the implications of the model estimates on costs, the effect of competition, and efficient project allocation.

3.6.1 Estimates

The estimates for the government cost distribution and the distance cost are contained in Table (3.2). As expected, larger projects and projects that take longer to complete increase expected cost, while also increasing the expected winning bid in the auction market. Results from the dynamic model demonstrate that distance costs are substantial, with each additional 100 miles adding $23,400 to total costs. The average contribution of travel costs for projects taken by the government is 3% for all projects and 7% for projects that involve changing districts. Confidence intervals listed are generated via subsampling.

Table 3.2: Estimates

	Estimate	**95% C.I.**
Government Costs		
α		
Constant	0.8189	[0.6878, 1.2892]
Project Size	0.0019	[-0.006, 0.0023]
Working Days	0.4665	[0.4532, 0.7376]
ρ		
Constant	3.3371	[2.9715, 5.0990]
Project Size	0.0001	[-0.003,0.0002]
Working Days	-0.0320	[-0.0907, -0.0278]
θ		
Distance (100's of miles)	0.0234	[0.0102, 0.0535]
Entry Costs		
λ		
Constant	-3.9215	[-4.9163, -2.8764]
Project Volume	0.3386	[0.2680, 0.4297]
Working Days	-0.1009	[-0.2762, 0.0388]
Winning Bid Distribution		
μ		
Constant	2.3525	[2.3259,2.3777]
Project Size	0.0267	[0.0250,0.0285]
Working Days	0.0009	[0.0006,0.0012]
Number of Bidders	-0.0035	[-0.0054,-0.0016]
γ		
Constant	0.7364	[0.4465,1.0197]
Project Size	-0.0870	[-0.1077,-0.0667]
Working Days	0.0018	[-0.0009,0.0057]
Number of Bidders	0.0122	[-0.0145,0.0411]

3.6.2 Model Fit

Simulated results using the model estimates are listed in Table 3.3. To obtain the model predictions the model was simulated 500 times using the estimated values. The model matches the percentage of government projects outsourced and the total contract costs from outsourcing well. Total accumulated distance by government vessels is slightly overestimated by the model. Average project characteristics for both in-house projects and outsourced projects also fit model predictions well. Figure 3.2 plots winning bids against the predicted values on a log scale for auctions that had at least two bidders.

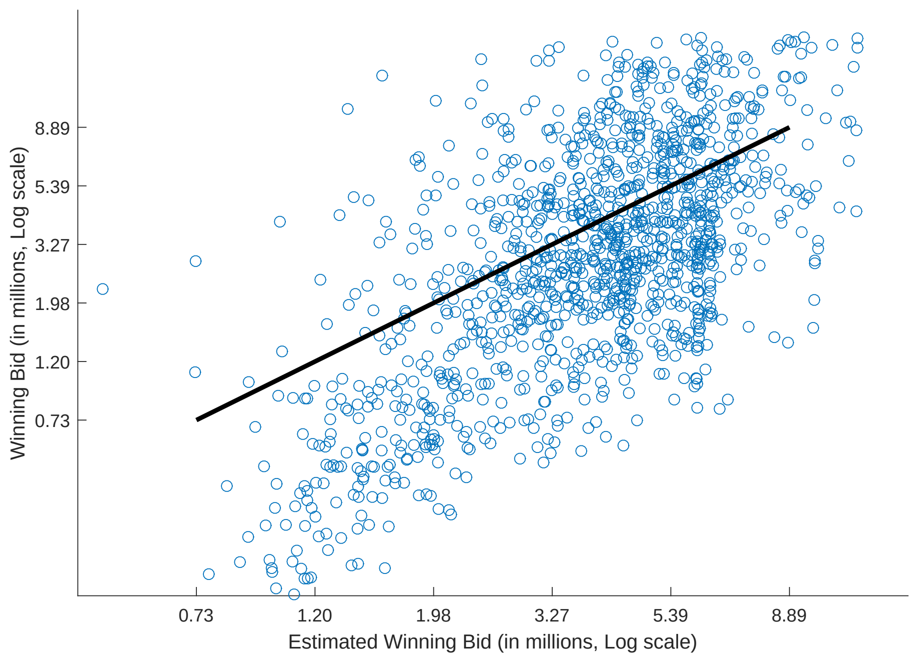
Table 3.3: Model Fit

	Data	Predicted
In-house projects (pct.)	50.98	49.46
Annual Contract Costs (millions)	$472.7	$492.0
Govt. distance traveled per project	136.6	132.4
Govt. cu. yds. per project (thousands)	273.7	274.7
Firm cu. yds. per project (thousands	1,177	1,166
Working days per project (govt.)	17.95	15.28
Working days per project (firms)	125.8	125.4

3.6.3 Comparing Government and Firm Costs

Using the estimated from the structural model it is possible to analyze the relative effects that competition and costs have on project allocation. Figure 3.3 displays the cost distribution for the government plotted against the winning bid distribution for auctions with three bidders and the distribution of firm costs for three levels of project size quantiles. The quantiles are for both project volume and length: the 0.25 quantile corresponds to a project with the 0.25 percentile for cubic yards of material dredged and the 0.25 percentile for working days. As can be seen from

Figure 3.2: Predicted vs. Actual Winning Auction Bids

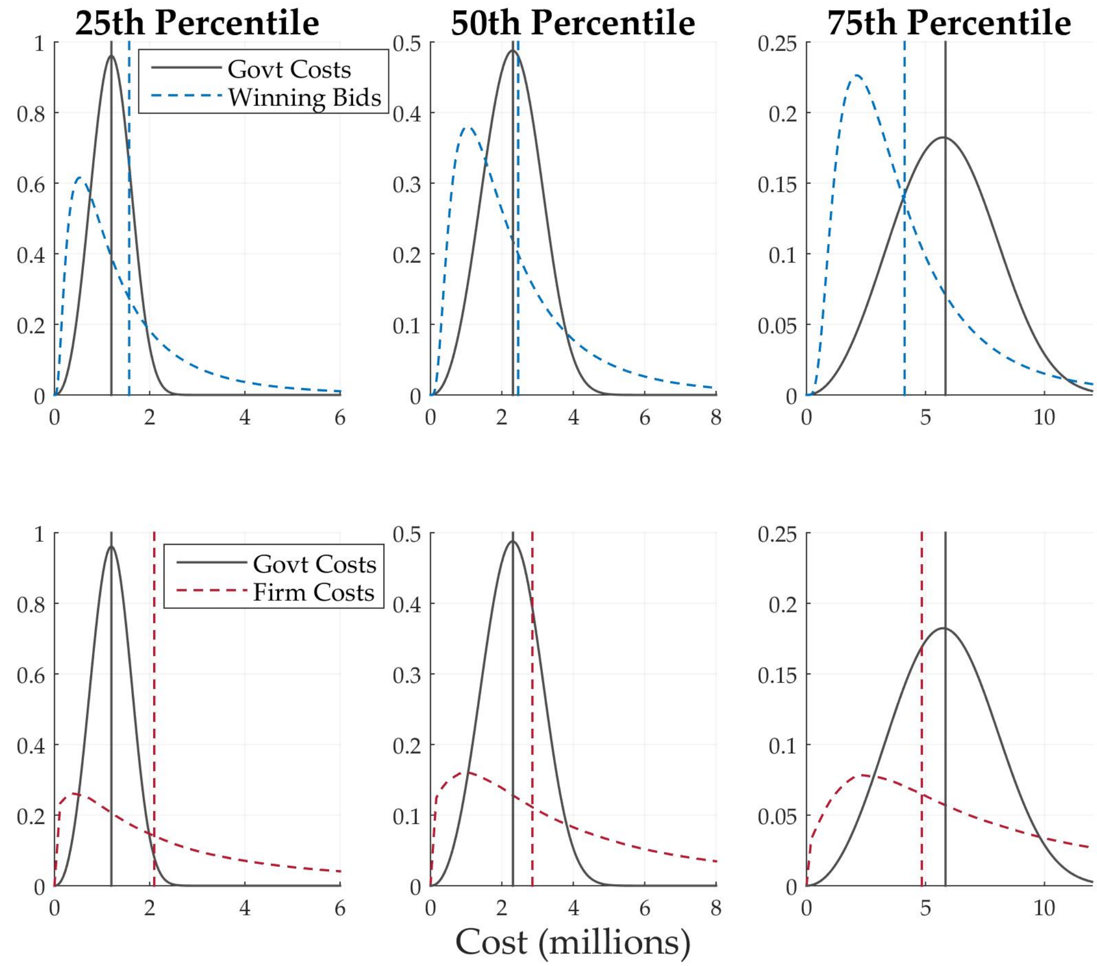


the top three tables, the mean government cost of project completion is lower than the expected winning bid for the 0.25 project size quantile, while being approximately even at the median project size and substantially greater than the winning bid at the 0.75 quantile. The relationship between firm costs and government costs is similar, although as is to be expected the firm cost distribution has both a higher mean and variance than the winning bid distribution. This leads to a government cost advantage on average for median-sized projects, while the expected winning bid is almost exactly equal to government costs. It is worth noting that the high variance in firm costs and the two-stage nature of the outsourcing process can lead to inefficient allocation of projects; I will quantify the extent to which this occurs in the following section.

These results suggest that the role of government in this market varies with the type of project being considered. For smaller projects that require less time and use of capital resources, government vessels act as the main source for project completion. Indeed, most of the projects that are smaller in scope are kept in-house. In contrast, for larger projects the government acts essentially as a fringe competitor: given the large difference in average costs for projects above the 75th percentile, a cost draw that would lead the government to forgo contracting the project out to a private firm would be a comparatively rare event.

It should also be noted that distance costs comprise a larger percentage of total costs for smaller projects; for this reason it may be cost-reducing for the government to contract out smaller projects in which it has a (static) cost advantage due to the costs associated with travel to the project site or dynamic considerations related to travel to future projects. For larger projects the effect of distance on the outsourcing decision is mitigated by the comparatively larger cost difference between private firms and the government.

Figure 3.3: Distributions of Government Costs, Winning Bids, and Firm Costs



Note: This figure compares the distribution of government costs with winning bid and firm cost distributions for the 0.25, 0.50, and 0.75 quantiles of project size. The three graphs in the top panel display government costs distributions plotted wth the winning bid distributions for auctions with 3 bidders, while the bottom three graphs shows firm cost distributions. Means associated with each distribution are displayed as vertical lines.

3.6.4 Allocative Efficiency

Using the structural estimates, the efficiency of the mechanism (as defined by allocation of projects to the lowest-cost producer) used by the government can be assessed. Specifically, I estimate the extent to which the government chooses to outsource a project with the ex-ante expectation of reducing costs but the ex-post realization of competition and cost draws leads to a firm with a higher cost than the government being awarded the project. The two-stage nature of the mechanism used by the government to allocate projects leaves open this possibility due to firms private costs of completion being unknown to the government when the outsourcing decision is made: a project contracted out may draw few bidders in the auction, each of whom may have costs higher than the government's cost threshold for outsourcing.

Let c^1_{ft} be the lowest cost of firms participating in a procurement auction in period t. The project is mis-allocated if

$$c^1_{ft} > c_{gt} + \theta\delta_t + \beta(V_{0t}(z_{t+1}) - V_{1t}(z_{t+1}))$$

where c_{gt} is the realization of the government's cost draw in period t. To determine the extent of inefficient project allocation I simulate the model and generate the lowest cost for each outsourced project by first drawing from the distribution of the number of bidders for the project's location and then generating costs for each bidder via the procedure described in Section 3.5.5. I find that 15.86% of outsourced projects are allocated to firms with higher costs than government. The welfare losses from these projects average \$70 million annually. This suggests that substantial welfare gains could be made by reforming the procurement method to allow for more direct competition between private firms and government.

3.7 Counterfactual Simulations

In this section I use the model estimate to run several counterfactual simulations to assess the importance of dynamics, the effectiveness of the allocation mechanism, and the effect of government fleet reductions. The first of these counterfactuals assesses the importance of dynamics by simulating the decisions of a myopic government decision maker by setting $\beta = 0$. Next, I investigate the effect of reductions to the government's dredging fleet in order to determine the importance of government dredging on total expenditures. Lastly, I introduce and implement an alternate procurement mechanism. In this mechanism the government directly participates in the auction by setting a dynamically optimal reserve price that takes into account both current and future costs of in-house completion.

3.7.1 Effect of Dynamics

In order to assess the importance of dynamics in the government's outsourcing decisions the discount factor β was set to zero and the resulting model was simulated 500 times. The results of the model simulations are summarized in Table 3.4. A myopic government keeps 7.6% fewer projects in-house, primarily as the result of increasing the average number of working days per in-house project by 27.3%. This leads to an increase in total costs of 3.1%, which equates to an increase of more than $225 million over the 15 year sample period. These results indicate the importance of taking future costs into consideration when assessing firm or government make-or-buy decisions.

Table 3.4: Model without Dynamics

	Prediction	% Change from Baseline Model
Avg. Annual In-house Projects	110.7	-7.6%
Avg. Annual Total Costs (millions)	$665.1	3.1%
Distance traveled per Project	133.7	0.98%
Govt. Working Days per Project	19.6	27.3%

3.7.2 Reduction in Government Capacity

In order to investigate the effect that government presence in the market has on total expenditures I perform a counterfactual policy simulation in which I reduce the government's capacity. Lessening the ability to complete projects in-house will indicate how important direct public sector involvement in project completion is for minimizing government expenditures. Additionally, fixed costs of maintaining dredges are high; the USACE estimates that annual costs for keeping a dredge operational run in excess of $2 million. Retiring under-utilized dredges may thus save costs through eliminating their associated fixed costs.

The counterfactual is run by simulating the model a sequence of times. For each iteration the vessel that was active for the fewest working days is removed from the government's fleet. The simulations track the number of projects kept in-house as well as total expenditures on dredging projects.

The results of the simulations are summarized in Figure 3.4. Small reductions in government fleet size have little effect on expenditures: reducing the fleet size by one increases annual outsourcing costs by $0.32 million and a reduction of 2 vessels increases annual outsourcing costs by $ 1.38 million. However, further reductions are more impactful. When four vessels are removed, annual government costs increase by over $9 million per year, and a four vessel reduction corresponds to a $15 million per year increase. These results suggest that while government may be slightly over-invested in dredging capacity, government dredges nevertheless remain important in lowering total expenditures.

3.7.3 Direct Government Competition

Motivated by the results that indicate that both full privatization and complete in-house production result in additional costs relative to the current mixed-delivery system, I perform a counterfactual policy experiment which features direct competition between the government and private sector firms for each project.[11] Specifically, I assume the government holds a second price auction for every project with a reserve rate set by the government's cost for doing the project and the future value components. If no bids are placed below the government's reserve rate, the project is kept in-house. Otherwise, the project is contracted out to the lowest-bidding firm, with the contract price determined by the second lowest cost (which may be the government's reserve price).

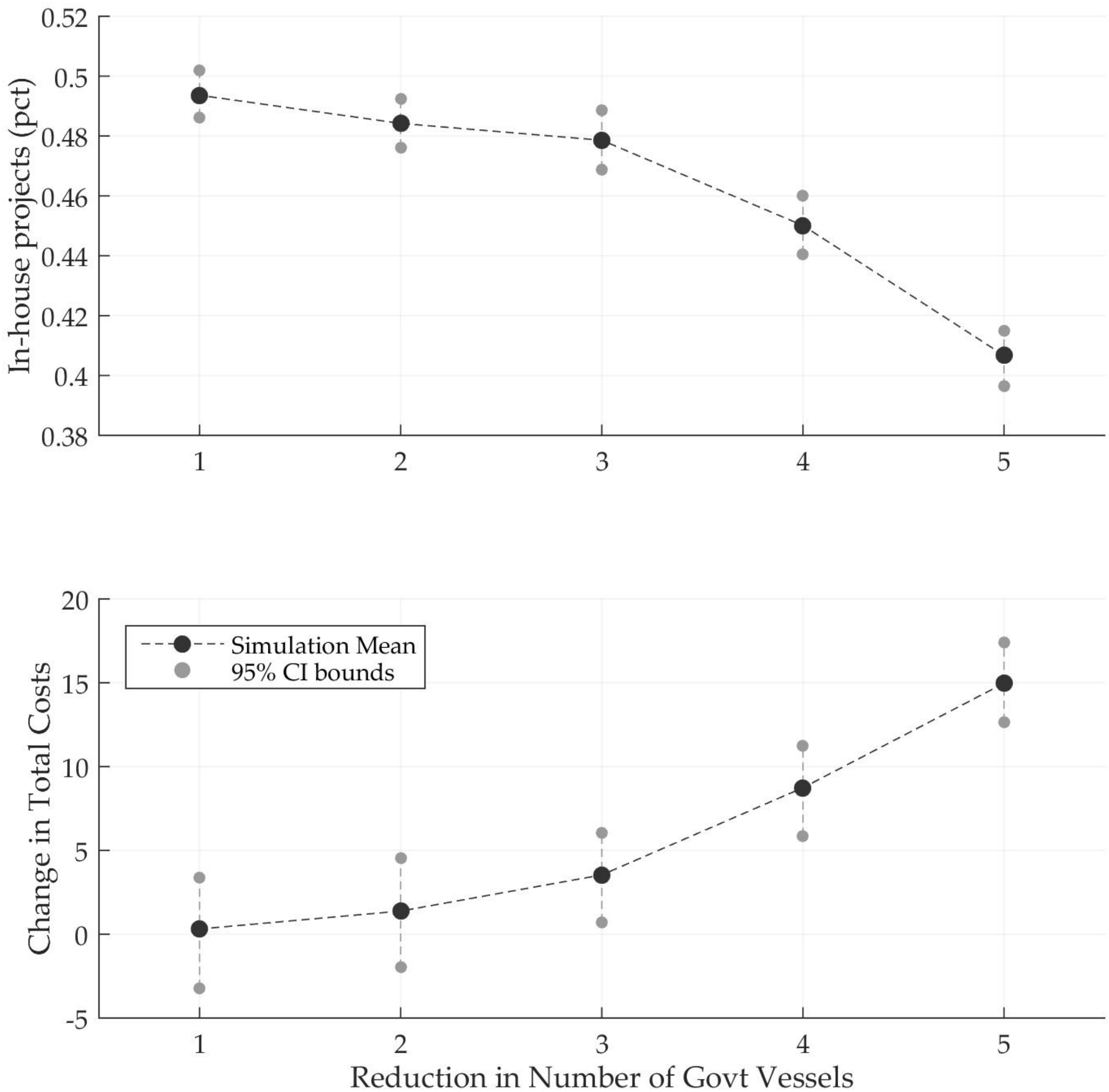
In the auction stage for a project in period t, the government has drawn a project cost c_{gt} with distance cost $\theta\delta_t$ and has expected future value terms $\overline{V}_{t+1}(z)$ for each $z \in \mathcal{Z}$. Then the maximum bid that the government is willing to accept in order to contract the project out is

$$r_t^* = c_{gt} + \theta\delta_t + \beta \sum_{z \in \mathcal{Z}} \left[\overline{V}_{t+1}(z_{t+1})(q_{1t}(z|z_t) - q_{0t}(z|z_t)) \right]. \tag{3.15}$$

Hence, the value in (3.15) gives the reserve price set by the government in each auction. The reserve price will also affect bidder entry, as the presence of a reserve price changes the expected

[11] This is a similar concept to the privatization competitions used in other situations by the Department of Defense; Snyder, Trost, and Trunkey (2001) empirically investigates these competitions.

Figure 3.4: Vessel Reduction Simulation Results



Note: Summary of the results of the capacity reduction counterfactual simulation. On the x-axis is the number of vessels subtracted from the baseline model. The y-axis on the two figures correspond to the percentage of projects kept in-house and the annual project costs (in millions of dollars), respectively.

profit obtainable by potential entrants. Modifying equation (3.1) to account for a reserve price r yields the new equilibrium cutoff condition:

$$e_r^* = \sum_{j=1}^{\overline{N}} \binom{\overline{N}}{j} \zeta(e_r^*)^j (1 - \zeta(e_r^*))^{\overline{N}-j} \mathbb{E}[\tilde{u}_i | r, n = j], \tag{3.16}$$

where $\mathbb{E}[\tilde{u}_i \mid r, n]$ is the payoff for player i in a second price auction with n total bidders and a reserve price r. The timing of the model is as follows:

1. Government draws its cost c_{gt} and sets reserve according to (3.15).
2. Entry costs for each firm are drawn from ζ. Firms with costs less than e_r^* enter the auction.
3. Firms learn their private costs c_f and bid in a second-price auction for the project contract.
4. If no firm's cost is lower than the government reserve, the project is kept in-house. Otherwise, the project is awarded to the lowest bidder.

The results of the counterfactual policy experiment, obtained from 500 simulations of the model, are contained in Table 3.5. Direct competition of government vessels against private sector firms lowers total expenditures by 17.1%. One of the key reasons for this is that the reserve price binds in many cases when the project would otherwise have been issued at a higher cost: a low-cost bidder may submit a bid greater than the government's cost of completing a project and still win the auction if the level of competition is low. The government reserve caps the amount awarded to the winning firm for these auctions, and in many such cases the project would have been kept in-house under the baseline model of choosing to outsource before the auction result was known. The "wait and see" approach of the direct competition model allows the government to opportunistically outsource projects after seeing how bidding unfolds, facilitating lower total expenditures.

Table 3.5: Results of Direct Government Competition Counterfactual Simulation

	Prediction	% Change from Baseline Model
Government Costs	$101.9	-38.26%
Outsourcing Costs	$442.8	-10.0 %
Total Costs	$544.7	-17.1 %

Note: Results of the counterfactual policy experiment of government reserve prices. Cost figures are average annual costs in millions of dollars.

3.8 Conclusion

This paper studies the outsourcing of dredging projects by the US Army Corps of Engineers. A dynamic discrete choice model of binary make-or-buy decisions is formulated and estimated using a novel identification strategy to identify the full distribution of the random component of government flow payoffs. I supply evidence of cost differences between the government and private firms that varies by project type, with in-house project allocation often proving optimal for smaller projects while larger projects are more likely to be contracted out. I find substantial private sector firm cost advantages for outsourced projects, averaging 23% lower costs than government provision, and also that government in-house provision remains optimal for a large share of projects. Additionally, future concerns about travel distance and capacity play an important role; I estimate that a myopic government decision maker would opt to keep 7.6% fewer projects in house. These findings demonstrate the importance of accounting for dynamics when analyzing make-or-buy decisions, as the boundaries of firms may often be determined by how current decisions affect future costs.

Using model estimates, I performed two counterfactuals. In the first, the total capacity of the government is reduced in order to investigate the effect of government presence in the dredging market. I find that a reduction of up to one sixth to government capacity would have little effect on total expenditures, while larger reductions prove more consequential. In the second counterfactual I feature direct bidding of private firms against the government through a dynamically optimal reserve price determined by government costs. The result is a 17.1% decrease in total government expenditures. Together, the results of the counterfactual experiments suggest that while government may be slightly over-invested in capacity, government presence in the market is important for cost reduction and may be utilized to that end more effectively through a change to the procurement mechanism that introduces direct competition between the government and private sector firms.

This paper places primary focus on government's role in mixed-delivery markets. However, firm activity in the these markets is also relatively unexplored. Variation in government activity may induce different investment or entry behavior among firms. As such, investigation of the effects of mixed-delivery of public goods on industry dynamics is a potential area of future research.

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Appendix A.1. Identification

Proof of Proposition 1. The proof proceeds in three stages. First, the identification of G from the static observations is shown. Next, an expression for the value function that makes use of the distribution estimated in the first stage is derived. Finally, identification of $\omega(\delta)$ is established by using techniques similar to Arcidiacono and Miller (2011).

First, take $\tau \in \mathcal{T}$. The conditional choice probability $p_{0\tau}(z_\tau)$ is

$$\begin{aligned} p_{0\tau}(z_\tau) &= \Pr\left(-c_{g\tau} - \omega(\delta_0) + \beta \sum_{z\in\mathcal{Z}} \overline{V}_{\tau+1}(z) q_{0\tau}(z|z_\tau) \geq -R(x_\tau, \overline{N}_{k_\tau}) + \beta \sum_{z\in\mathcal{Z}} \overline{V}_{\tau+1}(z) q_{1\tau}(z|z_\tau)\right) \\ &= \Pr\left(c_{g\tau} \leq R(x_\tau, \overline{N}_{k_\tau})\right) \\ &= G(R(x_\tau, \overline{N}_{k_\tau})|x_\tau) \end{aligned} \tag{17}$$

where the second equality follows from the assumption that $\omega(\delta_0) = 0$ and $q_{0\tau}(z|z_\tau) = q_{1\tau}(z|z_\tau)$ for all $z \in \mathcal{Z}$ and $\tau \in \mathcal{T}$. Then all choices in the set $\mathcal{T}$ are effectively static and depend only on $(x_\tau, \overline{N}_{k_\tau})$, so that $p_{0\tau}(z_\tau) \equiv p_{0\tau}(x_\tau, \overline{N}_{k_\tau})\ \forall \tau \in \mathcal{T}$. By assumption, $R^{-1}(x_\tau, c) : \mathcal{X} \times [\underline{c}, \overline{c}] \to \mathcal{H}$ exists. Hence,

$$G(c|x_\tau) = p_{0\tau}(x_\tau, R^{-1}(x_\tau, c)) \tag{18}$$

completing identification of G.

Identification of $\omega(\delta)$ proceeds by expressing the future value function in terms of observables. The first step is to use the inversion theorem of Hotz and Miller (1993) to establish the existence of a function $\phi(p_{0t}(z_t)) = v_{0t}(z_t) - v_{1t}(z_t)$. Because G is continuous and strictly increasing and $p_{0t} = \Pr(-c_{gt} + v_{0t}(z_t) \geq v_{1t}(z_t))$ it follows that $\phi(p_{0t}(z_t)) = G^{-1}(p_{0t}(z_t)|x_t)$.

Next we establish an expression for the expected government conditional on keeping a project in house:

$$\begin{aligned}
\mathbb{E}[c_{gt}| - c_{gt} + v_{1t}(z_t) \geq v_{0t}(z_t)] &= \mathbb{E}[c_{gt}|c_{gt} \leq v_{1t}(z_t) - v_{0t}(z_t)] \\
&= \mathbb{E}[c_{gt}|c_{gt} \leq -\phi(p_{1t}(z_t))]
\end{aligned}$$

As the distribution of c_{gt} is known and ϕ is given by the inversion theorem, this expression is known. Let $\xi(p_{1t}(z_t))$ denote this term. Following Arcidiacono and Miller (2011), we can write the value function as follows:

$$V_t(z_t) = \sum_{j=0}^{1} p_{jt}(z_t)v_{jt}(z_t) + p_{1t}(z_t)\xi(p_{1t}(z_t)).$$

Subtracting $v_{1t}(z_t)$ from each side yields

$$\begin{aligned}
V_t(z_t) - v_{1t}(z_t) &= \sum_{j=0}^{1} p_{jt}(z_t)v_{jt}(z_t) + p_{1t}(z_t) \cdot \xi(p_{1t}(z_t)) - v_{1t}(z_t) \\
&= \sum_{j=0}^{1} p_{jt}(z_t)(v_{jt}(z_t) - v_{1t}(z_t)) + p_{1t}(z_t) \cdot \xi(p_{1t}(z_t)) \\
&= p_{0t} \cdot \phi(p_{1t}(z_t)) + p_{1t}(z_t) \cdot \xi(p_{1t}(z_t)) \\
&\equiv \psi_1(p_t(z_t)) \qquad (19)
\end{aligned}$$

Using a similar procedure, we define $\psi_0(p_t(z_t)) \equiv p_{1t} \cdot \phi(p_{1t}(z_t)) + p_{1t}(z_t) \cdot \xi(p_{1t}(z_t))$. Note that as $p_{0t} \to 0$ then ψ_1 becomes the (unconditional) expected government cost, while as $p_{0t} \to 1$ the term ψ_0 goes to zero.

Now that expressions for the ψ_j terms have been derived we can appeal directly to the results of Arcidiacono and Miller (2011) for the remainder of the proof. Specifically, let $\{d'_\tau\}_{\tau=t+1}^{T}$ be any sequence of decisions from τ until T. Using the definition of $\psi_j(p_\tau(z_\tau))$ we can write the conditional value function for choice $d_t = 0$ as

$$v_{0t}(z_t) = \pi_{0t}(z_t) + \sum_{\tau=t+1}^{T} \sum_{z_\tau \in \mathcal{Z}} \beta^{\tau-t}[\pi_{d'_\tau \tau}(z_\tau) + \psi_{d'_\tau}(p_{d'_\tau \tau}(z_\tau))]\kappa_{\tau-1}(z_\tau | z_t, d'_t = 1) \tag{20}$$

with a similar expression for $v_{1t}(z_t)$. Noting that

$$v_{1t}(z_t) - v_{0t}(z_t) = \psi_0(p_t(z_t)) - \psi_1(p_t(z_t))$$

we can insert plug in the expressions for $v_{1t}(z_t)$ and $v_{0t}(z_t)$ and set $d'_\tau = 1$ for all $\tau > t$ to obtain, upon rearrangement

$$\omega(\delta_t) = R(x_t, \overline{N}_{k_t}) - \psi_0(p_t(z_t)) + \psi_1(p_t(z_t)) - \sum_{\tau=t+1}^{T} \beta^{\tau-t} \sum_{z_\tau \in \mathcal{Z}} [-R(x_\tau, \overline{N}_{k_\tau}) + \psi_0(p_\tau(z_\tau))](\kappa_{\tau-1}(z_\tau | z_t, 0) - \kappa_{\tau-1}(z_\tau | z_t,$$

(21)

This yields an expression for $\omega(\delta_t)$ in terms of functions of state variables which are known from normalizations ($R(x_\tau, \overline{N}_{k_\tau})$, the distribution of the unobserved term identified in the first stage ($\psi(p_\tau(z_\tau))$), or observed in the data ($\kappa_{\tau-1}(z_\tau \mid z_{\tau-1}, d_t)$), completing identification of $\omega(\delta_t)$.

■

Appendix A.2. Counterfactual Simulations

A.2.1 Fleet reduction simulations

For the counterfactual in which the government dredging fleet is reduced, first I identify the least-utilized vessel in the simulation of the model using the estimated parameters. This vessel is removed from the government's fleet, and the model is re-simulated, again identifying and subsequently removing the least utilized vessel. When removal of a vessel would leave a district unserved by any vessel in the government fleet, a vessel who covers the closest district within the vessel's region has their district coverage area expanded to include the district.

A.2.2 Government reserve simulation

To perform the counterfactual policy in which government sets a reserve price for each auction, it is necessary to re-compute the value function for each state as auction entry and bidding (and therefore expected winning bid) are affected by the establishment of a reserve price policy. Ex-ante value functions for each state are computed using the following sequence of steps, which is run for each fiscal year-region pair:

1. Starting in period T, government draws cost c_{gT}, sets $r^*(c_{gT})$ to be

$$r^*(c_{gT}) = c_{gT} + \theta\delta_t.$$

2. Expected profit conditional on reserve price $r^*(c_{gT})$ and j bidders for each $j \in \{1, .., \overline{N}_{k_t}\}$ is calculated by simulating the auction 200 times.

3. For each $n = 1, ..., \overline{N}_{k_t}$, the expected profit for each bidder conditional on entry is calculated by simulating auction outcomes 200 times for each number of bidders.

$$\mathbb{E}[\tilde{u}_i|n, x_T, r^*(c_{gT})] = \Pr(c_i < c_j \; \forall j \neq i) \times \mathbb{E}[b(c_i) - c_i \mid c_i < c_j \; \forall j \neq i, \; c_i \leq r^*(c_{gT})].$$

4. The expected profit and entry cost distribution are used to solve for the equilibrium entry

cutoff $\tilde{e}_k(x_T)$:

$$\tilde{e}_k(x_T; r^*(c_{gT})) = \sum_{j=1}^{\overline{N}_{k_t}} \left(\zeta(\tilde{e}_k(x_T; r^*(c_{gT})))^j [1 - \zeta(\tilde{e}_k(x_T; r^*(c_{gT})))]^{\overline{N}_{k_t} - j} \right) \cdot \mathbb{E}[\tilde{u}_i \mid j, x_T, r^*(c_{gT})].$$

5. Using the entry cost cutoff $\tilde{e}_k(x_T)$, the distribution over the number of bidders can be expressed

$$\Pr(n = j | x_T, \tilde{e}_k(x_T; r^*(c_{gT}))) = \zeta(\tilde{e}_k(x_T; r^*(c_{gT})))^j [1 - \zeta(\tilde{e}_k(x_T; r^*(c_{gT})))]^{\overline{N}_{k_t} - j}.$$

6. Draw from the number of bidders distribution and simulate the auction outcome: if a bidder has a lower cost than the government reserve, they are awarded the project and pay a bid equal to the second highest bid or the government reserve, whichever is lower. Otherwise, the project is taken by the government.

7. Average over simulations s to obtain CCPs and conditional payoffs: $\tilde{p}_{0T}(z_T) = \frac{1}{200} \sum_{s=1}^{200} \mathbb{1}\{d_{sT} = 0\}$, $\mathbb{E}[\tilde{V}_{0T}(z_T) | d_T = 0] = -\frac{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=0\}(c_{gsT}+\theta\delta_t)}{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=0\}}$, and $\mathbb{E}[\tilde{V}_{1T}(z_T) | d_T = 1] = -\frac{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=1\} b_s^1}{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=1\}}$ where b_s^1 is the winning bid in auction s.

8. Ex-ante value function computed as

$$\tilde{V}_T(z_T) = \tilde{p}_{0T}(z_T)\mathbb{E}[\tilde{V}_T | d_T = 0] + (1 - \tilde{p}_{0T}(z_T))\mathbb{E}[\tilde{V}_T | d_T = 1].$$

9. Iterating backwards from $t = T-1, .., 1$, draw 200 government costs c_{gst} for each t and z_t from $G(\cdot | x_t)$. Set reserve price $r^*(c_{gst}) = c_{gst} + \theta\delta_t + \beta \sum_{z \in \mathcal{Z}} \tilde{V}_{t+1}(z_t)(q_{0t}(z|z_t) - q_{1t}(z|z_t))$.

10 . Repeat steps 1 through 8, with $\mathbb{E}[\tilde{V}_{0T}(z_T) | d_T = 0] = -\frac{\sum_{s=1}^{200} \mathbb{1}\{d_{st}=0\}(c_{gst}+\theta\delta_t - \beta \sum_{z \in \mathcal{Z}} \tilde{V}_{t+1}(z) q_{0t}(z|z_t))}{\sum_{s=1}^{200} \mathbb{1}\{d_{st}=0\}}$,

and $\mathbb{E}[\tilde{V}_{1T}(z_T)|d_T = 1] = -\frac{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=1\} b_s^1 - \beta \sum_{z \in \mathcal{Z}} \tilde{V}_{t+1}(z) q_{1t}(z|z_t)}{\sum_{s=1}^{200} \mathbb{1}\{d_{sT}=1\}}$.

The simulation is run by beginning at the first project for each region and fiscal year, drawing cost c_{gt} and setting the reserve price using the simulated value functions, and simulating the entry process and auction outcome. If the lowest cost for private sector firms in the auction is lower than the reserve price, the project is outsourced. Otherwise, the project is kept in-house. Then the state variables are updated and the simulation proceeds to the next stage. The simulation is run 500 times for each fiscal year-region pair. .

Appendix A.3. Data and Sample Construction

The United States Army Corps of Engineers is tasked by Congress with maintaining all navigable waterways in the United States. Prior to 1972, all dredging work on these waterways was carried out directly by the Corps. In 1972 Congress passed the Minimum Fleet Act which authorized the Corps to contract out to private firms as much dredging work as possible while keeping costs reasonable and insuring enough capacity for emergency work. Data is available from Navigation Data Center, which is a division of the USACE responsible for compiling and reporting data relating to US waterways. Dredging project data is available for the previous 15 years. Dredging projects are carried out at the district level with 34 districts located on waterways throughout the United States.

A.3.1 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 (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 able to accommodate in many cases. 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 3625 observations across 31 districts.

A.3.2 Variable Definitions

Project size s_t: A measure of the total volume of material that is displaced by the dredging project in cubic yards. When possible, the estimated number of cubic yards is used. When this is not available, the actual reported number of cubic yards dredged is used instead. If neither figure is available in the data, the project is removed from the sample.

Working days w_t: The number of days required to complete the project. When available, the estimated number of days is used. When this information is missing, the actual reported number of days required for project completion is used instead. If neither figure is available in the data, the project is removed from the sample.

Competition $\overline{N}_k$: The number of active competitors for projects in district k. There are two projects in the Kansas City district where no auctions are held leading to an undefined number for the average bidders. For these two observations it is assumed that the government takes the project with probability one.

Distance δ_t: The distance in miles from the nearest Corps dredge to the current project. The distance data is obtained from the 2012 Distances Between US Ports publication, issued jointly by the U.S. Department of Commerce, the National Oceanic and Atmospheric Administration, and the National Ocean Service. Distances between ports are given in tables that are divided into four regions: Gulf ports, Atlantic ports, river system ports, and Pacific ports. When distance between two ports not listed on the same table is needed the following procedure is used. For district m_1 located in region 1 and district m_2 located in region 2, first the district m^* in region 1 that is closest to region 2 is identified (e.g. the closest district in the Atlantic region to the Gulf region is Jacksonville) and the distance from m_1 to this district is calculated. That distance is added to the distance from m^* to m_2 to obtain the overall distance. This is the procedure recommended within the text of the publication, and there is at least one city overlap between region tables that makes this calculation possible for all districts.

Winning Bids b_t: The winning bid for the auction in period t.

Number of Bidders n_t: Number of firms placing bids in auction t.

A.3.3 Corps Dredges Assignment

Each Corps-owned dredge complete projects within a specific geographic region; in most districts a single Corps dredge complete all projects the Corps elects to keep in-house for that district. Project characteristics and type of dredge account for the remaining eligibility of Corps dredges for various projects. A recommended dredge type is given for all projects, and when a Corps dredge doesn't match the recommended type it is not considered eligible to complete the project. The main dredge type criterion that is important for government outsourcing is hopper dredging; hopper dredges primarily complete larger projects involving repeated transfer of dredged material. I consider only hopper dredges to be eligible to complete dredging projects labeled as hopper dredging projects by the Corps. Given these restrictions, a dredge is considered able to complete a project if (a) it is the only dredge that completes projects in that district over the sample period or (b) the dredge is observed to complete projects in the same region in the sample and the dredge meets the dredge type criteria for the project. When multiple dredges are available to complete a project, only the closest is considered.

Table (6) provides a summary of each Corps dredge. Over the course of the sample, there are 14 Corps-operated dredges observed but only 12 are active at any given time: the dredge *Goetz* replaced the *Thompson* in 2005 and the *Murden* replaced the *Fry* in 2011.

Table 6: Corps-owned dredges

Dredge Name	**Region of Operation**	**Number of Projects Completed**	**Dredge Type**
Hurley	Inland Waterways	15	Dustpan
Wheeler	Gulf Coast	87	Hopper
McFarland	Atlantic	111	Hopper
Essayons	Pacific	203	Hopper
Yaquina	Pacific	218	Hopper
Potter	Inland Waterways	180	Dustpan
Thompson	Inland Waterways	30	Pipeline
Jadwin	Inland Waterways	214	Dustpan
Currituck	Atlantic	355	Non-conventional
Fry	Atlantic	215	Sidecaster
Merritt	Atlantic	280	Sidecaster
Schweizer	Atlantic	2	Sidecaster
Goetz	Inland Waterways	27	Pipeline
Murden	Atlantic	8	Non-conventional

A.3.4 USACE Districts

The USACE maintains district headquarters in 34 locations. Each Corps-owned dredge has a primary district, but dredges travel between and complete projects in other districts frequently. The overall schedule of projects and the Corps dredging budget is determined at the national level, and all details relating to individual projects – such as developing plans, overseeing projects, and holding auctions when necessary– are done at the district level.

Table 7: USACE Districts

District	**Total Projects**	**Corps Projects**	**Contracted Projects**	**Mean Project Size** (thousands)	**Mean Number of Bidders**
Alaska	51	2	49	401	1.6122
Baltimore	112	112	73	537	2.7671
Buffalo	78	0	78	206	2.5385
Charleston	79	25	54	1,099	2.6667
Chicago	33	0	33	94	2.4545
Detroit	232	0	232	54	2.6164
Galveston	215	0	215	1,747	3.2372
Honolulu	8	2	6	94	1.3333
Huntington	31	0	31	86	1.0000
Jacksonville	189	17	172	624	2.6105
Kansas City	2	2	0	47	0
Little Rock	4	0	4	1,251	2.2500
Los Angeles	48	12	36	827	2.3889
Louisville	16	1	15	945	1.0000
Memphis	24	17	7	6,555	2.0000
Mobile	127	16	111	1,296	2.2973
New England	96	62	34	114	2.9706
New Orleans	562	235	327	1,763	2.3394
New York	138	26	112	524	2.8750
Norfolk	203	80	123	270	2.2927
Philadelphia	270	152	118	433	2.0000
Pittsburgh	14	0	14	10	1.0000
Portland	380	310	70	414	2.5143
Rock Island	18	11	7	269	2.1429
Sacramento	8	0	8	258	1.3750
San Francisco	104	67	37	454	1.9459
Savannah	43	0	43	2,798	2.5349
Seattle	72	28	44	491	2.6591
St. Louis	190	186	4	273	1.0000
St. Paul	66	46	20	312	2.3500
Tulsa	1	0	1	530	1.0000
Vicksburg	86	68	18	765	2.2778
Walla Walla	1	0	1	11	3.0000
Wilmington	654	541	113	240	2.5664

Table 8: 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

Appendix A.4. Estimation

A.4.1 Government Costs

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 distance parameter consists of using the estimates from the first two stages in the dynamic problem. Since the time horizon is finite, for each parameter we can use backwards induction to find an expression for the value function at each time period. In the final period T there is no future value term, so the conditional valuation v_{jt} is simply the flow utility associated with this choice. This can be expressed only in terms of the parameter of interest and the state variables, which gives the ex-ante value function in period T for each state. Working backwards for each period $T-1, T-2, ..., 1$, the ex-ante value function can be expressed in terms of the parameter θ, the state in that period, the state transitions, and the next period's ex-ante value function.

A convenient feature of the data is that the set of possible distances for each dredge is finite: given a set of possible districts in which to complete projects and the distance between them, the set of possible distances is the same as the number of edges in a fully connected graph with the number of edges given by the number of districts, with one additional state representing zero distance. Hence, the number of possible states for a vessel that services k districts is $k(k-1)/2+1$. In the data this ranges from zero (a vessel that only completes projects in one district) to 56 (the *McFarland* completes projects in 11 districts over the sample period). This greatly eases the computational burden of estimation and allows for feasible backwards induction estimation of the distance cost parameter.

The state space is constructed by tracking vessel locations and availability for each project during each fiscal year. The USACE districts are divided between five non-overlapping regions: two in the Atlantic (roughly split between north Atlantic and south Atlantic regions), the Gulf of Mexico coastal region, the inland waterway system consisting of the Mississippi River and its tributaries, and the Pacific coastal region. The highest number of government vessels active in a region is four (occurring in the Atlantic coastal area). Tracking location and availability status for each vessel quickly causes the state space to grow unfeasibly large. To solve this problem, I consider the state for each vessel to be the period in which that vessel most recently completed a project. This gives the availability status and location for each vessel, as both of these can be discerned from the last completed project, and results in a smaller state space that makes estimation practical.

A.4.2 Entry costs

To estimate the entry cost distribution the expected profit for each number of bidders is needed. Using the firm cost estimates this can be calculated directly when $n \geq 2$. When $n = 1$, I use the bid distribution from the auctions with only one bidder and the distribution of firm costs to find the bidding function and the number of bidders. Sepcifically, I fit the bid distribution of one-bidder auctions to a Weibull distribution whose parameters depend on project characteristics. Using this distribution, the distribution of firm costs F, and the monotonicity condition that $b(c) > b(c') \iff c > c'$, this allows me to integrate over the profit function $b(c) - c$ for the one bidder case to find expected bidders' expected profit.

Appendix A.5. Other Figures and Tables

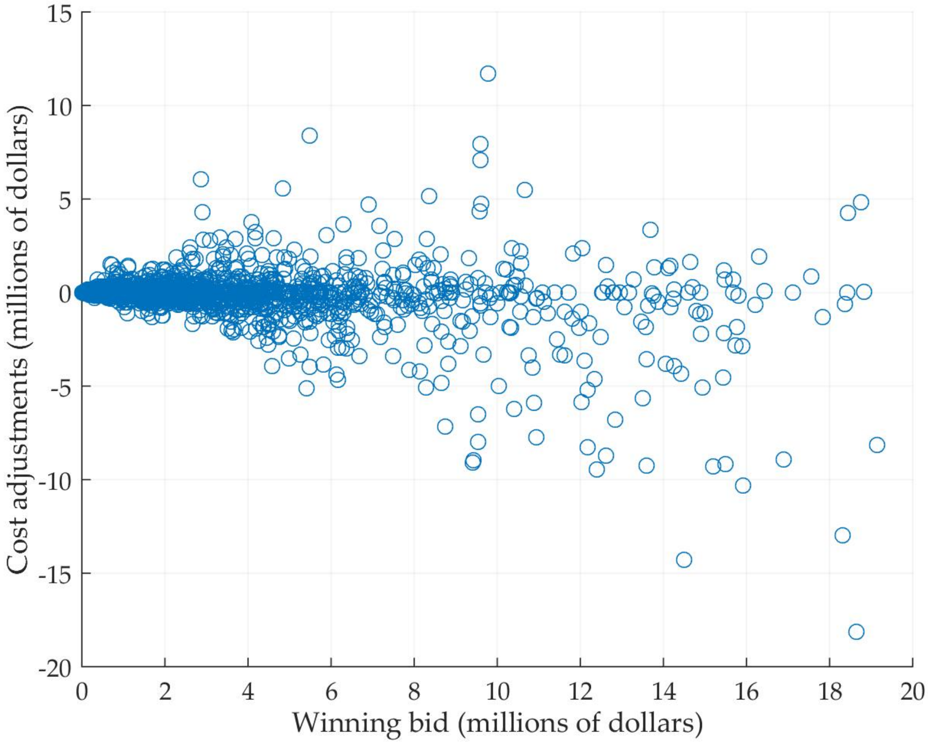


Figure 5: Plot of winning bids against the ex-post changes in payment to the contracted firm. There is no readily observable pattern that suggests cost adjustments correlate more strongly with smaller or larger projects; if anything, very large projects are more likely to have reductions made to the initial bid.

Table 9: Regressions of variables on number of bidders

Variable	**Coef.**	**Std. err**	**Coef.**	**Std. err**
log(Working Days)	0.009***	0.002	0.008***	0.002
log(Project Volume (cu. yds.))	-0.039	0.029	-0.079*	0.039
Ongoing Projects	-0.028	0.015	-0.025	0.016
Govt. Estimate			0.079	0.048
Consant	1.656***	0.205	0.737	0.577
District	Yes		Yes	
N	1777.000		1777.000	
* p<0.05, ** p<0.01, *** p<0.001				

Note: 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.

Figure 6: US Army Corps of Engineers district map. Not all districts oversee dredging operations; see the data appendix for more details

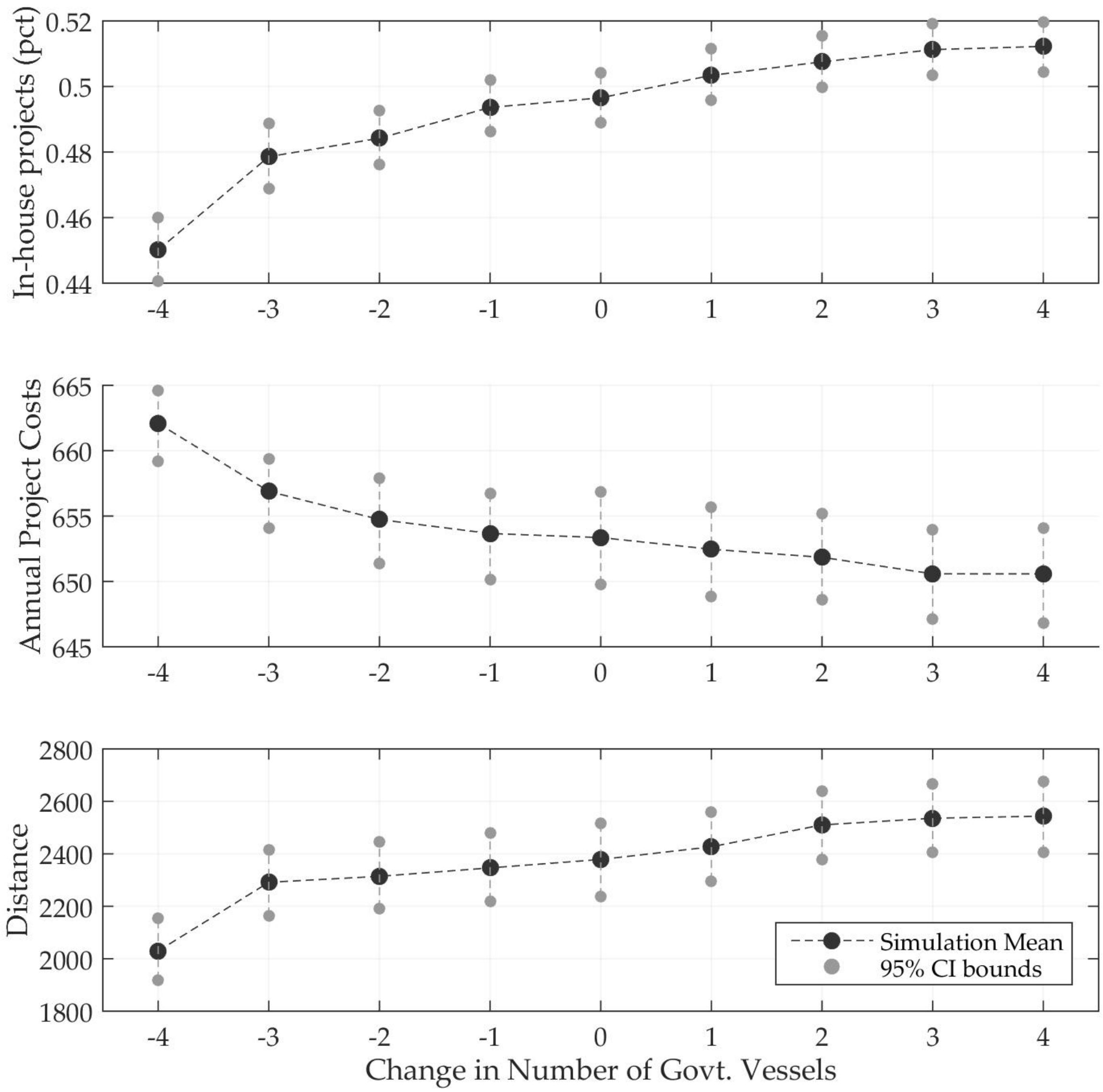
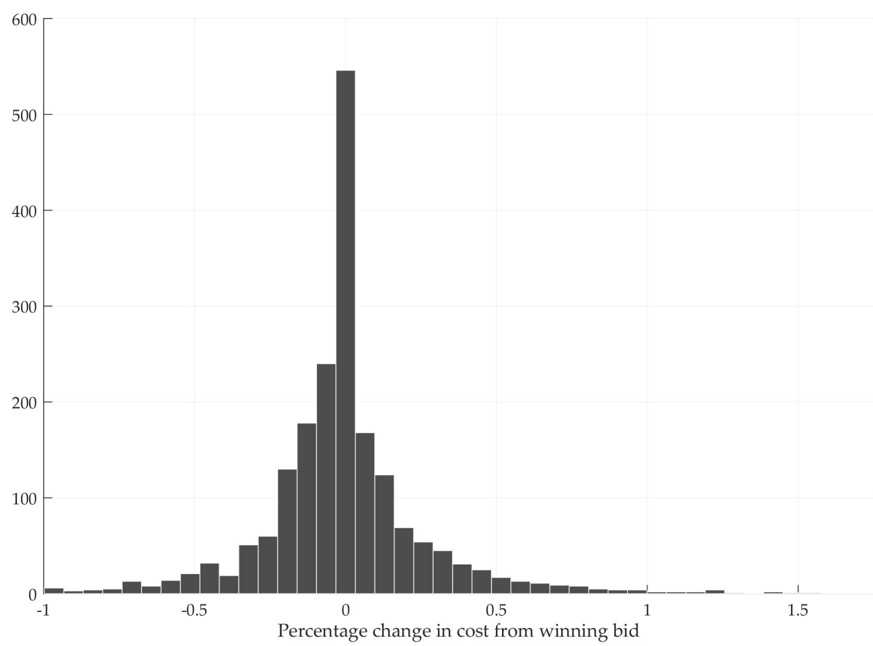


Figure 7: Expanded results of the capacity change counterfactual simulation to include vessel additions. On the x-axis is the number of vessels added or subtracted from the baseline model. The y-axis on the three figures correspond to the percentage of projects kept in-house, the annual outsourcing cost for projects contracted out (in millions of dollars), and the total distance traveled by government vessels (in hundreds of miles), respectively.

Figure 8: 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.