The “Shadow of the Future” in Procurement Auctions

A THESIS
SUBMITTED TO THE FACULTY OF THE GRADUATE SCHOOL
OF THE UNIVERSITY OF MINNESOTA
BY

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IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
Doctor of Philosophy

GEORGE JOHN, ADVISOR
OM NARASIMHAN, CO-ADVISOR

JUNE, 2015

Acknowledgements

I extend my sincere thanks to many people who helped me complete this thesis. I am deeply indebted to my advisers George John and Om Narasimhan, my mentors, co-authors, and my friends, for their constant support, encouragement, and guidance. They have made every step of this way possible, and I will always be grateful for all the time and efforts they have devoted to me. I have learned tremendously from them, and their enthusiasm and critical attitudes have been and will always be inspiring to me.

I would also like to thank my other three committee members: Ravi Bapna in the Informaiton Decision System Program of Carlson School of Management for his interest in this thesis and kind support, especially his crucial role in helping me obtain the data for this dissertation; Linli Xu in the Marketing Department for all the time and help she has given; and Thomas Holmes from the Economics Department for his sound advice and help. Their valuable insights, support, and interest in my dissertation have undoubtedly assisted me greatly along the way.

I am extremely grateful to all the other professors in the Marketing Department. Each of you has helped me and influenced my path as an academic in different, but all positive ways. I thank Mark Bergen, Akshay Rao, Deborah John, and Joe Redden, in particular, for their support and faith in me, continuous interest and enthusiasm in my research, and spending numerous hours preparing me for the job market presentation.Tony Cui deserves special mention, for coaxing me into joining the PhD program in Minnesota, and constantly helping me in research.

I also wish to thank my PhD cohort for making it a fun, exciting and creative environment. Ranjan Banerjee and Madhu Viswanathan, my co-authors, big brothers, and dear friends, deserve special mention for constant help and leading me toward my research. Paola Mallucci was particularly helpful, acting as a sounding board for my research ideas. Yajin Wang was always standing by my side as a good friend who I could turn to during the difficult times. Jen Stoner, my roommate, made this time in this program fun.

I would also like to thank the staff in the Marketing cluster and PhD program office: Jill Johnson, Melissa Grass, Vicki Lund, Earlene Bronson, Elizabeth Lenzen and Bonita Bartholomew, for their assistance on numerous administrative tasks.

I would like to extend my gratitude to my host family, Eldon College and Janis College, for all the help they have given me in the past 5 years.

Lastly, I would like to thank my late parents. Their love has been a constant source of motivation.

Dedication

To those who held me up over the years

Abstract

Buyer behavior for procuring large, complex, customized items consists of initial phases where firms first specify the needed item(s) and pre-qualify vendors, following which an auction is used to choose the contractor. Despite the rigid rules and detailed specifications accompanying auctions, it is striking that procurement auctions in industries like information technology (IT) display very large differences between the initially agreed-to payment and the actual payments because of revisions negotiated during the execution phase. However, these revisions are ignored in the theoretical and empirical auction literature. After developing a mathematical model to specify how bidders accommodate post-auction modifications, I develop a method to take my model to a comprehensive dataset of IT procurement auctions.

I find that the prospects of modifications lower bidders' latent costs, leading to more aggressive bids, especially by bidders without a previous contract with the buyer. To fix the magnitude of this effect, I consider a buyer who credibly commits to a no-modification policy, and find that such a commitment would increase bids by 27%, all else is equal. I also find that the size of this shadow of the future is larger for lump-sum bids. To fix this magnitude, I consider a buyer who switches the auction bid format from a lump-sum bid to a more flexible bid format (e.g., time and materials), and find that bids are lower by 16%, all else being equal. These large effects form the basis of my recommendations for improving procurement auctions. They also contribute to long-standing theory concerns studied in transaction cost economics.

My findings support the Williamsonian critique of procurement auctions as a solution for the ex-post monopoly problem; my estimates demonstrate that ex post modifications remain an intrinsic aspect of procurement auctions. However, auctions remain a valuable procurement device for customized goods in complex, fast-moving environments, particularly when used with more flexible payment formats.

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Chapter 1

Introduction

An important, and growing aspect of modern economies concerns the procurement of costly, customized goods and services by private and public enterprises. Pharmaceuticals, electronics and autos are all prominent instances of industries where procurement is prominent; perhaps the most visible sector in this regard is information technology (IT). One estimate is that global expenditure in IT services outsourcing was $952 billion in 2013, and it is expected to exceed $1,000 billion starting from 2014 (KPMG, 2013).

Marketing scholars (e.g., Webster and Wind, 1972) have described the organizational buying (procurement) processes across different circumstances. For repetitive, small-ticket items, the process is simple. Even large-ticket item procurement becomes routinized over time because suppliers manufacture multiple units of the identical piece of equipment. The most complex, and non-routine procurement processes involve customized products and services. Here, there is no pre-existing market of suppliers offering competing products. Instead, would-be suppliers must be engaged to create the customized product. Here, the first major stage of procurement consists of the buyer's efforts to translate the needs into a set of product requirements. [1] This stage includes extensive interactions with possible suppliers, often referred to as requests for information (RFI). In the next stage, the buyer winnows down the original list of contacts to a much smaller list of qualified vendors. At the same time, a package of documents specifying the design and scope of work, timelines, etc. is created and the buyer formulates

[1] To minimize repetition, I shall use product to refer to both products and services.

requests for proposals (RFP) or requests for quotes (RFQ) to be sent to the qualified vendor list.

At this point, a very significant decision is made about the manner in which the winning supplier will be selected: negotiations versus auctions. Under *negotiations* (also known as pitches or beauty contests) with potential suppliers, the selection process is not transparent to third parties, as the buyer does not disclose the scoring rules or other formula used to evaluate suppliers' proposals. Negotiations almost always proceed sequentially, beginning with the most promising qualified vendor, and moving on to the next qualified vendor in case of a breakdown. The second approach is a procurement auction (also called a reverse auction). Here, the buyer sends the developed product specifications as an RFP or RFQ to the short list of qualified vendors, and invites them to enter a bid. The bid scoring rule is always disclosed, and in the case of public enterprises, they are legally bound to follow the disclosed formula for choosing the winner. In contrast to sequential negotiations, procurement auctions involve all the invited vendors simultaneously. While many auction types exist (e.g., ascending, descending, open-outcry, sealed bid, first price, second price, etc.), procurement auctions for customized industrial products and services resemble a sealed bid, first-price auction.

Auctions are considered superior to negotiations (e.g., Bulow and Klemperer, 1994a) because competition between bidders drives down prices, even when the product is customized to the buyer. They are also fairer and less susceptible to corruption, so the public sector often mandates auctions. [2] Over the last twenty years, there has been an upsurge in private sector procurement auctions, including e-sourcing supported by the growth of online auction tools. However, there is a small, but longstanding stream of scholarly work in transaction cost economics (e.g., Goldberg, 1977) highlighting the drawbacks of procurement auctions. The informal argument is that customized product specifications inevitably contain gaps that present themselves during execution, which exposes the buyer and winning bidder to opportunistic bargaining over the initial terms. In other words, the supposed benefits of auctions over negotiations might be dissipated

[2] For instance, the Competition in Contracting Act (CICA) requires full and open competition in government procurements (41 U.S.C. sect. 253a(a) (1) (A) (2000)).

given these incompleteness problems. These arguments notwithstanding, we see large, complex, customized products in technically sophisticated settings such as information technology (IT) being procured increasingly via auctions (e.g., IDC 2013).

Real-world IT procurement auctions differ from the formal auction models in a crucial way: large differences are very commonly observed between the initially agreed-to terms of work and bids versus the final payments. Given the pace of IT advancements, it is not surprising that newer technologies, software tools, and industry standards become available during the execution phase. It is in the interest of the buyer to adapt to these newer, better technologies. While best-efforts and industry-practice clauses allow relatively small adjustments to agreed-upon auction terms, significant changes require new contracts to replace the winning bid. Indeed, in the database of IT procurement transactions (IDC, 2013) that I employ, the original auction contract is replaced with a new contract (with the original winner) over 90% of the time. The dollar value of these modifications range from -10% to +250% of the original bid, and the large majority are revised upward. [3]

Despite the prevalence of such follow-on negotiations with the winner, the formal auction literature has developed without accommodating this real-world aspect (see Bajari et al., 2014, for a notable exception). Industry observers (e.g., Weigand, 1980) have long noted that far-sighted bidders fold in these anticipated revisions to buy into the business; thus, our formal models might grossly under- or over-estimate the efficiency of auctions over negotiations since these episodes are more properly described as *auctions plus follow-on revisions*. In contrast to the formal modeling stream, the transaction cost and incomplete contracting work predicts the inevitability of these revisions following auctions. Williamson's (1976) case analysis of the Oakland cable TV franchise auction illustrates the gaps that inevitably necessitate revisions for complex, customized products. Both the buyer and supplier are implicated here. The bidder may systematically

[3] This phenomenon is not confined to the IT industry. Bajari, Houghton and Tadelis (2014) describe highway construction bids in California, where a large fraction were subsequently revised during execution, although the magnitude of revisions was smaller, presumably on account of the slower pace of technical changes, and the larger fraction of material inputs in construction leading to greater completeness in the specifications.

under-bid in order to buy into the business by exploiting the gaps in specifications. On the other hand, bidders may over-bid to safeguard themselves against opportunistic revisions by the buyer as proposed and shown by Ghosh and John (2005).

I have two goals for my study. First, I seek to build and estimate a more realistic, formal model of a procurement auction with follow-on revisions that informs us about the direction and magnitude of bid skewing. My second goal is to compare the two most common procurement auction bid formats with respect to the skewing effect; viz. lump-sum bids versus unit-price bids. Lump-sum bids require bidders to declare one overall price for the entire project, while unit-price bids require bidders to declare their itemized price per unit of each specified dimension of work such as hours of labor and/or lines of code.

1.0.1 Summary of Findings and Contributions

I specify a rational expectations model of far-sighted bidders in a procurement auction, and derive the optimal bidding solution. I need to estimate this model, particularly the parameter which captures the direction and degree to which a dollar of anticipated revisions are folded into the bid. The extant methodology developed by Bajari et al. (2014) requires that the econometrician observes all the bids across a set of auctions, but this is almost never available in private-sector auctions. I develop significant extensions (parametric and non-parametric) to their approach for a setting where one observes only the winning bid.

My estimates reveal that upward modifications lower bidders' latent costs which lead to more aggressive bids. In order to quantify this downward pressure on bids, I consider the following thought experiment. What if modifications were ruled out by the buyer? This is eminently realistic; indeed, we find public sector buyers are required to forgo follow-on modifications with the winning bidder. Employing my structural estimates to compute this counterfactual scenario, I find that such a commitment would cost the buyer dearly because the winning auction bid increases by 27%. To put this into perspective, the average value of a contract in my sample is worth 135.39 million dollars, which means the modification effect is worth 36.55 million dollars on average.

My second research goal concerns the choice of auction payment formats. IT procurement auctions use two payment forms: a lump-sum payment, or a unit-price payment such as time and materials where bidders specify the price per unit of labor and other metrics such as KLOC (thousands of lines of code). These unit prices are applied to the quantities stipulated in the RFP/RFQ documents to arrive at the total payment. The transaction costs literature (e.g., Goldberg, 1977; Williamson, 1975) asserts that lump-sum payment terms are relatively harder to modify ex post, which generates much of the subsequent contract choice literature in this tradition (e.g., Crocker and Masten, 1991). While some analytical work (e.g., Bajari and Tadelis, 2001) supports this intuition, there is no empirical evidence.

I test this assertion with the following thought experiment. What if a buyer switched from an observed unit-price format to a lump-sum format? Employing my structural estimates to compute this counterfactual scenario, I find that this switch increases the winning bid by 16%, i.e., it makes the procured product costlier. For an average contract in my sample, this result suggests that adopting the unit-price format will lead to a reduction in price of 21.66 million dollars, when compared to an otherwise identical lump-sum format contract. This is, to my knowledge, the first empirical evidence supporting the TCE assertion that lump-sum payment terms are harder to modify, and actually quantifying the magnitude of this difficulty.

Contributions: My work contributes to the practice of procurement. First, negotiations versus auctions is a false dichotomy. Managers contemplating procurement auctions should accept the inevitability of ex post revisions during the execution phase. Indeed, although buyers can commit to a no-modification policy, this is unwise; accommodating modifications is better for buyers as it lowers bids. Furthermore, unit-price auction payment formats are actually superior to lump-sum payment formats in their ability to govern the inevitable ex post modifications, although managerial commentary often suggests that lump-sum bidding is more competitive.

I contribute to the transaction cost literature by demonstrating that procurement auctions for customized, complex projects can accommodate the inevitable revisions without losing the gain from competition in the bidding phase. Buyers who accommodate ex post modifications gain from aggressive buying-in bidding behavior, particularly with bidders who had not been engaged previously. Thus, I am able to explain the widespread use of auctions for procuring complex IT projects.

Finally, I contribute to the methodology on the structural estimation of formal auction models. I develop non-parametric and parametric approaches to estimate bidders' latent costs for auctions with ex post modifications even when we are only able to observe the winners bids.

The rest of this dissertation is organized as follows. Chapter 2 reviews the relevant literature. Chapter 3 summarizes the research context. Chapter 4 introduces the data and discusses the estimation approach. Chapter 5 presents the empirical results from the non-parametric estimation. Chapter 6 presents the parametric estimation and thought experiments. I conclude with suggestions for future research in Chapter 7.

Chapter 2

Literature Review

2.1 Auctions

There is considerable literature in economics on auctions, with a growing emphasis on empiricism (see Paarsch and Hong (2006) for a review). In this chapter, I selectively review the theoretical and empirical auction literature. This dissertation focuses on procurement auctions between firms (empirical contexts and details provided in Chapter 3); therefore, I direct more attention to these matters. I first introduce elementary theory as used in modeling procurement, and then review the principal empirical findings from the literature.

2.1.1 Procurement Auctions

An important aspect of modern economies is large transactions between firms, or between the government and firms,[1] for buying complex goods and services, often tailored specifically for the buyer. Common examples are governments engaging construction firms to construct highways, and corporate firms outsourcing the management of billing, customer service, or information systems to specialist vendors. This practice of having certain job functions done outside a company instead of having an in-house department or employee handle them is also called outsourcing. In practice, these purchases are often conducted through auctions, which are called *Procurement Auctions*. Procurement

[1] As much as 10% of US GDP is estimated to be comprised of government procurement

auctions are also commonplace in the public sector ranging from traditional public works projects like road construction to complex military projects. In fact, governments in many countries mandate or strongly favor auctions for government procurement because auctions are considered to engender competition, lower prices and promote fairness.

Technically, a procurement auction is an auction, where sellers declare their offering price (bids) for their product or service, and the "best" bid defined by the auction rules wins the contest. The details of bid collection and the determination of the winner varies across different auction formats.

There are many different formats of auctions, but four of them are predominant and have been extensively studied by academic scholars: English auctions, First-Price Sealed-Bid auctions (FPSB), Dutch auctions, and Vickrey auctions. These auction formats differ along two principal dimensions: bid collection practices, and winners' payoff (Milgrom and Weber, 1982; Paarsch and Hong, 2006).

(1) English Auctions

In an English auction, the auctioneer begins the bidding at some low price and then bidders will keep raising the price by at least some directed amount until no one else bids a higher price and the auction is closed (auctioneers shout out going once, going twice, sold to). In the bidding process, all the bidders will see the movement of the bidding price, and the bidder with the highest price wins the auction. This oral, ascending-price auction is called an English auction, and it is the most frequently used auction type in practice (Paarsch and Hong, 2006).

In a procurement auction, this English format is as follows: the seller (bidder) who proposes the lowest price wins and receives his submitted price. On-line procurement auctions typically employ some variation of this format (e.g., see Engelbrecht-Wiggans, Haruvy and Katok, 2007).

Milgrom and Weber's (1982) *Clock Model* is the best theoretical summary of this auction format. A clock is set initially at some minimum (reserve) price (zero in the absence of a reserve price). Then the price continuously rises, and the bidders decide whether to continue or to exit. The auction ends when all but one of the bidders drops out. Based on these mechanics, the N potential bidders have ordered valuations:

$$v_{(N:N)} < v_{(N-1:N)} < ... < v_{(2:N)} < v_{(1:N)}$$

where $v_{(i:N)}$ stands for the i^{th} highest valuation among all the bidders. Therefore, the bidder with valuation $v_{(N:N)}$ drops out first, followed by the bidder $v_{(N-1:N)}$. And the bidder with the highest valuation $v_{(1:N)}$ will be the last bidder and also is the winner when the second to last bidder with valuation $v_{(2:N)}$ drops out. For this reason, the price the winner pays will be equal to $v_{(2:N)}$. It is for this reason that English auctions are also referred to as Second-Price auctions. The equilibrium as $b^i = v^i$, i.e., every bidder bids his true valuation. This simple equilibrium is also advantageous for estimation purposes.

Applied to procurement auctions, the Clock Model's setup remains essentially the same. The N potential sellers have ordered *latent costs*:

$$c_{(N:N)} > c_{(N-1:N)} > ... > c_{(2:N)} > c_{(1:N)}$$

where $c_{(i:N)}$ stands for the i^{th} lowest latent cost among all the bidders. Therefore, the bidder with the highest cost $c_{(N:N)}$ drops out first, followed by the bidder $c_{(N-1:N)}$. And the bidder with the lowest latent cost $c_{(1:N)}$ will be the last bidder and is the winner when the second to last bidder with cost $c_{(2:N)}$ drops out. Following the same logic, each bidder's optimal bidding rule is $b^i = c^i$.

(2) First-Price, Sealed-Bid Auctions

In First-Price, Sealed-Bid (FPSB) auctions, the bids are submitted in a sealed envelope which cannot be seen by other bidders. The highest bid wins the auction.

FPSB auctions are the classic form of procurement auctions, and remain the go-to approach, especially in traditional, off-line settings while English auctions are more often seen in on-line procurement auctions because the latter require the actual presence of the bidders, which can be very expensive. However, with on-line technology, the bidders can readily observe each other's bids without being present in the same auction room (Milgrom, 1989).

As discussed in Chapter 3, my dissertation uses the FPSB setup to approximate the procurement auctions in my data. Below, I summarize the basic theoretical framework of these auctions, focusing on risk-neutral bidders and bids based on private information on their latent costs. (See Section 2.2 for Extensions). Assume we have N potential competitive bidders bidding simultaneously for a project, which has value v for the buyer. Bidder i's private type is $c^i (i \in I)$, which is defined as his private cost of the project.

Assumption 2.1: The bidders private types are i.i.d. distributed with F_c as CDF of private type, and f_c as corresponding *pdf*.

Bidder i proposes the bid b^i based on his private cost without observing other bids; the bidding rule is $b^i = \sigma^i(c^i)$, where $\sigma^i(\cdot)$ is the optimal bidding strategy given any private cost of the bidder i (c^i). In the base model, we focus on the symmetric Bayes-Nash equilibrium, so N potential bidders are using a common bidding role $b^i = \sigma(c^i)$ and bid independently.

After collecting bids, the buyer will score bids according to a scoring system s^i, $s^i = s^i(b^i)$. To make the case simple, we assume $s^i = b^i$. Thus, the optimal score is $\min(s^i) = \min(b^i)$. The winning bid, w, is denoted as $w = argmin(i \in I), s^i$. Bidder i's expected revenue from bidding for a project is:

$$\pi^i(b^i, c^i) = [R(b^i) - c^i] * Pr\{b^i < b^j \; for \; all \; j \neq i\} \tag{2.1}$$

where

$$Pr\{b^i < b^j \; for \; all \; j \neq i\} = Pr\{b^i < b^1, b^i < b^2, \ldots, b^i < b^N\} = \prod_{j \neq i}[1 - F_{c^j}(b^i)] \tag{2.2}$$

According to Assumption 2.1,

$$\prod_{j \neq i}[1 - F_{c^j}(b^i)] = [1 - F_c(b^i)]^{N-1} \tag{2.3}$$

Equation (2.1) is a classical First-price Sealed-bid auction result, where

$$R(b^i) = b^i \tag{2.4}$$

By $b^i = \sigma(c^i)$, we have

$$c^i(b^i) = \sigma^{-1}(b^i) \tag{2.5}$$

The optimal bidding strategy for bidder i in a Bayesian Nash Equilibrium is as follows. The *F.O.C.* (w.r.t. b^i) of expected profit equation (2.1) is:

$$\begin{aligned}&[1 - F_c(\sigma^{-1}(b^i))]^{N-1} + \\ &\qquad [b^i - c^i](N-1)[1 - F_c(\sigma^{-1}(b^i))]^{N-2}[-f_c(\sigma^{-1}(b^i))]\frac{\partial(\sigma^{-1}(b^i))}{\partial(b^i)} = 0\end{aligned} \tag{2.6}$$

By Eq(2.5)

$$\frac{\partial(\sigma^{-1}(b^i))}{\partial(b^i)} = \frac{1}{\sigma'(c^i)} \tag{2.7}$$

Substituting Eqation(2.7) into Equation(2.6), I have

$$b^i = c^i + \frac{\sigma'(c^i)[1 - F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))} \tag{2.8}$$

From this result, we can see bids of any bidder i consists of two parts, the private cost of completing the project, and the term $\frac{\sigma'(c^i)[1-F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))}$ which can be interpreted as the competitiveness of the auction.

Proposition 2.1: Given that all bidders' strategic consideration is symmetric, the winner at a First-Price Sealed-Bid procurement auction will be the bidder with the lowest cost $c_{(1:N)}$ (or highest valuation if in an auction $v_{(1:N)}$).

Proposition 2.2: There is no linear correlation between private cost c and bid b, because of the competitiveness term $\frac{\sigma'(c^i)[1-F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))}$. For example, more bidders participating in a procurement auction can drive the equilibrium bids lower (or higher if it is a seller auction).

Proposition 2.2 is a very important characteristic of a FPSB auction. Compared to other formats (e.g. English auctions, where the equilibrium bid reveals the private cost or valuation), this proposition reveals the phenomenon denoted the "winner's curse" which refers to the winner over-paying in some fashion. I discuss more on this issue in Section 2.2.2. To summarize, I use this FPSB procurement auction model and adjust it for my context, as I show in detail later (Chapters 3 and 4).

(3) Dutch auctions

It is believed that a Dutch auction format comes from the flower auctions in Amsterdam in the Netherlands. The price is set initially very high and then allowed to drop continuously by a pre-set clock. Each potential bidder has an electronic device with a button by which he can signal his bid price. When some bidder presses the button, the clock stops, and that bidder wins the auction at the currently listed price. Notice each bidder has to decide when to signal his or her willingness to pay based on his or her private valuation, which is the equivalent decision in First-Price Sealed-Bid auctions. It can be shown that given risk neutral bidders with private valuations, Dutch auctions and First-Price Sealed-Bid auctions are strategically equivalent (Paarsch and Hong, 2006). This result also holds for procurement auctions.

(4) Vickrey Auctions

Vickrey Auctions are named for William Vickrey's contribution. Like the FPSB auction, bidders present their bids in an envelope, but that the winner (highest bidder) only pays for the first losing bid instead of their own bids. Vickrey auctions are most visibly used in U.S. Treasury auctions. However, despite its attractive theoretical properties, Vickery auctions are rarely seen in industrial procurement (e.g., see Rothkopf et al., 1990), so I do not discuss this format further.

2.1.2 Private-, Common- and Affiliated-Values

The information structure across the bidders determines who knows what and when, and how the information influences bidder behaviors and payoffs. One can distinguish three different information structures, each of which are elaborated below.

(1) Private-Values Paradigm

Private-Values Paradigm (PVP, Independent Private-Values Paradigm, (IPVP) in some papers), is defined as N bidders having an independent and identically distributed value of an item (e.g., product in an auction, or project in a procurement auction). The distribution of value can be written as $F_v(v)$.

This is also the most commonly investigated paradigm. In most cases, one also assumes the bidders are symmetric, i.e., they all follow the same distribution of the valuation.

(2) Common-Value Paradigm

Common-Value Paradigm (CVP) is defined as an environment where the value of the item is common knowledge to all bidders. Research under this paradigm include oil-exploration auctions (e.g., Hendricks and Porter, 1988; Hendricks, Porter and Wilson, 1994; Hendricks, Pinkse and Porter, 2003), where the value of a specific oil block is the same for all bidders. Bidding for items with a resale market commonly available to all bidders is also reasonably viewed as CVP. Crucially, in a CVP environment, auctions play no important allocation role, and the only explanation for heterogeneous bids from different bidders in the same auction is individual opinions of the item's true value. Hence, as the number of bidders increases, the winning bid at a FPSB auction under CVP will converge almost surely to the true value (Wilson, 1977). In the Empirical Findings section, I review the issue of ascertaining from data whether the information structure is IPVP or CVP.

(3) Affiliated-Values Paradigm

The Affiliated-Values Paradigm (AVP) lies between the IVP and CVP extremes, and assumes the value of an item in an auction consists of a common value and a private value. Although from a theory point of view this Affiliated-Value Paradigm includes both an IPVP part and an CVP part and hence is richer, the technological disadvantage is also clear: models within this paradigm are often unidentified (Laffont and Vuong, 1996).

(4) Distinction between Private-Values and Common-Value Models

I borrow from Athey and Haile (2007) to summarize the essential theoretical difference between the PVP and CVP paradigms.Assume there are N risk neutral bidders participating an auction, and let N_{-i} denote the set of competitors faced by bidder i. The valuation of bidder $i \in \{1, ..., N\}$ (i.e., utility he would receive from the good by winning the auction) is U_i, and $U = (u_1, u_2, ..., u_N)$. Bidder $i's$ private information consists of a signal x_i. Let $X = (x_1, x_2, ..., x_N)$. This private signal is informative, i.e., the expectation $E[U_i|X_i = x_i, X_{-i} = x{-}i]$ strictly increases in x_i for all realizations x_{-i} of $i's$ opponents' signals. Assume the set of bidders and the joint distribution $F_{X,U}(\cdot;N)$ of bidders' signals and valuations are common knowledge. The private values models and common value models can be distinguished based on the following rules:

Bidders have private values if $E[U_i|X_1 = x_1, ...X_N = x_N] = E[U_i|X_1 = x_1]$ for all $x_1, ...x_N$ and all i. Bidders have common values if $E[U_i|X_1 = x_1, ...X_N = x_N]$ strictly increases in x_j for all i, j, and x_j.

In a common value model, each bidder i would update his beliefs about his valuation U_i if he learned an opponent's signal x_j in addition to his own signal x_i. The most essential difference is that a bidder would like to know his competitor's private information *only* for strategic reasons; by contrast, in a common value model, knowledge of opponents' signals would alter a bidder's expectation of his own valuation.

Foreshadowing my detailed discussion later, in this dissertation, I study IT Procurement as FPSB auctions with PVP for two reasons. First, in my setting, the contractor's private cost is confidential and only observed by himself (bids are sealed in envelopes). Second, these bidders only bid once for each project, and there is no secondary or resale market for projects. Hence, there is no opportunity to "learn" about another firm's private costs, or to update "beliefs" of a bidder's expectation of his valuation or cost within one auction. In this fast-moving industry, the different IT projects are quite distinctive, so learning across auctions about other bidders is also limited.

2.2 Empirical Takeaways

I review the large, and growing empirical literature so as to isolate the gaps which I intend to close with my work. As such, I discuss selected findings organized into the following categories.:

- Independent versus Related Bidders
- Non-cooperative versus Collusive Bidders
- Symmetric versus Asymmetric Bidders
- Risk-Neutral versus Risk-averse Bidders
- Exogenous versus Endogenous Participation
- Static versus Dynamic Auctions
- Complete versus Incompletely Observed Bid Data

2.2.1 Independent versus Related Bidders

Recall that PVP bidders formulate their bids based on their independent, private valuation of the project (or private cost in procurement auctions). However, as we saw , many environments might exhibit some linkages between bidders; i.e., common value and incomplete information at the same time. In many cases, this arises from the fact that the auctioned good is not consumed immediately. As such, bidders may form correlated expectations about the future states of the good. For example, in the oil-exploration case, bidders form their expectations about the value of an oil tract from two sources, a common value which is the same for all the bidders, and private information gleaned by individual bidders from their own research. In other cases, these common values arise from the presence of resale markets for the auctioned good. All the bidders' valuations are endogenously determined and reflect anticipated profit from trading in the resale market, which now implies common knowledge regarding the future value in the resale market, as well as private information.

Can we tell from observational data whether an auction is PVP or CVP? Early attempts (e.g., Paarsch 1991, 1992) use data from timber and tree planting auctions based on the prediction that lower bids with larger numbers of bidders point to CVP environments. However, this is not a dispositive test because as Laffont and Vuong (1996) show, any CVP model is observationally equivalent to some PVP model. Relatedly, Pinkse and Tan (2005) show that reduced-form tests generally cannot distinguish CVP from IPVP models in First-Price auctions, because in equilibrium, strategic behavior can cause bids to increase or decrease in the number of opponents under either paradigm.

Haile, Hong, and Shum (2003) reconsider this problem of detecting CVP by exploiting binding reserve prices and variation in the number of bidders. Their tests were based on the following distinction between a private values auction and a common value auction in terms of each bidder's conditional expectation of the value of winning an auction: in a private values auction the expectations are invariant to the number of opponents each bidder faces, while with common values they are decreasing in the number of opponents. Monte Carlo experiments showed these tests can perform well in samples of moderate sizes. They also applied the test to U.S. forest service timber auctions and consistently failed to find evidence of common values.

A related approach to this problem involves estimating the magnitude of the "winner's curse" which theoretically occurs only in CVP environments. Briefly, the winner's curse describes the winner as over-paying (or under-charging) on account of the need to beat opponents with common values. Haile (2001) proved that when the bidders' valuations are endogenously determined, a resale opportunity can change the equilibrium bidding strategies. Hong and Shum (2002) empirically assessed the winner's curse effect employing a monotone quantile approach which facilitates the estimation of a model incorporating both common and private value components.

Applying this approach to data from New Jersey Transportation Department auctions, they conclude that common values in bidders' costs are evident. Bajari and Hortaçus (2003) examined E-bay auctions for coins to pin down an estimate of the winner's curse. Experimental data have also been brought to bear on this issue. Georganas and Kagel (2011) conducted an experiment involving asymmetric bidders and found that weak bidders bid more with resale, but not as much as the theory predicts. Furthermore, bid distributions for weak and strong types are more similar with resale than without resale.

Despite these empirical findings, it is important to reiterate that data are not sufficient to distinguish PVP from CVP environments. As Pinkse and Tan (2005) show, the underlying mechanisms used to detect and assess the winner's curse, viz. the non-monotonically increasing relationship between the equilibrium bid and the number of bidders, can also occur in an affiliated private-value model where the winner's curse is absent. For my purposes, these findings reinforce the need to justify my PVP choice by appealing to the institutional features of the environment rather than data patterns.

2.2.2 Non-cooperative versus Collusive Bidders

Many of the theoretical analyses emphasize non-cooperative bidders. However, given the profitability and possibility of bid rigging, it is important to incorporate the possibility of collusive behavior into both theoretical and empirical auction models. Unfortunately, detecting collusion is non-trivial and depends highly on specific auction formats. Porter and Zona (1993) developed a rank-based empirical test of bid rigging. Using highway construction contracts from Long Island in the early 1980s, the authors developed evidence of cartelization with a non-structural procedure. Porter and Zona (1999) extended this method to study Ohio school milk markets and detected firm behavior consistent with collusions (viz. complementary bids), and estimated the average collusive effect on market prices as about 6.5%. Baldwin, Marshall and Richard (1997) examined timber auctions in the Forest Service Sales Program, and found bidder collusion can better explain the winning bids across their alternatives. Bajari and Ye (2003) extended the approach to identify and test for bid rigging in highway procurement auctions. They proved that conditional independence and exchangeability are necessary and sufficient conditions for a distribution of bids to be rationalized by competitive bidding, and rejected the hypothesis of collusive behavior in procurement auctions conducted in Upper Midwestern states.

2.2.3 Symmetric versus Asymmetric Bidders

In the base model summarized previously, all the bidders are symmetric actors. However, it is quite straightforward to contend that bidders can differ from each other in many ways. Three types of heterogeneity have been examined. I consider them in turn.

Observed Heterogeneity

When bidder-specific covariates are observable and vary across auctions, the distribution of valuations of the good can be identified by controlling for these observed covariates. This approach to control for heterogeneity has been adopted in many other types of models, including the Roy model of labor supply (Heckman and Honore, 1990) and competing risks models (Heckman and Honore, 1989. See Athey and Haile, 2007 for more details). Bajari et al. (2014) proposed a semi-parametric auction model based on this method. In this dissertation, I develop this method further by adopting the Campo at al. (2003) method for my data as detailed later in the Estimation Section.

Unobserved Heterogeneity

Although the method in the previous section is straightforward, asymmetries between bidders may vary across auctions due to factors that are common knowledge to bidders, but which are unobserved by me. Here, identifying the distribution of valuation of bidders can be very challenging and highly dependent on the data. Only recently has this problem been addressed (and only partially). For example, Li and Zhang (2009) developed a semi-parametric model in a First-Price auction and estimated the marginal distribution of valuations using a Bayesian method after assuming a functional form for the unobserved heterogeneity.

Asymmetric Preferences

Aside from controlling for heterogeneity as summarized above, another way to understand the asymmetric bidders is by assuming asymmetric distributions of valuations. Assuming that entrant and incumbent in an auction follow different bidding rules, De Silva, Dunne, and Kosmopoulou (2003) show that entrants bid more aggressively and win auctions with significantly lower bids than do incumbents in road construction projects. This method is especially useful in evaluating government policies favoring certain bidders. Using California data from road construction auctions, where small firms receive a 5% bid preference in auctions for projects using only state funds, but no preferential treatment on projects using federal aid, Marion (2007) showed that procurement costs are higher overall with these preferences. Larger firms lower their bids while smaller firms increase bids. Based on these results, they attribute the higher procurement costs to reduced participation by lower-cost large firms. Flamboard and Perrigne (2006) also examined snow removal procurement auctions with asymmetric types of bidders, and found very similar results.

2.2.4 Risk-Neutral versus Risk-Averse Bidders

Most empirical studies on auctions assume risk neutrality of bidders. Risk neutrality is a natural assumption in settings with traded, profit maximizing firms. However, risk aversion can become an issue when auctions involve high value goods, especially when policy questions like optimal reserve price is the focus of study. For ascending auctions, risk aversion has no effect on equilibrium bidding with private values, which suggests that distinguishing risk aversion and hence identifying bidders' preferences are impossible. For First-Price auctions, since bidding less aggressively leads to a lower likelihood of winning the auction but higher profit conditional on winning, a more risk averse bidder will be less willing to favor this result than a less risk averse bidder. Hence, in principle, risk aversion can be identified but requires observation of all choices because bidding involves a gamble in this case. Since variations in bidders' valuations are private information and cannot be observed by econometricians, preferences and the distribution of valuations have to be identified separately relying on some type of observable exogenous variations (Athey and Haile, 2007). For example, Bajari and Hortaçsu (2005) relied on exogenous variations in the number of bidders for identification as it changes the equilibrium probability that each given bid wins and the choices (lotteries) available to bidders.

2.2.5 Exogenous versus Endogenous Participation

In the base model, there is no distinction between potential bidders and actual bidders, and any proposed bid is valid because there is no binding reserve price. In practice, participation in an auction is an endogenous decision of the bidder because of the following reasons:

- Binding reserve prices
- Costly information acquisition and entry
- Bidders' uncertainty about the auction

Bajari and Hortaçus (2003) examined a Second-Price Sealed-Bid auction with endogenous entry to quantify the winner's curse and entry cost. In more recent work, Li and Zhang (2009) modeled both endogenous entry decisions and bidding strategies at the same time in a First-Price Sealed-Bid auction, and quantified and compared entry and competition effects in Texas transportation auctions.

2.2.6 Static versus Dynamic Auctions

Until very recently, almost all structural empirical auction models have considered static models. Under this assumption, individual auctions are treated as independent games. However, this assumption might not hold if there is a link between auctions. This can result from learning-by-doing (in either the cost or valuation of a project), capacity constraints or some other cause. There are two ways in which dynamics have been incorporated into auctions:

- Bidders' valuation distribution in different auctions changes across time as a function of auction outcomes, which is observable by all bidders.
- Bidders' behavior in one auction affects opponents' beliefs about his valuation distribution in future auctions, changing the equilibrium of the auction game in each period.

The first type represents learning-by-doing. If a bidder wins an auction today, he might have stochastically lower costs (higher valuations) in the future, or by participating in an auction, the bidders reveal their types in an incomplete information game. Capacity constraints in procurement auctions also fall into this category. Both cases can occur together in practice. By winning one auction, the bidder actually foregoes the opportunity to participate in other auctions in the near future, but lowers the cost of another auction in the far future.

There are very few empirical papers with dynamics in the structural model, with all of them considering dynamics of the first type listed above. Jofre-Bonet and Pesendorfer (2003) investigated sequential auctions for highway construction and found that firms with higher capacity constraints face higher latent costs. In Bajari and Hortaçus (2003), dynamics is considered in another way, viz. the format of endogenous entry decisions. Zeithammer (2006) explicitly considered dynamics in a very different variable, viz. the waiting times between auctions. Given forward-looking bidding behavior, waiting time until the next auction of the same type increases bids, the same type offered in the next five auctions decreases bids, and the impact of another offering in the new future decreases with the number of intervening auctions.

2.2.7 Complete versus Incomplete Observed Bid Data

Almost all the existing empirical auction work has exploited the assumed observability of all bids from each auction. However, it is quite common that the losing bids are not observed by the analyst, and sometimes not even by opponents. One typical example is the Dutch auctions. Here, bidding ends as soon as the winner makes his bid, and hence only the winning bid is observable. Another example is procurement auctions, where the losing bids are actually observed only in very rare cases. Many procurement projects are awarded through First-Price Sealed-Bid auctions; the bids are private information to bidders and only the winning bid is published. According to Brendstrup and Paarsch (2003), one approach is to treat a First-Price Sealed-Bid auction as equivalent to a Dutch auction. Although the two auctions follow rather different rules, they are strategically equivalent assuming the same information is observable prior to bidding.

In this dissertation, I consider my data to be generated by a First-Price Sealed-Bid procurement auction with only winning bids observable. I am obliged to develop the extant methodology further to accommodate the observability of winning bids only. I do so both parametrically and non-parametrically, and discuss the need to do so later in the dissertation.

2.3 Auctions as Incomplete Contracts

Although the winner of an auction executes work under a contract, the consequences of costly, incomplete contracting are largely overlooked in the auction literature. Here, I briefly survey the ramifications of incompleteness in contracts per se, and then recap the single study on auctions that considers ex post revisions.

2.3.1 Contract Incompleteness

Although it is well accepted that real-world contracts are incomplete to some significant degree, researchers have formed no consistent conclusions on the economic effects of contractual incompleteness. There are two main streams of thought.

The first approach is Tirole (1986) and Hart and Moore (1988), who view contractual incompleteness as the inability to commit to a division of the contractual surplus before making their non-contractible investment decisions. In this property rights stream, theory emphasizes residual control rights over assets, which determines the bargaining power in the ex post determination of the surplus. In the modeling, the set of feasible outcomes is restricted through the imposition of limitations on the set of allowable contracts (Tirole 1999). However, renegotiation of these incomplete contracts proceeds costlessly, so the economic consequence is the distortion in ex ante investments.

The contrasting approach is Williamson's (1985) verbally reasoned model, which emphasizes the role of ex post opportunism and costly bargaining. Contracts set in uncertain or complex environments are necessarily incomplete, thereby permitting parties to engage in *economically costly efforts* to redistribute the surplus as uncovered contingencies arise. Thus, in this latter approach, contracts are viewed as both costly to write initially, as well as to revise subsequently.

Contract Forms and Ex Post Revisions

In the Williamsonian approach, different contract forms are presumed to have different levels of revision costs; e.g., lump-sum contracts are harder to revise than are contracts that specify mainly time and materials. The comparative analysis of alternative contract forms in the transaction cost economics tradition relies crucially on the magnitude of these revision costs. Based on observations that the procurement problem is primarily one of ex post adaptations rather than ex ante screening, Bajari and Tadelis (2001) developed a model where renegotiation costs affect the choice of initial contract forms, viz. more complex products have a less complete design and are more likely to be procured under cost plus contracts. As friction increases, the loss from inefficient renegotiation of a fixed-price contract increases, making it less desirable.

Empirical work links several factors to contract choices including uncertainty (Crocker and Masten 1991; Crocker and Reynolds, 1993), contract duration (Crocker and Reynolds 1993), contractors' dispute history (Crocker and Reynolds 1993), and contractors' reputation (Banerjee and Duflo, 2000). However, the literature lacks any estimates of the comparative size of these revision costs across fixed and flexible price formats.

2.3.2 Ex Post Issues in Auctions

Put simply, auctions are contracts, so they must face the same incompleteness issues reviewed above, but there is very limited literature on these issues. A few papers in marketing and operations have examined on-line auctions following their popularity, coincidently with the Internet boom at the turn of the century (see Jap, 2002; Haruvy and Jap, 2012, for reviews) with companies like Freemarkets.com (later sold to Ariba) promoting their use. These papers conclude that on-line procurement auctions met with much less success than originally expected (e.g., see Engelbrech-Wiggans and Katok, 2006; Engelbrecht-Wiggans, Haruvy and Katok, 2007). Customized products are virtually impossible to specify in sufficient detail ex ante; hence, the rigidity of auction rules pose ex post adaptation problems.They suggest a hybrid form might do better by combining an auction with a non-competitive award at the auction-determined price. Similarly, auctions where the buyer retains the discretion to award the project to any of the bidders might do better. Evidence from laboratory data and analytical models are marshaled to support these hybrid mechanisms. From my perspective, this stream of work supports my contention that ex post modifications need to be folded into the analysis of procurement auctions. However, there is no work on estimating the underlying parameters of these non-traditional auctions, so my challenge is to develop an appropriate methodology.

To my knowledge, there is a single study in the literature that develops and estimates a formal auction model to accommodate ex post modifications. Bajari, Houghton and Tadelis (2014) show that bidders incorporate rationally expected revisions into their original bids. These authors study highway paving unit-price auctions that were invariably renegotiated ex post with the winning contractor in the execution period. Using unusually detailed data, including all the bids on each auction, as well as engineering estimates of the scope of work, they developed an econometric methodology to show that up to 15% of the winning bid price arises from the strategic response of bidders to ex post modifications. The paper leaves us with two gaps:

- How do ex post revision costs differ across formats? Their methodology applies only to unit-price auctions, so comparisons between lump-sum and unit-price auctions remain unresolved.

- Do ex post revisions skew bids (up or down)? Their methodology does not permit one to ascertain the impact of the ex post revisions on the bids themselves; i.e., are the bids skewed upwards or downwards?

Below, I look at the broader literature on these two unresolved two issues: a) the magnitude of comparative revision costs, and b) the impact of revisions on bids for likely clues to their effects.

2.3.3 Payment Format and Comparative Revision Costs

The transactions cost literature (sometimes labeled the Coase-Williamson paradigm) is related to this issue of comparative revision costs. Here, contracts are a means of establishing procedures for adapting exchange and resolving disputes rather than acting only as incentive mechanisms (e.g., Crocker and Masten, 1991). Given the real resources lost in maladaptation, the comparative contractual costs of adaptation are a central concern in this literature. However, since these costs are unobserved, the empirical work focuses on the observed consequences of choosing one type of agreement, e.g., a lump-sum, or fixed price versus another type, e.g., a cost-plus arrangement.

As noted above, exogenous shocks (Crocker and Masten, 1991), contract duration (Crocker and Reynolds, 1993), contractor quarrelsomeness (Crocker and Reynolds, 1993), and a buyer's reputation for good-faith dealing (Banerjee and Duflo, 2000) have all been shown to correlate with the use of more flexible payment formats (including cost-plus), and move away from fixed, lump-sum arrangements.

The underlying argument is that lump-sums are harder (costlier) to adjust ex post so they are less useful in settings where adaptation to changing circumstances is more valuable. However, as noted above, the sole paper that structurally estimates a procurement auction with ex post modification (Bajari et al. 2014) only employs data from highway construction auctions that all employ an identical payment format (viz., a unit-price format specifying the price per unit of asphalt, labor, etc.), so the relative merits of lump-sum versus other payment formats remain unresolved.

From my perspective, an empirical setting with multiple payment formats is necessary to address this gap. In fact, the IT procurement auctions in this study feature both lump-sum and other types of payments, so this is an advantage. I turn to this institutional setting in Section 3.

2.3.4 Revision Effects on Initial Bids

Do rationally expected ex post revisions invite initial bids that are skewed upwards or downwards? Both possibilities are considered in some prior work.

"Supplier Buying-In" Lowers Bids

Observers of industry practice have described suppliers of customized goods and services who purposefully lower their bids to "buy-in" into future non-bid business. Once the winner becomes the incumbent, she is in a better position to manage ex post modifications to her own advantage. In the public policy arena, this fragility of auctions to ex post changes is the central theme of Williamson's (1976) criticism of the Posner-Demsetz suggestion of using franchise bidding (procurement auctions) to solve natural monopoly problems in water, gas, electricity, and cable TV markets. Notice that while the original bids are posited to be skewed downwards, these gains to the buyer are critical because of the losses from the revisions.

Buyer Opportunism Increases Bids

Based on the same transaction cost logic, the opposite argument is made in Ghosh and John's (2005) work on component procurement practices by original equipment manufacturers (OEMs). Realizing that their OEM-specific investments required to produce customized components will leave them vulnerable to opportunistic OEMs during the inevitable ex post revisions, suppliers protect themselves by initially negotiating more favorable terms. Of course, these arguments do not necessarily extend to auctions with competition between suppliers, but the broad implication is that bids are skewed upwards.

Unfortunately, these opposing effects are not distinguished in the extant literature. While the Bajari et al. (2014) paper does offer an estimate of the magnitude of the impact of ex post revisions on bids, the estimation methodology does not allow us to distinguish the direction of the effect. These unresolved issues call for building a formal model and estimation methodology that is flexible enough to accommodate either possibility (upward or downward pressure on bids), so that my estimates will allow me to speak to the the direction and magnitude of the skew.

Chapter 3

Empirical Context

3.1 IT Procurement Market

I study procurement auctions in the Information Technology (IT) industry. The largest data vendor in tis industry, IDC, collects detailed information on this industry, I have access to 8,065 private sector IT procurement contracts signed between 1989 and 2013. This is a very large, global industry with expenditures expected to reach $1,000 billion in 2014, so this is a particularly appropriate industry to study procurement. Some of the salient features of this industry are reported below.

High growth rates Over the last two decades, this industry has grown about 10% annually (Caldwell and McGee 1997). Meta Group estimated in 2003 that 70 percent of companies outsource and all companies would embrace the model by 2006 (Computing, 2003). Today, virtually every Fortune 500 company in the US and an increasing number of companies throughout the world outsource some significant portion of their IT services. Figure 3.1 shows the number of contracts signed worldwide every 5 years, starting from 1989.

Global Reach My data records the regions and countries where the work is delivered. For convenience, I recognize four macro markets or regions; Asia-Pacific, Americas, Europe-MiddleEast-Africe (EMEA), and projects delivered globally. See Figure A.3 for market share of projects from different macro markets. The growth patterns also show some global variation. In the most mature market, North America, as buyers continue to fuel growth, they seek to transition more IT work to annuity-managed service relationships for more predictability in IT costs. In newer regions like Asia-Pacific, Latin America and Greater China, the growth rates are expected to outstrip the North American market.

Diverse Clients In my data, I observe 22,506 clients from 17 sectors[1] engaged in IT procurement: Government, Retail Trade, Communication & Media, Banking, Professional Services, Securities and Investment Services, Transportation, Process Manufacturing, Discrete Manufacturing, Consumer & Recreational Services, Wholesale, Utilities, Resources Industries, Insurance, Construction, Healthcare Services, and Education. Table A.1 summaries the distribution of the clients' industries. As can be seen in the table, the US Department of Homeland Security (DHS), as the biggest buyer in this market, has signed 309 agreements, followed by the US Army (288 agreements), US Space and Naval Warfare Systems Center Atlantic (SCC Atlantic, 287 agreements), US General Services Administration (GSA, 270 agreements), and US Air Force (USAF, 245 agreements). The ten largest buyers in this market are all government institutions.

I restrict my analyses to private sector clients because of various constraints imposed on public sector clients. The largest private sector client is Chunghwa Telecom Co. Ltd. (CHT), a Taiwan-based company providing local and long distance phone services, which has signed 85 agreements. However, most clients signed fewer than 5 projects (92.49%), as shown in Table A.1.

On average, the clients have 13,583 employees, and $7.92 billion dollars annual revenue, with wide variation in both headcounts and revenues. See Table A.2 and Table

[1] These IDC-classified sectors do not correspond to Census definitions

A.3 for detailed information.

3.2 Characteristics of IT Procurement Projects

Scale and Scope IT procurement projects are multi-year work assignments. Among all 49,072 projects in my data, an average transaction lasts for 39 months, with 32% exceeding 5 years. The average contract is worth \$65 million, with 5,775 contracts (12%) exceeding \$100 million. The projects also have increased significantly in their scale of work. In 2001, the largest outsourcing contract was valued at less than \$100 million; in 2003, almost half were between \$100 and \$249 million (IDC, 2004; Halvey and Melby, 2005).

IDC categorizes the work content of these projects into 11 major types based on four factors: duration, goals, deliverables, and activities. Table A.4 summarizes the number of projects by engagement type, while Table A.5 summarizes the main differences between the various engagement types. In the recent past, trends such as business process outsourcing, offshoring, internet-enabled outsourcing, and most of all the need for globalization, have added new categories of engagement like Consulting, Education and Training to the traditional categories like IT Outsourcing, Business Outsourcing and System Integration. Many projects include work spread over multiple segments. For example, a Business Process Outsourcing (BPO) project normally includes work in HR and Finance & Accounting. My data vary considerably in the number of segments reported (1 to 27 sub-segments). Among the 49,072 contracts in the sample, 8,622 of them have more than 2 segments.

There are some tradeoffs between multiple segments and signing multiple contracts. If there are too many segments, a single transaction becomes too complex so clients will sign multiple transactions instead. Therefore, although it is common that a contract has multiple segments, 99% of projects have 5 or fewer segments (8, 410 contracts, (17%) have between 2 to 5 segments).

Negotiations vs. Auctions A contractor is chosen in two distinct ways: negotiations and auctions (competitive bidding). Among my observed contracts in force as of 2013, IDC recorded 30,590 (62.34%) as competitive bids, and 18,482 contracts (37.66%) as awarded in a non-competitive fashion, i.e., through negotiations.

For contracts in force prior to the mid-2000s, negotiations and auctions were used evenly. For contracts in force prior to 2006, more competitive bidding were used. In the period up to 2013, around 70% of the new signed contracts each year were awarded through competitive bidding. In what follows I denote an auction-based award of an IT outsourcing contract as a "procurement auction." In my analyses, I focus solely on these auctions.

Conctractual incompleteness. To paraphrase Tirole (1999), incompleteness of contracts arise from one or more of the following three ingredients: unforeseen contingencies (parties cannot define ex ante all contingencies that may occur), costs of writing contracts (even if one could foresee all contingencies, they might be so numerous that it could be too costly to describe them in a contract), and costs of enforcing contracts (courts must understand the terms of the contract and verify the contracted upon contingencies and actions in order to enforce the contract). Snir and Hitt (2000) apply similar criteria to conclude that outsourcing contracts are significantly incomplete. My conclusion is similar.

Regardless of whether the project is awarded via an auction or negotiations, my IT outsourcing contracts are likely to be highly incomplete in many respects on account of the the technical and business complexities of the work, and the multi-year time horizons documented above, which make it virtually impossible to foresee all contingencies. Additionally, the customized nature of each project makes it very difficult, if not impossible for third parties to verify performance.

Some sense of the pervasive incompleteness of these IT contracts is seen in one surprising feature of these contracts. They almost never contain clauses specifying state-contingent incentive schemes. Instead, contracts contain the structure and guidelines for future adjustments. It is commonly believed that performance incentive clauses are not enforceable. In my data, considering the 49,072 projects since 1989, only 160 projects included performance incentive clauses (i.e., 0.04% of fixed-price contracts and 1% of the remainder include incentive clauses). This is in stark contrast to many other industries where savings-sharing, or performance bonuses, as well as other contingent rewards are often included.

3.3 Stages of a Procurement Auction

Figure A.4 summarizes the timelines and major milestones of a large outsourced IT project. The following points are worthy of emphasis. Procurement auctions do not occur immediately after clients make the internal decision to proceed with a project. There is a serious vendor pre-screening and qualification process. It takes about 12-18 months from initiation to signing for the typical contract in my data.

3.3.1 Request for Information

The first observable step consists of clients sending out a Request For Information (RFI) to potential vendors to obtain information about their capabilities, finances, technology resources, experience with the relevant technology, industry experience, their employees, recent rollouts, their customer base and references. Such a pre-screening process accomplishes two things: it screens out the vendors who do not meet requirements, and also shrinks the number of potential vendors to be examined even more intensively in the next stage.

If the client elects to employ a competitive bidding process, it develops a Request for Proposal (RFP) document which is described in Section 3.3.2. Competitive bidding is the most preferred approach these days. (In my dataset, competitive bidding accounts for more than 60% of all the projects from 1989 to 2013.) Competitive bidding is preferred because it adds to project legitimacy, demonstrates high due diligence was performed, leads to lower competitive pricing and service levels, enables the customer to use the possibility of other interested vendors as a negotiating tool, and provides access to alternative solutions and technologies (Halvey and Melby 2005).

It should be noted that negotiations and auctions proceed quite differently following the RFI. With negotiated deals, the client will first open negotiations with the most attractive vendor, and proceed to the next one only if the parties cannot reach an agreement. In the negotiations case, a formal RFP is not necessary.

3.3.2 RFP Process and Content

Scope of work. This is a technical description of the task and expected outcomes (IDC Taxonomy, 2013). This is a costly and time-consuming process (which can usually take several months), and clients often hire a third-party consulting firm to assist with the creation of the RFP. Starting in the late 2000s, clients increasingly began to build their own teams to design the scope of work due to cost considerations.

RFP Recipients. The RFP is sent to a very small sub-set of the original RFI contact list. Inclusion in an RFP list is generally acknowledged by potential vendors as the most important milestone. More than 6 vendors are almost never selected to receive an RFP, with the vast majority of clients engaging between 2 and 5 potential vendors. Both the client and potential vendors actively engage with each other at this phase. Even when a vendor has an existing tie to a client, and client has been satisfied with past work, the client will still include multiple vendors on their RFP list. Other than previous projects with the clients, the size and reputation of both the clients and vendors also matters at this stage. Plainly, with larger, high visibility clients, it is harder for a vendor to break into the short list of firms that can receive an RFP; for larger vendors with good reputations, it is relatively easier to be invited to bid through RFPs. Not surprisingly, this process is highly expensive and time-consuming. Clients have to assemble primary and secondary data on potential vendors, sometimes even refer information from prior vendors, visit the vendors' websites, and gather annual reports and industry surveys to form the short list receving RFPs. In my analysis, I also consider relevant information of both the clients and vendors.

Completing the RFP. In the RFP, the client provides the background information, services to be provided (a crucial step to writing the final Service Level Agreements, SLA), how the performance will be evaluated, management procedures, change order procedures, pricing structure, and termination conditions. Vendors are required to complete the the RFPs to describe their proposed solution (technology, configuration, committed resources, risks, etc.), their ability to deliver services (experience, skill levels of staff, proposed schedules, physical and data security, compliance, disaster recovery/business continuation, etc.), ability to implement new systems (technical resources/ability, access to new technologies, flexibility, open system versus proprietary systems, implementation schedules, remedies for failing to meet schedules, etc.), ability to meet performance standards (methodology, proposed service levels, etc.), value-added services (profit sharing, incentive mechanisms, cross-marketing, etc.), financial proposal (pricing, cost savings, IT budget comparison, ability to increase or decrease services, cost-of-living adjustments, taxes, payment schedule, etc.), human resources (number of employees to be transitioned, salary, health benefits, bonuses, etc.).

Scoring the bid. The vendor will pay close attention to the scoring system described in the RFP, particularly the distinction between "considered" issues and "for the record" issues. The score is calculated based on the "considered" issues only.

To illustrate, consider an RFP to be used in an auction with a lump-sum (fixed-price) bid. In such an RFP, bidders know that the total fee they propose in the bid will be entered by the client into the auction; however, the number of people to be deployed, and the hourly cost of each person is only included "for the record."

On the other hand, consider a time-and-materials (flexible) RFP. With such an RFP, vendors know that the number of people they propose to deploy and the quantity of materials they propose are important, but also that their price for each person and for each unit of materials will be directly counted in the final bid score. On each scoring element, each vendor is assigned a score. Thus, each vendor gets a final score weighted by the factors begin being considered. The client discloses these weights in the RFP.

These weights and factors differ across the different projects in my data, but as I discuss later in detail, the short listing process reduces the non-price differences between the final few bidders. Figure A.5 summarizes the distribution of the number of bidders for each project.

RFP recipients have to submit their completed RFPs by the denoted submission date. The buyer will examine each completed bid package, score them, and announce the winner. On occasion, there may be some revisions allowed to a completed bid, but generally, the completed RFP is considered a final bid.

Ex-post Modifications. A striking feature of my contract data is the almost-universal occurrence of ex post revisions negotiated with the contractor during execution. Of the contracts in force as of December 2013, most are ongoing (and thus right-censored), but I observed 1,717 contracts that had either been completed, or has been revised and work was proceeding under the revised contract. Of these contracts, only 7.4% (129) contracts were completed under the original, signed agreement without changes. In another words, as far as I can see from contracts of which outcomes had been revealed, the vast majority of them were modified.

In some respects, the modifications are not surprising. Earlier, I remarked that these IT contracts were seriously incomplete, and the lack of incentive clauses hinted at the pervasiveness of renegotiation.

The institutional setting lends weight to these issues. IT is a very dynamic industry with ongoing changes in software and hardware. Technology and methodologies incorporated into the solution are often out of date before the completion of the project.

For example, the recent rise of the mobile Web has forced the re-engineering of many platforms and solutions mid-stream. Similar pressures come from the move to "cloud-based" solutions. As one long-term industry observer at a consulting firm puts it "...IT *outsourcing contracts are simply a projection of future requirements, and renegotiations are now seen as a normal adjustment to changing business conditions ...*" (Steve Tuppen, Director, ISG).

The pervasiveness of modifications can be seen in the institutionalized responses. Industry standard terms have been developed to describe and categorize modifications. For example, the US Federal Acquisition Regulations (FAR) recognize seven categories of modifications. In my contracts, the most common types of modifications involved a) new work added to the scope of the original contract, and b) revisions to the delivery terms.

These revisions involved costly efforts by both parties, with involvement from various departments (e.g., finance, accounting, legal, business, IT, HR, PR, marketing) Vendors have to summarize all the tasks completed, calculate all the costs to date, and propose specific revisions. Clients have to evaluate the contractor's performance to date, and assess the net benefits to the proposed changes.

Once the engineering details have been agreed to, new financial terms have to be worked out. Quite commonly, both parties will engage third parties to assist with this process. In sum, it is a far cry form the costless bargaining envisioned in the property rights tradition.

It is useful to recognize the costs of complete breakdowns. A notorious example is the dispute between British Sky Broadcasting (BSkyB) and its IT supplier, Electronic Data Systems (EDS). In 2000, BSkyB hired EDS to build a £48 million customer relationship management system (CRM). In 2002, BSkyB claimed EDS allegedly acted "dishonestly" and misrepresented its capabilities, and claimed damages of £709 million. While BSkyB claimed EDS failed to complete the task, EDS claimed that BSkyB did not have a clear idea of what it wanted from the system and that the constantly changing requirements of the customer were the cause of the delayed roll-out.

Following a breakdown in negotiations, BSkyB took the case to court in 2002. Eighteen months later, the verdict was that EDS "failed to exercise reasonable skill and care or conform to good industry practice," and awarded BSkyB £318 million. BSkyB ended up building the system itself at a cost of £265 million.

Breakdowns and legal actions may be rare, but "tough renegotiations and restructurings will be a key future characteristic of outsourcing relationships" and renegotiation and delivering more for less is the norm (Steve Ranger, 2013).

Chapter 4

Estimation Strategy

4.1 Model Setup

In this section, I describe a structural model capturing the contractors' bidding behavior of anticipating future receipts from contract modifications. There is some redundancy with my earltier descriptions of the model setup in this chapter.

I follow the Bajari et al. (2014) setup with appropriate modifications as needed to accommodate my observational structure. I approximate the procurement auctions in my data as a First-Price Sealed-Bid auction. Assume we have N potential competitive bidders bidding simultaneously for a project, which has value v for the buyer. Bidder $i's$ private type is $c^i (i \in I)$, which is defined as his private cost of the project.

Assumption 4.1: The bidders' private types are $i.i.d.$ distributed with F_c as CDF of private type, and f_c as corresponding pdf.

Bidder i enters a bid b^i through the RFP based on his private cost without observing other bidders' bids; the bidding rule is $b^i = \sigma^i(c^i)$. I rely on the symmetric Bayes-Nash equilibrium, so all N bidders use a common bidding role $b^i = \hat{\sigma}^i(c^i)$ and bid independently.

I model the buyer scoring the bids according to a scoring system s^i, $s^i = s^i(b^i)$. To keep the case simple, I assume $s^i = b^i$, and the optimal score is $min(s^i) = min(b^i)$. So the winner's bid w for the project is defined as $w = min_{i \in I} s^i$. Bidder i's expected revenue is:

$$\pi^i(b^i, c^i) = [R(b^i) - c^i] * Pr\{b^i < b^j \ for \ all \ j \neq i\} \tag{4.1}$$

where

$$Pr\{b^i < b^j \ for \ all \ j \neq i\} = Pr\{b^i < b^1, b^i < b^2, \ldots, b^i < b^N\} = \prod_{j \neq i}[1 - F_{c^j}(b^i)] \tag{4.2}$$

According to Assumption 4.1,

$$\prod_{j \neq i}[1 - F_{c^j}(b^i)] = [1 - F_c(b^i)]^{N-1} \tag{4.3}$$

Equation (4.1) is a classic First-Price Sealed-Bid auction result. Now I incorporate ex post modifications as follows:

$$R(b^i) = b^i + \tau E^i(A^i) \tag{4.4}$$

A bidder's total receipts from winning the contract consists of two parts, payment under the original contract, i.e., the bid, b^i, and some additional receipts from future modifications $E^i(A^i)$. A^i is an *i.i.d.* modification value of the current contracts awarded to the incumbent contractor.

Assumption 4.2: The bidders are symmetric and rational in their expectation about ex post revision and revision costs, i.e., $E^i(A^i) = E(A) = A \in [-b^i, +\infty]$.

where τ describes how much of the modification amount, A, is folded into the bid, i.e., a discount factor.

I do not constrain either the sign or magnitude of τ. Indeed, there are important differences for various regions of this parameter. Assuming positive gross receipts from modifications, the range $(0 < \tau < 1)$ indicates that these gross receipts are discounted to reflect both production costs of the revised work, and adjustment/negotiation costs incurred by the bidder. In contrast, the range $(\tau > 1)$ is an implausible region. Finally, $(\tau < 0)$ suggests that gross positive receipts from modifications yield a net reduction to the bidder, presumably on account of very large production and adjustment costs exceeding the modification receipts. A parallel set of implications can be drawn for negative modification values.

By $b^i = \sigma(c^i)$, I have:

$$c^i(b^i) = \sigma^{-1}(b^i) \tag{4.5}$$

I solve for the optimal bidding strategy for bidder i in a Bayesian Nash Equilibrium as follows. The *F.O.C.* (w.r.t. b^i) of the expected profit equation (4.1) is:

$$\begin{aligned}[1 - F_c(\sigma^{-1}(b^i))]^{N-1} + [b^i + \tau E(A) - c^i]\times \\ (N-1)[1 - F_c(\sigma^{-1}(b^i))]^{N-2}[-f_c(\sigma^{-1}(b^i))]\frac{\partial(\sigma^{-1}(b^i))}{\partial(b^i)} = 0\end{aligned} \tag{4.6}$$

By Eq(4.5)

$$\frac{\partial(\sigma^{-1}(b^i))}{\partial(b^i)} = \frac{1}{\sigma^{'}(c^i)} \tag{4.7}$$

Substituting Eq(4.7) into Eq(4.6), I have

$$b^i = c^i - \tau E(A) + \frac{\sigma^{'}(c^i)[1 - F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))} \tag{4.8}$$

$$b^i - c^i = -\tau E(A) + \frac{\sigma^{'}(c^i)[1 - F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))} \tag{4.9}$$

The model yields two results that are quite subtle. Consider them in turn.

Modification Effect. As can be seen from Equation (8), the expected receipts from modification contracts will affect the bidding price if $\tau * E(A) \neq 0$. Thus, for the contracts where no new, revised contract is signed (29 contracts in my dataset, see details in section 4.2), the bid is identical to a contract with no ext post revisions. For the remaining contracts, the direction of impact on bids depends on the sign of gross receipts (A) and the size of the discount factor (τ). Since the vast majority of our data exhibit positive A, I discuss this setting in more detail.

Recall the latent cost, $c^i - \tau E(A)$, which I define as bidder $i's$ valuation of the project. Equation (4.8) describes the bidder's optimal strategy: bid one's latent cost $c^i - \tau E(A)$ with a mark up of $\frac{\sigma'(c^i)[1-F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))}$. From Eq(4.8), if $\tau > 0$, modifications will lower the latent cost, and the bidders' optimal strategy is to lower their bids; if $\tau < 0$, modifications will increase the latent cost, and the bidders' optimal strategy is to increase their bids.

The former result is congruent with an industry practice of suppliers labeled "buying-in" behavior where they lower their bids knowing that changes will bring them more money later. In our model, we see that bidders who expect net positive receipts from positive modification receipts (net of additional production and adjustment costs), anticipate that some of these future receipts are passed on to the buyer in the form of a lower bid.

In contrast, the latter result reflects a situation where the net receipts from gross, positive receipts (net of additional production and adjustment costs) are actually negative. Why? First, it is unlikely that pure adjustment costs are high enough to turn gross positive receipts into net negative receipts. It is more likely that this reflects an opportunistic buyer who presses for a lot of additional follow-on work at a very low margin (perhaps at cost). Anticipating this, the bidder safeguards himself against such buyers by increasing his bid.

Payment Format Effect. If τ is larger (smaller) for lump-sum auctions versus per-unit price auctions, bidders will decrease (increase) their bids for that auction type versus the other type, all else being equal. Recall the core assumption from the original transaction cost literature (e.g., Williamson, 1976) that lump-sum payments are harder to modify than more flexible payment schemes such as time and materials, or cost-plus. My estimation allows me to test this assumption empirically because the contract type is linked to the bids through the discount factor.

4.2 Data and Variables

I have access to 8,065 private sector IT procurement contract auctions signed between 1989-2013. Each of these contracts was a new contract as distinguished from a modification of an existing contract. I tracked each of these contracts from the time it was signed until Dec. 31, 2013, which was the cut-off date for my observational period. As of this cut-off date, I observed outcomes for 360 of these contracts - the remainder were right-censored. Below, I describe the available data about four aspects: i) the project, ii) the client, iii) the vendor, and iv) the modifications, which are a crucial part of my research question. Table A.6 summarizes sample statistics. Note that while some of these characteristics are in the nature of raw data, some others are constructed measures. I point out how the measure was constructed if that is the case.

Project Characteristics

Size. As shown in Table A.6, the average contract was $135 million in value and lasted 69 months. Presumably, such large projects are important to buyers and contractors, so we would expect extensive pre-screening. They are also quite complex, as evidenced by their average length, and the large number of distinct business/technology segments. I use $\ln(size)$ to control for the skewed distribution of this variable.

Complexity. I developed two measures of complexity from the data. First, I adapt Susarla's (2010) complexity measure based on three facets of the task at hand: a) whether a task involves business transformation (i.e., objectives are defined in terms of improvements in effectiveness; see Goo et al., 2004, Xia and Lee, 2004), b) whether a task involves new system development (i.e., custom development of systems specific to the company; Anderson and Dekker 2005, Gopal et al., 2003), and c) whether the task requires access to specific expertise (i.e., when the contract specification mentions the domain expertise which is essential for performing the task; Goo et al., 2004, DiRomuldo and Gurbaxani, 1998) or the specialized consulting services provided by the vendor which draws on their specific expertise (Anderson and Dekker 2005). As summarized in Chapter 3, IDC categorizes contracts into 15 mutually exclusive engagement types. In this sample (360 procurement auctions with the outcome revealed), each contract can be categorized into one of the 11 mutually exclusive engagement types (see Table A.7 for details). Applying the Susarla approach, I use these classifications to develop a 3-level complexity score (see Table A.8 for scoring details).

My second measure of complexity was inspired by Bajari and Tadelis (2001) who equate project complexity with the design intensity of the projects. I reason that the number of discrete sub-segments in the project captures design intensity. A relatively simple project is likely to include only one discrete segment of work (e.g., HR), while a complex project inevitably includes multiple segments of work (e.g., HR and F&A). In my data, projects range from one segment to 27 sub-segments, with most ranging from 1 to 5.

Uncertainty. Following Crocker and Reynolds (1993), I use the contract duration as my uncertainty measure. Greater technological and business changes are present with longer time horizons. Parenthetically, duration is likely to be correlated with complexity, since complex projects should need more hours to complete.

Signing Regions. I control for institutional differences in contract execution with dummy variables for the different signing regions, which is usually the country headquarters of the client. There are three large signing regions (Americas, EMEA, and Asia Pacific), accounting for 180 countries globally. (See Figure A.6).

Number of Bidders. I observe the number of bidders submitting bids through the RFP, but only the winning bid amount (and bidder's identity) is recorded in the data.

Client Characteristics

Experience. The cumulative ln($value$) of prior projects undertaken by a specific client as of the signing date of a specific project is my measure of the experience of the buying firm with these auctions.

Size. I dichotomize the clients based on the number of employees to develop my dummy variable size measure. We know that the buying process is heavily influenced by the bureaucratization of a firm, which in turn is dependent on a threshold level of employees. IDC categorizes clients into one of the following types based on the number of employees: small firms (less than 10 employees), middle sized firms (11∼100 employees), large firms (101∼1000 employees), enterprises (1001∼ 5000 employees), and global enterprises (more than 5000 employees). I borrow their categorization rule. (See Table A.2 for details)

Vendor Characteristics

Prior Experience. Paralleling the client measure, I use the cumulative $log(value)$ of prior auctions won by the vendor as my measure of experience.

Prior Projects. A long-standing tenet of business-to-business marketers is that history matters. Indeed, much of the supposed downside of procurement auctions is the damage to existing buyer-seller ties from requiring bidders to compete with each other (e.g., Jap, 2002). Bidders with a previous relationship with the clients are likely to behave differenetly in the auction because adjustment costs are likely lower, enabling them to net a larger fraction of the same gross modification receipts. My measure is the number of outsourcing projects between a specific customer-vendor pair that existed before the signing date of the specific project.

Modifications

I observe 360 contracts with an observed outcome. Each of these is coded into one of five outcome categories: extended, expanded, extended and/or expanded, expired, and cancelled (Table A.9). Of these, "expired" indicates that the work was completed under the original contract. In all other cases, the original contract was replaced by a new contract number on a specified date.

I categorize 360 contracts in my data into two categories: a) executed as-is ("expired" and b) modified ex post. I further categorize modified contracts into the following types of modifications: new work added, extensions and both. Of the 360 contracts with observed outcomes, 331 were modified, while 29 were executed as-is.

Modification Value (A). To illustrate this variable, consider Washington Mutual Inc.'s 10-year contract with IBM signed in 1996 for data center management, desktop management, and network management for $533 million. The client's rapid growth in the next few years led to a revised contract in 1999 that expanded the scope of the work. This new 10-year contract was worth $550 million and pushed the end date of the contract to 2009.

I calculate the modification value as follows: the value of the new contract minus the unpaid part of the original contract, i.e., $550 million- $533 million$*(1-30\%)$ equals $176.9 million. Figure A.7 describes the distribution of Modification Value; both negative and positive values can be seen, but most values are in the positive range.

Modification Ratio (A/w). This variable normalizes the modification value as follows: divide the Modification Value by the original contract value. In the example above, this calculation yields $176.9/533 = 33.19\%$. The variable ranges from -0.1 to almost 2.5. Figure A.8 describes the distribution of this variable.

4.3 Multi-Attribute Scoring

I approximate the bidding process by a First-Price Sealed-Bid auction with a single decision variable for each bidder, viz. i, the bid price b^i. Recall, however, I described in Chapter 3 that the RFP process included multiple dimensions along which the bids were scored. For example, the RFPs typically specify many performance/quality dimensions other than bidding price. Here, I provide my arguments for my approximation.

For the given attributes and weights denoted by the buyer, the game is a scoring auction with independent private valuations. There are several papers on scoring auctions in the literature (Che, 1993; Asker and Cantillon, 2008; Barjari et al., 2014). Two factors are prominent in their setups and solutions: (i) how price enters the scoring rule function, and (ii) whether private information is independently distributed across suppliers.

In my context, according to the RFPs, price enters linearly into the scoring rule. Similar examples include the “A+B bidding” (for example, A can be quality, and B can be price) for highway construction work in the Unites States, where the government provides estimated quantity of materials and weights (in highway construction case, “A+B” stands for a general linear weighted summation function, and it can be more than 2 dimensions), then evaluates the weighted costs submitted by the bidders. In Che’s (1993) two-dimensional auction, where firms bid on both price and quality, and the bidder devises a scoring rule, he finds that when price is entered linearly into the scoring rule, the optimal scheme is implemented (when private information is one-dimensional). Asker and Cantillon (2008) studied the properties of scoring auctions in which price is entered linearly into the scoring rule but they extend the model into a systematic analysis where suppliers’ private information is multidimensional. They proved that the multidimensionality of suppliers’ private information can be reduced to a single dimension (“pseudotype”) that is sufficient to characterize equilibrium outcomes in these auctions. The most relevant finding in their paper is that the equilibrium inherits properties of the corresponding standard IPV auction (existence and uniqueness of equilibrium, efficiency). Based on these findings, I approximate the procedure of IT procurement auctions in my context assuming the following:

1. The scoring rule is a linear function of price and several other factors.

2. For each auction, all the bidders are provided the same information through RFPs including clearly denoted dimensions and weight for each dimension in the scoring rule. The only decision variables for the bidders are how much to bid for each dimension listed.

3. Independent private costs of bidders are single-dimensional.

4. The buyer is able to commit to a scoring rule.

There are a few papers studying non-commitment scoring auctions. In this dissertation, I follow the commitment case. This is a reasonable approximation because, as shown in Chapter 3, the scoring rule is publicly known to both buyers and all the bidders. As for the non-commitment case, Che (1993) first proved that alternative scoring rules (First-Scoring, Second-Scoring, and Second-Preferred Scoring) will yield the same expected utility for the buyer (referred to a two-dimensional extension of the revenue equivalence theorem). The lack of commitment power yields more-than-optimal quality.

There are two challenges in estimating scoring auctions: (1) identification of the functional form for the costs, and (2) identification of the distribution of private information (Asker and Cantillon, 2008). Empirically, estimation of scoring auction models rests on observing the scoring rule and the bid information on each scored dimension. Barjari et al. (2014) is an example. In their paper, the authors followed the above four scoring rules: the scoring rule is a linear function of cost of all the materials which is public information to all the bidders, the government provide weights and estimated quantities, and the bidders only submit a bidding price for each dimension based on their independent private costs. The estimation strategy relies on detailed information of the scoring rule (weights) and bidding prices of all the materials.

In this dissertation, I also follow the four rules above, and as I described in Chapter 3, the RFPs consist of both quality and price scores. However, I face additional challenges: (1) I do not observe either the weights of bids in the RFPs, (2) I do not have access to bids on all the dimensions except the bidding price, and (3) I do not observe the losing bids. Therefore, in my estimation, I make the following additional assumption:

Assumption 4.3: The observed winner of the scoring auction will be the same as if the bidders had bid only on price.

Given this assumption, my approximation of the scoring auction as a single-dimension auction in price is reasonable as summarized below:

1. In general, scoring auctions will change the optimal bidding strategies of single-dimensional bids because the bidders can switch the bids between different dimensions without changing the final score (and hence without changing the probability of winning the auction). Che (1993) first proved that the equilibrium in the First-Score auction (quasi-linear scoring rule where the winner is selected by the highest score and the contract results from the score) is reduced to the equilibrium in the First-Price auction if quality is fixed. Therefore, when quality is not fixed, this approximation is biased if there is heterogeneity across bidders in the quality dimensions such as financial ability, skills, previous experience, and reputation. I argue that on account of the extensive qualification screening described earlier, only qualified bidders (only 2 to 5 bidders) who are likely to be close on these quality dimensions are accepted, with price being the principal remaining dimension.

2. I use only private sector procurement auctions. Here, the choice of employing an auction is made by the buyer, not mandated by regulatory bodies as is often the case in the public sector. Even after the RFI stage, the buyer may still opt to negotiate rather than set up an auction if the pre-screening reveals significant gaps between between bidders in quality dimensions.

Some evidence of the price competitiveness of these auctions can be seen in win-loss patterns across pairs of large bidders who appear repeatedly in my data. If firm A were to repeatedly beat firm B across auctions, that would suggest that the auctions are truly beauty contests in disguise, and are picking up significant unobserved quality differences. For example, there are 121 projects involving both IBM and HP. HP beat IBM on 52 projects, IBM beat HP on 32 projects, and they were both beat by some other vendors on the other 37 projects. A similar pattern holds for competition between AT&T-Verizon, CSC-IBM, and Microsoft-Unisys. Clearly, these auctions are price competitive with the RFP process attenuating the non-price differences across bidders.

4.4 Parametric vs. Non-Parametric Estimation

The most crucial step is the estimation of the distribution of valuations of bidders, denoted as $F_v(v)$. In Equation (1.8), I solved for the optimal bidding strategy in FPSB auction as $b^i = c^i + \frac{\sigma^{'}(c^i)[1-F_c(\sigma^{-1}(b^i))]}{(N-1)f_c(\sigma^{-1}(b^i))}$. Note that this is an implicit function, where the $\sigma^{'}(c^i)$ is bidder i's bidding strategy. Below, I summarize the pros and cons of taking a parametric or nonparametric approach to this problem.

4.4.1 Parametric Estimation

The parametric approach assumes some functional form for the distribution of valuations, and recovers the parameters assuming the bids are Bayes-Nash equilibrium (BNE) bids. Only a few distributions are tractable; three estimators proposed include Piecewise Pseudo-Maximum Likelihood Estimator (MLE, Donald and Paarsch, 1996), Simulated Nonlinear Least-Squares Estimator (SNLLS, Laffont, Ossard, and Vuong, 1995) based on the importance sampling technique, and Extreme-order, Generalized Method-of-Moments Estimator (EGMME, Donald and Paarsch, 2002).

Both MLE and EGMME have been criticized because of the numerical complexity associated with the computation of the Bayesian Nash equilibrium strategy and that it is very difficult to implement on a computer. Thus, only very simple parametric specifications of the latent distribution of private values have been entertained. For this reason, only uniform distribution was used in Donald and Paarsch (1996). Instead, SNLLS replaces the laborious calculation of definite intervals and inverse functions with simulation based on importance sampling, which allows for more general parametric specifications. Furthermore, SNLLS is the only parametric method that has been applied to First-Price Sealed-Bid auctions with only winning bids available. As such, I employ SNLLS here.

4.4.2 Non-Parametric Estimation

The non-parametric strategy follows a quite different method: infusing no explicit assumptions of functional forms, and instead, letting the data tell the econometricians the distributions of the valuations. Therefore, although the bidding function itself is unknown, its inverse function can be easily obtained empirically. This explicitly expresses the relationship between the latent cost (valuations) and the observed bids. The leading work is Guerre et al. (2000), which has been widely used in empirical structural estimation in auction models. In this dissertation, I also follow Guerre et al. (2000)

However, I have to extend his approach significantly to accommodate my data observability. Guerre et al. (2000) is developed for the base model described in section 4.1. Fortunately, several extensions including observed heterogeneity in auctions (Li, Perrigne and Vuong, 2000), unobserved heterogeneity (Krasnokutskaya, 2011), asymmetric bidders (Campo, Perrigne and Vuong, 2003; Flambard and Perrigne, 2006), random reservation price (Li, Perrigne and Vuong, 2003) exist, so I am able to draw on these advances.

Comparison

The strength of non-parametric estimation strategies is two-fold: (a) it does not involve any explicit assumption about the functional form. so in this sense, it is more general and hence robust to misspecification, and (b) it imposes a much smaller computational burden because it does not involve solving differential equations or numerical integration.

The weakness of parametric strategies is very straightforward. All these parametric methods, in general, have to make use of an explicitly expressed bidding function in estimation. In addition, because all of these methods are based on BNE bidding functions, the theory results cannot hold anymore when extending the models to incorporate asymmetric bidders. Despite of all of these criticisms, for my purposes, one strength of the parametric estimation is its ability to address what-if questions based on counterfactuals or thought experiments.

4.4.3 Estimation

Considering the advantages and disadvantages of both methodologies, I conducted analyses under both strategies in this dissertation, and introduced significant extensions in each stream to fit my context and better answer my question.

In FPSB auctions, the bidders' optimal strategy is determined by the baseline latent cost adjusted by a markup. Lower latent costs lead to lower bids in equilibrium (Jofre-Bonet and Pesendofer, 2003).

In the next section, I propose a method to recover the latent costs of each contract, and quantify the effects transferred to bids. Donald and Paarsch (1996), Paarsch (1997) and Laffont et al. (1995) have proposed parametric estimation methods that rely upon a parametric specification of the bidders' private value (latent cost) distribution. One big limitation of these methods is that only very simple parametric specifications of the distribution of latent costs can be used due to the numerical complexity associated with the computation of the Bayesian Nash equilibrium strategy. Guerre, Perrigne, and Vuong (2000) established the optimal rate of convergence for estimating the density of the latent cost and constructed an estimator that attains this rate. This breakthrough has the important feature that it requires neither parametric assumptions nor computations of the Bayesian Nash equilibrium strategy. There have been a number of recent papers in this stream, extending the original model. For example, Li, Perrigne and Vuong (2003) extended the strategy to incorporate random reserve prices. Krasnokutskaya (2011) proposed a new framework to incorporate unobserved auction heterogeneity.

I follow the Guerre, Perrigne, and Vuong (2000) procedure to obtain the latent costs of contractors, and estimate the distribution of margins of auctions.[1] Then I test how three factors, [A(modifications),$Type$(per unit price contract =1),$prior relationship$ (partners with prior relationship =1)], affect the margins to suggest some policy conclusions. The following steps are involved in my procedure

Step 1: Estimate the distribution of the winners' bids: Optimal bidding strategy in Symmetric Bayesian Nash Equilibrium (First Price Sealed Bid auction).

Remember that I only observe the winner's bid for each auction. As proved in Athey and Haile (2007) and Paarsch and Hong (2006), when only the winning bids are observable instead of all bidders' bids, the distribution of private values is non-parametrically identified if the total number of bidders is observable. To incorporate this idea into my estimation strategy, I follow the transformation of model (4.8):

Let $F_S(s)$ and $f_S(s)$ denote the CDF and PDF of bid s, and $F_W(w)$ and $f_W(w)$ the CDF and PDF of the winning bid w. Under assumption 1 and 2, for each auction l

$$F_W^l(w) = F_S^l(w)^{N^l} \tag{4.10}$$

[1] In Section 5, I provide the parametric results following Laffont, Ossard and Vuong (1995). Note that both parametric and non-parametric approaches give me similar results, which is comforting from a robustness standpoint.

$$f_W^l(w) = \frac{1}{N^l} F_S^l(w)^{N^l} \tag{4.11}$$

Equation (4.9) can be rewritten as

$$w^l(X^l) + \tau A^l - c^l(X^l) = \frac{N^l[1 - F_w(w^l|X^l)}{(N^l - 1) f_w(w^l|X^l)} \tag{4.12}$$

where

$$X^l = [Cons, Complexity, Duration, Number\ of\ Segments, ClientSize,$$
$$ClientExp, VendorExp, Prior\ Relationship, Signing\ Region, Macro\ Delivery\ Region,$$
$$Customer\ Industry\ Dummies] \tag{4.13}$$

Then

$$w^l(X^l) - [c^l(X^l) - \tau A^l] = \frac{N^l[1 - F_w(w^l|X^l)}{(N^l - 1) f_w(w^l|X^l)} \tag{4.14}$$

Let

$$\phi^l(X^l, A^l) = c^l(X^l) - \tau A^l \tag{4.15}$$

Then $\phi^l(X^l, A^l)$ can be seen as the latent costs which are the pseudo costs adjusted for modifications A. Then Eq(4.13) can be written as:

$$w^l(X^l) - \phi^l(X^l, A^l) = \frac{N^l[1 - F_w(w^l|X^l)}{(N^l - 1) f_w(w^l|X^l)} \tag{4.16}$$

Equation (4.15) is appealing in theory, but it is difficult to apply in a fully general nonparametric estimation method, because the dimensionality of covariates is a problem. I solve this problem by using a homogenization process following Haile, Hong, and Shum (2003). Define homogenized winner's bid $w^{Hl} = w^l - \hat{\Gamma}(X^l)$, and assume $\phi^l(X^l, A^l) = c^l(X^l) + \Gamma(X^l)$, then Eq(4.15) can be written as

$$w^l(X^l) - \phi^l(X^l, A^l) = \frac{N^l[1 - \hat{F}_w(w^{Hl})}{(N^l - 1) \hat{f}_w(w^{Hl})} \tag{4.17}$$

Haile, Hong, and Shum (2003) has proved that w^{Hl} is a consistent estimate of bidding strategy $w^l = \sigma(c^l)$, which is applied by Krasnokutskaya (2011) and Bajari et al. (2014).

Step 2: Recover the distribution of the latent costs of the contractors:

Step 2.1: The latent private cost for each contract l:

$$\hat{\phi}^l(X^l, A^l) = w^l - \frac{N^l[1 - \hat{F}_w(w^{Hl})}{(N^l - 1)\hat{f}_w(w^{Hl})} \tag{4.18}$$

Step 2.2: Trimming

Recover $\sigma(X^l, F_w, N^l) = w^l - \frac{N^l[1-\hat{F}_w(w^{Hl})}{(N^l-1)\hat{f}_w(w^{Hl})}$

Apply the following trimming function to recover the latent cost $\hat{c^l}$:

$$\hat{\phi^l} = \{ \begin{matrix} \sigma(X^l, F_w, N^l) & \text{if } \sigma(X^l, F_w, N^l) \in [w_{min} + 0.5 * h, w_{max} - 0.5 * h] \\ \text{Trimmed} & \text{Otherwise} \end{matrix} \tag{4.19}$$

where h is the optimal bandwidth in Step 2.1

Among the 360 auctions in my dataset, 99 auctions were trimmed.

Step 3: Assess the effects on the latent costs from three factors (A , contract type, and prior relationship), their interactions, and other control variables.

$$\begin{aligned} \frac{\phi^l}{w^l} &= \alpha^0 + [\tau^0 + \tau^1 * I\{Perunit\, Contract = 1\} \\ &+ \tau^2 * I\{Prior\ Relationship = 1\}] * \frac{A^l}{w^l} + Control\, Variables + \eta^l \end{aligned} \tag{4.20}$$

Chapter 5

Estimation Results

Table A.10 and A.11 describe the estimated values of the parameters from the non-parametric procedure described in the previous chapter. Below, I offer some intuition into the results, particularly as they relate to the bids.

Conclusion 5.1: τ^0 is significantly negative ($\tau^0 = -0.21$) and less than 1; hence latent costs are decreasing with positive modifications A^l.

Recall that bids depend on the bidder's latent cost in auction l. This latent cost can be thought of as a baseline, based on which bidders adjust their bids using a markup. The values of τ in Table 5.1 tell us that these latent costs are decreasing in A^l; i.e., larger gross receipts from modifications induce more aggressive (lower) bids. Given the characteristics of auction l, the bidders expect that their gross receipt will be w^l from the current contract, and $E(A^l)$ from future changes. The bidder's direct private cost on the current project is $c^l(X^l)$.

In a classic auction, without future modification (A^l), the bidders will bid based on their direct private cost $c^l(X^l)$ (for example, production costs, management costs), and a markup which is determined by the competitiveness of the bidding. When they take the future receipt $E(A^l)$ into account, their gross receipt is actually higher, and they are willing to sacrifice part of their receipt today. This is equivalent to the case where their bidding baseline, i.e., their latent cost, is $c^l(X^l, A^l) = c^l(X^l) - \tau E(A^l)$. Based on this new latent cost $c^l(X^l, A^l) = c^l(X^l) - \tau E(A^l)$, instead of the direct cost $c^l(X^l)$, they follow the optimal bidding strategy $w^l = \sigma(c^l) = c^l(X^l, A^l) + \frac{\sigma'(c^l)[1-F_c(c^l)]}{(N^l-1)f_c(c^l)}$.

Conclusion 5.2: The coefficient of the interaction between the modification ratio and type dummy ($\tau^1 = -0.15$) is significantly negative; hence, modification values under lump-sum payment are discounted to a smaller degree than other payment types. Stated differently, lump-sum payments reduce latent costs by a smaller amount than an equal modification amount under unit-price payments.

The intuition is as follows. Recall that the previous literature (e.g., Banerjee and Duflo, 2000; Corts, 2011) showed lump-sum payment contracts were correlated with smaller adjustments because of their presumed higher adjustment costs. My results provide empirical support for the underlying assumption: lump-sum payment contracts are costlier to modify. In my model, higher adjustment costs leave a smaller fraction of the gross receipts from positive modification being netted by the contractor, so their drop in latent costs is smaller, leading to less aggressive bidding under lump-sum auctions.

Conclusion 5.3: The coefficient of prior ties ($\tau^2 = 0.17$, $p > 0.1$) is positive, but not significant; hence, a bidder's prior work with a buyer has no meaningful effect on the degree to which modifications are folded into the bid. While surprising at first glance, a little reflection renders it less so. In my data, most pairs of vendors and clients have either 0 or 1 prior project between them. The highest number of prior projects between pairs is 2. Given this, it is not surprising that we find an insignifcant effect.

Chapter 6

Thought Experiments

Recall my first goal was to specify and estimate a more realistic model of procurement auctions that accommodated the inevitable modifications during the execution phase. My estimates and discussion above can be summarized as follows: positive modifications, A^l, lead to lower (more aggressive) bids. Below, I focus on the relative magnitude of these lower bids under different circumstances. First, what is the magnitude of the reduction in bids? Second, and relatedly, what is the effect of an additional dollar in gross modification receipts on bids? Thirdly, what is the relative magnitude of these effects on the two most common forms of auction payment formats: lump-sum bids and unit-price bids?

Methodological Note: My nonparametric procedure reported in the previous chapter comes at a cost. I cannot track the distribution of these costs from the observed circumstances of interest. In order to address these questions, in this chapter, I extend the approach discussed in Laffont, Ossard and Vuong (1995) to my setting where I only observe the winning bids.

I assume that latent costs follow a log-normal distribution, and estimate the distribution parametrically. Based on the recovered distribution of latent cost from the parametric estimation, I conduct 3 thought experiments (details described in sections 5.2-5.4).

Specifically, for each though experiment, I follow a 4-step strategy:

Step(1): Recover $f(c)$ using the estimated parameters

Step(2): Simulate $S = 500$ points from distribution $f(c)$ given $X_{recover}$ and $X_{counter}$

Step(3): Calculate w^l_s

Step(4): Calculate $w^l_{recover} = \sum_{s=1}^{S} w^l_{s_{recover}}$ and $w^l_{counter} = \sum_{s=1}^{S} w^l_{s_{counter}}$

6.1 Parametric Estimation

I extend the Simulated Non-linear Least Square Estimator (SNLLS) discussed in Laffont, Ossard and Vuong (1995). Recall that the bidder's optimal bidding strategy for each auction l is:

$$w^l = \sigma(c^l) \tag{6.1}$$

Then

$$\sigma(c^l) - c^l = \frac{1 - F_c(c^l)}{(N^l - 1) f_c(c^l)} \sigma'(c^l) \tag{6.2}$$

Following the previous literature, I assume that the private cost $c^l(X^l, A^l)$ follows a log-normal distribution for each auction. Let this distribution depend on auction characteristics,

$\mathbf{X}^l = [lnT^l, lnClientExp^l, ClientSize^l, lnVendorExp^l, Complexity^l, Type^l, Prior^l,$
$MacroRegion^l]$

where

lnT^l: Log(duration in months) of original contract

$lnClientExp^l$: Log (total dollar value of prior hosted projects) of clients

$ClientSizes^l$: Dummy variables of clients' sizes

$lnVendorExp^l$: Log (total dollar value of prior hosted projects) of vendors

$Complexity^l$: [Number of sub-segments, 3-level Complexity Score]

$$Type^l : \begin{cases} 0 & \text{Lump-sum Price Contract} \\ 1 & \text{Per-unit Price Contract} \end{cases}$$

$$Prior^l : \begin{cases} 0 & \text{No prior contracts between the pair before contract } l \text{ is signed} \\ 1 & \text{At least one contract between the pair before contract } l \text{ is signed} \end{cases}$$

$MacroRegion^l$: Region Dummy =[Americas, EMEA,Asia Pacific, Global],

and A^l is the Modification Value.

Specifically, I assume that the mean of the logarithm of latent cost is a linear function of the above variables:

$$Elogc^l = \mu^l = \alpha_0 + \beta \mathbf{X}^l - \tau \frac{A^l}{w^l} \tag{6.3}$$

and the variance

$$\gamma^{l2} = \gamma^2 \tag{6.4}$$

To make sure the interpretation of estimated parameter τ is consistent with theory model (4.8), the sign of modification ratio $\frac{A^l}{w^l}$ is negative. I use the Simulated Nonlinear Least Square Estimator (SNLLS) to estimate $\theta = [\alpha_0 \;\; \beta \;\; \tau \;\; \gamma^2]$.

Invoking the Milgrom and Weber (1982) revenue equivalence rule, $w^l = \sigma(c^l) = E(c_{(I-1)}|c_{(I)} = c^l)$, where $c_{(I-1)}$ is the second-lowest cost, and $c_{(I)}$ is the lowest cost.

Hence,

$$E(w^l) = m_l(\theta) = E[c_{(I-1)}|c_{(I)} = c^l] = \int\limits_{c_l} \dots \int\limits_{c_l} u_{(I-1)} f_c(u_I) du_1 \dots du_I \tag{6.5}$$

The SNLLS estimator minimizes $Q_L(\theta) = \frac{1}{L}\sum_{l=1}^{L}(w^l - m_l(\theta))^2$. Because $m_l(\theta)$ is not readily available, $\bar{X}_l(\theta)$ replaces $m_l(\theta)$. Because $\bar{X}_l(\theta)$ is not a consistent estimator for a fixed number of simulations S as L increases to infinity, I use the following simulated NLLS objective function:

$$Q^*_{S,L}(\theta) = \frac{1}{L}\sum_{l=1}^{L}[(w^l - \bar{X}_l(\theta))^2 - \frac{1}{S(S-1)}\sum_{s=1}^{S}(X_{sl}(\theta) - \bar{X}_l(\theta))^2] \tag{6.6}$$

where

w^l: winning bid for auction l;

$X_{sl}(\theta) = u^S_{(I-1)l}\frac{f_l(u^S_{1l})\cdots f_l(u^S_{Il})}{g_l(u^S_{1l})\cdots g_l(u^S_{Il})}$;

$\bar{X}_l(\theta) = \frac{1}{S}\sum_{s=1}^{S} X_{sl}(\theta)$;

S: simulation number;

I: number of bidders for each auction l;

$X_{sl}(\theta)$ is simulated following importance sampling, and I assume the function $g()$ follows a log normal distribution as follows:

$$E[g(c_l)] = \beta^0 = \bar{w}^l \tag{6.7}$$

$$Var[g(c_l)] = (\frac{st(w^l)}{\bar{w}^l})^2 \tag{6.8}$$

where $st(w^l)$ is the standard deviation from the sample.

Specifically, I follow six steps:

(1). Simulate U^L_{S*I} $[L*S*I]$ matrix ($L=360,\ S=300,\ I=N^l$), where for each auction $l=[1,\dots,L]$, $u^l(S*I)\sim g(c^l)$;

(2). For each $l=[1,\dots,L]$ and $s=[1,\dots,S]$

$u^l_{S(I-1)}$ is the second-lowest number among $[u^l_{S1},\dots,u^l_{SI}]$

(3). For each auction l, given initial θ^0, simulate $[X_{sl}(\theta^0)]$
where $X_{sl}(\theta^0)=u^S_{(I-1)l}\frac{f_l(u^S_{1l})\cdots f_l(u^S_{Il})}{g_l(u^S_{1l})\cdots g_l(u^S_{Il})}$

(4). Calculate $\bar{X}_l(\theta^0)=\frac{1}{S}\sum_{s=1}^{S}X_{sl}(\theta^0)$

(5). Form $Q^0_{S,L}(\theta^0)=\frac{1}{L}\sum_{l=1}^{L}[(w^l-\bar{X}_l(\theta^0))^2-\frac{1}{S(S-1)}\sum_{s=1}^{S}(X_{sl}(\theta^0)-\bar{X}_l(\theta^0))^2]$

(6). Repeat (3) to (5), and

$\theta^*=argminQ^*_{S,L}(\theta)=\frac{1}{L}\sum_{l=1}^{L}[(w^l-\bar{X}_l(\theta))^2-\frac{1}{S(S-1)}\sum_{s=1}^{S}(X_{sl}(\theta)-\bar{X}_l(\theta))^2]$

This optimization-based method is based on the "revenue-equivalence" theorem: in a IPVP model, all auction formats will lead to the same revenue results (strategically equivalent). Specifically, the winner (with the lowest bid) will bid exactly the valuation of the bidder with second lowest bid (who also has the second lowest valuation). Table A.12 reports the results of this procedure.

Conclusion 6.1: τ^0 (0.17, p <0.01) is significantly positive ($\frac{\partial c^l}{\partial(A^l/w^l)}=-\tau^0<0$), and less than 1.0; hence latent costs are decreasing with positive modifications A^l.

Conclusion 6.2: The significant positive coefficient for the interaction effect between modification ratio and type dummy (0.32, p <0.01) means that modifications under lump-sum payment auctions carry a smaller discount factor, and hence reduce latent costs to a smaller degree than under unit-price payment auctions.

These results are consistent with the corresponding conclusions from the non-parametric estimation (*Conclusions 5.1* and *5.2,* respectively). The robustness of the estimates of the underlying paramters strengthen the thought experiments below.

6.2 Thought Experiments

Experiment 1: What if the buyer were to commit to a no-modification policy at the outset? The law requires some public sector buyers not to re-negotiate awarded contracts, or at least puts severe restrictions on them.

I set all $A^l_{counter}$ to zero and keep $\mathbf{X}^l_{recover}=\mathbf{X}^l_{counter}$. Using my recovered parameters of the latent cost function $f(c)$, I simulate the observed winner's bids ($S = 500$). I measure winner's bids change by $\frac{\sum_{s=1}^{S} w^l_{s_{counter}} - \sum_{s=1}^{S} w^l_{s_{recover}}}{\sum_{s=1}^{S} w^l_{s_{recover}}}$. I find that the winners bids will go up by 27%.

This conveys an important bit of intuition. Buyers in fast-moving and complex procurement settings inevitably find that their carefully drawn up contracts are seriously incomplete during execution. However, instead of viewing this as an invitation to engage in value-destroying costly adjustments that are to be avoided, my analysis concludes that procurement auctions invite lower bids when the buyers accommodate ex post revisions. Put differently, procurement auctions are not as fragile as Williamson (1976) suggested in his critique of franchise bidding auctions. The marginal impact of greater modifications shows this effect even more clearly, as seen below.

Experiment 2: What if the modification receipts go up by 1%? I calculate the change in the winners' bids when the gross receipts from modifications increase 1% as follows.

I set all $A^l_{counter} = A^l_{current} * (1 + 1\%)$, and keep$\mathbf{X}^l_{recover} = \mathbf{X}^l_{counter}$. Using the recovered parameters from my latent cost function $f(c)$, I simulate the winner's bids ($S = 500$). I measure the bid change as $\frac{\sum_{s=1}^{S} w^l_{s_{counter}} - \sum_{s=1}^{S} w^l_{s_{recover}}}{\sum_{s=1}^{S} w^l_{s_{recover}}}$. I find that the bid goes down by 0.33% for a 1% increase in gross receipts from the modifications.

This reinforces Experiment 1 showing the benefit of modifications to the buyer. Not only are modifications inducing lower bids, but larger modifications lower bids even more. Buyers should embrace modifications, as I illustrate below.

Experiment 3: What if only lump-sum procurement auctions were used? I assembled the 177 unit-price auctions in my data ($Type^l = 1$, $N = 177$), and set the $Type^l_{counter}$ to 0, and left the observed characteristics and modification amounts unchanged, $\mathbf{X}^l_{recover} = \mathbf{X}^l_{counter}$, $A^l_{recover} = A^l_{counter}$. Using recovered parameters from my latent cost function $f(c)$, I simulate the winner's bids ($S = 500$) and measure the bid change as $\frac{\sum_{s=1}^{S} w^l_{s_{counter}} - \sum_{s=1}^{S} w^l_{s_{recover}}}{\sum_{s=1}^{S} w^l_{s_{recover}}}$. I find that the bids will go up by 16%.

This is a remarkable result. Intuitively, it would seem that the salience of a lump-sum payment disciplines bidders and fosters greater competition among them. Some industry observers note that bidders dislike lump-sum bids because of such effects.

However, my analysis demonstrates the gain from considering equilibrium behavior. Bidders simply bid less aggressively when confronted with this payment format. Put simply, when procurement auctions are used in a setting such as this industry where modifications are inevitable, there is a significant advantage to using per-unit payment formats over lump-sum payments. Table A.13 summarizes the takeaways of the three thought experiments.

Chapter 7

Conclusion and Discussion

Despite the growing prominence and scholarly interest in auctions, the evidence-to-theory ratio regarding procurement auctions remains low. Marketing scholars and transaction cost economists have often commented about the weaknesses of auctions in procuring complex, customized services (e.g., Jap, 2002; Williamson, 1976). These critiques center on the cost and consequences of the inevitable gaps in specifications leading to ex post revisions that, in turn, undermine the competition-inducing benefits of auctions. Nevertheless, we see auctions used all the more commonly to procure such items. Unfortunately, ex post revisions to work scope and associated payments have been almost completely ignored in the auction literature. In this study, I extend and implement a method to estimate the direction and magnitude of the effect of ex post revisions on the original bids. Data from a large set of IT procurement auctions show results that speak to practice and scholarship.

I find conclusive evidence that buyers who accommodate ex post modifications face much lower bids (by 27%, on average). These ex post revisions are sufficiently valuable in that they overcome the adjustment costs of the negotiations and the added production costs of the new work. These revisions are not trivial bargains since they are large in relation to the original contract itself. The implications for practice are as follows.

When technological and economic circumstances make modifications inevitable (as they are in this industry), far-sighted buyers and sellers accommodate these revisions, and this pays off. For instance, using payment formats other than lump-sum bids (e.g., time and materials or other unit-price formats) enhances these gains significantly. Insisting on a lump-sum format evokes bids that are 16% higher than unit-price bids according to my calculations. This is evidence supporting the transaction cost assumption that these formats are harder or costlier to revise.

This dissertation has contributions in both theory and methodology. First, it contributes to the transaction cost literature by demonstrating that procurement auctions for customized, complex projects can accomodate the inevitable revisions without losing the gain from competition in the bidding phase. Buyers who accommodate ex post modifications gain from aggressive buying-in bidding behavior, particularly with bidders who have not been engaged previously. This finding helps to explain the widespread use of auctions for procuring complex IT projects. Second, this is the first empirical support of conjectures that two formats of contracts (lump-sum vs. flexible payments) are different in their costs of modifications. Lastly, it contributes to the methodology on structural estimation of formal auction models. To the best of my knowledge, this is the first time structurally estimating a formal auction model incorporating ex post modifications non-parametrically and parametrically based only on winners' bids has been done.

The generalizability of my results stem largely from the data and context. While marketing scholars have often focused on the hazards arising from opportunistic renegotiation to exploit incomplete contracts, and the safeguarding costs to protect against these actions (e.g., Ghosh and John, 2005), my IT projects feature significant prospective gains from incorporating new technology that emerges during execution. It may well be that the latent costs are *raised*, not lowered by revisions undertaken in other, less technologically complex settings. For instance, in the only other study on procurement auctions with ex post revisions, Bajari et al. (2014) conclude from their estimates that " ... because adaptation costs erode more than any positive gains from change orders, firms increase their bids" (p. 1317).

How do we reconcile these opposing results? Highway construction is a much less technology-intensive environment, and new, cost-reducing or value-enhancing technologies are unlikely to become available during the execution phase. Most of the revisions are the result of inadequate oversight or mis-estimation of the work itself, and the modification values of their highway projects are much smaller than those observed in my data. In contrast, it is not credible to argue that adaptation costs could exceed the multi-million dollar revision receipts observed in my data.

I close by noting that my methodology can be readily applied to either case. Recall that I do not constrain τ in sign or magnitude. Cases where the goal of renegotiations is to bargain over payments for work that has already been done but has been done improperly according to the buyer are thus accommodated. The empirical effects are likely to significantly change.

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Appendix A

Tables & Figures

Table A.1: **Distribution of Client Industry**

Client Industry	N Clients in Each Industry	Agreements Signed in Each Industry
Government	4,300	16,369
Retail Trade	926	1,392
Communication & Media	2,029	5,894
Banking	1,874	3,981
Professional Services	2,597	3,566
Securities and Investment Services	705	1,012
Transportation	1,201	2,618
Process Manufacturing	1,500	2,490
Discrete Manufacturing	1,538	2,626
Consumer & Recreational	814	1,188
Wholesale	769	1,008
Utilities	762	1,565
Resources Industries	279	506
Insurance	940	1,715

Construction	262	346
Healthcare Services	1,092	1,517
Education	861	1,191
Others	27	34

Table A.2: **Distribution of Client Employee Numbers**

N Employee Numbers	Freq. of Clients
Less than 10 Employees	191
11 $\sim$ 100 Employees	1,665
101 $\sim$ 1,000 Employees	5,595
1,001 $\sim$ 5,000 Employees	4,944
More than 5,000 Employees	4,624

Table A.3: **Distribution of Client Revenues**

Revenues	Freq. of Clients
Less than 1 million	14,777
1 $\sim$ 5 million	14,595
5 $\sim$ 10 million	14,094
10 $\sim$ 50 million	13,681
50 $\sim$ 100 million	11,836
100 million $\sim$ 1 billion	10,614
1 $\sim$ 10 billion	5,074
More than 10 billion	1,268

Table A.4: **Engagement Types of Projects**

Engagement Types	Freq. of Projects
Systems Integration Engagement	18,169
IT Outsourcing Engagement	14,787
Business Outsourcing Engagement	6,282
Deploy and Support Engagement	4,969
Application Development Engagement	1,452
Other Outsourcing Service Engagement	1,281
IT Consulting Engagement	925
Business Consulting Engagement	604
IT Education and Training Engagement	233
Other Consulting Engagement	118
Other Services Engagement	107
Learning and Education Engagement	97
Business Support Engagement	34
Contract Labor and Capacity Engagement	12
Production Coordination Engagement	2

Table A.5: **Detailed Description of Engagement Types**

Engagement Types	Duration	Goal	Deliverables	Activities
Systems Integration Engagement	Project based, with defined beginnings and ends; once delivered, operations of the system typically cut over to the customer's organization, and the systems integrator is under no oblication to conduct ongoing operations	To create a system of people, processes, and technology designed to address customer's specific technical or business needs	A system meeting a stated objective and fulfilling predetermined system specifications	IT site preparation, IT installation, IT project management, custom software development, packaged software custmization

IT Outsourcing Engagement	Ongoing, with contract terms ranging anywhere from 1 year to more than 10 years	To transfer the responsibility for the ongoing management and execution of an activity, a process, or a functional area to an external service provider to expand efficiencies and improve performance	Provision of ongoing management and operations to the specifications defined in the SLA	IT asset management, administration and operations, network management, and related archiving and recovery activities

Business Outsourcing Engagement	Ongoing, and contract terms may range anywhere from 1 year to more than 10 years	To transfer the responsibility for the ongoing management and execution of a business activity, process, or functional area to an external service provider to gain efficienties and improve performance	Provision of ongoing management and operations to the specifications defined in SLA	HR, Logistics, and customer care
Application Development Engagement	Short-term arrangements that contract labor on an as-needed, project, or on an hourly basis	To deliver customized development of software applications and interfaces, and enhancements to existing packaged applications or pre-engineering templates	Software code, the support and maintainance of custom applications, troubleshooting, problem isolation, and installation of patches and workarounds	Includes but not limited to custom software development, testing and debugging, re-engineering, and maintenance

IT Consulting Engagement	Project based, with defined beginnings and endings; typically under no further obligation for successful implementation or execution of recommended strategies and plans.	To assist executives and managers with decision making by providing objective assessment, analysis, and advice	Analysis, recommendations, advice, plans, and designs, in the form of written reports, presentations, and live consultation	IT strategy, operations assessment, IT design, IT supplier assessment, IT maintenance planning
Business Consulting Engagement	Project based, with defined beginning and endings	To assist executives and managers with decision making by providing objective assessment, analysis, and advice	Analysis, recommendations, advice, plans, and designs	Strategy formulation, process improvement, change management, benchmarking, business process reengineering, and skills assessment

IT Education and Training Engagement	Incident based, short term, long term, or ongoing	To encompass education to enhance the knowledge of IT and expand its use	A mix of event-based courses, licenses, or permissions to use self-paced courseware, etc.	Traning for IS/technical skills, desktop skills, professional IT certification, IT learning augmentation
Learning and Education Engagement	Incident based, short term, long term, or ongoing	To enhance the knowledge of business skills, processes, or organizational competencies in all areas	A mix of event-based courses, licenses, or permissions to use self-spaced courseware; the ongoing management of learning activities or an organization; the development of specific/customized courses and the creation of education plans	Traning delivery, professional certification, learning augmentation services, and learning administration

Business Support Engagement	Ongoing or incident based	To provide assistance, information, content, analysis, and administration to enable the proper development or ongoing operation of a business process	Specialized assistance, telephone and online consultation	Varies widely, depending on the business process
Contract Labor and Capacity Engagement	Short term, long term, or indefinite	To provide work on an as-needed basis	Completion of assigned work to the specifications established in the contract	Associated with contract labor and capacity engagement

Production Coordination Engagement	Varies in duration according to the time required to complete the job or project	To transfer the responsibility for the completion of a specific project to a service provider	Successful completion of the project to the specifications of the contract	Production and coordination engagement, varies widely depending on the industry, functional area, and the nature of the project

Table A.6: **Sample Statistics (with outcome)**

Variable Categories	Variable	Obs	Description	Mean	Min	Max	Std. Dev
Project Characteristics	Start Year	360	Year Projects Start	2004	1994	2013	3.43
	Duration (Months)	360	Total Length of Contracts	69.30	3	156	29.88
	End Year (Signed)	360	Year Projects End	2010	2000	2021	3.48
	Modified Year	360	Year Modifications Happened	2008	1997	2013	3.45
	Total Value ($ Million)	360	Values of Contracts	135.39	4.8	640.2	152.32
Client Characteristics	Client' Size	267	Number of Employees of Clients	10312	25	528458	61912

	Clients' Prior Experience		Total Dollars of Prior Projects Held In The Past By the Same Client ($ Million)	424	0	24800	1740
			Total Number of Prior Projects Held In The Past By The Same Client	1.79	0	35	3.84

Vendor Characteristics	Vendors' Prior Experience	83	Total Dollars of Prior Projects Held In The Past By the Same Vendor ($ Million)	26600	0	242000	48000
			Total Number of Prior Projects Held In The Past By the Same Vendor	148.41	0	1783	228.65

	Prior Projects	301	Total Number of Prior Projects Between the Same Pair of Clients and Vendors	0.07	0	2	0.28

Table A.7: **Engagement Types in Sample**

Engagement Types (In Sample)	Freq.
IT Outsourcing Engagement	206
Systems Integration Engagement	17
Other Outsourcing Services Engagement	9
Business Consulting Engagement	0
Business Outsourcing Engagement	115
Deploy and Support Engagement	8
IT Consulting Engagement	1
IT Education and Training Engagement	0
Application Development Engagement	3
Other Services Engagement	1
Business Support Engagement	0

Table A.8: **Complexity Levels**

Complexity Score	Standards
1	Involving business transformation alone Access to expertise alone Involving new system development alone
2	Involving business transformation and access to expertise Involving business transformation and new systems development Access to expertise and new systems development
3	All three involved

Table A.9: **Contract Outcome**s

Categories of Outcomes	Definition
Extension	Contracts have been renewed and extended under similar terms.
Expansion	Contracts have been expanded in scope.
Extension and Expansion	Contracts have been extended and expanded in scope. (Scope and term of original contracts have been significantly changed)
Expired	Contracts have expired and not been renewed.
Cancelled	Contracts have been cancelled

Table A.10: **Nonparametric Estimation Results**

Variables	Parameters		Coef (Std Err)
$\frac{A^l}{w^l}$	τ^0	τ	-0.21 (0.09) **
$\frac{A^l}{w^l} * I\{Per-unit\, Contract == 1\}$	τ^1		-0.15 (0.02) ***
$\frac{A^l}{w^l} * I\{Prior\ Relationship == 1\}$	τ^2		0.17 (0.28)
Control Variables	Included		
** $p < 0.01$, *** $p < 0.001$			

Table A.11: **Effects of Modifications for Different Contracts and Contractor Types**

	Lump-sum Price Contract	Per-unit Price Contract
No Prior Relationship	$\tau^0 = -0.21$ ($N = 114$)	$\tau^0 + \tau^1 = -0.36$ ($N = 125$)
Prior Relationship Exists	$\tau^0 + \tau^2 = -0.04$ ($N = 7$)	$\tau^0 + \tau^1 + \tau^2 = -0.19$ ($N = 15$)

Table A.12: **Parametric Estimation Results**

Variables	Parameters		Coef (Std Err)
Constant	α_0		-8.06 (0.99) ***
Contract Duration	β		1.78 (0.16) ***
Client's Prior Experience			0.003 (0.02)
Client's Size			0.64 (0.04) ***
Vendor's Prior Experience			-0.02 (0.02)
Number of Sub-segments of Projects			0.41 (0.04) ***
Project Complexity			0.90 (0.21) ***
Contract Type (Lump-sum vs. Per-unit)			-0.75 (0.10) ***
Number of Prior Projects Between Clients and Vendors			0.99 (0.27) ***
Modification Ratio	τ^0	τ	0.17 (0.01) ***
Contract Type * Modification Ratio	τ^1		0.32 (0.11) **
Prior Project * Modification Ratio	τ^2		0.33 (0.25)
γ			1.38 (0.06) ***

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

Table A.13: **Thought Experiments**

Thought Experiment	Counterfactual Question	Calculation	Effect on Winning Bids
Experiment 1	What if the buyer commits to non-modification	$A_{counter} = 0$	+27%
Experiment 2	What if the modification receipts goes up by 1%	$A_{counter} = A_{currernt} * (1 + 1\%)$	−0.33%
Experiment 3	What if only lump-sum procurement auctions were used	$Type_{per-unitprice} = 1$	+16%

Figure A.1: **Number of Projects Signed Across Time**

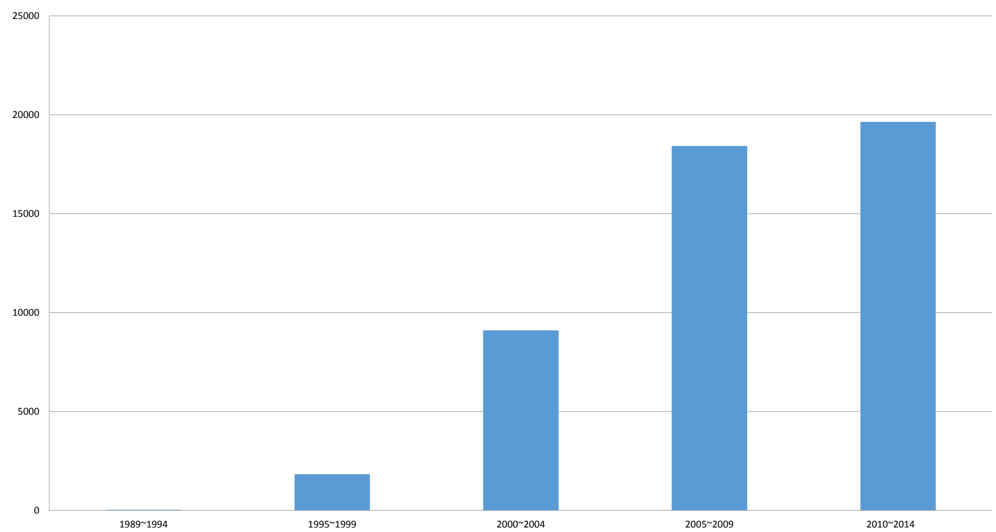


Figure A.2: **Total Value of Projects Signed Across Time**

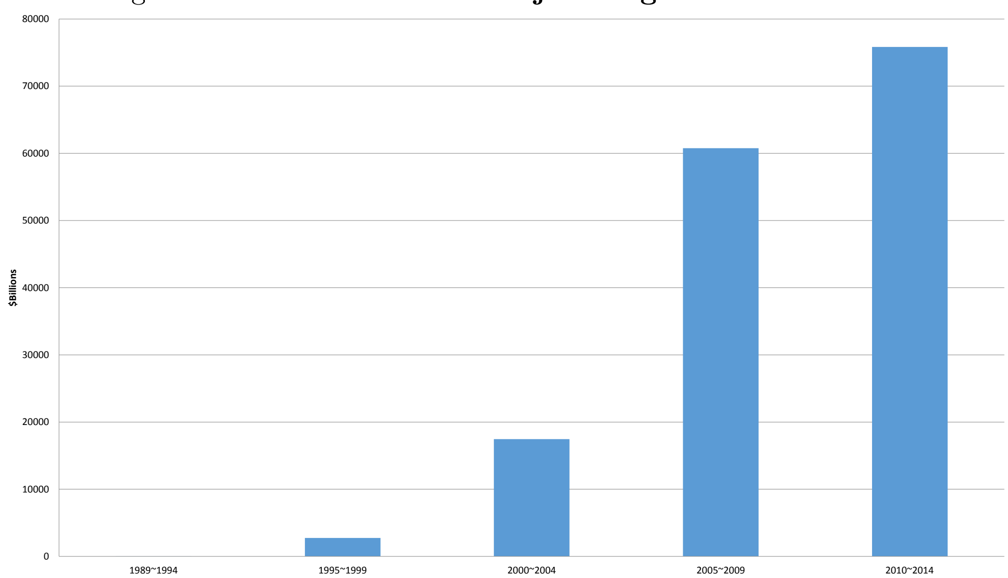


Figure A.3: **Market Share of Projects from Different Macro Markets**

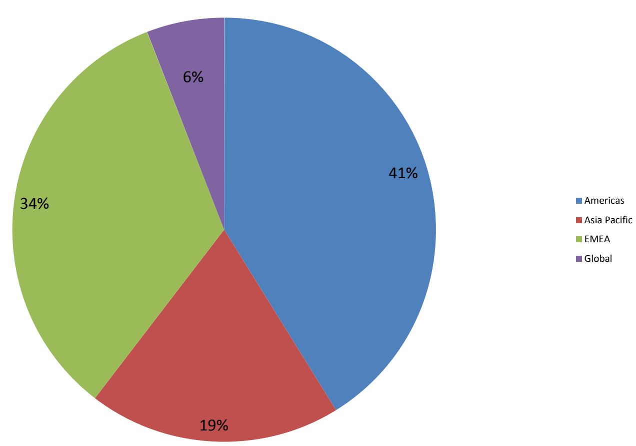
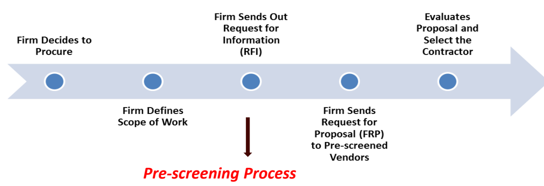


Figure A.4: **Timeline and Procedures of IT Procurement Projects**



Source: Halvey and Melby (2005), IDC (2013)

Figure A.5: **Distribution on Number of Bidders for Each Project**

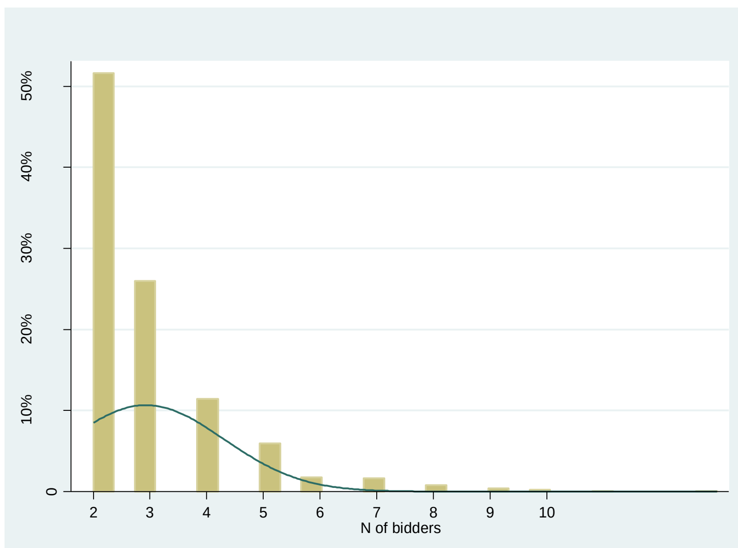


Figure A.6: **Project Signing Regions**

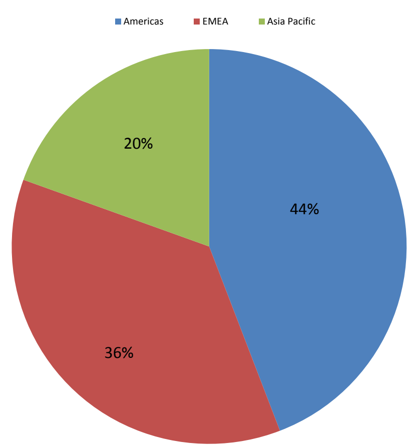


Figure A.7: **Distribution of Modification Values**

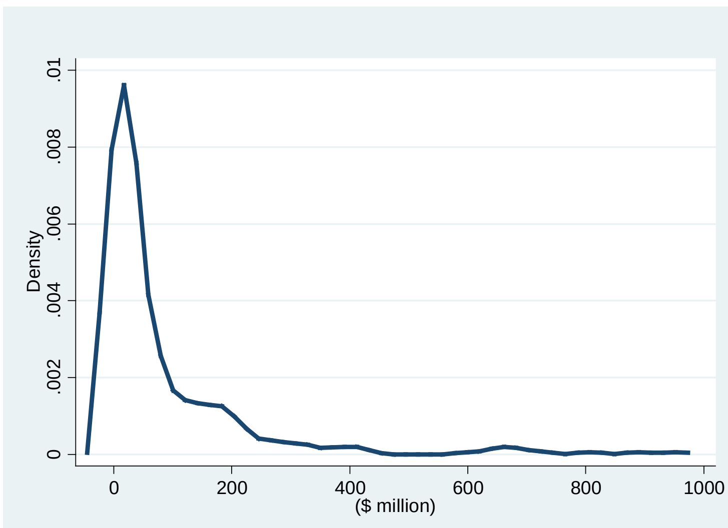


Figure A.8: **Distribution of Modification Ratio**