Costly Bidding in Online Markets for IT Services

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Eli M. Snir and Lorin M. Hitt

Abstract

Internet-enabled markets are becoming viable venues for procurement of professional services. We investigate bidding behavior within the most active area of these early knowledge markets: the market for software development. These markets are important both because they provide an early view of the effectiveness of online service markets and because they have a potentially large impact on how software development services are procured and provided. Using auction theory, we develop a theoretical model that relates market characteristics to bidding and transaction behavior, taking into account costly bidding. We then test our model using data from an active online market for software development services, which yields contracts for 30%-40% of posted projects. In its current format, however, the studied market may induce excessive bidding by vendors. Consistent with our theoretical predictions and those of Carr (2003), higher value projects attract significantly more bids, with lower average quality. Greater numbers of bids raise the cost to all participants, due to costly bidding and bid evaluation. Perhaps as a consequence, higher value projects are also much less likely to be awarded.

Keywords: Internet, Electronic Markets, Software Contracts, Reverse Auctions, Bidding

1. Introduction

The Internet is becoming a universal platform for the development of new electronically mediated markets. While many of the initial online markets focused on the exchange of physical commodities (books, CDs, collectibles), there has been a recent emergence of marketplaces directed at the trade of services. Given that services are estimated to account for 70% of gross domestic product in the U.S. (Quinn, 1992), this greatly expands the scope of economic efficiencies and new business opportunities enabled by the Internet. Moreover, the emergence of these markets represents the continuation of an ongoing trend toward less hierarchical forms of organization and a more market-based economy (Malone, Yates and Benjamin, 1987; Gurbaxani and Whang, 1991; Malone and Laubacher, 1998).

One of the largest and most active areas of these service markets is the trade of information technology (IT) expertise such as software development and web design (Slayter, 2002). Most existing knowledge- or expertise-trading sites[1] provide the ability to trade IT services, and these tend to be very active compared with other types of services transacted in these markets, such as accounting, technical writing, or administrative support. These markets are interesting to study not only because they provide insight into how Internet-based service markets might evolve, but also because they could potentially represent a significant new method of IT service procurement, enabling the benefits of market-based procurement (e.g., vendor competition, specialized skills) for "small"[2] projects that would otherwise be staffed internally or though temporary employment agencies.

A typical transaction in these markets is conducted as a procurement auction (or "reverse auction") where vendors tender bids. This online market process deals effectively with the complexities inherent in IT procurement: price discovery, resolution of vendor quality, and identification of vendor fit with the buyer or project. It is the latter processes that give rise to significant costs of participation for both buyers and vendors. Specifically, such a market supports the following process. A buyer creates a Request for Proposal (RFP) that describes the

[1] Examples include freeagent.com, eLance.com, and eWork.com that utilize a request for proposals and reverse auction model (bidding on projects). All are at a relatively early stage, so little is publicly known about their profitability. For further discussion see Malone and Laubacher (1998).

desired services (i.e., project description, scope, deliverables, relevant deadlines) and posts the RFP to the online marketplace. Meanwhile, IT vendors continually search the site for RFPs that match their areas of expertise. When the vendors find a suitable RFP, they prepare and submit a bid package that includes an asking price as well as supplementary information such as a description of their capabilities, and a proposed method of completing the project. The buyer then reviews all of the bids and chooses the best bid, presumably the best tradeoff between price, vendor quality, and fit. The cost and complexity of each step drives some participants out of the market. The effort involved in preparing bids persuades some vendors not to bid. Buyers may opt not to participate or not to contract in an auction if bid evaluation costs are prohibitive.

The primary role of the site is to help buyers find vendors (and vendors find buyers) by reducing frictional transactions costs. These markets are unique in that the dramatic reduction in transactions costs enables considerably greater participation, especially by international vendors, enabling buyers to realize lower costs and improved quality through increased vendor competition and greater chance of vendor-buyer fit. In addition, online marketplaces serve the secondary role of reducing opportunistic behavior by maintaining and disseminating public reputations for market participants. Typically, buyers or vendors (or both) pay a transaction fee (levied on project value) and, in some cases, membership fees for these services.

Although these markets are essentially procurement auctions, they also have characteristics that distinguish them from offline auctions for physical goods (especially auctions for commodity goods). The RFP and bidding process must result in the exchange of much more information because projects and qualifications are not standardized. In addition, unlike the trade of physical commodities where a part number, industry standard (e.g., MIS-SPEC, ANSI, ISO, etc.) or engineering drawing can be sufficient to fully describe the required good, IT services are highly customized and idiosyncratic, and there are no accepted standard for the formal description of service requirements comparable to those available for many physical products. Moreover, unlike many physical commodities that have objective tests of quality (e.g., composition, strength, reliability), IT services are evaluated subjectively. As such, the range of possible characteristics and quality levels of services is virtually unlimited. Because of this

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[2] Most of the projects traded in these markets would be considered "small," involving less than six person-months of effort (McConnell, 1996). As a reference point, these projects would fall in the lowest decile of project size considered in software cost estimation studies (see, e.g., Kemerer, 1987, pages 53, 79 and 114).

inherent complexity in the transaction, both buyers and vendors bear substantial costs of bidding and evaluating bids. As shown by Samuelson (1985), costly bidding alters many of the qualitative predictions of the theoretical auctions literature. Since, in these markets, the effects of costly bidding are likely to be large, the success of these markets will depend on their ability to manage these problems.

In this paper we develop and test a model of buyer and vendor behavior in online service markets. We begin by using auction theory to construct a theoretical model of reverse auctions, which accounts for both costly bidding and variation in vendors' cost and quality. Carr (2003) extends this analysis to account for the market characteristic of costly bid evaluation. These models predict that when bidding is costly, buyers with a higher willingness to pay for project quality will receive more bids, and those bids are of lower average quality. While this may seem surprising, the intuition behind this result is that higher value projects create greater rents for low-quality bidders, encouraging them to participate, even when their likelihood of success is small. When bid evaluation is costly, this "excess bidding" may discourage contracting by buyers (Carr, 2003). We find empirical support for these predictions using data drawn from one prominent online IT service market. In that market, nearly two-thirds of the buyers opt not to transact after receiving bids. This behavior is consistent with costly bidding and substantial bid evaluation costs. Our contribution in this paper is developing a theoretical model relating costly bidding to auction outcomes and verifying empirically that costly bidding and bid evaluation have a measurable influence on market outcomes. Specifically, we find that participation costs limit the ability to transact high value projects in these markets.

2. Background and Literature Review

Online spot markets are one way that the Internet is profoundly changing the way business is organized and transacted (Malone and Laubacher, 1998; Lee and Clark, 1996; Malone, Yates and Benjamin, 1987; Malone and Rockart, 1991). Internet-based auctions represent a continuation of the long running trend of decreased coordination and transaction costs enabling a shift from internal production to market-based procurement (Coase, 1937; Williamson, 1975; Gurbaxani and Whang, 1991). Online markets have become increasingly favorable due to the ongoing reduction in communications costs, the near universal reach of the Internet, the standardization of complex transactions, and innovations that support trust and quality assessment in otherwise anonymous markets (Dellarocas, 2003; Maes, 1994; Resnick and Varian, 1993). The emergence of online service markets may suggest that transactions costs are now sufficiently low to favor market procurement, at least for some types of services (Malone and Laubacher, 1998). IT services have proven particularly attractive for early online service markets because they can be delivered digitally and the transaction participants are typically comfortable with online business interaction.

2.A. Markets for IT Services

While contracting for IT services is similar to other types of business procurement, it has additional complexity due to the degree of customization, the lack of standardization, and difficulty in assessing the quality of a largely intangible work product. Moreover, this complexity is further compounded by challenges in the management of software projects, which often have substantial deviations from original specifications of time, cost or functionality (Standish Group, 1995). As a consequence, both the frictional transactions costs (search, vendor selection, negotiations)[3] and potential for vendor or buyer opportunism in IT outsourcing can be quite high.

Similar to physical goods markets, online markets for IT services have the potential to lower frictional transactions costs by aggregating supply and demand, facilitating competitive price discovery, broadening reach, and lowering direct procurement costs. They also appear to offer specific advantages over the alternative means of procuring IT services: lower cost than temporary placement firms and more flexibility than hiring specialized staff. However, the rapid and anonymous nature of the transaction may increase the potential for opportunism or limit the use of outsourcing practices that improve contractual performance, such as the promotion of relationship-specific investment (see Saarinen and Vepsalainen, 1994; DiRomualdo and Gurbaxani, 1998). As a result, we would generally expect online IT service markets to be prevalent in small-scale projects where transaction risks (opportunism) and needed mitigation measures are limited, and where search and other frictional costs are likely to be large in proportion to the transaction size.

[3] For instance, Barthelemy (2001) surveyed outsourcing clients and found that contracting costs amounted to 6% of contract value for contracts less than $10 million.

2.B. Bidding in Auctions

The use of auction-like mechanisms for product and service procurement has been well studied in the economics and management literature. Because auctions enable price discovery, they are a desirable way to facilitate trade, especially for those goods and services without a standard market price (McAfee and McMillan, 1987; Milgrom, 1989). Under a standard set of assumptions, many common types of private value auctions are equivalent to an open, ascending bid (English) auction (Vickrey, 1961; Riley and Samuelson, 1981), which has a number of desirable properties such as allocative efficiency and truthful revelation of private value. Despite a rich and robust literature on auction theory and an emerging literature on online auctions,[4] significantly less is understood about how these results apply to service auctions. We know of no prior work on online auctions for services.

In this paper, we focus most specifically on the issue~~s~~ of costly bidding. In most physical goods auctions, bidders generally submit simple bids (price, and perhaps quantity) and sellers can follow simple algorithms to determine the winner (e.g., choose the highest bid). Thus, bidding and bid evaluation costs are likely to be low. In service auctions, each bid is unique and must be customized for a given offer. This creates the potential for significant costs in evaluating RFPs, estimating project costs, reviewing bid packages, evaluating prospective vendors, and ranking the bids against complex, subjective criteria. In regular "forward auctions," Samuelson (1985) shows that when bidding is costly, only bidders with values above a certain threshold participate. Somewhat counter-intuitively, Samuelson shows that this threshold *decreases* as the value of the good increases – lower valuation bidders trade off greater bidding costs against the greater surplus to be gained from success and opt to participate. In the procurement context (a "reverse auction"), this implies that a buyer that sends a larger project to the market, or has a high demand for quality (thus a greater willingness pay), will attract a larger pool of bidders with lower average quality. By itself, this would not be problematic if bid evaluation were free, since a buyer could then costlessly determine the best offer. However, if bid evaluation is costly, extra bids incur additional evaluation costs without any compensating benefit to the buyer, which at a minimum decreases value to the buyer (Carr, 2003). In modeling

[4] See, e.g., Beam and Segev (1998); Klein (1999); Lucking-Reiley (2000); Arora *et. al.* (2003).

procurement auctions, we reframe Samuelson's model of costly bidding to incorporate the price-quality tradeoff faced by vendors and buyers.

3. Model: Reverse Auctions for Services

We model a single reverse auction within a general procurement market for services. The model is not unique to online auctions but characterizes the market studied here. Our model is based on standard auction theory techniques incorporating the additional features of quality variation and costly bidding. In deriving the model we assume that bid evaluation cost is sufficiently low so as to not deter contracting after bidding is completed. Carr (2003) complements this research by extending this model to auctions where bid evaluation costs are sufficiently large such that buyers may choose to not contract when too many bids are received.

Figure 1: <u>Time Line</u>

Stage 1	**Stage 2**	**Stage 3**
Buyer posts RFP, indicating her value (v).	Vendors learn of project and buyer's value (v). Based on this value, his own quality (q), and the distribution of vendor quality in the market $F(q)$, each vendor decides whether to bid. Bidding vendors submit asking price and incur bidding cost.	Bidding ends. Buyer observes characteristics of bids (p,q) and selects winning bidder.

Consider a single buyer interested in finding a vendor to provide her[5] with a well-defined service (a "project") using a 3-stage sealed-bid auction facilitated by a marketplace (Figure 1). The process begins with a buyer submitting a project to the market in the form of an RFP. In the RFP, she details the nature of the service required and the criteria that will be used to evaluate replies. This information enables vendors to evaluate their suitability for the project and to discern the value of the project to the buyer. There are n vendors in the market. This number is less than the total number of vendors in a domain because some vendors have capacity constraints or may not be monitoring the market at the time the RFP arrives. Vendors of heterogeneous quality examine the RFP and decide whether to bid (Stage 2). Bidding vendors prepare a bid description and set a fixed price for project completion. At the end of the auction

[5] We use the convention of female for the buyers and male for vendors.

(Stage 3), the buyer selects the bid that maximizes her surplus (trading off price and quality), given the information in the bids and from the marketplace (ratings, descriptions, etc.).

3.A. Model Assumptions and Structure

Figure 1 describes an extensive-form game with n+1 participants (n vendors and a single buyer) and two decision nodes of vendor participation and price setting and vendor selection.

The buyer is assumed to have a multi-attribute utility function $V(q,p)$ where q is quality of the selected vendor and p is price paid. For tractability we also assume a linear relationship between quality and value, hence: $V(q,p) = vq - p$. Assume the buyer communicates v through the RFP. Appendix 1 catalogs notation.

Vendors are risk neutral and have a cost of performing the required project, which depends only on their quality (type), denoted by q. For tractability we assume that cost is linear in quality ($C(q)=cq$, $c<v$ where c is a constant cost per unit of quality). Thus, it is more costly for a higher quality vendor to complete the project. All vendors also have an identical fixed cost of bidding, c_T. A vendor that bids a project at price (p_q) and is awarded the project has a total profit of $p_q= p_q-cq-c_T$, a vendor who bids but is not awarded a project has profit $p_q= -c_T$, and profit is zero if a vendor chooses not to bid. All parameters are common information except for vendor quality (type), which is drawn independently[6] (IID) from a market-wide vendor quality distribution over $[\underline{q}, \overline{q}]$ with a commonly-known, continuous, strictly increasing, cumulative distribution function $F(q)$. Vendors know their own quality, other vendors know only the distribution of quality, and the buyer knows only the distribution of quality until Stage 3 where the quality of all bidders is revealed through evaluating bids. A vendor's strategy involves deciding whether to bid and a bid price in Stage 2. Since some vendors opt not to bid, the realized number of bids (n_b) is less than n.

[6] In general, in a service market the IID assumption is restrictive because vendor quality may be correlated across projects (see Arora *et. al.*, 2003), with high-quality vendors providing exceptional service to many similar customers. It is, however, justified in this context from the heterogeneity in projects and the diversity of vendor qualifications.

3.B. Equilibrium Behavior

The sub-game perfect, Nash, equilibrium strategies are determined by backward induction. We consider an equilibrium in which buyers and vendors maximize profit conditional on their information at each stage and the constraints of the problem. In Stage 3, since we assume that bid evaluation costs are low enough such that the buyer always evaluates bids, the buyer is faced with the trivial decision to choose the best vendor, trading off price and quality, with full information on vendor quality:

$$\max_{\{q\}} \quad vq - p_q \tag{1}$$

In Stage 2, each vendor evaluates the buyer's RFP and decides his optimal action, whether to bid and an asking price that maximizes his expected profits. The expected profits comprise three terms – bidding costs (c_T), the surplus earned from completing the project ($p_q - cq$) if awarded, and the probability of being awarded the contract. For a given vendor, the probability of winning the project depends on the probability the vendor offers the highest surplus. Let $P_q(q,p_q,F(q),n)$ denote the chance of a vendor of quality q offering the highest surplus to the buyer, when there are n competing vendors. Thus, each vendor solves:

$$\max_{(p_q)} \mathrm{E}[p_q(q)] \equiv p_q = (p_q - cq)P_q(q,p_q,F(q),n) - c_T \tag{2}$$

$$\text{s.t. } p_q \geq 0$$

A vendor's optimal action in this formulation depends on the optimal actions of other vendors (through the $P_q(q,p_q,F(q),n)$ term) – each vendor trades the extra surplus gained from a higher price with a decreased chance of winning. Since vendors are *ex-ante* symmetric, we restrict attention to symmetric bidding strategies. Proposition 1 asserts existence of an equilibrium bidding strategy for vendors in this game.

Proposition 1: In the auction game described above, there exists a symmetric, pure strategy, Nash, sub-game perfect equilibrium vendor bidding strategy in which: (a) Higher quality vendors offer more surplus to the buyer; (b) Vendor profit is continuous and increasing in quality; and (c) Only vendors with quality (q) above a threshold (q_m) bid, where q_m is defined as the solution to:

$$(vq_m - cq_m)[F(q_m)]^{n-1} - c_T = 0. \tag{3}$$

(Proof: See Online Appendix.)

From Proposition 1 there exists a threshold quality level (q_m) such that all vendors with quality above q_m bid and earn non-negative profit in expectation; vendors below this level opt not to bid. Of key interest in this research is the characterization of the break-even quality level. Proposition 2 discusses the comparative statics of this threshold quality level. Carr (2003) argues that these properties hold for every vendor even when the buyer faces bid evaluation costs sufficiently high to deter contracting by the buyer in some circumstances.[7]

Proposition 2: For the equilibrium in Proposition 1, if $c_T>0$ then $q_m \in (\underline{q}, \bar{q}]$ and q_m is increasing in n, c, and c_T while decreasing in v.

(Proof: See Online Appendix.)

The proposition shows that as the cost of service provision increases, either through increased cost of bidding (c_T) or due to increased cost of servicing a contract (c), the quality threshold increases. Increasing competition (n) has a similar effect – competition lowers expected profit. This result also implies that if bidding costs are negligible, all vendors bid on every contract, including vendors of extremely low quality. Such a market could collapse under the onslaught of mediocrity (Akerlof, 1970). By sustaining reasonable bidding costs on vendors, the market can limit participation by low-quality vendors.

Interestingly, however, the buyer-quality preference (v) has the opposite result. Buyers who are interested in attracting high quality vendors induce participation by <u>lower</u> quality vendors, drawn to the auction because higher buyer willingness-to-pay means higher expected profit, despite their low chance of winning. Increased participation by lower quality vendors diminishes the average quality of bidders. This is shown in Figure 2, where vendors' expected profit is shown as a function of quality (with parameters: n=10, c=2, c_T=0.5, d=1 and q~U[0,1]), for different levels of v. As seen in Figure 2, some low quality vendors earn negative expected profit if they choose to bid. The profit for a vendor of threshold quality (q_m) is zero, $p_q(q_m)=0$. From

[7] The possibility that buyers do not complete transactions when too many or too few bidders arrive introduces an additional stage into the game in which buyers have to decide whether to evaluate bids. Since vendors must also take this decision into account when they place their bids, this alters equilibrium bidding behavior. Carr (2003) argues that a similar equilibrium structure holds even when this is a possibility. This point is useful in explaining some of our empirical results later in the paper and extending our bidding results to a setting where *ex-post* non-contracting is a possibility.

Figure 2, greater willingness-to-pay lowers the break-even quality level that bids, decreasing average bid quality and increasing the expected number of bids.

INSERT FIGURE 2 HERE

3.C. Hypotheses

These theoretical observations form the core of our empirical investigation. Costly bidding generates a threshold in quality (q_m) that chooses to bid. This threshold is decreasing in buyer value (v), from Proposition 2. Carr (2003) conjectures that this relationship holds when bid evaluation is costly, as well. Because buyers with a higher valuation for the requested service can expect lower quality vendors to tender bids, we posit that:

Hypothesis 1: Buyers with high value projects attract, on average, lower quality vendors.

We test this hypothesis by investigating the relationship between project value, bidder feedback ratings and other proxies for vendor quality. However, an easier test of the model's prediction can be performed examining the number of bids (which is the same as the number of bidders in this market). Unlike quality assessment, which is likely to be imperfect, the number of bidders is objectively measurable. With the expected number of bidders monotonically decreasing in the break-even vendor quality (from $E[n_b]=n(1-F(q_m))$, a decline in q_m yields an increase in the expected number of bidders. Thus, we test the second implication of our model:

Hypothesis 2: Higher value projects receive more bids.

Our model predicts that more expensive projects attract lower quality vendors and a greater number of vendors. Increased participation with lower average quality has two negative effects for the buyer: increased cost of evaluating more bids, and greater difficulty in discerning vendor quality. This is compounded by the fact that these problems are most acute for buyers where quality is important. At a minimum, these costs lower buyer surplus. Moreover, Carr (2003) shows that these bid evaluation costs may drive quality-sensitive buyers to decide not to evaluate bids, and abstain from choosing a winning vendor. This is only one explanation for why higher value projects induce greater participation. Alternately, participation and quality could be correlated because some high quality vendors bid solely on high value projects. This would suggest that higher value projects receive higher quality bids. Similarly, failure to consummate trade may be driven by unobserved buyer characteristics. These potential explanations and other alternatives are considered and analyzed in section V.

4. Empirical Analysis

4.A. Data

The unique aspect of this analysis is the opportunity to evaluate participation in a real-world setting for service procurement. This type of online market offers a large data set that is rarely available in offline markets. The data for this study includes all Software Development RFPs posted and closed on a prominent online service market from January 1, 2000 to August 24, 2001. This site was chosen because it was one of the few sites that has a comprehensive history of projects and bidding available online. Moreover, the market appears sufficiently developed to evaluate equilibrium bidding behavior. In all, 5,587 software development projects were posted in the chosen timeframe. Of these projects, we omitted projects with incomplete data, "invitation only" projects restricted to only a few vendors, projects that received no bids, and those at the extreme end of the value range (below $10 or greater than $100,000).[8] The result was a dataset with a total of 4,887 observations. Of these projects, detailed data on bidding (e.g., bidder feedback) is available for only 3,761 projects due to the way the site retains bid information on some older projects, so some analyses are necessarily restricted to this subset.

Table 1 presents descriptive statistics for our data. Overall, the descriptive statistics indicate that the market is viable and able to attract a wide variety of software projects. The majority of RFPs sought application development services, although a significant number involved database projects as well. More complex areas (e.g., handhelds) were significantly less common.

INSERT TABLE 1 HERE

The average project in this market receives 15 bids (from a pool of ~3,500 unique bidders) at an average price of $2,480. Figure 3 shows the distribution of project values. Median project value is, however, nearly $600, which indicates that the bulk of the projects are relatively small. This low median price is consistent with the argument that the lower costs in this electronic

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8 Projects at the low end of the range likely do not represent regular project prices, either because they represent an hourly rather than a by-project rate, or they represent a non-market price. Very large projects (above

market might be particularly attractive to buyers with small projects that could not be economically outsourced by other means. Variation in prices across projects is driven by both variation in preferences for quality and variation in the size of projects – the projects range from simple programming tasks with an average bid less than $100 to development of full e-commerce sites with an average bid of $10,000 or more. Of the 4,887 projects in the study, 1,828 (38%) culminate in contracts in which the buyer chooses one of the bidding vendors. The average price for awarded contracts is $800. We later discuss possible reasons, both theoretical and practical, for the large number of unconsummated auctions. Auction length, an important factor in studying market participation, indicates that vendors bid for a little over nine days, on average. The average expected time for project completion was nearly 39 days. Inspecting the final project price, we find that, on average, buyers pay 20% less than the average bid. Feedback ratings in this market are sparse and high. Less than half the vendors earned feedback while the average score is 4.6 out of 5. Upward bias in feedback may be a result of buyers' only rating vendors they have selected and approved, and vendors' incentives to build positive reputations (Dellarocas, 2003).

INSERT FIGURE 3 HERE

Variables from our theoretical analysis in the previous section, variables prevalent in the literature, and variables crucial to this emerging market all provide the basis for our econometric model. The following is a list of these variables, with some discussion of each.

Number of Bids (n_b) is the number of bids per project. Our theoretical model makes direct predictions about the number of bids as a function of other project variables.

Average Bid (v) is the average bid price (across vendors) for a project. There are a number of possible metrics to evaluate project value. We choose averaging vendors' bids on the project as a proxy for project value.[9] We use the natural log of this variable.

Market Maturity (M) is the overall age of the online market (in days) at the time of project posting (starting date of the auction). It is used to measure changes in market structure over time,

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$100K) are rarely transacted in this market and are sufficiently large that it is unlikely that this market is the only forum in which the project is open for bid.

9 We would prefer to use a measure of client value, such as an Initial Estimate of the project's cost. This variable, however, is available for only a small subset of projects, in the first six months of our dataset. The rank-order correlation between Initial Estimate and Average Bid, in this subsample, is 0.78 ($p<0.01$).

such as positive network effects and growth in the number of participants. We use the natural log of this variable.

Auction Length (*T*) is the duration (in days) over which the auction is open for bidding. The length of an auction determines the number of vendors that have an opportunity to see the posting and bid on the project. As the buyer lengthens the auction, more bids should be expected if bidders arrive by some sort of random process. We use the natural log of this variable.

Project Length (*P*) is the length of the project in days, as described in the buyer's RFP. Given that project value is driven both by preferences for quality and project size, we require a control for project size to isolate our hypothesized quality-preference effect. Given that the key driver of cost in IT projects is duration, we use project length as a control for project size. We use the natural log of this variable.

Feedback is the average rating of the vendors participating in an auction. Each participating vendor may have zero or more feedback instances (on a 0-to-5 scale) received from prior projects, which are likely to be a reasonable proxy for vendor quality. One approach to measuring the quality of the vendor pool is to average the feedback of participating bidders with prior feedback. As less than half of the vendors have any feedback instances, this variable is missing for many projects. As another indicator of quality, we consider as an alternative measure: the fraction of bidders that have non-zero feedback. Other variables are also considered to gauge this effect (see next section).

Sub-category (S_j) is a set of dummy variables describing how the buyer categorizes the project among five choices: Application Development, Database, Engineering & CAD, Handheld Devices and Other Software Services (used as the baseline). Different categories are likely to have a different vendor pool, thus implying different values of n and $F(q)$ in our model. We control for this exogenous variation in the vendor pool by including these dummy variables.

"Preferred" Vendor is a binary variable reflecting whether a particular vendor has elected "preferred status." This entails a process in which the vendor must pay greater membership fees, undergo a background check, and adhere to higher standards of conduct (including mandatory use of a dispute resolution service when problems arise). The online market provider sets the terms and fees of this status.

"Preferred" Project is a binary variable that reflects whether only "preferred" vendors are allowed to bid. A buyer may opt to designate a project as such, limiting participation.

4.B. Econometric Specification and Estimates

4.B.1. Project Value and Quality (Hypothesis 1)

Testing Hypothesis 1 (higher project value induces participation by lower quality vendors) is difficult in practice due to the difficulty of objectively defining and measuring quality. However, we can use a number of measures as proxies for vendor quality. The first and most common metric is the feedback rating given to the vendors by the buyers who use the online market. Although feedback ratings have limited variance (due to the high average ratings) and are missing for many vendors, the rank-order correlation between average feedback and project value is negative (r=-0.13) and significant (p<0.01), as suggested by Hypothesis 1.[10]

A second proxy for a vendor's quality is the presence of a feedback rating for that vendor. The presence of a rating suggests that the vendor has surmounted at least three tests of quality: another buyer screened him, he won a prior auction, and he completed a prior project. If we use the fraction of participating bidders with feedback as a sign of quality of the bidder pool, we also find a negative correlation (r=-0.10, p<.01). We find similar results using measures constructed from the proportion of vendors with average feedback greater than a threshold (e.g., greater than 4.75 or greater than 4.5 on average).

The comprehensive information available in this online market allows us to investigate various other measures of vendor quality and to verify the hypothesized relationship between project value and quality (See Table 2). Two useful metrics in this analysis are the number of bids submitted by a vendor in all projects, and a vendor's propensity for winning. Both of these metrics support our hypothesis. Higher valued projects induce participation by more active vendors, on average[11] (r=0.40, p<0.01) and, on average, by vendors with lower contract award rates[12] (r =-0.42, p<0.01). A third measure of potential vendor quality is tenure in the market.

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10 Throughout this sub-section, we report rank-order correlations. Rank-order correlations avoid the problems of skewed variables and of biases arising from extreme values.

11 We observe that vendors who bid the most frequently tend to provide uninformative or poorly structured bids, which we interpret as a negative signal of quality. As it is infeasible to evaluate the quality of the more than 60,000 bids in our dataset, this appears to be a reasonable proxy for bid quality.

12 These correlations represent the relationship between Average Bid and the average score for all vendors that bid on the project, similar to the correlation between Average Bid and Feedback discussed earlier.

We again find that larger projects tend to attract vendors with less time in the market (r=-0.05, p<0.01), suggesting greater possible problems with vendor opportunism due to a lack of reputational capital at risk.

INSERT TABLE 2 HERE

4.B.2. Project Value and the Number of Bidders (Hypothesis 2)

In addition to predicting that the quality of the bidder pool decreases with increasing project value, our model also suggests that the number of bids increases with increasing project value (Hypothesis 2). This hypothesis is more easily tested because the number of bids is objectively measurable and our model yields a specific relationship between number of bids and project value. To derive our estimating equation, we take the natural logarithm of both sides and rearrange equation (3) to find a structural relationship between project value and the number of bidders:[13]

$$n = 1 + \frac{\ln(v-c)}{-\ln(F(q_m))} + \frac{\ln(\frac{c_T}{q_m})}{\ln(F(q_m))} \qquad (3a)$$

We are interested in estimating n_b the number of bids submitted by n vendors. $E[n_b] = n(1 - F(q_m))$. Since $\ln(1+x) \approx x$ for small x, we have: $E[n_b] \approx -n\ln(F(q_m))$. So:

$$E[n_b] \approx \ln(v-c) + \ln\left(\frac{q_m}{F(q_m)}\right) - \ln(c_T)$$

Although q_m is a function of v, the variation in $\ln\left(\frac{q_m}{F(q_m)}\right)$ is likely to be small relative to the variation in $\ln(v)$ as long as there is a moderate number of potential bidders (thus $q_m \approx \bar{q}$ and $F(q_m) \approx 1$). For example, in Figure 2 a 5-fold increase in v leads to a less than 20% reduction in q_m. Taking the Taylor expansion of $\ln(v - c)$ around the point $-c$ and noting that c_T is constant across projects generates the structural relationship between project value and the expected number of bids:

$$E[n_b] = b_0 + b_1\ln(v_i)$$

13 Note that $F(q_m)$ is a cumulative density function, so $\ln(F(q_m))$ is negative.

and our base estimating equation (with index i referring to projects):

$$n_{b,i} = b_0 + b_1\ln(v_i) + e_i$$

To this equation we add control variables for market maturity, auction length, and project length (complexity). Our base model is thus:

$$n_{b,i} = b_0 + b_1 ln(v_i) + b_2 ln(M_i) + b_3 ln(T_i) + b_4 ln(P_i) + e_i \quad (4)$$

Column (a) of Table 3 contains the estimates of Equation (4). The results support our hypothesis that buyers' willingness to pay increases participation by vendors. If bidding were costless, the number of bids would depend only on the service required, not on the buyer's project value. The coefficient on project value is positive and significant, with a value of approximately 1.65. This coefficient translates into the increase in bidding associated with an increase in project value. A $100 project receives approximately 12 bids, on average, while a $1,000 project receives almost 16 bids, on average.

INSERT TABLE 3 HERE

Other important results from column (a) in Table 3 are that the number of bids is increasing with increases in auction length (consistent with a random arrival explanation in which more bidders arrive the longer the auction is open), and that as the market ages, more bidders participate (consistent with the presence of positive network effects). We also find that the coefficient on project length is significant, suggesting that this variable is successfully capturing at least some of the heterogeneity in project size as intended.

In the latter columns of Table 3, we consider two generalizations of our model in which bidding can vary by market segment (Application Development, Handhelds, Database, Engineering and Other). This accounts for the possibility that the exogenous parameters (e.g., n and $F(q)$) may vary by market segment. In column (b), we allow the level of bidding to vary by market segment and in column (c), we allow both the level and the responsiveness of bidding to value to vary by market segment.

Overall, while we find that bidding does vary by segment, our principal results are robust to these modifications. There is more bidding (than in the baseline category of "Other") in Application Development and Databases, while bidding is lower in the smaller categories of Engineering and Handheld Devices. These results indicate that bidding activity is consistent with project posting. More active sub-markets have a larger community and thus more bids. When we allow the value-bidding relationship to vary by market (shown in Table 3 column (c)), we find that there is a similar heterogeneity in the responsiveness of bidding to value. All sub-markets except Engineering show a positive relationship between number of bids and project value.[14] Since the Engineering sub-market is small, both in terms of number of projects and number of bidders, these results do not change our assertion that higher value projects attract more bids.

The inconsistent results for the Engineering domain may indicate that some service markets demonstrate behavior similar to commodities markets where participants self-regulate their bidding activity. If vendor qualifications for Engineering projects are easy to assess before choosing a vendor, vendors without the required competencies are unlikely to bid, even on high value projects.

5. Project Awards

The richness of our data set allows us to explore another important aspect of participation in the market, buyer participation and awards of contracts. In our model, intense bidding on high-value projects is predicated on participation by low-quality vendors. When bid evaluation is costless, buyers are indifferent to excessive bidding. However, when buyers incur a cost of evaluating bids and discerning the optimal bid, excessive bidding can impede vendor selection (Carr, 2003). Evaluation costs increase with the number of bids either from the cost of comprehensive evaluation or from the cost of incomplete evaluation and choosing an inferior vendor. These two possibilities may create a situation in which evaluation costs exceed the buyer's expected surplus from consummating trade and the buyer abstains from contracting.

Testing buyer participation also enables us to examine the most likely alternative hypothesis to our model. An alternate premise is that participants are self-regulating, with higher value projects generating participation by higher quality vendors. One possible justification is that high-quality vendors require greater compensation for their service, bidding only when buyers indicate greater willingness-to-pay. This alternate premise implies that higher value projects

[14] When regressing only Engineering projects, Average Bid has a negative coefficient (-0.227) that is not significant (p>0.5).

increase the chance of awarding the contract. These two predictions can be clearly distinguished empirically.

Returning to Figure 3, we find that the probability of contracting in the Software Development market decreases with project value. In our sample, while 38% of all RFPs culminate in contracts, this proportion is 47% for projects under $1000, but only 24% for projects over $1000.

To test this relationship formally, we use a logistic (Logit) regression of the probability of awarding a contract as a function of the average bid size. Table 4 presents these results, with and without controls for sub-markets, as discussed earlier. The coefficient on "Average Bid" is consistently around –0.25 and significant across all models. Overall, these results indicate that the pool of vendors tendering bids for higher valued projects is ***not*** of higher quality (as perceived by buyers) than those participating in lower valued projects. This result supports our original theoretical prediction that low-quality bidders opportunistically bid on high-value projects, thereby leading to high bid evaluation costs. From inspection of the interaction effects of sub-markets and project value, it appears that this result holds across the different markets with a similar propensity for not contracting (Table 4, column (c)). All interaction terms have negative and insignificant coefficients, except for Handheld Devices.[15] Because of the sparseness of data for this sub-market, it is difficult to ascertain whether this is a systematic difference.

INSERT TABLE 4 HERE

A difficulty of drawing strong conclusions from this supplementary analysis is that buyers might behave opportunistically, utilizing the online market as a way of gathering data without intending to actually enter into a contract, or possibly bypassing the market and contracting directly with their preferred vendor[16] (Weber, 1994). Because both the marginal value of better information on vendor pricing and the incentive to bypass the market are likely to increase with the size of a project, this type of opportunistic behavior would be more prevalent for large projects. This problem is of significant practical importance – opportunistic buyers create both

[15] Handheld Devices seems to behave differently, with a positive coefficient for the interaction term. When analyzed separately, the coefficient is positive (0.29) but insignificant (***p***>0.1).

[16] The online market we investigate charged a commission from vendors based on the size of the contract awarded. This offers an incentive for participants to bypass the market, avoiding these commissions.

deadweight loss and a wealth transfer out of the market, which is costly to all market participants.

Without knowing buyers' intentions or having the ability to observe their offline behavior, it is difficult to ascertain whether this type of buyer opportunism is widespread. However, we can examine whether it affects our results by examining different segments of the market where we expect these opportunistic behaviors to be less prevalent. Within our data, we can identify two segments that meet these criteria. First, we can restrict our analysis to buyers who transact through the market. Under the assumption that buyer opportunism is an inherent trait, this trait is less likely to be present in buyers that have demonstrated they will complete transactions. Also, experienced buyers might have a better understanding of bid evaluation costs, thereby making it less likely they would fail to complete a transaction due to unexpectedly high bid evaluation costs. Table 5 column (a) reports the results for the 3,002 projects from buyers with at least one completed contract event throughout our dataset. We find that the effect of project value on the probability of contracting is essentially at the same rate as across the entire population.

Alternatively, we can consider buyers who register their projects for "preferred" status, which restricts bidding to "preferred" vendors. If a buyer is using the market for information to obtain leverage over another outside supplier in negotiation, it is in their best interest to have as many bids as possible. Thus, opportunistic buyers would skew auction conditions to attract low cost and low quality suppliers. We would not expect buyers that restrict the auction to "preferred" status vendors to be entering the market opportunistically. Again, results in Table 5 column (b) show that even these buyers for the 648 projects requiring "preferred" status are more hesitant to contract for higher value projects, with a coefficient of –0.9.

INSERT TABLE 5 HERE

6. Discussion and Conclusion

Online service markets have demonstrated that, despite a variety of potential problems, it is viable to transact for services in anonymous markets. Overall, nearly 2,000 projects with an average value of $800 per signed contract were executed over the 20-month period considered. Moreover, the average price of the selected vendor was 20% lower than the average submitted bid, suggesting a substantial and measurable benefit of utilizing this market. Growth in this market attests to the market's success, as well. Our target site grew from about 100 projects posted per month for the first three months of our sample period, to about 500 projects per month 18 months later -- an annualized growth rate of nearly 200%.

Current market design and strategic behavior, however, are likely to reduce the efficiencies of this market due to excessive bidding by vendors and the attendant costs of bid evaluation. While this provides the appearance of an active market, it has negative consequences. If bid evaluation were perfect and costless, the loss from costly bidding would be due only to the direct cost of bidding. However, as shown in Carr (2003), in the presence of costly evaluation there are two additional sources of welfare loss on the buyer's side: the direct cost of bid evaluation and the social cost of buyers with potentially surplus-creating projects opting out of the market. These factors cause reduced participation in the market by both buyers and vendors ***ex-ante***. Such a market is especially likely to lose those buyers with preferences for high quality (and high cost) projects and those high-quality vendors who would serve these projects. Thus, costly bidding and evaluation, and the strategic responses to them, may limit the liquidity of these markets for larger transactions.

Our model suggests that an online market can remedy this situation by some combination of screening the quality of vendors, decreasing the cost of bid evaluation for buyers, or increasing the cost of bidding to vendors. For instance, the site could invest in additional external audits or ratings, or perhaps require offline references or certifications to augment the somewhat sparse online feedback. Technological solutions provided by the market could also speed the process of bid evaluation. Greater standardization of the RFP and bidding process could lead to partial automation, which reduces human labor. Such tools could help buyers reject large numbers of low-quality bids, score the top candidates, and focus evaluation efforts on high-quality candidates. Alternatively, the site could impose a bidding charge that discourages low-quality bidders and indiscriminate bidding. It would raise the minimal quality of participants, but the client would still have to evaluate remaining bidders.

Our analysis is principally focused on vendor participation and the types of analyses that can be performed observing bidding and transaction behavior in a non-experimental, nearly anonymous, setting. There are other interesting and important issues, both theoretical and empirical, that can be examined in these markets, including equilibrium buyer participation behavior (including the optimal disclosure of information in a RFP), bidding behavior of vendors, mechanisms that induce truthful revelation of private value, and the effectiveness of screening technologies for evaluating bids, especially feedback systems, which have proven useful in online auctions for physical goods. Carr (2003) provides one such analysis, evaluating the implications of costly bid evaluation. While theoretical analysis of these questions is possible through formal techniques similar to ours, the challenge will be to design the appropriate real experiments or identify suitable natural experiments that enable otherwise hidden factors such as private project valuation, true project structure or vendor capability to be objectively assessed apart from transaction behavior.

Our results highlight both the opportunities and the challenges that might be expected transacting services through online markets. As many types of services produce digital products and do not require large-scale production capital that drives the formation of large firms, the service industries should be even more amenable to increased outsourcing and the erosion of firm boundaries. Especially in the IT domain, technologies that promote interoperability (e.g., object-oriented techniques) and best management practices (e.g., the practice of subdividing larger projects into smaller stages (McConnell, 1996)) also favor the outsourcing of small-scale projects. However, the ability of online services to augment or displace other governance structures relies on the ability to handle larger transactions sizes. Our results suggest that the "sweet spot" for projects in this market is relatively small, in the lowest decile of typical IT projects (c.f. footnote 2), a concern that might be reduced if issues of costly bidding and bid evaluation could be more effectively addressed. However, there are also other concerns of larger projects that might arise, especially vendor opportunism, which we have not considered in our analysis.

Given the early stage of these online markets, it is difficult to make robust conclusions about how such markets might evolve when they are orders of magnitude larger than they are now. It should be noted that this market is currently small, with only about $1.5 million transacted during the study period, but is growing rapidly. Given the overall size of the IT services industry (over $100Bn in the US alone), these markets have the potential to grow by many orders of magnitude, provided that larger projects (which likely make up most of commercial IT contracting) can be transacted effectively online. Yet, clients would not want the number of bids to grow by orders of magnitude (Carr, 2003). Clearly, online markets need to consider scalability and the natural laws by which patterns of participation change as a function of market size. If these markets are managed correctly, however, they have an opportunity to dramatically change the methods of procuring services.

Appendix 1: Notation

Variable	**Description**
n	Number of vendors
$V(q,p)$	Buyer's multi-attribute utility function
Q	Quality of service received
P	Price paid for service
n_b	Realized number of bids in an auction
v	Buyer's quality valuation, measured empirically by average bid
q	Inherent quality of vendor q
P_q	Price charged by vendor q
$\underline{q}$	Lowest possible quality
$\overline{q}$	Highest possible quality
$F(q)$	Continuous c.d.f. of vendor quality
cq	Cost of providing quality service q
c_T	Cost of placing a bid
$C(q)$	Cost of providing service and placing a bid
$P_q(q,p_q,F(q),n)$	Probability of acceptance for a vendor of quality q
p_q	Expected profit for a vendor of quality q
q_m	Break-even quality level
M	Market maturity (in days)
T	Auction Length (in days)
P	Project Length (in days)
S_j	Sub-category j; j=[0..4]

Appendix 2: Proofs

Proof of Proposition 1:

The following bidding strategy of price as a function of quality, $p^*(q)$, is shown to be an equilibrium[17] which satisfies conditions (a), (b) and (c) in Proposition 1:

$$p^*(q) \quad = \quad \left\{ \begin{array}{llll} & No - bid & & q < q_m \\ & v\,q_m & & q = q_m \\ cq \quad + & \dfrac{(v-c)\int_{q_m}^{q}[F(z)]^{n-1}dz}{[F(q)]^{n-1}} & + \quad \dfrac{c_T}{[F(q)]^{n-1}} & q > q_m \end{array} \right\} \qquad \text{(A.1)}$$

where q_m is defined by: $(vq_m - cq_m)[F(q_m)]^{n-1} - c_T = 0$

We begin by showing that the surplus offered by the vendor to the buyer under this strategy is increasing in vendor quality, which guarantees that the highest quality vendor always wins the auction. Let buyer surplus be represented by: $S(q,p^*(q)) \;=\; vq \;-\; p^*(q)$, then for $q>q_m$

$$S(q,p^*(q)) \;=\; vq \;-\; cq \;-\; \frac{(v-c)\int_{q_m}^{q}[F(z)]^{n-1}dz \;+\; c_T}{[F(q)]^{n-1}} \qquad \text{(A.2)}$$

$S(q,p^*(q))$ is continuous at $q=q_m$ from the definition of q_m and for other values of q by inspection.

Taking the derivative w.r.t. q yields:

$$\frac{\partial S(q,p^*(q))}{\partial q} \;=$$

$$(v-c) \;-\; \frac{(v-c)([F(q)]^{n-1})^2 \;-\; [(v-c)\int_{q_m}^{q}[F(z)]^{n-1}dz \;+\; c_T](n-1)[F(q)]^{n-2} f(q)}{([F(q)]^{n-1})^2} \;=$$

$$+ \;\; \frac{[(v-c)\int_{q_m}^{q}[F(z)]^{n-1}dz \;+\; c_T]}{[F(q)]^{n}}(n-1)f(q) \;>\; 0$$

This observation, which commonly arises or is assumed in the auctions literature (Riley and Samuelson, 1981; Samuelson, 1985; McAfee and McMillan, 1987; and in this setting see Carr, 2003), enables a simple characterization of the probability of a vendor winning the auction. A vendor of quality q wins the auction, only if all other vendors are of lower quality. This occurs with probability $P_q(q,p_q,F(q),n) = [F(q)]^{n-1}$. The profit for a vendor of type q is therefore:

$p(q) = (p(q) - cq)P_q(q,p_q,F(q),n) - c_T$

or: $p(q) = (p(q) - cq)[F(q)]^{n-1} - c_T$

Substituting bid price from A.1 into the profit expression yields:

$$p\,(p^*(q)) = \left\{ \begin{array}{ll} 0 & q < q_m \\ 0 & q = q_m \\ (v-c)\displaystyle\int_{q_m}^{q} [F(z)]^{n-1} dz & q > q_m \end{array} \right\}$$

which is continuous in q. Continuity at q=q_m is immediate.

Taking the derivative of profit with respect to quality shows that $\frac{\partial p}{\partial q} = 0$ for $q \le q_m$ and

$\frac{\partial p\,(p^*(q))}{\partial q} = (v-c)[F(q)]^{n-1} > 0$ for $q > q_m$. Thus, under this strategy, profits are weakly monotone in quality. There exists a lowest quality level that earns non-negative profits given by the solution to $(vq_m - cq_m)[F(q_m)]^{n-1} - c_T = 0$. Profits are monotonically increasing above this threshold. Note that a vendor of quality q_m offers a price equal to the buyer's reservation value (vq_m), extracting all surplus from the buyer, if awarded the contract.

Finally, we complete the proof by showing that indeed the price strategy asserted in A.1 is a Nash equilibrium. Consider a vendor of type q who is choosing an optimal bidding strategy when all other (n-1) vendors are bidding according to $p^*(q)$ as described by A.1. Because buyer surplus is monotone and continuous in quality under strategy $p^*(q)$ for all bidding vendors, there exists a mapping between vendor quality and buyer surplus. A vendor of quality q, in choosing his best response, can choose to offer the buyer surplus equivalent to their actual quality (q) or

17 The equilibrium can be constructed following the methodology in Snir (2000).

offer surplus equivalent to any other quality (denote this alternate quality by w). For $p^*(q)$ to be an equilibrium, the optimal choice for vendor of type q, masquerading as w, is to choose $w=q$ (i.e., $\frac{\partial p\,(q,w)}{\partial w} = 0$ at $w=q$). As before, our candidate vendor wins the auction only when all the other vendors bid such that they offer less surplus. Because of the mapping from vendor quality to buyer surplus, this happens with probability $[F(w)]^{n-1}$. Therefore, the vendor faces a probability $[F(w)]^{n-1}$ of winning the contract. A vendor at or below the threshold q_m earns negative expected profit for any acceptable bid, so we can restrict our attention to $q \geq q_m$. In this context, the profit for a vendor of type q, when bidding as w, can be written as:

$$p(w,q) = vq[F(w)]^{n-1} - S(w)[F(w)]^{n-1} - cq[F(w)]^{n-1} - c_T$$

The first term is the social value from vendor q bidding as w. The second term is the buyer's expected surplus from this bid, and the third term is the vendor's expected cost. The expected profit is derived by subtracting bidding cost. Rearranging:

$$p(w,q) = (v-c)q[F(w)]^{n-1} - B(w) - c_T \tag{A.3}$$

Where $B(w) \equiv S(w)[F(w)]^{n-1}$

We need to show that:

$$\frac{\partial p\,(w,q)}{\partial w} = 0 = (v-c)q\frac{d}{dw}[F(w)]^{n-1} - B'(w) \qquad \text{at } w=q \tag{A.4}$$

Note that at $w=q$:

$$B(q) = (vq - p(q))[F(q)]^{n-1}$$

Inserting $p^*(q)$ we have

$$B(q) = (v-c)q[F(q)]^{n-1} + (v-c)\int_{q_m}^{q}[F(z)]^{n-1}dz - c_T$$

Therefore:

$$B'(q) = (v-c)[F(q)]^{n-1} + (v-c)q\frac{d}{dq}[F(q)]^{n-1} - (v-c)[F(q)]^{n-1}$$

$$B'(q) = (v-c)q\frac{d}{dq}[F(q)]^{n-1} \tag{A.5}$$

Substituting A.5 back into A.4 yields the required result.

To complete the proof we need to show that $p(w,q)$ attains a global maximum at $w = q$. From A.4 and A.5:

$$\frac{\partial p\,(w,q)}{\partial w} = (v-c)(q-w)\frac{d}{dw}[F(w)]^{n-1} = (v-c)(q-w)F'(w)[F(w)]^{n-2}$$

By assumption $v>c$, $n>1$, $F(w)>0$, $F'(w)>0$. Therefore, $sign\frac{\partial p\,(w,q)}{\partial w} = sign(q-w)$ which implies that $w<q$ the profit function is increasing, $w>q$ the profit function is decreasing, and zero only at $w=q$. Therefore the profit function attains a unique global maximum at $w=q$.

Q.E.D.

Proof of Proposition 2:

In the equilibrium described in Proposition 1, higher quality vendors offer more surplus to the buyer, and the highest quality vendor is awarded the contract. From equation (3) in subsection III.B.:

$p(q_m) = (vq_m - cq_m)[F(q_m)]^{n-1} - c_T = 0$

To show the $q_m > q_L$ we show that for the lowest quality expected profit from bidding according to $p^*(q)$ is negative, while for the highest quality, expected profit is positive. Coupled with monotonicity and continuity of $p(q_m)$ (from Proposition 1) and the Fixed-point Theorem, this assures that their exists a break-even quality $q_m \in (\underline{q}, \overline{q}]$.

For the lowest quality $F(\underline{q})=0$, $p(\underline{q}) = -c_T$. For the highest quality $F(\overline{q})=1$. When only the highest quality participates, $p(\overline{q}) = (v\overline{q} - c\overline{q}) - c_T > 0$ by assumption.

The other results arise from investigating the expected revenue for the break-even quality bidder, $(vq_m - cq_m)[F(q_m)]^{n-1}$, and the cost, c_T, of submitting a bid.

Define a given parameter vector (n^0, c^0, v^0, c_T^0) such that $p(q_m^0) = 0$.

If $n^1>n^0$ then $[F(q_m^0)]^{n_1-1} < [F(q_m^0)]^{n_0-1}$ and $p(q_m^0) < 0$

If $c^1>c^0$ then $(vq_m^0 - c^1 q_m^0) < (vq_m^0 - c^0 q_m^0)$ and $p(q_m^0) < 0$

If $v^1<v^0$ then $(v^1 q_m^0 - cq_m^0) < (v^0 q_m^0 - cq_m^0)$ and $p(q_m^0) < 0$

If $c_T^1 > c_T^0$ then $p(q_m^0) < 0$

For any of these changes (an increase in *n*, *c*, c_T or a decrease in *v*), the vendor of quality q_m^0 earns negative profit from participating. From the monotonicity of *p(q)* and $p(\bar{q})>0$, the break-even quality level increases under each of these changes.

QED

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Table 1 - Descriptive Statistics

	Variable	**Notation**	**Number of Observations**	**Mean**	**Standard Error**	**Median**
	Number of Bids	n_b	4,887	15.1	13.25	11
	Average Bid ($)	V	4,887	$2,480	6785	$594
	Market Maturity (Days)	M	4,887	400.6	157.15	435
	Auction Length (Days)	T	4,887	9.2	10.05	7
	Project Length (Days)	P	4,887	38.9	68.16	21.0
	Avg. Feedback (Scale of 0 – 5)		2,938	4.6	0.431	4.7
	Contract Awarded		4,887	0.38	0.485	0
	Winning Bid (when contracted)		1,828	$787	2861	$200
	Preferred Vendor		4,109	0.37	0.353	0.29
	Preferred Project		4,832	0.12	0.328	0
Sub-Categories	**Application Development**	S_1	4,887	0.56	0.496	1
	Database	S_2	4,887	0.21	0.405	0
	Engineering	S_3	4,887	0.029	0.169	0
	Handheld Devices	S_4	4,887	0.028	0.164	0
	Other	S_0	4,887	0.16	0.366	0

Variable	**Correlation Matrix**						
	Number of Bids	**Average Bid ($)**	**Market Maturity**	**Auction Length**	**Project Length**	**Contract Awarded**	**Feedback**
Number of Bids	1.000	0.163***	0.074***	0.270***	0.127***	-0.094***	-0.080***
Average Bid ($)	0.163***	1.000	-0.012	0.103***	0.198***	-0.144***	-0.041***
Market Maturity (Days)	0.074***	-0.012	1.000	-0.130***	0.033**	-0.035**	0.441***
Auction Length (Days)	0.270***	0.103***	-0.130***	1.000	0.247***	-0.237***	-0.100***
Project Length (Days)	0.127***	0.198***	0.033**	0.247***	1.000	-0.123***	-0.047**
Contract Awarded	-0.094***	-0.144***	-0.035**	-0.237***	-0.123***	1.000	-0.006
Feedback	-0.080***	-0.041**	0.441***	-0.100***	-0.047**	-0.006	1.000

* $p< 0.1$; ** $p<0.05$; *** $p<0.01$

Figure 2 – Vendor Profit as a function of Quality

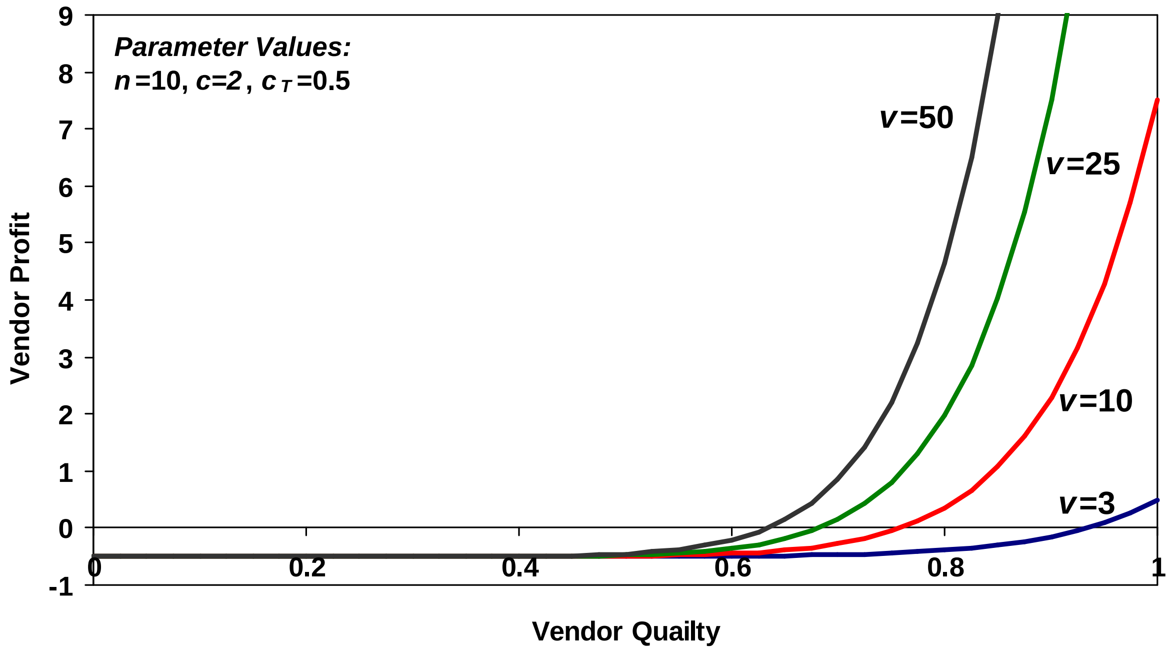

Figure 3 – Distribution of Project Values

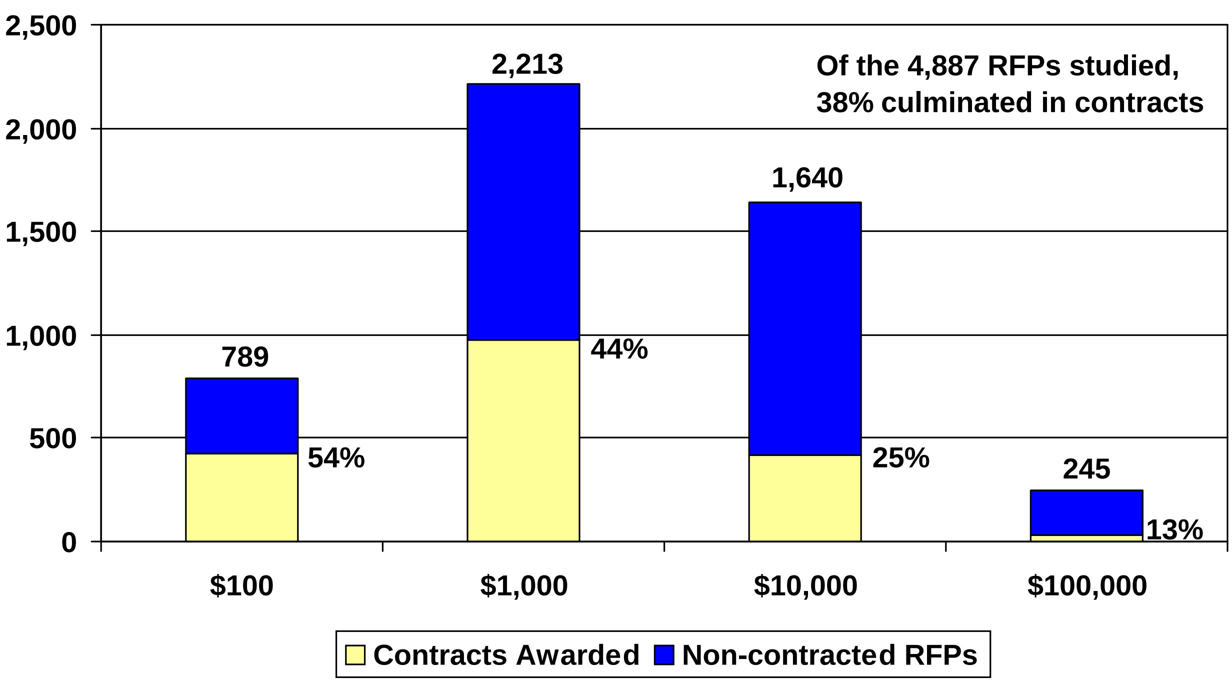

Table 2 – Correlations between Project Value (Average Bid) and Vendor Characteristics

Rank-order Correlations

Variable	Feedback	Number of Ratings	Number of Bids	Winning Propensity
Correlation	-0.132***	-0.186***	0.40***	-0.41***
N	3,471	3,739	3,739	3,739

Table 3 – Statistical Analyses

Dependent Variable - Number of Bids

	Variable	Model 1 (a)	Model 2 (b)	Model 3 (c)
	Constant	-19.83*** (1.598)	-24.03*** (1.533)	-18.71*** (1.866)
	ln(Average Bid)	1.65*** (0.117)	1.62*** (0.109)	0.71*** (0.216)
	ln(Market Maturity)	2.44*** (0.248)	2.42*** (0.233)	2.43*** (0.232)
	ln(Auction Length)	3.90*** (0.236)	4.31*** (0.220)	4.35*** (0.219)
	ln(Project Length)	0.74*** (0.224)	0.53** (0.209)	0.46** (0.208)
Sub-Categories	**Application Development**	---	3.95*** (0.441)	-2.27 (1.543)
	Database	---	11.95*** (0.518)	-0.62 (2.034)
	Engineering	---	-4.69*** (1.003)	4.73 (3.964)
	Handheld Devices	---	-2.99*** (1.036)	-8.90 (5.535)
Interaction	**Application Development*ln(Average Bid)**	---	---	1.05*** (0.245)
	Database*ln(Average Bid)	---	---	2.05*** (0.320)
	Engineering*ln(Average Bid)	---	---	-1.32** (0.590)
	Handheld Devices*ln(Average Bid)	---	---	0.990 (0.740)
	N	4,887	4,887	4,887
	R^2	0.195	0.304	0.312
	Regression F-Stat	295.85***	266.53***	184.56***
	ΔR^2		0.109***	0.08***

Standard Errors in parentheses
* $p< 0.1$; **$p<0.05$; ***$p<0.01$

Table 4 – Impact of Project Value on RFP Outcome

Dependent Variable – Probability of a contract being awarded

	Variable	**Model 1** **(a)**	**Model 2** **(b)**	**Model 3** **(c)**
	Constant	3.15*** (0.303)	2.86*** (0.312)	2.78*** (0.388)
	ln(Average Bid)	-0.25*** (0.023)	-0.26*** (0.023)	-0.25*** (0.048)
	ln(Market Maturity)	-0.15*** (0.046)	-0.13*** (0.047)	-0.13*** (0.047)
	ln(Auction Length)	-0.87*** (0.048)	-0.86*** (0.048)	-0.87*** (0.048)
	ln(Project Length)	0.14*** (0.043)	0.13*** (0.043)	0.13*** (0.043)
Sub-Categories	**Application Development**	---	0.41*** (0.091)	0.53 (0.328)
	Database	---	0.34*** (0.106)	0.77* (0.432)
	Engineering	---	-0.117 (0.224)	0.007 (0.877)
	Handheld Devices	---	0.22 (0.228)	-3.04** (1.212)
Interaction	**Application Development*ln(Average Bid)**	---	---	-0.02 (0.055)
	Database*ln(Average Bid)	---	---	-0.07 (0.071)
	Engineering*ln(Average Bid)	---	---	-0.02 (0.139)
	Handheld Devices*ln(Average Bid)	---	---	0.44*** (0.162)
	N	4,887	4,887	4,877
	AIC	5699.278	5681.586	5679.444
	-2 Log L	5689.278***	5663.586***	5653.444***

Asymptotic Standard Errors in parentheses
* $p < 0.1$; **$p<0.05$; ***$p<0.01$

Table 5 – Impact of Project Value on RFP Outcome for Certain Groups of Buyers

Dependent Variable – Probability of a contract being awarded

	Variable	Model 4 (1) Transacting Buyers (a)	Model 5 (2) "Preferred" Projects (b)
	Constant	3.05*** (0.494)	11.27 (7.758)
	ln(Average Bid)	-0.25*** (0.060)	-0.90** (0.455)
	ln(Market Maturity)	-0.12* (0.062)	-0.84 (1.146)
	ln(Auction Length)	-0.80*** (0.059)	-0.77*** (0.142)
	ln(Project Length)	0.28*** (0.058)	0.25* (0.132)
Sub-Categories	**Application Development**	0.21 (0.411)	-4.48 (3.161)
	Database	0.52 (0.572)	-3.954 (3.377)
	Engineering	-0.39 (1.189)	-0.44 (10.760)
	Handheld Devices	-3.75** (1.521)	-6.19 (3.880)
Interaction	**Application Development*ln(Average Bid)**	0.01 (0.068)	0.67 (0.466)
	Database*ln(Average Bid)	0.02 (0.093)	0.60 (0.493)
	Engineering*ln(Average Bid)	0.07 (0.188)	-0.13 (1.622)
	Handheld Devices*ln(Average Bid)	0.54*** (0.206)	0.95* (0.539)
	N	3,002	648
	AIC	3626.726	736.795
	-2 Log L	3600.726***	710.795***

Asymptotic Standard Errors in parentheses
* $p< 0.1$; **$p<0.05$; ***$p<0.01$

(1) Subset of those buyers that have at least one transaction in the market
(2) Subset of projects where participation was limited to "Preferred" vendors