Market Design for Procurement: Empirical and theoretical investigation of buyer–determined multi–attribute mechanisms

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PRELIMINARY DRAFT. PLEASE DO NOT QUOTE WITHOUT PERMISSION FROM THE AUTHORS
June 2005

Abstract
Reverse auctions are fast becoming the standard for many procurement activities. In the past, the majority of such auctions have been price–based, but recently multi–attribute procurement auctions have started to gain momentum. In multi–attribute auctions bidders can specify attributes other than price as part of their bid. The buyer uses a scoring function to compare bids, and the bid with the highest score wins. We investigate two mechanisms commonly used by FreeMarkets, a major provider of reverse auction services, in a setting in which buyer's welfare is affected by non–price attributes. Under both mechanisms, bidders bid based on price, but in the "buyer determined" mechanism the buyer is free to select the bid that maximizes her surplus, while in the "price bid" mechanism, the buyer commits to awarding the contract to the low price bidder. We find, both in theory and in the laboratory, that the "buyer determined" mechanism increases the buyer's welfare only as long as enough bidders compete in the auction. If the number of bidders is small, the buyer is better off with the "price bid" mechanism.

JEL Classification Numbers: C72, D83, D44, C91
Keywords: Auction Theory, Multi–Attribute Auctions, Experimental Economics

This is a preliminary draft. Do not circulate.
Engelbrecht-Wiggans and Katok gratefully acknowledge the support of the National Science Foundation. Katok gratefully acknowledges the support from the Supply Chain Research Center and the Smeal College of Business through the Summer Grants Research program.

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1. Introduction

One of the most significant developments in procurement in recent years is the growing trend of leveraging Internet-enabled technologies to improve the strategic procurement process. Since product design and sourcing jointly determine approximately 80% of a product's cost (*C*hen-Ritzo et al. 2005) it is not surprising that major corporations such as IBM, Cisco and Hewlett-Packard invest substantial resources in improving procurement processes (Baljko 2002). Revenues from e-Sourcing activities are projected to increase to $3.13 billion by 2005—a growth of close to 400% from the 2001 level of $820 million[1].

e-Sourcing refers to a variety of procurement-related Internet-enabled activities, and includes various ways of facilitation competitive and collaborative interactions among buyers and suppliers, such as requests for information, quotes and proposals (RFx), on-line negotiations, and reverse auctions. The use of reverse auctions often saves buyers considerable amounts of money by lowering prices. For example, on its website, Ariba, Inc.'s customers routinely report average savings attributed to sourcing events in the 15% to 20% range (Ariba.com, 2005). Examples of companies that report successful use of reverse auctions include General Electric (Kwasnica and Thomas 2002), Mars (Hohner et al. 2003), Owens Corning (Moozakis 2001) major retail chains such as Wal-Mart (Sheffi 2004), and the list continues.

Reverse auctions are not without their critics (some quite vehement), partly because buyers are not always able to fully realize the negotiated savings due to ambiguity inherent in the process of purchasing complex products (Aberdeen 2002); partly due to the detrimental effect reverse auctions sometimes have on long-term buyer/supplier relationships (Emiliani and Stec 2001); and partly because suppliers often feel that by focusing on price, reverse auctions prevent them from adequately informing buyers about the non-price attributes of their products and cause their products to become "commoditized" (Jap 2002).

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[1] The Aberdeen Group is an independent research analyst firm that specializes in analyzing trends in the use of IT, and the figures we cite are reported in Aberdeen Group (2002).

While extremely effective for price discovery in settings with homogeneous products, standard auctions may be less effective in settings in which non-price attributes contribute to the buyer's welfare in substantial ways. It is this multi-attribute setting that is the focus of our paper.

Options for dealing with multiple attributes fall into three categories: RFx, reverse auctions, and multi-attribute auctions. The class of mechanisms common in practice and referred to as RFx, includes Request for Information (RFI), Request for Proposals (RFP) and Request for Quotes (RF*Q*) . The main difference between RFI and RFP/*Q* is that with an FRI a buyer does not commit to selecting any supplier, but simply requests information for the purpose of evaluating the possibility of dealing with a supplier, thus an RFI is a completely non-binding mechanism. In the RF*Q* process the buyer develops a detailed set of specifications, suppliers submit quotes that must meet those specifications, and the buyer commits to awarding the contract to the lowest cost supplier. In contrast, the RFP process involves evaluating proposals along technical and cost dimensions, and awarding the contract to the supplier who achieves the best overall score.

The reverse auctions, as they are currently being used in practice, can be viewed as structured versions of the RF*Q* and RFP mechanisms. In standard *binding* reverse auctions, that we will call *price-bid* (PB) mechanisms, the buyer starts with preparing a set of detailed specifications as in an RFQ, but suppliers respond through a live bidding event. All the bidding is done in terms of price only, and at the end of the auction, just as in the RF*Q* process, the buyer commits to awarding the contract to the lowest bidder, provided that bidder can meet the specifications.

Another reverse auction mechanism, commonly offered by FreeMarkets (now part of Ariba) as well as used by such companies as Wyeth and DuPont is the *non-binding*, or *buyer-determined* (BD) mechanism[2]. This mechanism is, essentially, a structured version of an RFP: suppliers respond through a live auction even, and bid on price, but the buyer does not commit to awarding the contract to the lowest bidder, but instead reserves the right *to* select the winner based on a scoring rule that combines cost with a set of technical parameters.

[2] Anderson and Frohlich (2001, p. 60) report that "clients do not <u>normally</u> make award decisions on bid day. In the days and weeks that follow the bidding event, buyers examine bid results, review supplier information (such as supplier capability, quality certifications, and manufacturing processes), and sometimes conduct a buyer audit before making a final decision. The client does not have to select the lowest bidder ." Jap (2002, p. 510) reports that "the vast majority of [FreeMarkets procurement] auctions used in the marketplace today do not determine a winner… and the buyer may reserve the right to select a winner on any basis." Accordingly, the dynami*C* auction data displayed in Anderson and Frohlich (2001) and Jap (2002) are for BD mechanisms.

Full blown *multi-attribute* auctions allow bidders to place bids on multiple dimensions--not just price. Such formats are used in auctions for electricity reserve supply (Bushnell and Oren, 1994; Wilson, 2002), auctions for highway construction works in the U.S. (Herbsman et al., 1995), and auctions for Department of Defense Contracts (Fox, 1974; Che, 1993). In theory, such formats are likely to offer the most socially efficient mechanism for dealing with multi-attribute products, but in practice such auction formats are rarely implemented. One can speculate that the reluctance to adopt such auctions has to do with the fact that some critical attributes (brand equity, quality, service, relationship, trust, corporate culture) are not easily quantifiable.

Che (1993) and Branco (1997) study auctions with two dimensions (price and quality) in which bidders have private information over their types. In such auctions, a change of variables establishes an analogy between scoring auctions and IPV auctions, allowing for the transfer of known IPV properties including the useful revenue equivalence theorem. Asker and Cantillon (2004) extend these results to multiple quality dimensions, analyze dynamic and sealed-bid versions of the multi-attribute auction and show that in a variety of settings such auctions dominate PB auctions as well as several other auction mechanisms. Multi-attribute auction mechanisms are also beginning to be tested in the experimental laboratory. Bichler (2000) was the first laboratory study of this nature. In this study the bidding took place across two dimensions in the context of OTC financial derivatives, with human participants in both, buyer and seller roles. The study confirmed that a multi-dimensional auction offers gains over a single dimensional auction. Chen-Ritzo at al. (2005) report on a study in which the bidding took place over three dimensions (price, quality and delivery time). The results were largely consistent with Bichler (2000) in that the multi-attribute auction increased efficiency and buyer's welfare, especially when the experiment was conducted with experienced bidders. We will return to the issue of bidder experience later, when we describe our own study, but do note that the Chen-Ritzo et al. (2005) results are indicative of the fact that the issue of bidder experience may be critical when studying complex mechanisms in the laboratory.

Two issues regarding what may be impeding the use of multi-dimensional auctions in practice are worth noting at this point. First, in practice, bidding across multiple dimensions and evaluating bids across multiple dimensions is complex. Understanding trade-offs between cost and non-monetary attributes well enough to correctly use these tradeoffs in an auction is difficult, and the level of difficulty increases with the number of dimensions. In a dynamic version of the auction, the buyer should provide feedback to bidders about these tradeoffs, and do so more or less in real time. The Chen-Ritzo et al. (2005) experiment is clever and innovative in that it uses a mechanism that provides bidders with tradeoffs between price, quality and lead-time using the same type of feedback as the RAD mechanism for combinatorial auctions (Kwasnica at al. 2005). Experienced bidders are able to process this information across three dimensions and use it to bid effectively, but the extent of the ability of bidders to process such information across more dimensions is likely application-specific.

The second issue that may be impeding the use of multi-attribute auctions in practice is that when the product is complex, buyers may not be able to construct a scoring rule without first seeing offers. In other words, a buyer may be able to compare two offers and determine which one is better, but not able to say, a priori, what the scoring rule was that would ultimately lead to this conclusion. In this case, a buyer may not be able to provide accurate feedback to bidders during the auction. Ultimately the two issues we raised above are empirical in nature. It may well be that in some cases the tradeoffs are natural and transparent, and multi-attribute auctions are feasible. It may also be that there are other settings in which the problem is so complex that bidding on multiple dimensions is not practical. Surely the area of multi-attribute auctions offers many rich opportunities for further research, both theoretical and experimental.

Mechanisms we commonly observe, however, (RFx and reverse auctions) involve primarily bidding on price, with the non-monetary attributes treated as if they were exogenous. To be sure, sometimes non-monetary attributes are exogenous or close to being so (for example, geographical location, reputation and the previous relationships, brand name, access to specific technical expertise or production processes) and thus cannot be changed by the bidder in the short run. Sometimes non-monetary attributes can be changed at a cost, but the number of potential options is small. For example, lead-time can be reduced by using alternative distribution channels; reliability can be improved by using more expensive materials or quality control processes. In these situations a bidder could respond to an RFP, for example, by offering two delivery options (slow and cheap or fast and expensive) and the buyer could select the higher value option. So in fact treating non-monetary attributes as if they were exogenous, might be appropriate for many realistic applications.

The theoretical results of Asker and Cantillon (2004) and Chen-Ritzo et al. (2005) rely on the non-monetary attributes being costly and endogenously determined by sellers. Essentially, the intuition is that in the price-based auction, since non-monetary attributes are not rewarded, sellers will provide the minimum possible levels. However, we show that when sellers' non-monetary attributes are fixed the buyer may be able to obtain higher quality at reduced price with a price-based mechanism, and, as we will show, this happens when the number of bidders is small.

Some theoretical research is aimed at identifying the optimal mechanism in environments with exogenously differentiated sellers is worth noting. In Manelli and Vincent (1995), sellers are privately informed about their qualities. In Rezende (2004), buyers are privately informed about their preferences over sellers. However, these papers are limited to price-based mechanisms and do not seek to analyze buyer-determined mechanisms. Manelli and Vincent (1995) consider sequential offers as an alternative to auctions in their setting. Rezende (2004) offers a bias-adjustment, whereby the buyer announces a bias-adjustment in favor of preferred sellers, after which sellers can compete on price without the need to consider qualities[3]. In other words, sellers always end up competing on price. Shachat and Swarthout (2003) compare a BD-mechanism[4] to a new mechanism they propose called the reverse auction with bidding credits and find that, contrary to theoretical analysis, the reverse auction with bidding credits is more efficient in the laboratory than the BD mechanism. They also report that inexperienced bidders perform poorly in the BD mechanism.

The goal of our research is to better understand procurement mechanisms used in practice today, both theoretically and empirically. In our baseline model we study a setting in which suppliers have exogenous non-monetary attributes and bid on price. We compare a stylized version of the RF*Q* (that we call the PB mechanism)—a sealed-bid reverse auction in which the buyer commits to award the contract to the supplier who placed the lowest bid—to a stylized version of the RFP (that we call the BD mechanism)—a sealed-bid reverse auction in which the

[3] Rezende (2004) also considers a no-commitment environment, where the buyer cannot commit to select the winner of the auction. That environment too reduces to a price-based environment since the buyer finds it optimal to reveal its private preferences to all sellers.

[4] Shachat and Swarthout (2003) call this mechanism RFQ, although the buyer awards the contract to the highest value as opposed to the lower cost bidder, and in that the mechanism is closer to the RFP. In practice, however, the lines between the RFx mechanisms are blurred.

buyer is free to award the contract to any supplier. The contribution of our paper is the following three findings:

1. We show theoretically that contrary to intuition, the BD mechanism is better for the buyer only when there are enough competing bidders. When the number of bidders is small, the PB mechanism results in higher buyer welfare in a wide variety of setting.
2. We test the theory in the laboratory and find that the actual behavior is close, on average, to theoretical benchmarks, and specifically, when the number of bidders is small, we find that a PB mechanism results in higher buyer welfare, but with more bidders, the BD mechanism dominates.
3. Bidder experience matters, especially for the BD mechanism. Experienced bidders bid much more effectively than naïve bidders.

2. Theory and Hypotheses

In this section we present theoretical results about the PB and BD mechanisms. In our setting, all non-monetary attributes are summarized through a measure we refer to as the *quality*. We assume that sellers do not make trade-offs between the quality and the price, and thus we treat the seller quality as fixed. Since sellers are unable to lower quality in the price-only auction, the buyer may get high quality at bargain prices by increasing price competition. We show that in a sealed-bid environment, the BD mechanism has a unique efficient equilibrium. At this equilibrium, the BD mechanism yields higher expected buyer's surplus than the PB mechanism under various distributions of cost and quality as long as the number of sellers (*N*) is high enough. However, when *N* is low, the price-based sealed-bid mechanism can produce the higher expected buyer's surplus.

In our basic setting, N ($N \geq 2$) sellers, or "bidders," compete to provide one unit to a buyer. Bidder *i* has a privately-known cost C_i of providing the unit. The buyer's value for a unit depends on which seller provides the unit. We refer to this as a seller specific *quality*, Q_i. The quality Q_i is known to both bidder *i* and to the buyer (but not to the rest of the bidders), and neither can affect this quality. We say that the outcome is efficient if the unit is supplied by the seller with the highest $V_i \equiv Q_i - C_i$. Assume that the Q_i's and the C_i's (and, therefore, also the V_i's) are independent across *i*; however, we do not assume that Q_i is independent of C_i. (For ease of exposition, also assume that the V_i's, the Q_i's, and the C_i's have density functions.) Also assume that the distributions of both *C* and *Q* have positive variance, where *C* and *Q* denote a generic C_i and Q_i.

The first-price buyer-determined (FPBD) mechanism may be viewed in two ways. In one version, sellers offer prices. Let $B(C_i, Q_i)$ denote the price offer of seller *i*. The buyer selects the seller *i* with the highest score $S(C_i, Q_i) \equiv Q_i - B(C_i, Q_i)$ and pays that winner an amount $B(C_i, Q_i) = Q_i - S(C_i, Q_i)$. Alternatively, it will often be convenient for us to think in terms of sellers bidding scores directly. Specifically, let $S(C_i, Q_i)$ denote the score offered by bidder *i*'s bid. The buyer again selects the seller with the highest score and pays that winner an amount $Q_i - S(C_i, Q_i)$. Clearly, looking at the problem in terms of bids $B(C_i, Q_i)$ is equivalent mathematically to looking at it in terms of scores $S(C_i, Q_i)$.

We can also define a corresponding second-price buyer-determined (SPBD) mechanism. Let j^* denote the seller with the highest losing score $S(C_{j^*}, Q_{j^*})$. As before, sellers may submit either price offers or scores and the highest score wins. Now, however, the winner, bidder *i*, is paid an amount equal to the $Q_i - S(C_{j^*}, Q_{j^*})$. Again, mathematically, it clearly does not matter whether bidders make price offers or bid scores.

Proposition 1:

A) Each seller *i* offering a price of $B_{BD}(C_i, Q_i) = C_i + \dfrac{\int_{z \le Q_i - C_i} F(z)dz}{F(Q_i - C_i)}$ or, equivalently, each bidder *i* bidding a score of $S_{BD}(C_i, Q_i) = V_i - \dfrac{\int_{z \le V_i} F(z)dz}{F(V_i)} = (Q_i - C_i) - \dfrac{\int_{z \le Q_i - C_i} F(z)dz}{F(Q_i - C_i)}$ gives a symmetric efficient equilibrium to the FPBD mechanism and this is the unique symmetric efficient equilibrium, where *F* is the cumulative probability distribution of the largest of the *N*-1 other sellers' V_j's.

B) For each seller *i*, offering a price of C_i (or, equivalently, bidding a score of $Q_i - C_i$) is a dominant strategy in the SPBD mechanism. Each seller *i* offering a price of C_i (or, equivalently, bidding a score of $Q_i - C_i$) gives an efficient equilibrium.

C) At the equilibria described above, the FPBD and the SPBD mechanisms result in the same expected cost (and, therefore, also the same expected surplus) to the buyer.

Proof: See the appendix for all proofs.

Just as Vickery (1961) proposed the SBSP auction as a model of the oral auction and showed that it generated the same expected price at equilibrium as the SBFP auction, we can view the SPBD mechanism as a model of the FreeMarket dynamic non-binding auction. Specifically, what distinguishes the FreeMarket mechanism from the SPBD mechanism is that bidders may adjust their bids based on earlier bids by others. Therefore, barring such more sophisticated bidding, the FreeMarket mechanism generates the same expected cost as the SPBD and FPBD mechanisms.

The price-based (PB) mechanism is simply a reverse auction. The first-price price-based (FPPB) mechanism has sellers submitting price offers, the lowest offer wins, and the buyer pays the winner an amount equal to the winning offer; the second-price price-based (SPPB) mechanism is similar except that the buyer pays an amount equal to the lowest losing offer.

Proposition 2:

A) Each seller *i* offering a price of $B_{PB}(C_i, Q_i) = C_i + \frac{\int_{z \geq C_i} (1 - F_C(z))dz}{1 - F_C(C_i)}$ gives a symmetric efficient equilibrium to the FPPB mechanism and this is the unique symmetric efficient equilibrium, where F_C is the cumulative probability distribution of the largest of the N-1 other sellers' C_j's.

B) For each seller *i*, offering a price of C_i is a dominant strategy in the SPPB mechanism. Each seller *i* offering a price of C_i gives an efficient equilibrium.

C) At the equilibria described above, the FPPB and the SPPB mechanisms result in the same expected cost (and, therefore, also the same expected surplus) to the buyer.

We now turn to the question of which mechanism yields the higher expected surplus to the buyer. Intuitively, BD dominates PD for large enough N. Specifically, as N goes to infinity, the bidders' price offers converge to their actual costs in both mechanisms. And also intuitively, if price offers are close enough to costs in both mechanisms, then the buyer does better by considering the sellers' qualities when choosing a winner.

Formalizing this intuitive result requires some technical assumptions and machinery. Specifically, let $\mathbf{\Omega}$ denote the support of the random vector (C,Q). Assume that $\mathbf{\Omega}$ is a compact (i.e., closed and bounded) set. Let $\boldsymbol{C}$ denote the subset of $\mathbf{\Omega}$ where C is minimized, and let C^* denote the minimizing value. Similarly, let $\boldsymbol{Q}$ denote the subset of $\mathbf{\Omega}$ where Q-C is maximized; let $(Q\text{-}C)^*$ denote the maximizing value. Since $\mathbf{\Omega}$ is a compact set, $\boldsymbol{C}$ and $\boldsymbol{Q}$ will be non-empty (closed) sets. (Note that the intersection of $\boldsymbol{C}$ and $\boldsymbol{Q}$ contains at most one point.) Assume that the conditional expectation $\mathrm{E}[(Q\text{-}C)|C]$ of Q-C conditional on C varies continuously in C as C approaches C^*. For example, if Q and C are independent, then $\mathrm{E}[(Q\text{-}C)|C] = \mathrm{E}[Q] - \mathrm{C}$. Alternatively, an example that we will consider later, if $Q = \alpha + \beta C + \gamma X$ where X and C are independent, then $\mathrm{E}[(Q\text{-}C)|C] = \alpha + (\beta\text{-}1)\, C + \gamma \mathrm{E}[X]$. In either case, $\mathrm{E}[(Q\text{-}C)|C]$ is continuous in C for all C.

Proposition 3:

A) If $\boldsymbol{C}$ is not a subset of $\boldsymbol{Q}$, then for large enough N, the BD mechanism generates a strictly greater expected buyer's surplus than does the PB mechanism.

B) If $\boldsymbol{C}$ is a subset of $\boldsymbol{Q}$, then the BD and PD mechanisms will yield the same expected buyer's surplus in the limit as N goes to infinity.

The results depend on $\boldsymbol{C}$ not being a subset of $\boldsymbol{Q}$. If Q and C are independent, then $\boldsymbol{C}$ is not a subset of $\boldsymbol{Q}$. Alternatively, consider the case of $Q = \alpha + \beta C + \gamma X$ where X and C are independent. If $\beta \geq 1$ or $\gamma \neq 0$ (and X is a not constant), then is $\boldsymbol{C}$ is also not a subset of $\boldsymbol{Q}$. Since $\boldsymbol{C}$ is not a subset of $\boldsymbol{Q}$ in these two examples, the BD mechanism yields a greater expected buyer's surplus than does the PB mechanism for sufficiently large N. However, if $\gamma = 0$ and $\beta <$

1, then not only is $\boldsymbol{C}$ a subset of $\boldsymbol{Q}$, but the BD and PB mechanisms always give the same result—the same winner, the same payment, the same buyer's surplus—for every N. Note that when $\gamma = 0$ then $\mathrm{Cor}(C,Q) = -1$ if $\beta < 0$, and $\mathrm{Cor}(C,Q) = 1$ if $0 < \beta < 1$; no amount of correlation between C and Q is sufficient to make one mechanism yield a higher expected buyer's surplus than the other. [5]

We next examine the case of a small number of bidders. In the first-price mechanism, the price bids will now exceed the sellers' costs, and they will exceed the costs by different amounts in the two mechanisms. Therefore, it is possible that the PB mechanism dominates the BD mechanism for a sufficiently small number of bidders.

In comparing the expected surplus between the two mechanisms for small N, we will compare the expected value of the second largest or second smallest sample to the mean. In the case of symmetric distributions, the expected value of the median is the mean. More generally, define $W_{(i)}$ as the i-th largest of N independent samples of some random variable W, and define N_W^* as the smallest N ($N \geq 2$) such that $\mathrm{E}[W_{(2)}] \geq \mathrm{E}[W]$. Since E[smallest W] < $\mathrm{E}[W]$, $N_W^* \neq 2$, and therefore, $N_W^* \geq 3$. If the distribution of W is symmetric or skewed such that E[median] > $\mathrm{E}[W]$, then $N_X^* = 3$. The following proposition establishes what happens for small N when the Q_i are independent of the C_i:

Proposition 4:

A) If C_i and Q_i are independent, then the PB mechanism yields a greater expected buyer's surplus than does the BD mechanism when $N = 2$.

B) If C_i and Q_i are independent and each has a symmetric distribution, then the BD and PB mechanisms yield the same expected buyer's surplus when $N = 3$.

C) If C_i and Q_i are independent and each has a symmetric distribution, then the BD mechanism yields a greater expected buyer's surplus than does the PB mechanism when $N > 3$.

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[5] There are also many other examples in which $\boldsymbol{C}$ is a subset of $\boldsymbol{Q}$. For example, imagine that (C,Q) has some smooth distribution over the triangle that has corners at (0,2), (1,0) and (2,0). In this case $\boldsymbol{C} = \boldsymbol{Q} = \{(0,2)\}$, and the two mechanisms will generate the same expected buyer's surplus in the limit as N goes to infinity (but not necessarily for all N as happened in the previous example).

D) If C_i and Q_i are independent, then the BD mechanism yields a greater expected buyer's surplus than does the PB mechanism when $N > \max\{N^*_{Q-C}, N^*_C\}$.

In practice, C and Q may well be correlated because firms with higher Qs (for example, higher product reliability or established reputation for customer service) may also tend to incur higher costs. So we now consider the case of $Q = \alpha + C + \gamma X$ with C and X independent. Here the correlation ($Cor(C,Q)$) may be varied by changing γ. Specifically, $\mathrm{Cor}(C,Q)$ goes from zero up to one and back down to zero as γ goes from minus infinity to zero to plus infinity. The following Proposition establishes that, and how, the ranking of the mechanisms varies with γ.

Proposition 5: Assume that $Q = \alpha + C + \gamma X$ with C and X independent.

A) If $\gamma \geq 0$ ($\gamma \leq 0$), and $N < N^*_X$ ($N < N^*_{-X}$) then the PB mechanism yields a higher expected buyer's surplus than does the BD mechanism when γ is large enough (negative enough). However, if γ is close enough to zero, then the BD mechanism yields a higher expected buyer's surplus than does the PB mechanism

B) If $N = 2$, then the PB mechanism yields a higher expected buyer's surplus than does the BD mechanism when γ is large enough or negative enough. However, if γ is close enough to zero, then the BD mechanism yields a higher expected buyer's surplus than does the PB mechanism

C) If $\gamma \geq 0$ ($\gamma \leq 0$), and $N \geq N^*_X$ ($N \geq N^*_{-X}$) then the BD mechanism yields a higher expected buyer's surplus than does the PB for all $\gamma \geq 0$ ($\gamma \leq 0$).

Intuitively, the more positively correlated C and Q are, the more the BD mechanism gains in strength relative to the PB mechanism. The Proposition 5 seems to support this intuition; for $N = 2$, the BD mechanism yields a greater expected buyer's surplus than does the PB mechanism only when γ is close enough to zero, or, equivalently, only if the correlation is close enough to one. However, for $N > 2$, the BD mechanism always yields a greater expected buyer's surplus than does the PB mechanism.

Before going on, note the important practical implication of Propositions 4 and 5. For $N = 2$, the PB mechanism may yield a greater expected buyer's surplus than does the BD mechanism. For big enough N, the BD often generates the greater expected buyer's surplus. So, a real world buyer's choice between these two mechanisms may well vary with the number of sellers.

We now consider a specific parameterization that we will use in our laboratory experiment. Consider the case in which $C_i \sim$ Uniform(0,100), $X \sim$ Uniform(0,1) and $\alpha = 0$. Proposition 5 implies that the PB mechanism yields a higher expected buyer's surplus than does the BD mechanism when γ is far enough from zero, but when γ is close enough to zero, the BD mechanism yields a higher expected buyer's surplus than does the PB mechanism. The following proposition establishes the critical value of γ at which the mechanisms' ranking changes:

Proposition 6 (Laboratory Example): If each $C_i \sim$ Uniform(0,100), $X_i \sim$ Uniform(0,1) and each $Q_i = C_i + \gamma X_i$ with C_i and X_i independent, then the PB mechanism yields a higher expected buyer's surplus than does the BD mechanism if and only if $N = 2$ and $\gamma > 200$.

Hereafter, we focus on this particular case. The following Corollary presents explicit expressions for the equilibrium bids and a bidder's expected probability of winning in each mechanism:

Corollary to Propositions 1 and 2: If each $C_i \sim$ Uniform(0,100) $X_i \sim$ Uniform(0,1) and each $Q_i = C_i + \gamma X_i$ with C_i and X_i independent (and $\gamma \neq 0$), then:

A) The equilibrium price offer in the BD mechanism is $B_{BD}(C_i, Q_i) = C_i + (Q_i - C_i)/N$.

B) The equilibrium bid score in the BD mechanism is $S_{BD}(C_i, Q_i) = (Q_i - C_i)(N-1)/N$.

C) The probability that a bidder who offers a price of B and has a quality Q wins when the other bidders make equilibrium price offers in the FPBD mechanism is

$$Pr\text{-}win(B,Q)_{BD} = \left[\frac{N}{N-1} \frac{(Q-B)}{\gamma} \right]^{N-1}.$$

D) The equilibrium bid in the PB mechanism is $B_{PB}(C_i, Q_i) = (100/N) + (C_i(N-1)/N)$.

E) The probability a bidder who bids B wins when the other bidders make equilibrium bids in the FPPB mechanism is

$$Pr\text{-}win(B)_{PB} = \left[1 - \frac{N}{N-1}\frac{(B-100/N)}{100}\right]^{N-1}.$$

We now consider specific hypotheses for the setting in which $\gamma = 300$, and $N = 2$ or 4. The reason we focus on these parameters is that when $\gamma > 200$, the theory predicts that the BD mechanism yields a greater expected buyer's surplus than the PB mechanism does when $N = 4$ but that the PB mechanism yields the higher expected buyer's surplus when $N = 2$. We wish to test this prediction which is very consequential for buyers facing a choice of which mechanism to use.

Hypothesis 1: When γ=300 and N=2, average buyer's surplus in the BD mechanism will be smaller than the average buyer's surplus in the PB mechanism. The expected buyer's surplus is 100 from BD and 116.67 from PB.

Hypothesis 2: The above relationship will reverse when γ=300 and N=4. The expected buyer's surplus is 180 from BD and 130 from PB.

We also wish to examine the effect of experience on the buyer's surplus. The mechanisms considered in this paper are procurement auctions which typically involve professional buyers and sellers. Past experimental research (Chen-Ritzo et al. 2005 is particularly relevant since it is done in procurement auctions) has shown that experience reduces bidder mistakes and increases bidder welfare[6]. We expect to find a similar pattern.

Hypothesis 3: Bidder experience will lead to lower average buyer's surplus under both mechanisms.

However, we expect even experienced bidders to underbid, consistent with past experimental research.

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[6] Kagel, Harstad and Levin (1987) report that experience does not diminish overbidding in second price auctions with affiliated values. More recently, however, Garratt, Walker and Wodders (2004) showed that with experienced eBay bidders, there is no significant overbidding. Other market anomalies are also reduced by bidder experience. For example, Kagel and Richard (2001) show that the winner's curse is lower with experienced bidders,

Hypothesis 4: Human bidders underbid, on average, relative to theoretical predictions for risk–neutral bidders.

Finally, we conjecture that human bidders are skeptical of other humans' ability to play equilibrium strategies.

Hypothesis 5: Human bidders do not expect other human bidders to play in equilibrium, so we expect the underbidding to be worse against human rivals (even experienced ones) than against robots programmed to bid according to the RNNE.

3. Experiments

The ten experimental conditions described here use the first-price sealed-bid mechanism. The characteristics of each of the conditions are shown in the table below.

Auction Format	Experience level	# of bidders	Opponents	Number of sessions	# of subjects
Price Based	Inexperienced	4	Human	2	16
Buyer– determined	Inexperienced	4	Human	2	16
Price Based	Experienced	4	Human	2	16
Buyer– determined	Experienced	4	Human	2	16
Price Based	Experienced	2	Human	2	16
Buyer– determined	Experienced	2	Human	2	16
Price Based	Inexperienced	4	Robot	2	31
Buyer– determined	Inexperienced	4	Robot	2	38
Price Based	Inexperienced	2	Robot	2	25
Buyer– determined	Inexperienced	2	Robot	2	37

Table 1 summary of experimental design

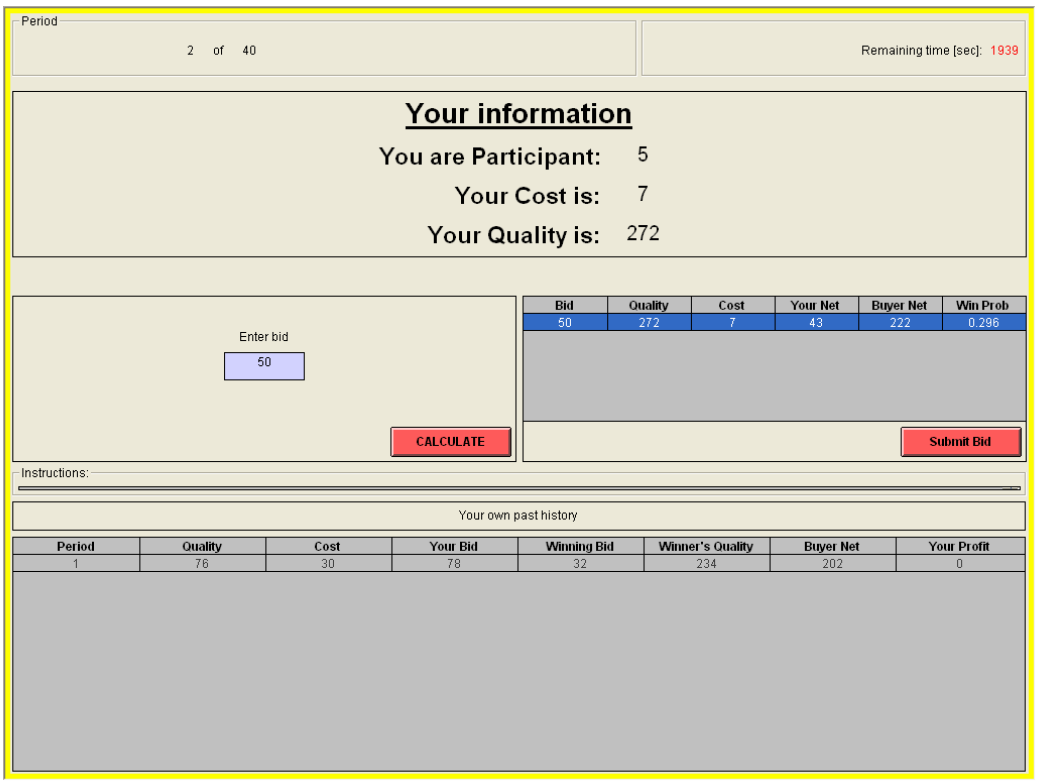
There are four web–based human vs. robot treatments and six laboratory all–human bidder treatments.

3.1 The laboratory experiments

All laboratory sessions included eight human subjects in the role of sellers and one automated buyer. When N=4, the sellers are divided into two groups. When N=2, the sellers are divided into four groups. There are 40 periods and the bidders are randomly reshuffled each period. The quality and cost for each seller is randomly drawn each period; $C_i \sim$ Uniform(0,100),

$X_i \sim$ Uniform(0,1) and each $Q_i = C_i + 300X_i$ with C_i and X_i independent. Thus, cost and quality are positively correlated.

The human bidder treatments use the zTree (Fischbacher 1999) interface shown in figure 1 and the information revealed during and following each period is the same for the BD and PB conditions. The sole difference between the PB and BD conditions is in how the winner is determined. That is, in the PB condition, the lowest price bidder wins, whereas in the BD condition, the highest score (quality minus price) bidder wins. Note, however, that in both conditions bidders submit a price (not a score) bid.



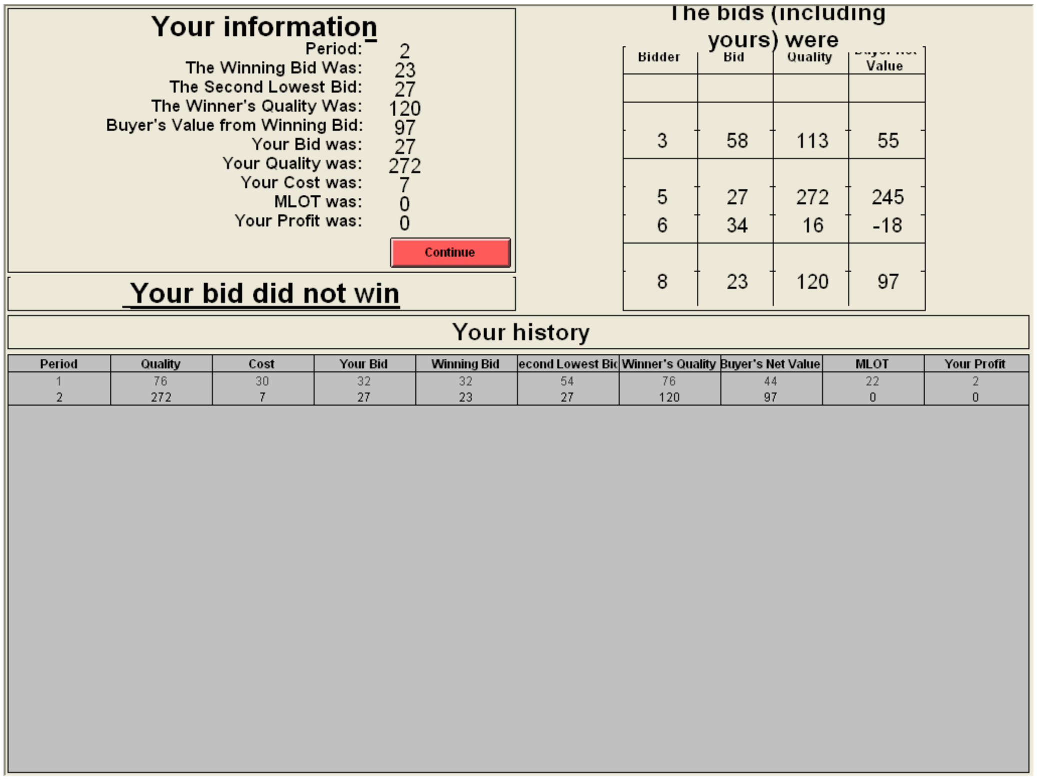


Figure 1. A screenshot of the experimental interface

During each period, prior to submitting their bids, participants are shown (using the computer interface) the profit to them if they win and the net surplus to the buyer if their bid wins. Participants are also asked for a final confirmation before their bid is finalized. Following each period, subjects learn the bids and qualities of the other bidders they were matched against and the winner in that period's auction. Participants have a history screen available to them at all times that shows all past winning bids and the quality and buyer surplus associated with them.

In the laboratory sessions with experienced subjects, subjects were asked to come back following their participation in one inexperienced web session (described in the next sub-section). The majority (approximately 90%), of the subjects were asked to come back. The few subjects who were not asked to come back were ones who performed extremely poorly in the web experiments and did not show any improvement over time. For example, there was one person who lost money in the web experiment by always bidding above cost—this person was not asked to come back[7]. The experienced laboratory subjects and inexperienced web subjects

[7] We wish to remind the reader that the cost was known, and the profit (or in the case of the participant in question, loss) was displayed on the confirmation screen.

had access to two pieces of information that were not available to inexperienced laboratory subjects: the probability of winning, and the difference between their bid and the next best bid whenever they won. Win probability is the probability of winning against robots in the web experiments. Experienced subjects in the lab were told that the winning probability displayed is what this probability would have been had they been bidding against computerized rivals in the web experiments.

3.2. Web Experiments

Inexperienced subjects consistently overbid in forward SBFP auctions (see for example Kagel and Levin, 1993; Harstad, 1990), which translates to underbidding in reverse auctions. Bidding in the multi-attribute auction in the BD condition is significantly more complex than bidding in a single-dimensional auction, and this is expected to result in fewer equilibrium choices. For example, in the Shachat and Swarthout (2003) study few subjects' choices corresponded to Nash equilibrium in the BD environment. This finding was attributed to the inability of subjects to implement non-linear Nash equilibrium strategies (see also Chen and Plott, 1998 and Goeree and Offerman, 2002). While we acknowledge that the inability of laboratory subjects to play non-linear strategies is interesting, we also believe that professional bidders with years of experience are not directly comparable to naïve laboratory subjects. For example, Harrison and List (2005) show that experienced sportscard traders are less likely to fall prey to the winner's curse than inexperienced laboratory subjects. We therefore wish to examine behavior by both inexperienced and experienced subjects.

We increased bidder experience by requiring participants in the experienced sessions to first bid in a large number of auctions against computerized rivals in sessions implemented over the internet.

The interface for the internet sessions is a PHP program with feedback similar to the zTree interface. Each subject was given an individual login and password and asked to log in from home. The experiment lasted 200 periods and involved 40 different cost– quality profiles, each of which was repeated for 5 periods. Though the individual's profile remained fixed each 5-period block, the profiles of the computerized bidders were randomly drawn each period from $C_i \sim \text{Uniform}(0,100)$, $X_i \sim \text{Uniform}(0,1)$ and each $Q_i = C_i + 300X_i$ with C_i and X_i independent. The three computerized opponents facing each subject were programmed to play RNNE strategies.

Subjects were informed only that the robots had been programmed to maximizing their own expected earnings if they were bidding against similarly– programmed rivals.

Following each period, subjects were shown whether they won or lost, the winning bid, the buyer's surplus from the winning bid, the buyer's surplus from the second highest scoring bid, and the difference between their own bid and the next best bid if their bid won.

One advantage of having subjects compete against robots in on–line auctions is that we can have subjects play a large number of rounds and allow them to have repeated experience with the same costs and quality parameters, that we conjecture speeds up learning. In fact, some e-Sourcing platforms also offer potential bidders similar kind of hands-on experience before actual bidding events (see AlphaSource.com).

This method allows us to quickly create experienced bidders for laboratory auction experiments. Though we lose the characteristic that subjects are representative of the larger naïve student population, since we intend to characterize behavior in B2B auctions, where bidders are experienced and significantly more sophisticated, this tradeoff should increase the external validity of our study. As experimental economics methods become more accepted outside economics, in more applied fields such as supply chain management or marketing, the question of the experience of laboratory participants becomes more daunting. Our method of dealing with this problem is not without tradeoffs. By exposing participants to auctions against opponents programmed to bid according to the RNNE we may well be conditioning them to behave closer to theoretical benchmarks. This conditioning decreases the power of our test. On the other hand, using inexperienced subjects in testing a complex mechanism also decreases the power of the test because inexperienced subjects are more likely to make errors. Testing complex mechanisms using experienced professional bidders in the field as opposed to students in the laboratory, increases the external validity of the test, but decreases its internal validity because the field does not offer the same level of control as the laboratory. On balance, in the context of our study, we believe that the benefits of providing bidders with experience of bidding against computerized opponents outweigh the costs. As researchers learn more about the actual bidding behavior in complex situations, ways of improving this method may become apparent. For example, it may be that the computerized opponents should be programmed to bid differently from the RNNE.

A second advantage of this method is that the robot bid function is known and so we can compute and report to subjects the probability of winning associated with any given bid. It has been shown that reporting to subjects the probability of wining improves the quality of their decisions in standard forward auctions (see for example Armantier and Treich 2003 and Dorsey and Razzolini 2003). Instructions for the treatments in this study can be found at http://lema.smeal.psu.edu/katok/mauction_instructions.pdf.

4. Results

The comparisons in the buyer surplus are presented in Table 2. The laboratory treatments have two profiles per treatment (pre–generated randomly prior to the experiment), which are the same over treatments. We show the actual average buyer surplus in each treatment, and in square brackets we show the expected (predicted) buyer surplus for the generated profiles.

	Mechanism					
	BD			PB		
N	Inexperienced	Experienced	Robots	Inexperienced	Experienced	Robots
4	226.12 [184.25]	196.36 [184.25]	202.36* [202.09**]	143.72 [133.80]	130.59 [133.80]	126.34* [132.29**]
2		123.31 [102.88]	114.32* [99.60**]		132.37 [123.54]	124.46* [121.69**]

* These numbers are only from auctions in which humans won.
** These numbers are only from auctions in which humans would have won in equilibrium.
Table 2. Actual and [predicted] buyer surplus

In our setting, *C* and *Q* are correlated, so to analyze individual bidding behavior we estimate the following models:

$$B - C = constant + \beta(Q - C) \text{ (for BD)} \quad (1)$$

$$B - C = constant + \beta(100 - C) \text{ (for PB)} \quad (2)$$

An added advantage of this formulation is that the estimated coefficients are more natural to compare between PB and BD, since the predicted coefficients are equal for a given *N*. We use random effects modeling because the constant is now an error term relative to the prediction. Also, *t*–tests can now be used naturally over the slope coefficient.

	Mechanism						
	BD			PB			
N	Inexperienced	Experienced	Robots	Inexperienced	Experienced	Robots	Prediction
4	0.05 (0.0118)	0.24 (0.0076)	0.29 (0.0041)	0.17 (0.0125)	0.24 (0.0375)	0.43 (0.0057)	0.25
2		0.48 (0.0257)	0.55 (0.0046)		0.58 (0.0060)	0.44 (0.0094)	0.50

Table 3. Random Effects Regression of the equations: (1) for PB and (2) for BD. The estimates of β (and standard errors below in parenthesis).

The slopes are significantly different between the robot, inexperienced, and experienced treatments for all formats at the 0.01 significance level. From Tables 2 and 3 we see that:

(1) The prediction that BD will produce higher average buyer surplus than PB when N=4 but lower average buyer surplus than PB when N=2 is confirmed (hypotheses 1 & 2). For N=2, PB surplus is 132; BD surplus is 123. The p-value for hypothesis 1 is 0.0038. For N=4, PB surplus is 131; BD surplus is 196. The p-value for hypothesis 2 is 0.0249.

(2) Bidder experience significantly reduces underbidding in BD and PB (supporting hypothesis 3).

(3) Underbidding persists in both PB and BD even after experience, except for PB N=4 (mostly supporting hypothesis 4). There is some underbidding in the PB auctions but substantial underbidding in the BD auctions.

(4) Humans behave differently against other humans than against robots (supporting hypothesis 5).

One startling observation is the extent to which participants underbid in the BD treatments, and this observation raised a concern that participants may have difficulty incorporating qualities into their bids. Pre–experiment quizzes and post–experiment questioning revealed that subjects were highly aware of the relationship between quality and expected probability of winning and did their best to incorporate quality into their bids. However, all subjects, but especially inexperienced ones bidding against other human bidders, exhibited substantial underbidding, especially when endowed with high Q's.

Figure 2 shows the mark-ups over cost ($B – C$) in all treatments. In the BD treatments the mark-ups are shown as a function of $Q – C$, and in PB treatments as a function of $100 – C$. In all cases, for clarity of exposition, we averaged the bids over $Q – C$ and $100 – C$ categories in blocks of size 10. We note several regularities:

(1) While the RNNE bid functions are linear in $Q - C$ (and $100 - C$ in PB treatments), the observed bid functions are clearly non–linear.

(2) In the BD robot and experienced treatment, there is substantial underbidding relative to RNNE for intermediate values of $Q - C$, and this underbidding disappears at very high values of $Q - C$. There is not much underbidding at very low values of $Q - C$, which is not surprising because there is not much room for underbidding in that region.

(3) The behavior is markedly different in the inexperienced (N=4) BD treatment because participants fail to adjust for high Q's, and as a result underbid severely at high levels of $Q - C$.

(4) In the BD N=2 treatment the underbidding is worse in the experienced human treatment than in the robot treatment. The differences are relatively small, and almost completely disappear in the N=4 treatment.

(5) The observed bid functions in the PB treatments are also non–linear.

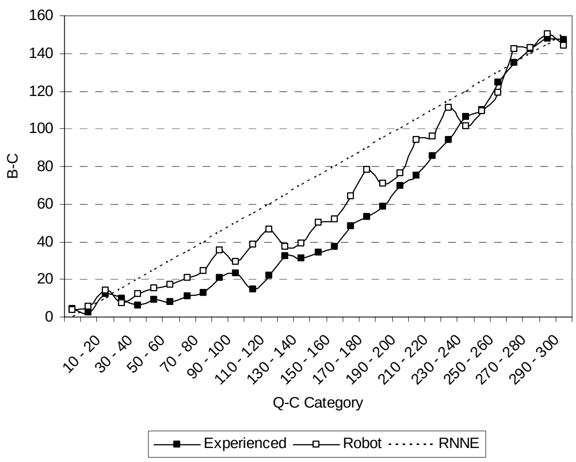
(6) In the N=2 PB treatments, in the robot treatment we observe some underbidding relative to the RNNE at medium– range values of $100 - C$, and just like in the BD treatment this underbidding decreases at very high levels of $100 - C$.

(7) In the all human experienced treatment for PB N=2, participants bid slightly above the RNNE at high levels of $100 - C$, and slightly below at low levels.

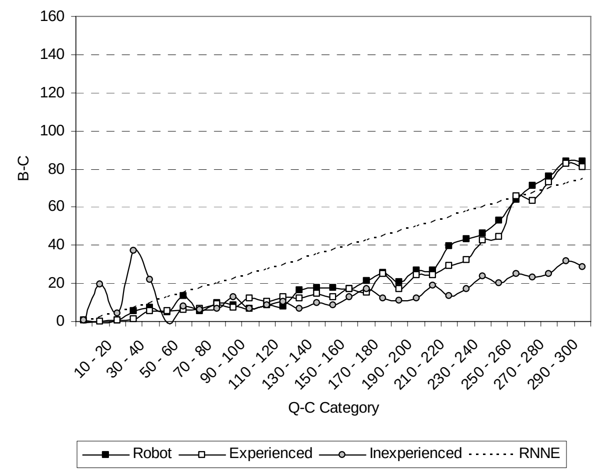
(8) On average, bids are lower in the robot treatment than in the experienced human treatment, in the PB N=2 condition.

(9) In the PB N=4 condition, participants overbid substantially at high levels of $100 - C$ in the robot treatment, and continue to overbid, although at lower levels, in the experienced treatment. There is no similar overbidding in the inexperienced treatment.

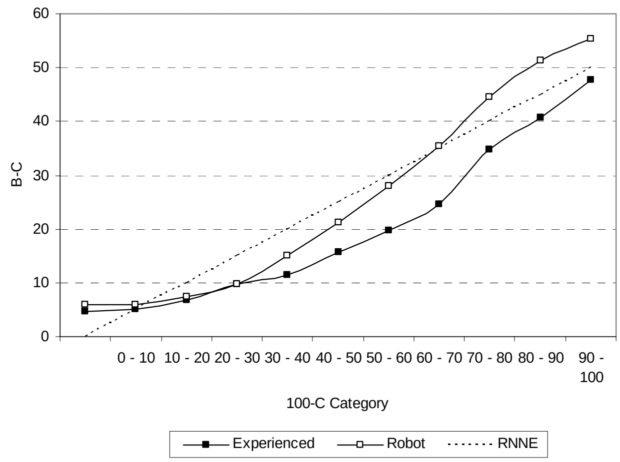
(10) In the PB N=4 condition, at medium and low levels of $100 - C$ there is some underbidding relative to RNNE, and this underbidding is worse in the inexperienced treatment than in the other two treatments.



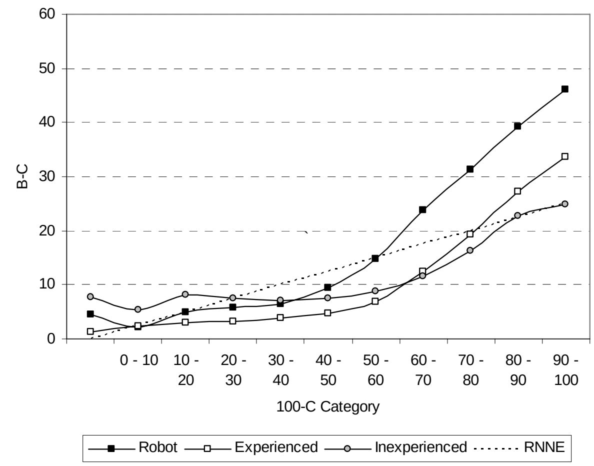
(a) BD N=2



(b) BD N=4



(*C*) PB N=2



(d) PB N=4

Figure 2. Average mark– up over cost as a function of quality – cost (for BD treatments) or 100 – cost (for PB treatments.

Our results can also be summarized in terms of buyer surplus. The main findings are that

(1) Buyer surplus is higher in BD for N=4 but lower for N=2.

(2) The underbidding in the inexperienced sessions results in higher buyer surplus in these sessions relative to sessions with experienced bidders. Figure 3 shows graphically how this underbidding relative to the theoretical benchmark affects buyer surplus.

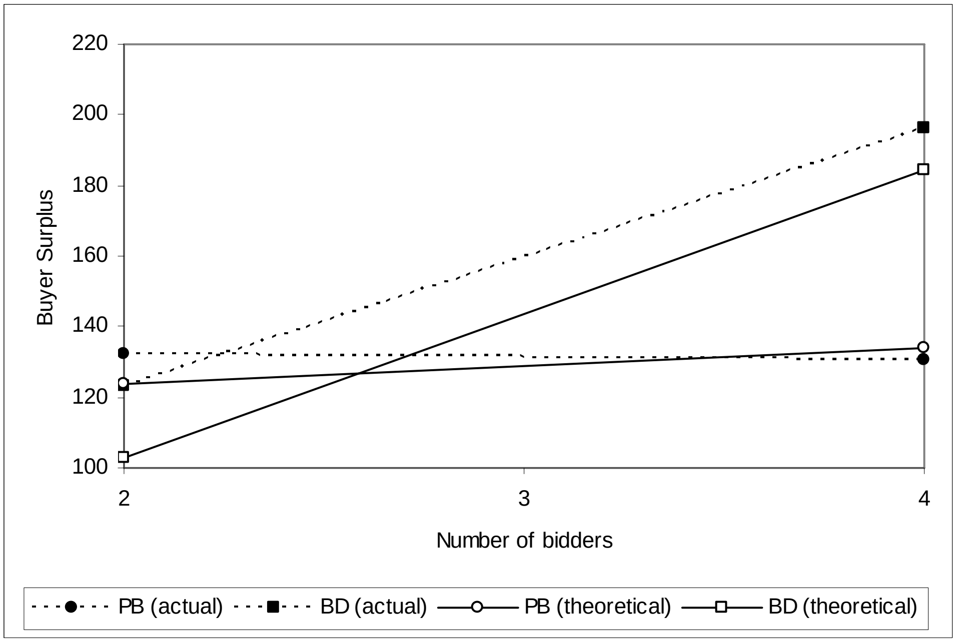


Figure 3. Buyer surplus as a function of the number of bidders.

In all *N*=4 treatments, inexperienced bidders bid lower than experienced bidders, and this underbidding is especially severe in the BD condition. We explore two potential explanations for this regularity. It may be that bidding in the multi-dimensional setting under the BD mechanism is a more difficult task than it appears to be on the surface. Our results indicate that the buyer benefits a great deal from the BD mechanism—more in actuality than in theory—and the buyer benefits at the expense of the suppliers. In fact, suppliers do not like reverse auctions in practice (see for example Jap 2000 for an excellent empirical study). Our results are suggestive of a potential explanation for why suppliers dislike auctions so much: incorporating quality into the bid is too difficult, especially for inexperienced bidders, so suppliers realize they will not do well in a BD auction.

The second explanation goes directly to bidder experience. Can experienced bidders bid significantly better than naïve bidders in this complex environment? Our results suggest they do. Virtually all laboratory evidence on auctions hitherto comes from experiments with fairly naïve student subjects. The only reliable method for testing the effect of experience is to call participants back. To the extent there is any evidence on whether experience matters in multi–attribute auctions, it is that it does (Chen-Ritzo et al. 2005 have an experienced treatment, and indeed bidding in that treatment is more rational than in the other treatments). But calling back subjects from earlier sessions has some downsides. Subjects can learn from participating in a single session, but the learning experience can be better controlled in a session against computerized rivals. There are interaction effects and self– selection biases, since the experimenter cannot control who will actually show up[8]. The method we proposed is new and may offer better control in some situations, although as we acknowledged earlier, the method has potential down-sides as well—there are trade-offs.

6. Conclusion

We set out to investigate and compare two alternative auction formats – price-based auctions and buyer-determined auctions. In price-based auctions, price is the only factor used in determining a winner. In buyer-determined auctions, sellers submit price bids but the buyer is allowed to pick any seller at the end of the auction. Identifying the buyer-determined auction as an important auction mechanism is important since it is one of the key formats we observe in business-to-business procurement. Its principal difference from multi-attribute auctions typically considered in that seller quality is not endogenously determined and is not one of the dimensions on which bidders compete, although it does enter the decision criteria. The main practical difference is that, at least in theory, a buyer can benefit from a price-based auction over a buyer-determined auction if the number of bidders is small.

In the lab, we see that BD auctions dominate PB auctions by a much wider margin than theory would predict. We found that the surplus from BD auctions could grow due to (1) mistakes by inexperienced bidders, and to (2) systematic underbidding against human opponents.

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[8] To be fair, we also cannot control who actually show up, so our method also suffers from some self– selection bias, but we can control for interaction effects.

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Appendix

Proof for Proposition 1:

First, we consider the SPBD mechanism. The winner bidder *i* will be paid an amount equal to the $Q_i - S^*$, where S^* denotes the highest score of the other bidders. So, regardless of how the other bidders ended up with a highest score of S^*, *i* would like to win whenever $C_i < Q_i - S^*$, or, equivalently, whenever $S^* < Q_i - C_i$, and *i* would like to lose whenever $S^* > Q_i - C_i$. By bidding a score of $S(C_i, Q_i) = Q_i - C_i$, *i* always wins when he would like to win and always loses when he would like to lose; so this is a dominant strategy for him. If everyone follows a dominant strategy, then the result is an equilibrium. And, if each bidder *i* is bidding his true $Q_i - C_i$, then the buyer will make the efficient choice.

Second, we consider the FPBD mechanism, and establish the cost equivalence along the way. The derivation of the equilibrium bidding strategy for the FPBD mechanism follows the standard approach described already by Engelbrecht-Wiggans (1983) and applied cleanly to sealed-bid first-price auctions, for example, by McAfee and McMillan (1987).[9] Our setting differs from the traditional sealed-bid first-price auction in that we consider a reverse auction. Furthermore, in order that the highest bidder wins, we have bidders bidding "scores" rather than prices. But now the winning bidder is paid his Q_i minus the amount of his bid rather than being

[9] In fact, it should be possible to characterize the equilibrium in more general, affiliated signals setting following the derivation of Milgrom and Weber (1982), but we have no use for such a more general result.

paid the amount of his bid.[10] However, as we will see, exactly the same approach as previously used for traditional sealed-bid first-price auctions works in our setting.

Let $B(C_i, Q_i)$ denote a bidder's price offer. The buyer selects the seller *i* with the highest score $S(C_i, Q_i) \equiv Q_i - B(C_i, Q_i)$. From here on, when we talk about a bidder's bid, we are referring to the bidder's score $S(C_i, Q_i)$ as his bid. Then, rearranging the equation that defined $S(C_i, Q_i)$, we get that the winner gets paid an amount $B(C_i, Q_i) = Q_i - S(C_i, Q_i)$

Consider the version of the BD mechanism in which bidders bid scores. The mechanism will be efficient if and only if the score $S(C_i, Q_i) = g(Q_i - C_i) = g(V_i)$ for some function $g(V_i)$ that increases monotonically in $V_i \equiv Q_i - C_i$. Since we are interested in finding efficient equilibria, we presume that $g(V_i)$ is a monotonically increasing function of V_i (and later verify that it is).

Imagine that bidder *i* bids *s* when all other bidders *j* bid $g(V_j)$. If bidder *i* wins, his profit is $(Q_i - s) - C_i$. He wins if $s > g(V_j)$ for all $j \neq i$, or equivalently, if $V_j < h(s)$ for all $j \neq i$, where *h* denotes the inverse of the function *g*. Therefore, the bidder's probability of winning is $F(h(s))$, where *F* is the cumulative distribution function of the largest of the other bidders' *V*'s, and *f* is the corresponding density function. His expected profit is $\Pi(s, C_i, Q_i) = ((Q_i - s) - C_i)F(h(s))$, and the first order condition for an optimal bid is

$$\frac{d\Pi}{ds} = ((Q_i - s) - C_i)(N-1)f(h(s))h'(s) - F(h(s)) = 0$$

when $s = g(V_i)$. This implies that $F(V_i)g'(V_i) = (V_i - g(V_i))f(V_i)$. The appropriate boundary condition is that a seller who has the lowest possible value of V_i and none-the-less wins has zero expected profit from doing so. Therefore, if V_i^* denotes the smallest possible V_i, then $g(V_i^*) = V_i^*$.

The unique solution to the previous differential equation satisfying this boundary condition is $g(V_i) = \dfrac{\int_{z \le V_i} z f(z) dz}{F(V_i)}$.

[10] Shachat and Swarthout (2003) assume that the largest possible C_i is no greater than the smallest possible Q_i. This assures that the V_i's will be non-negative and makes it natural to interpret V_i as the value to the buyer of a unit provided by seller *i*. Mathematically though, as our derivation shows, there is no need to assume that the V_i's are non-negative.

Notice that this may be interpreted as the expected value of the largest other V_j conditional on all the other V_j's being less than V_i. Since this is exactly what the second highest bid would be in the second-price mechanism, and since both the first and second-price mechanism are efficient and therefore have the same winner, the two mechanisms generate the same expected payment.

Integrating by parts gives $g(V_i) = V_i - \frac{\int_{z \le V_i} F(z)dz}{F(V_i)}$, or, equivalently,

$$S_{BD}(C_i, Q_i) = (Q_i - C_i) - \frac{\int_{z \le Q_i - C_i} F(z)dz}{F(Q_i - C_i)}.$$

For future reference, note that $g'(y) = \frac{f(y)\int_{z \le y} F(z)dz}{F(y)^2}$.

Our derivation assumed that $g(y)$ is a monotonically increasing function of y. Clearly $g'(y) > 0$ for all *y* within the support of the V_i's, and so $g(y)$ has the required property.

Finally, we also need to check that this solution to the first order condition is a best response. To do this, imagine that for given C_i and V_i, bidder *i* bids $s = g(y)$ while all the other bidders *j* bid $g(V_j)$. As before, but now writing things in terms of *y* rather than *s*, the expected profit of bidder *i* is $\Pi(y, C_i, Q_i) = ((Q_i - g(y)) - C_i)F(y)$, and the derivative of the expected profit is $\frac{d\Pi}{dy} = ((Q_i - g(y)) - C_i)f(y) - g'(y)F(y)$.

Replacing $g(y)$ and $g'(y)$ by the previously derived expressions gives

$$\begin{aligned}\frac{d\Pi}{dy} &= ([Q_i - \{y_i - \frac{\int_{z \le y} F(z)dz}{F(y)}\}] - C_i)f(y) - (\frac{f(y)\int_{z \le y} F(z)dz}{F(y)^2})F(y) \\ &= (V_i - y + \frac{\int_{z \le y} F(z)dz}{F(y)})f(y) - \frac{f(y)\int_{z \le y} F(z)dz}{F(y)} \\ &= (V_i - y)f(y)\end{aligned}$$

which clearly has the same sign as $(V_i - y)$. Therefore $\Pi(y, C_i, Q_i)$ is maximized when $y = V_i$; bidder *i* should bid $g(V_i)$, and therefore everyone bidding according to the above specified function g is an equilibrium. Furthermore, the previous derivation established that it is the only candidate for an efficient symmetric equilibrium.

Proof for Proposition 2: This follows directly from basic results for traditional sealed-bid first-price auctions; the details are a simplified version of the proof to Proposition 1.

Proofs for Proposition 3:

A) If $\boldsymbol{C}$ is not a subset of $\boldsymbol{Q}$, then for all but at most one point, $Q\text{-}C < (Q\text{-}C)^*$ and therefore, $E[(Q\text{-}C)|C{=}C^*] < (Q\text{-}C)^*$.
   In the BD mechanism, the buyer's surplus is the second largest (Q-C). As N goes to infinity, this goes to $(Q\text{-}C)^*$.
   In the PB mechanism, the buyer's expected surplus is the Q-C of the seller with the lowest C, minus the difference between the lowest and the second lowest C. As N goes to infinity, the lowest C goes to C^*. Since we assumed that $E[(Q\text{-}C)|C]$ is continuous in C as C approaches C^*, we have that E[(Q-C) of the seller with the lowest C] converges to $E[(Q\text{-}C)|C{=}C^*]$. Also, the difference between the lowest and second lowest C converges to zero. So, the buyer's expected surplus converges to $E[(Q\text{-}C)|C{=}C^*]$, which we previously noted must be strictly less than $(Q\text{-}C)^*$ so long as $\boldsymbol{C}$ is not a subset of $\boldsymbol{Q}$.
B) If $\boldsymbol{C}$ is a subset of $\boldsymbol{Q}$, then $\boldsymbol{C}$ consists of a single point and $Q\text{-}C = (Q\text{-}C)^*$ for that point. So, a similar, the proof is similar, but simpler than, the proof to Proposition 1. ■

Proofs for Proposition 4:

Given the previously established price equivalence, we will work in terms of the second price version of each mechanism. First a technical point: since C_i and Q_i are independent and both have density functions, $Q_i - C_i$ is a random variable (as opposed to being a constant).

A) In the SPPB mechanism, the buyer nets a surplus equal to the Q of the winning bidder minus the C of the losing bidder. Renumber the bidders so that winner is bidder one. Then the buyer's surplus is $Q_1 - C_2$. In the SPBD mechanism, the buyer pays the winning bidder i an amount equal to Q_i minus the lower of the two scores. The buyer gets a unit worth Q_i. So, the buyer nets a surplus equal to the lower of the two scores; the buyer's surplus is equal to $\min\{(Q_1 - C_1), (Q_2 - C_2)\}$. Since C_i and Q_i are independent, $E[(Q_1 - C_2)] = E[(Q_2 - C_2)]$, and clearly, using the previously made technical point,

$E[\min\{(Q_1 - C_1), (Q_2 - C_2)\}] < E[(Q_2 - C_2)]$.

B) In the SPBD mechanism, the buyer pays the winning bidder *i* an amount equal to Q_i minus the second highest score. The buyer gets a unit worth Q_i. So, the buyer nets a surplus equal to the second largest (*Q*-*C*), and the expected buyer's surplus is E[2^{nd} largest (*Q*-*C*)]. Since *Q* and *C* each have symmetric distributions, *Q*-*C* will also have a symmetric distribution. For symmetric distributions, the expected value of the median is the mean. If N=3, the second highest sample is the median. Therefore, the buyer's surplus in the SPBD mechanism is equal to the median; and the expected buyer's surplus equals E[*Q*-*C*], which in turn equals E[*Q*] – E[*C*].

In the SPPB mechanism, the buyer nets a surplus equal to the *Q* of the bidder with the lowest *C* minus the second smallest C. Since *C* and *Q* are independent, the expected buyer surplus in the SPPB mechanism is E[*Q*] – E[2^{nd} smallest *C*]. If $N = 3$, the 2^{nd} smallest *C* is the median C, E[2^{nd} smallest *C*] = E[*C*], and the expected buyer's surplus is equal to E[*Q*]-E[S]. So, for N=3, the two mechanisms yield the same expected buyer's surplus.

C) Similar to case B, but now the expected value of the second largest (*Q*-*C*) is greater than E[*Q*-*C*] = E[*Q*] – E[*C*]. Also, now E[2^{nd} smallest *C*] > E[*C*], and therefore E[*Q*] – E[2^{nd} smallest *C*] < E[*Q*] – E[*C*]. So, the BD mechanism yields a greater expected buyer's surplus than does the PB mechanism.

D) Similar to part C, but now using N_X^* instead of the symmetry of the distributions. ■

Proofs for Proposition 5:

Preliminaries: Since we can replace γX by γ'X' where $\gamma' = \gamma$ and X' =X, the proof for $\gamma \leq 0$ follows immediately from that for $\gamma \geq 0$. Therefore, we restrict our attention to the case where $\gamma \geq 0$.

The expected buyer's surplus in the BD mechanism is the second largest *Q*-C, or, equivalently, $\{\alpha + \gamma X\}_{(2)}$, where $\{W\}_{(i)}$ (or more simply $W_{(i)}$ when the brackets can be dropped without causing confusion) denotes the i-th largest of N independent samples W. The expected buyer's surplus is $\alpha + \gamma \mathrm{E}[X_{(2)}]$.

The expected buyer's surplus in the PB mechanism is the winning supplier's Q minus the second smallest C, or, equivalently, the winning supplier's $\alpha + C + \gamma X$ minus $C_{(N\text{-}1)}$. Since the winner is the supplier with the lowest C, and since C and X are independent, this surplus has an expected value of $\alpha + \mathrm{E}[C_{(N)}] + \gamma\, \mathrm{E}[X] - \mathrm{E}[C_{(N\text{-}1)}]$.

The expected buyer's surplus in the BD mechanism exceeds that in the PB mechanism by an amount

$$\Delta \equiv (\alpha + \gamma\, \mathrm{E}[X_{(2)}]) - (\alpha + \mathrm{E}[C_{(N)}] + \gamma\, \mathrm{E}[X] - \mathrm{E}[C_{(N\text{-}1)}])$$
$$= \gamma\, (\mathrm{E}[X_{(2)}]) - \mathrm{E}[X]) + (\mathrm{E}[C_{(N\text{-}1)}] - \mathrm{E}[C_{(N)}]).$$

Since C is not a constant, $\mathrm{E}[C_{(N\text{-}1)}] - \mathrm{E}[C_{(N)}] > 0$. Similarly, $\mathrm{E}[X_{(2)}]) - \mathrm{E}[X] < 0$ when $N < N_X^*$, and $\mathrm{E}[X_{(2)}]) - \mathrm{E}[X] > 0$ when $N \geq N_X^*$.

A) So, if $N < N_X^*$ and γ is large enough, then $\Delta < 0$; the PB mechanism yields a higher expected buyer's surplus than does the BD mechanism. However, if γ is small enough (i.e. close enough to zero), then $\Delta > 0$; the BD mechanism yields a higher expected buyer's surplus than does the PB mechanism.

B) Since $N_X^* \geq 3$ for any distribution, part B) is a corollary to part A).

C) If $N \geq N_X^*$, then $\Delta > 0$ for all γ; the BD mechanism always yields a higher expected buyer's surplus than does the PB mechanism. ■

Proof for Proposition 6:

The buyer's expected surplus in the SPBD mechanism is $\mathrm{E}[(Q_i - C_i)^{\text{2nd largest}}] = \frac{N-1}{N+1} d$ In the SPPB mechanism, each buyer bids C_i. The expected second lowest bid is $200/(N+1)$. The expected Q associated with the lowest bid is $0.5d + \frac{100}{N+1}$. The expected buyer's surplus is the difference between the two and is equal to $0.5d - \frac{100}{N+1}$.

The expected buyer's surplus in the BD mechanism minus the expected buyer's surplus in the PB mechanism is then $\frac{(N-3)d+200}{2(N+1)}$. Given the restriction that $N \geq 2$, this expression is negative if and only if $N = 2$ and $\gamma > 200$. ■