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Designing Experimental Auctions for Marketing Research: The Effect of Values, Distributions, and Mechanisms on Incentives for Truthful Bidding

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Abstract

Accurately estimating consumer preferences for new products is an arduous task made difficult by the fact that individuals tend to exhibit a number of biases when answering hypothetical survey questions. Experimental auctions have advantages over conventional methods of estimating consumer preferences because they provide incentives for consumers to truthfully reveal their preferences. However, there is currently little information available to determine which mechanism to select among the class of incentive compatible mechanisms. In this paper, we provide insight into the theoretical properties of several incentive compatible value elicitation mechanisms including the Becker, DeGroot, Marschak (BDM) mechanism, Vickrey nth price auctions, and the random nth price auction. In particular, we draw attention to the shapes of the payoff functions and illustrate that the mechanisms differ with respect to the expected cost of deviating from truthful bidding. We show that incentives for truthful bidding depend on the distribution of competing bidders' values and/or prices and individuals' true values for a good. Our approach can be viewed as a diagnostic tool to aid in selecting between preference elicitation mechanisms.

KEYWORDS: auction, payoff function, preference elicitation, willingness-to-pay

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1. Introduction

Because of the high failure rate among new products, marketers are continually seeking ways of better forecasting new product success (Urban and Hauser, 1993). Traditional approaches of investigating consumer preferences and willingness-to-pay (WTP) for new products include conjoint analysis, focus groups, surveys, market tests, and laboratory pre-test markets. When choosing a method to elicit WTP for a new product or product extension, an important issue to consider is incentive compatibility—i.e., whether an elicitation method provides an incentive for people to truthfully reveal their preferences. Over the past decade, a wealth of evidence has accumulated in the economics literature suggesting that people overstate the amount they are willing to pay in hypothetical settings as compared to when real money is on the line (e.g., see the review in List and Gallet, 2001). Recently, Ding, Grewal, and Liechty (2005) showed that "incentive aligned" elicitation mechanisms, where subjects are held accountable for the decisions they make, more accurately predict purchases than traditional hypothetical elicitation mechanisms. Ding, Grewal, and Liechty (2005) concluded, "Our research suggests that marketing researchers should use incentive alignment to assess consumer preferences and continue to conduct further research in the context of conjoint and other experiments that pertain to consumer behavior." When attempting to determine consumer preferences in order to determine the optimal price for a product, it is clear that non-incentive compatible value elicitation mechanisms will provide biased estimates of WTP, which could lead to inaccurate pricing decisions and sales forecasts.

Experimental auctions are one tool that can be used to create incentives for people to reveal their "true" preferences. In a typical incentive compatible experimental auction, subjects bid to obtain one or more goods. The highest bidder(s) win the auction and pay a price that is determined exogenously from the individual(s)' bid(s). Preferences for a new product are determined by comparing bids for a new good to bids for a pre-existing substitute or by directly eliciting bids to exchange a pre-existing substitute for a new good. The advantage of using experimental auctions as a marketing research tool is that they create an environment where people have an incentive to truthfully reveal their preferences. That is not to say that people cannot misrepresent their preferences or be influenced by other social-psychological factors. Rather, experimental auctions impose real economic costs when people offer bids that deviate from their true values.

Although there is general agreement on the need to employ elicitation mechanisms that are incentive compatible, little guidance exists as to which mechanism to employ amongst the class of incentive compatible mechanisms. A number of mechanisms are incentive compatible, but theory provides little guidance as to which mechanism should be preferred over another. Despite the empirical findings that incentive compatible auctions can generate divergent results (e.g., see Cox, Roberson, and Smith, 1982; Kagel, Harstad, and Levin, 1987; Lusk, Feldkamp, and Schroeder, 2004; Rutström, 1998), no formal theory has yet been advanced to explain *why* there might be systematic deviations from predictions.

The purpose of this paper is to provide insight into the theoretical properties of several of the most widely used incentive compatible value elicitation mechanisms: the Becker, DeGroot, Marschak (BDM) mechanism, Vickrey n^{th} price auctions (the Vickrey second-price auction being one example), and a random n^{th} price auction. This insight can help practitioners make more informed decisions in designing experimental auctions to determine consumer WTP. Previous literature has identified several empirical regularities. We propose a model that helps explain some of these empirical regularities. We show that incentives for truthful bidding can differ across mechanisms, and even within a mechanism, depending on: a) the distribution of competing bidders' values in n^{th} and random n^{th} price auctions, b) the distribution of the random price generator in the BDM, and c) the magnitude of individuals' true values for a good. Our approach can be viewed as a diagnostic tool to aid in selecting between mechanisms. By exposing the theoretical underpinnings of experimental auctions, practitioners can better judge the merits of experimental auctions as a marketing research tool.

2. Background on Experimental Auctions

In a seminal study, Hoffman et al. (1993) used an incentive compatible, fifth-price auction to illustrate the usefulness of experimental auctions in an application to new beef packaging. The Vickrey-style fifth-price auction used by Hoffman et al. (1993) involved participants submitting sealed bids with the top four bidders winning the auction and paying the fifth highest bid for the good. Since that time, a wealth of studies have surfaced using experimental auctions to value novel goods and services (e.g., see Buhr et al., 1993; Dickinson and Bailey, 2002; Fox et al., 1998; Fox, Hayes, and Shogren, 2002; Hayes et al., 1995; Huffman et al., 2003; Lusk et al., 2001a, 2001b; Lusk, Feldkamp, and Schroeder, 2004; Melton et al., 1996; Noussiar, Robin, and Ruffieux 2002, 2004a; Roosen et al., 1998; Rousu et al., 2004; Umberger et al., 2002). Lusk and Shogren (2007) show that more than 100 academic studies have utilized experimental auctions for the purpose of preference elicitation. In one recent example, Wertenbroch and Skiera (2002) proposed using the incentive compatible Becker, DeGroot, Marschak (BDM) mechanism to elicit consumer WTP at the point of purchase.[1] With the BDM mechanism, an individual bids against a randomly drawn price.[2] If the individual's bid is greater than the randomly drawn price, he or she purchases one unit of the good. In addition to the BDM mechanism and the Vickrey auctions, there are other incentive compatible auctions that have been used to elicit consumer WTP in pre-test markets. One such mechanism is the random nth price auction proposed by Shogren et al. (2001), which combines features of the BDM and the second price auction. In a random nth price auction, *N* individuals bid on an item. After bids are submitted, one of the bids (the random n^{th} bid) is drawn from the sample. All individuals with bids greater than the random n^{th} bid win the auction and pay a price equal to the random n^{th} bid.

Bidding behavior in BDM, second-price, and random n^{th} price auctions has been investigated in several induced-value experimental studies, where individuals are assigned a value for the auctioned good. Because true values are known in induced-value studies, the method permits direct tests of whether actual bidding behavior conforms to auction theory (see Smith (1976) for the theoretical foundation for induced-value experiments). Irwin et al. (1998) and Noussiar, Robin, and Ruffieux (2004b) investigated whether BDM bids were consistent with actual values in induced-value studies. Both studies concluded that the BDM mechanism was demand-revealing. In the first studies on the second price auction, Coppinger, Smith, and Titus (1980) and Cox, Roberson, and Smith (1982) found that it generated truthful bidding in induced value experiments, but a later study by Kagel et al. (1987) suggest a tendency for people to bid higher than induced values in second price auctions. More recent studies by Shogren et al. (2001), Noussiar, Robin, and Ruffieux (2004b), and Parkhurst et al. (2004) have concluded that the second-price auction is demand-revealing.

3. Empirical Comparisons of Auction Mechanisms

Several previous studies have compared bidding behavior in the second price, BDM, and random nth price mechanisms. Theoretically, all mechanisms should yield the same result with people submitting bids equal to values; however, previous studies suggest that these mechanisms can yield divergent results. Much

[1] Prior to Wertenbroch and Skiera, the BDM mechanism had been used extensively in economics literature to elicit WTP, but most applications were carried out in the laboratory. Lusk et al. (2001a) and Lusk and Fox (2003) have used the BDM mechanism to elicit WTP in a grocery store setting at the point-of-purchase. List (2002) has shown how Vickrey auctions can be used in a field setting at the point of purchase.

[2] The BDM is not strictly an auction so much as it is an individual decision-making mechanism, however, for convenience, we will occasionally refer to the BDM mechanism as an auction. With the BDM people bid against a random number (price) generator instead of other bidders, as in a more conventional auction.

of the findings seem to relate to how well a mechanism performs for people with relatively high values versus people with relatively low values. One of motivations behind Shogren et al.'s (2001) introduction of the random nth price auction is that in the second price auction, only one person wins, and thus unless one has a relatively high value for the good they may be "disinterested" in the auction especially if people participate in multiple auction rounds. With the BDM, by contrast, there is a reasonable chance any auction participant, regardless of their value, might win. A random nth price auction shares the property of the BDM that all participants have a reasonable chance of winning and combines with it the property from the second price auction that participants bid against other people. These insights have led to investigations of bidding behavior for people with high values to those people with low values in various auctions.

Second Price Auction

In their empirical analysis, Shogren et al. (2001) sought to compare the bidding behavior of people with relatively high values to that of people with relatively low values. Shogren et al. (2001) conducted auctions over several repeated rounds and classified people as "on-margin" or "off-margin" bidders. They defined an off-margin bidder in round t as one whose bid was at least \$1 less than the market-clearing price in round t-1. Because people's values remained constant across rounds, "on-margin" bidders are likely those with high values, whereas "off-margin" bidders are likely those with low values. There is, of course, not a perfect correlation between the terms "high value" and "on-margin," but it should be clear that the concepts are highly related.

In Shogren et al. (2001), four groups of 8 to 10 subjects participated in an induced value experimental auction. Depending on the session, people either participated in: a) 5 rounds of the second price auction, followed by 5 rounds of the random nth, which was followed again by 5 rounds the second price auction, or b) 5 rounds of the random nth price auction, followed by 5 rounds of the second price auction, which was followed again by 5 rounds the random nth price auction. In each series of 5 rounds, a person was assigned an induced value, v_i, by randomly drawing a number from a uniform distribution on [0, 10]. Subjects earned an amount equal to

$$v_i - p^* \text{ if } b_i > p^* \text{ and}$$
$$0 \qquad \text{if } b_i \le p^*,$$

where v_i is participant i's induced value, b_i is participant i's bid, and p^* is the market price. In the second price auction, the market price was the second highest bid, whereas in the random nth price auction the price was set equal to a randomly drawn bid. In this induced-value framework, the accuracy of a mechanism can be investigated by comparing people's bids, b_i, to their induced values, v_i.

Shogren et al. (2001) found that on-margin bidders place bids closer to their true (induced) values in the 2nd price auction relative to off-margin bidders. In the second price auction, the mean squared deviation between bids and induced values decreased from a value of 0.805 for off-margin bidders to 0.593 for on-margin bidders. This result was confirmed in a separate study by Parkhurst, Shogren, and Dickinson (2004), who found a similar result. Lusk and Rousu (2007) also found that bidders with higher induced values bid closer to their induced value than bidders with low induced values in the second price auction. They found that the mean squared deviation between bids and induced values was 9.33 for people assigned relatively high induced values whereas the mean squared deviation was 28.79 for people assigned relatively low induced values. The results of these three studies point to an empirical regularity: in a second price auction, people with relatively high values submit bids more similar to induced values than people with relatively low induced values.

BDM mechanism and Random nth-Price Auction

In contrast to the second price auction, Shogren et al. (2001), Parkhurst, Shogren, and Dickinson (2004) and Lusk and Rousu (2007) found that the random nth-price auction was more accurate for off-margin/low-value bidders than for on-margin/high-value bidders. For example, Lusk and Rousu (2007) found for the random nth price auction that the mean squared deviation between bids and induced values was 33.18 for bidders assigned relatively high induced values but only 8.59 for people assed relatively low induced values. Lusk and Rousu (2007) also investigated the BDM mechanism and found a greater mean squared deviation for low-value bidders than high-value bidders (46.83 vs. 13.38). The results of these three studies point to a second empirical regularity: in the random nth price auction and BDM mechanisms, people with relatively high values tend to submit bids more similar to induced values than people with relatively low induced values.

Comparing Auctions

Both Shogren et al. (2001) and Lusk and Rousu (2007) found similar results for low-value/off-margin bidders: the random nth price auction performed better than the 2nd price auction at prompting accurate bids. Shogren et al. (2001) found the mean squared deviation was lower in the random nth price auction (0.051) than the second price auction (0.805) for low-value/off-margin bidders. Lusk and Rousu (2007) also found that the random nth price auction prompted relatively low-value bidders to bid closer to their induced values than the 2nd price auction (mean squared deviation of 8.59 vs. 28.79). Shogren et al. (2001) found that for on-margin bidders, the second price auction was more accurate than the random nth price auction, with the mean squared error for the random nth price auction significantly higher, 2.450, than the second price auction, 0.593. Lusk and Rousu (2007) found similar results.

Parkhurst, Shogren, and Dickinson (2004)'s results suggested neither the second price nor the random nth price auction performed without fault. Bidding in the second price auction was precise but biased; the highest value bidders tended to overstate their values, whereas the lowest value bidders tended to understate their values. In contrast, bidding in the random nth price auction was demand revealing across all induced values, but it was imprecise; the variance was relatively large.

Noussair, Robin, and Ruffieux (2004b) also conducted an induced value study comparing the second price auction to the BDM. Their analysis did not differentiate between high and low value bidders, but instead focused on the average results across mechanisms. They found that the second-price auction generated bids closer to true values than the BDM. They argued that differences in bidding behavior in the second-price auction and BDM may result from differences in incentives to bid truthfully.

Finally, a couple of studies have compared homegrown values (those values that individuals bring into an experiment) across competing incentive compatible auctions. Rutström (1998) found that BDM bids for chocolates were significantly lower than bids from a second-price auction. Lusk, Feldkamp, and Schroeder (2004) found that second-price, random nth price, and BDM auction bids for beef steaks were similar in initial bidding rounds, but that fifth round second-price auction bids were significantly greater than random nth price and BDM auction bids. Shogren et al. (2001b) found that the WTP measure of value was significantly less than the WTA measures of value for second-price auction, random nth price, and BDM auction in initial bidding rounds; however, over repeated rounds, the disparity between WTP and WTA disappeared in the second-price and random nth price auction, but persisted in the BDM auction. Shogren et al. (2001b) argued that the competitive nature of the random nth and second-price auction promoted more rational bidding as compared to the BDM auction, which is an individual decision-making exercise.

The literature reviewed in this section illustrates that despite the theoretical prediction that bids will equal induced values in incentive compatible experimental auctions, bidding behavior can be more or less accurate depending on whether people have a high or low induced value and depending on which mechanism is used to elicit values. Presently, there is very little understanding as to *why* such empirical results have been obtained. We do not claim to have a complete answer for this question, but in what follows, we show that incentives for truthful bidding can differ within and across mechanisms.

4. Payoff Functions and the Cost of Misbehaving

Some of the deviations from truthful bidding discussed in the preceding section might be attributable to the shape of the payoff function. If an auction is incentive compatible, the payoff function should be maximized when a person submits a bid equal to their true value. However, in real-world applications, people may have other priorities than maximizing the payoff defined strictly over experimental earnings. For example, a person may experiment with their bidding behavior out of curiosity or may bid in a way to try to "look good" to the experimenter. Further, it may be difficult for a person to ascertain that bidding true value is optimal even if explicitly told. Even if such considerations exist, it would be expected that people will respond to incentives. Thus, as the cost of deviating from the money-maximizing payoff increases, we would expect fewer departures from truthful value revelation. As we show in this section, the cost of deviating from the money-maximizing payoff depends on the shape of the payoff function: a shape which differs across mechanisms and across people with different values.

Suppose an individual derives a private value, v_i, from purchasing and consuming an auctioned good. The individual must decide how much to bid, b_i, in an auction to obtain the good. In general, a risk-neutral individual derives the following expected benefit or payoff from submitting the bid, b_i:

(1) $$E[\pi_i] = (v_i - E[\text{Price}|(\text{winning}|\ b_i)])(\text{Probability of winning}|\ b_i)$$

where E is the expectations operator and π_i is individual i's monetary benefit or payoff from the auction. Equation (1) states that an individual can expect to earn the difference between their value for the good and the expected price to be paid (conditional on winning the auction, which depends on the submitted bid b_i) multiplied by the probability that an individual wins the auction given b_i.

Formally, an auction is incentive compatible if the individual has an incentive to submit $b_i = v_i$. In each of the mechanisms we consider, participants have a weakly dominant strategy to submit a bid equal to their own value. This means that bidding true value yields a payoff at least as great as the payoff from all other strategies no matter what bidding strategies other rivals pursue. Although the dominant strategy does not depend on rivals' bidding behavior, the incentives for people to bid true value can depend on other's bids. However, all that is required in the approach that follows is the assumption that individual i knows the distribution of their rival's bids. That is, we do not necessarily assume all rivals are bidding true value, only that individual i can characterize the distribution of rivals' bids. Of course, with the BDM mechanism, the subjects bid against a random number generator and the distribution is typically made explicit by the researcher.

BDM Payoff Function

In the BDM mechanism, an individual submits a bid to purchase one unit of a good. Then a price is drawn from a known distribution, with a cumulative distribution function *F(p)* and probability density function *f(p)*, where *p* is the price. If the individual's bid is greater than the randomly drawn price, the individual wins the auction, purchases one unit of the good, and pays the randomly drawn price. If the individual's bid is less than the randomly drawn price, the individual pays and receives nothing. Given b_i, the expected price conditional on winning is $f(p| p< b_i) = \int_{-\infty}^{b_i} \frac{f(p)}{F(b_i)} pdp$ - i.e., the mean of the price distribution truncated from above at b_i. The probability of winning a BDM auction given b_i is simply $F(b_i)$. Thus, the expected payoff for the BDM auction is:

$$(2) \qquad E[\pi_i^{BDM}] = [v_i - \int_{-\infty}^{b_i} \frac{f(p)}{F(b_i)} pdp]F(b_i) \ .$$

It is straightforward to show that this function is maximized at $b_i = v_i$.

Vickrey Second-Price Auction Payoff Function

In a second-price auction, individual *i* with value v_i bids on one unit of a good against *N* other bidders with bids/values v_j independently drawn from a distribution with cdf given by $G(v)$ and pdf given by $g(v)$. The expected priceconditional on winning given b_i is $\int_{-\infty}^{b_i} (n-1)\left[\frac{G(v)}{G(b_i)}\right]^{(N-2)} \left[\frac{g(v)}{G(b_i)}\right] vdv$ and the probability of winning given b_i is $G(b_i)^{N-1}$. The expected price is the integral of the pdf of the distribution of the largest value of *N*-1 draws from the distribution $g(v)$, which is truncated from above at b_i, multiplied by *v*. This result follows from basic order statistics (e.g., see Balakrishnan and Cohen, 1991). The expected payoff for individual *i* submitting b_i is

$$(3) \qquad E[\pi_i^{2ndprice}] = [v_i - \int_{-\infty}^{b_i} (N-1)\left[\frac{G(v)}{G(b_i)}\right]^{(N-2)} \left[\frac{g(v)}{G(b_i)}\right] vdv]\left(G(b_i)\right)^{N-1} .$$

Two points about equation (3) are worth noting. First, the payoff function is maximized at $b_i = v_i$. Second, when $N = 2$, the payoff function for the second-price auction equals that of the BDM auction if $G(\bullet) = F(\bullet)$. From the standpoint of individual i, the expected payoff is the same regardless of whether he or she is bidding against a random price generator with distribution $F(p)$ or against one other bidder, whose bid is randomly drawn from a distribution $F(v)$.

Any n^{th}-Price Auction Payoff Function

The second price auction discussed above can be generalized to any n^{th} price auction. In an n^{th} price auction, the (n-1) highest bidders win the auction and pay the n^{th} highest price for a unit of the good. Based on the formula for the pdf and cdf for any given order statistic (see Balakrishnan and Cohen, 1991), it can be shown that the payoff function for any n^{th} price auction with individual i bidding against N other bidders with values/bids drawn from a distribution with cdf given by G and pdf given by g is:

$$E[\pi_i^{nth}] = \left[v_i - \int_{-\infty}^{b_i} \frac{\frac{(N-1)!}{(N-n)!(n-2)!} G(v)^{N-n} [1-G(v)]^{n-2} g(v)}{\int_{-\infty}^{b_i} \frac{(N-1)!}{(N-n)!(n-2)!} G(x)^{N-n} [1-G(x)]^{n-2} g(x) x dx} v dv \right] \left[\sum_{r=N-n+1}^{N-1} \frac{(N-1)!}{r!(N-1-r)!} G(b_i)^r [1-G(b_i)]^{N-1-r} \right] \qquad (4)$$

Although it is perhaps not initially obvious, if n = 2, equation (4) collapses to equation (3).

Random nth Price Auction Payoff Function

Conceptually, a random nth price auction is very similar to the BDM. However, there are two important differences. First, rather than bidding against a random price generator as in a BDM, in a random n^{th} price auction, an individual bids against N other bidders, whose values/bids are distributed according to G, as above. Second, unlike the BDM, one of the N bidders' values is drawn at random and that bid is set as the price. From the perspective of bidder i, there is a $(N\text{-}1)/N$ chance another individuals' bid will be drawn as the price, in which case the payoff function is simply the BDM. However, there is a $1/N$ chance that individual i's bid will be chosen as the random n^{th} bid, in which case individual i's payoff is zero. Therefore, the payoff function for individual i bidding b_i in a random nth price auction with N bidders is:

$$E[\pi_i^{randomnth}] = \frac{N-1}{N}\left[v_i - \int_{-\infty}^{b_i} \frac{g(v)}{G(b_i)} v dv\right] G(b_i). \qquad (5)$$

Equation (5) is simply (N-1)/N times the equation (2), with g and G substituted for f and F to signify that the relevant distribution in a random nth price auction is the distribution of other bidders' bids.[3]

Cost of Misbehaving

For all the auctions analyzed in this paper, it is optimal for an individual to submit a bid equal to true value. However, the mechanisms differ in terms of the expected payoff forgone by "misbehaving" or deviating from optimal bidding. There may be a variety of reasons why an individual may misbehave, but one prominent reason discussed in Harrison (1989, 1992) is that the payoff function may be relatively flat over a range of bids and the cost of misbehaving in terms of forgone expected income is relatively small in comparison to the cognitive cost of the individual attempting to determine the exact optimal bid. Let π_i^{k*} be individual i's optimal payoff in mechanism k that is achieved when an individual submits b_i equal to v_i. The expected cost of misbehaving for mechanism k is given by:

(6) $$ECM^k(v_i, b_i) = E[\pi_i^{k*} \mid v_i] - E[\pi_i^k \mid v_i, b_i].$$

ECM is simply the expected dollar-loss an individual will incur by making a bid that is not equal to the true value. *ECM* is a non-negative number that equals zero when $b_i = v_i$. Increases in *ECM* imply an increase in the cost of misbehaving. As show in equation (6), *ECM* for mechanism k is a function of a person's value and their bid. By definition, *ECM* increases as b_i deviates from v_i.

5. Payoff Function Shape and Bidding Behavior for Uniform Distribution

Equations (2) through (6) are stated very generally and relate to any number of bidders and distribution of bidders' values. However, all of the empirical studies discussed in the preceding section have been carried out by drawing prices and values from a uniform distribution. Fortunately, the uniform distribution greatly simplifies some of the preceding formulas and allows for some more concrete comparisons of the *ECM* for high and low value individuals within and across mechanisms.

First, consider the second price auction with N bidders, whose bids follow a uniform distribution defined on [0, T]. The expected cost of misbehaving in the second price auction with a uniform distribution is:

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[3] The payoff function for a random nth price auction can also be equivalently written as 1/N*($\pi^{2nd\ price}$)+ 1/N*($\pi^{3rd\ pricen}$) + . . . + 1/N*($\pi^{Nth\ price}$).

$$(7) \qquad ECM_i^{2ndprice} = \frac{v_i}{N}\left(\frac{v_i}{T}\right)^{N-1} - [v_i - \frac{N-1}{N}b_i]\left(\frac{b_i}{T}\right)^{N-1} .$$

The preceding literature review indicated that people's bidding behavior in the second price auction depended on whether they were high or low value. Because (7) provides a measure of people's incentives to bid truthfully, we can see how incentives change as values change. Before proceeding, we make a useful substitution, writing individual *i*'s bid as their value less a parameter γ_i that describes the degree of misbehavior, i.e., $b_i = v_i - \gamma_i$. This substitution allows us to investigate how changing a bidder's value effects *ECM* holding constant the degree of misbehavior. Plugging the misbehavior parameter into (7) yields

$$(8) \qquad ECM_i^{2ndprice} = \frac{v_i}{N}\left(\frac{v_i}{T}\right)^{N-1} - [v_i - \frac{N-1}{N}(v_i - \gamma_i)]\left(\frac{v_i - \gamma_i}{T}\right)^{N-1} .$$

To see how *ECM* changes with v_i, we take the derivative of (8), which yields

$$(9) \qquad \frac{\partial ECM_i^{2ndprice}}{\partial v_i} = \frac{v_i^N + (\gamma_i - v_i)^{N-2}[v_i^2 + v_i \gamma_i (N-2)]}{v_i T^{N-1}} .$$

What are the conditions under which (9) is positive? That is, when does increasing a bidder's value increase the incentives for truthful bidding in the second price auction? First, note that (9) equals zero when $\gamma_i = 0$. This makes sense because *ECM* is unaffected by one's value if the subject is bidding truthfully: by construction *ECM* is always zero when $b_i = v_i$. Second, note that equation (9) is at a minimum when $\gamma_i = 0$. This can be seen by taking the derivative of equation (9) with respect to γ_i, setting equal to zero, and solving for γ_i. Thus, equation (9) can never be less than zero and is only exactly equal to zero when $\gamma_i = 0$. This means that for any level of misbehavior, $\gamma_i \neq 0$, that equation (9) must be positive. This implies that in the second price auction, increasing one's private value increases *ECM* (the incentives for truthful bidding), unless of course people are already bidding truthfully. This analytical finding confirms the empirical findings that the second price auction yields more accurate bidding behavior for high-value people than low-value people when the distribution is uniform and thus suggests that the expected cost of misbehavior may be an underling cause for the empirical phenomenon.

Now, consider the expected cost of misbehaving in the random nth price auction assuming a uniform distribution of rivals bids defined on [0, T]:

(10) $$ECM^{randomnth} = 0.5\left(\frac{N-1}{N}\right)\left(\frac{v_i^2}{T}\right) - \left(\frac{N-1}{N}\right)\left(v_i - 0.5b_i\right)\left(\frac{b_i}{T}\right).$$

Making the same substitution as above, $b_i = v_i - \gamma_i$, yields:

(11) $$ECM^{randomnth} = 0.5\left(\frac{N-1}{N}\right)\left(\frac{v_i^2}{T}\right) - \left(\frac{N-1}{N}\right)\left(v_i - 0.5(v_i - \gamma_i)\right)\left(\frac{v_i - \gamma_i}{T}\right).$$

To see how changing bidder *i*'s value in a random nth price auction affects incentives for truthful bidding, we take the derivative of (11) with respect to v_i, which yields:

(12) $$\partial ECM^{randomnth} / \partial v_i = 0.$$

This result implies that the magnitude of an individuals' value has no effect on *ECM* in the random nth price auction. That is, incentives for truthful bidding remain unchanged as values change in the random nth price auction.[4] This analytical result stands somewhat in contrast to previous empirical results indicating the bidding behavior of lower value participants is more accurate than that of higher value participants in the random nth price auction. For a uniform distribution of bidders' values, the magnitude of an individual's true value is not related to the shape of the payoff function in the random nth price auction.

Figure 2 plots the *ECM* for the second and random nth-price auctions for "high" and "low" value individuals, where we have set T=10 and N=10. Figure 2 shows that for low value people (v_i = \$2), *ECM* from the random nth price auction always exceeds then that of the second price auction, except of course when $b_i = v_i$, in which case the *ECMs* are equal. Figure 2, thus corresponds closely with previous empirical findings: for a uniform distribution, relatively low-value individuals in a random nth price auction yield bids more similar to induced values than relatively low-value individuals in a second price auction with more than two bidders.

[4] Recall that the payoff function for the random nth price auction equals that for the BDM multiplied by a constant. Thus, this analytical result is also true for the BDM.

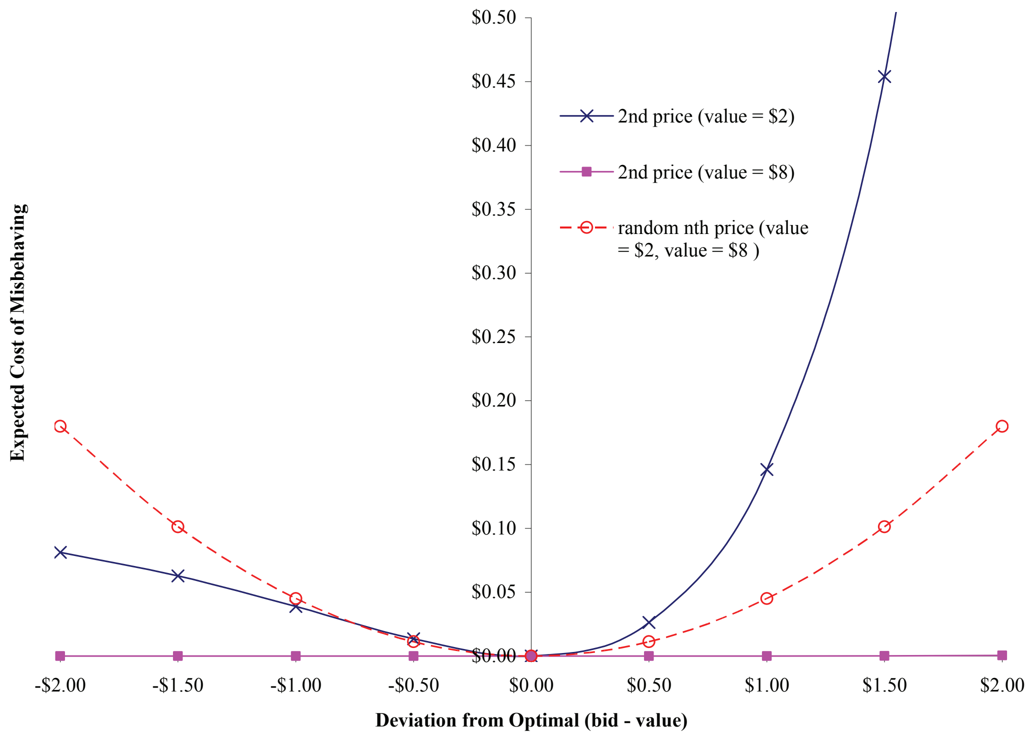

Figure 1
Expected Cost of Misbehaving for 2nd Price and Random nth Price Mechanisms with a Uniform Distribution with True Values Varied between $2 and $8

Figure 2 also shows that for relatively high value bidders (v_i = $8), *ECM* for the second price auction is strictly above that for the random nth for levels of over-bidding; however, for extensive under-bidding, *ECM* for the random nth price auction exceeds that for the second price. Nevertheless, the total area under the *ECM* curve is greater for high-valued second price auction bidders than for the random nth price auction. This analytical result is, again, consistent with previous empirical literature finding that relatively high-value individuals in a second price auction with more than two bidders submit bids more similar to induced values than relatively high-value individuals in the random nth price auction.

The analytical results presented in this section, while not perfectly corresponding to the empirical regularities reported in the literature, suggest that the shape of the payoff function is in fact related to bidding behavior and to the findings of previous empirical work. Differences in *ECM* across different people and mechanisms apparently have some power in explaining differences in bidding behavior.

6. Effect of Distribution, Value, and Mechanism on Cost of Misbehaving

The preceding section presented some analytical results related to the second price and random nth price auctions for a uniform distribution. In real-world applications, however, values/bids might be expected to follow different distributions. For example, Lusk and Shogren (2007) show that auction bids for controversial goods, such as genetically modified food, can be highly skewed with many low and high values, but with few in between. Because one of the primary goals in this paper is to offer some objective criteria (a diagnostic tool) to aid in selecting between mechanisms, it is prudent to further explore how *ECM* differs for a wider variety of distributions, mechanisms, and values. In what follows, we further investigate determinants of *ECM*. Recall that an auction with a higher *ECM* is preferred to an auction with a lower *ECM*, *ceteris paribus*, because an auction with a higher *ECM* is an auction that has greater incentives for truthful value revelation.

Description of Analysis

We investigate the effect of four variables on *ECM*: a) the distribution of $G(\bullet)$ and $F(\bullet)$, which is varied across 5 different distributions, all of which bound values/prices between \$0.00 and \$10.00; b) the magnitude of v_i, which is varied between \$2, \$5, and \$8; c) the degree to which an individual over- or under-bids relative to v_i, which we vary between -\$2, -\$1.5, -\$1, -\$0.5, \$0, \$0.5, \$1, \$1.5, and \$2; and d) the auction mechanism. To provide a full range of results, we look at four different auction mechanisms: a second price auction, a fifth price auction, a ninth price auction, and the BDM (explicit results for the random nth are not reported as they are simply $(N\text{-}1)/N$ that of the BDM). This generates 5×3×9×4 payoff function values, which are used to determine the *ECM* under different conditions. In computing *ECM,* we assume the distribution of rival's bids is common knowledge. To operationalize the expected payoff functions in equations (2) and (4), a distribution must be assumed for $G(\bullet)$ and $F(\bullet)$. To provide a robust investigation of the *ECM*, we assume the prices/values follow a beta distribution with bounds [A, B] and shape parameters a and b. The beta distribution is used because it is very flexible and can take on the shape of virtually any price/value distribution that might be encountered. In this study, we utilize five different beta distributions: right-skewed (RS), left-skewed (LS), U-shaped (US), pseudo-normal (NM), and uniform (UN). The parameters that generate each of these beta distributions are listed in Table 1, and the distributions are illustrated in Figure 2. It is important to realize that with the BDM mechanism, the distribution refers to the distribution of prices drawn from a random number generator (e.g., a bingo cage); whereas, in the n^{th} price auctions, the distribution refers to the distribution of competitors' bids in the auction. In the former case, the distribution is an endogenous experimental-design choice that a researcher can manipulate when carrying out marketing research; in the latter case, the distribution is exogenous to the researcher, but steps can be taken to form priors about the distribution. For example, the LS distribution identifies a case where most of the individuals have a relatively high value for the good, whereas the RS distribution is associated with the exact opposite case. Alternatively, the US distribution describes a situation where there are segments of the population that derive very high and low values from a new good, with few impartial individuals.

Table 1
Parameters of Beta Distributions Used in Analysis

	Beta Parameters			
Distribution	***a***	***b***	**A**	**B**
Left Skewed (LS)	4	2	0	10
Right Skewed (RS)	2	4	0	10
U-Shaped (US)	0.5	0.5	0	10
Pseudo-Normal (N)	3	3	0	10
Uniform (UN)	1	1	0	10

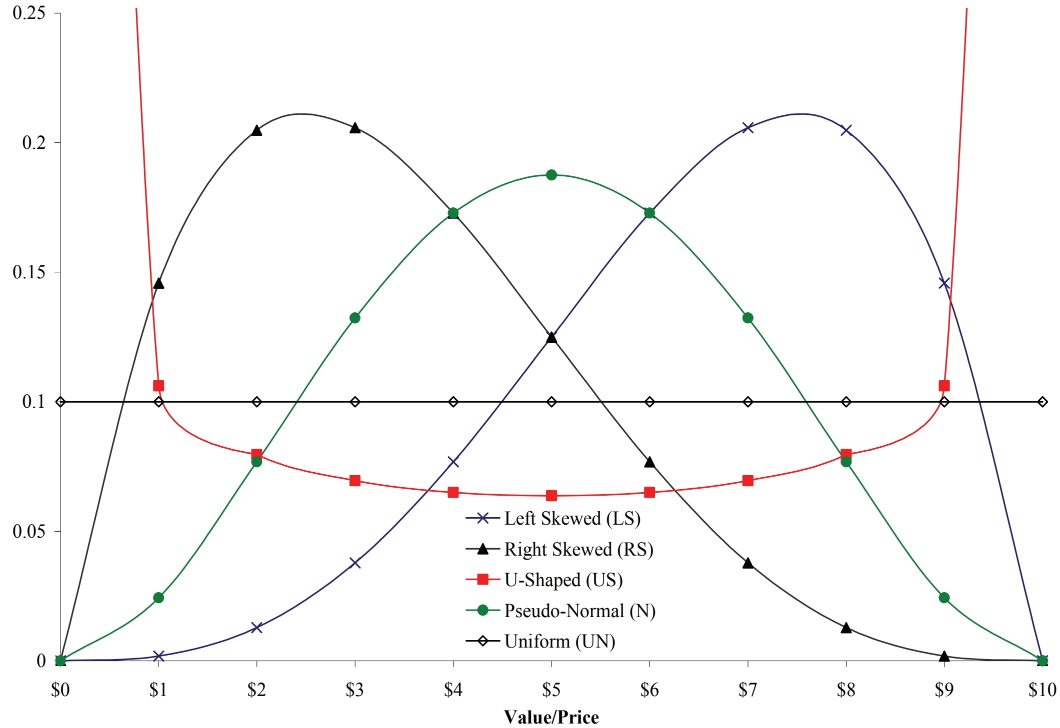

Figure 2
Probability Density Functions of Value/Price Distributions

The only remaining issue that must be resolved to carry out the analysis is the number of bidders in the nth price auctions. For this analysis, we set $N = 10$, which is slightly more than in the Hoffman study (which used sample sizes of eight) but slightly fewer participants than in other studies (e.g., Lusk, Feldkamp, and Schroeder had session sizes of about 15). Closed-form solutions for the payoff function when the distribution of bids is characterized by the beta distribution are not available. Thus, expected payoffs (and thus the *ECM*) were calculated computationally via simulation. In particular, for each of the experimental design parameters, we simulated 20,000 auctions, where in each simulated auction, rivals bids were drawn from the particular distribution of interest, and where the expected payoff for bidder i is the average payoff across the 20,000 simulated auctions. This means the results presented in the next section are approximate solutions. However, the approximations are likely to be quite accurate as we have found virtually identical values for *ECM* when we compare results from the simulation to analytical results obtained when the payoff functions have closed-form solutions (e.g., the uniform distribution).

7. Results

Results for the Second-Price Auction

Table 2 presents the *ECM* for the second-price auction. To aid in interpretation of results, the last four rows of the table report summary statistics. The last row of Table 2 reports the expected payoffs when an individual bids optimally ($b_i = v_i$). There are several important pieces of information that can be garnered from Table 2. First, optimal expected payoffs are very small for a low-value individual with a true value of $2. The expected payoff from an optimal bid for such an individual is approximately zero regardless of the value distribution, a result which arises because such an individual has an extremely small probability of winning the auction. This example suggests that the incentives for an individual to bid optimally in a second-price auction can be very weak, unless an individual's true value is relatively large or they bid against individuals with values drawn from very particular distributions, such as the RS distribution. A second finding from Table 2 is that, for all distributions except RS, as an individual's true value increases, the second-price auction punishes sub-optimal bids more severely. For example, if facing bidders with values drawn from a uniform distribution, an individual that bids $2 over their true value can expect to lose $0.000 if v_i = $2, $0.053 if v_i = $5, and $1.107 if v_i = $8. Thus, the incentives for truthful bidding generally increase as v_i increases in a second-price auction. Third, *ECM* is greater for over-bidding than under-bidding for the LS, BM, and UN distributions, regardless of v_i. For v_i = $2 and v_i = $5, the same result holds for the RS and NM distributions as well. Thus, for almost all of the distributions and values, an individual can expect to be punished more severely by over-bidding than by under-bidding. By under-bidding, an individual risks foregoing a profitable purchase; however, by over-bidding, an individual may actually incur negative profit by having to pay more than their true value for the item. The exceptions to this situation occur when v_i = $8 and the distribution is RS or NM. In these cases, the *ECM* of under-bidding is greater than over-bidding. When an individual has a relatively high value, he or she has a high probability of winning the second-price auction; consequently, by under-bidding, an individual is very likely to lose an auction that could have been won by bidding true value.

Results for Ninth-Price Auction

Table 3 presents results for a ninth-price auction. In a ninth-price auction, expected profits are relatively high, reaching as high as $6.78 for the BM distribution for high-value bidders. In terms of *ECM*, the results are a mirror image of the second-price auction. The cost of misbehaving is extremely small for high-value bidders, and it increases as v_i decreases (the only exception being the LS distribution). In fact, for the RS and NM distributions, an individual with

Table 2
Expected Cost of Misbehaving in Second-Price Auction

b_i - v_i	***Value Distribution***														
	Left-Skewed			Right-Skewed			U-Shaped			Pseudo-Normal			Uniform		
	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8
-2.0	0.000	0.000	0.023	0.000	0.082	0.583	0.000	0.002	0.025	0.000	0.001	0.414	0.000	0.001	0.081
-1.5	0.000	0.000	0.022	0.000	0.073	0.293	0.000	0.001	0.019	0.000	0.001	0.316	0.000	0.001	0.062
-1.0	0.000	0.000	0.019	0.000	0.051	0.106	0.000	0.001	0.011	0.000	0.001	0.179	0.000	0.001	0.038
-0.5	0.000	0.000	0.010	0.000	0.019	0.020	0.000	0.001	0.004	0.000	0.001	0.052	0.000	0.000	0.013
0.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.000	0.000	0.038	0.000	0.033	0.009	0.000	0.000	0.005	0.000	0.003	0.048	0.000	0.001	0.026
1.0	0.000	0.000	0.245	0.001	0.153	0.019	0.000	0.002	0.050	0.000	0.021	0.151	0.000	0.005	0.146
1.5	0.000	0.001	0.680	0.008	0.360	0.024	0.000	0.007	0.206	0.000	0.095	0.228	0.000	0.019	0.454
2.0	0.000	0.006	0.992	0.041	0.618	0.024	0.000	0.012	1.620	0.000	0.283	0.245	0.000	0.053	1.107
Mean ECM^a	0.000	0.001	0.225	0.006	0.154	0.120	0.000	0.003	0.216	0.000	0.045	0.181	0.000	0.009	0.214
Mean $ECM_U{}^b$	0.000	0.000	0.019	0.000	0.056	0.251	0.000	0.001	0.015	0.000	0.001	0.240	0.000	0.001	0.049
Mean $ECM_O{}^c$	0.000	0.002	0.489	0.013	0.291	0.019	0.000	0.005	0.470	0.000	0.101	0.168	0.000	0.020	0.433
$E[\pi_i^{2ndprice*}]$	0.000	0.000	0.023	0.000	0.085	1.837	0.000	0.002	0.042	0.000	0.001	0.491	0.000	0.001	0.107

[a]Simple average of *ECM* for each column of results
[b]Simple average of *ECM* for each column of results when an individual underbids, b_i - $v_i < 0$
[c]Simple average of *ECM* for each column of results when an individual overbids, b_i - $v_i > 0$

Table 3
Expected Cost of Misbehaving in Ninth-Price Auction

b_i - v_i	***Value Distribution***														
	Left-Skewed			Right-Skewed			U-Shaped			Pseudo-Normal			Uniform		
	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8
-2.0	0.000	0.369	0.211	0.487	0.049	0.000	1.049	0.098	0.009	0.032	0.687	0.001	0.483	0.231	0.006
-1.5	0.000	0.280	0.058	0.459	0.008	0.000	0.376	0.043	0.003	0.032	0.310	0.000	0.362	0.093	0.002
-1.0	0.000	0.160	0.008	0.285	0.001	0.000	0.122	0.014	0.001	0.030	0.093	0.000	0.174	0.030	0.000
-0.5	0.000	0.047	0.000	0.072	0.000	0.000	0.023	0.002	0.000	0.015	0.013	0.000	0.041	0.005	0.000
0.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.002	0.046	0.000	0.038	0.000	0.000	0.016	0.001	0.000	0.039	0.003	0.000	0.033	0.002	0.000
1.0	0.020	0.158	0.000	0.089	0.000	0.000	0.047	0.005	0.000	0.198	0.005	0.000	0.110	0.006	0.000
1.5	0.087	0.263	0.000	0.116	0.000	0.000	0.085	0.009	0.000	0.466	0.006	0.000	0.205	0.009	0.000
2.0	0.260	0.330	0.000	0.125	0.000	0.000	0.126	0.012	0.000	0.764	0.006	0.000	0.292	0.011	0.000
Mean *ECM*[a]	0.041	0.184	0.031	0.186	0.006	0.000	0.205	0.020	0.001	0.175	0.125	0.000	0.189	0.043	0.001
Mean ECM_U[b]	0.000	0.214	0.069	0.326	0.015	0.000	0.393	0.039	0.003	0.027	0.276	0.000	0.265	0.090	0.002
Mean ECM_O[c]	0.092	0.199	0.000	0.092	0.000	0.000	0.069	0.007	0.000	0.367	0.005	0.000	0.160	0.007	0.000
$E[\pi_i^{9thprice*}]$	0.000	0.442	3.084	0.487	3.359	6.359	1.049	3.800	6.782	0.032	1.857	4.851	0.483	3.008	5.996

[a]Simple average of *ECM* for each column of results
[b]Simple average of *ECM* for each column of results when an individual underbids, $b_i - v_i < 0$
[c]Simple average of *ECM* for each column of results when an individual overbids, $b_i - v_i > 0$

Table 4
Expected Cost of Misbehaving in Fifth-Price Auction

b_i - v_i	***Value Distribution***														
	Left-Skewed			Right-Skewed			U-Shaped			Pseudo-Normal			Uniform		
	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8
-2.0	0.000	0.001	0.624	0.003	0.823	0.008	0.012	0.162	0.337	0.000	0.127	0.456	0.001	0.176	0.473
-1.5	0.000	0.001	0.470	0.003	0.456	0.000	0.011	0.102	0.196	0.000	0.117	0.153	0.001	0.127	0.254
-1.0	0.000	0.001	0.252	0.003	0.170	0.000	0.008	0.052	0.090	0.000	0.086	0.032	0.001	0.068	0.101
-0.5	0.000	0.001	0.064	0.002	0.029	0.000	0.003	0.014	0.023	0.000	0.032	0.003	0.001	0.021	0.020
0.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.000	0.003	0.031	0.017	0.010	0.000	0.005	0.018	0.022	0.000	0.055	0.000	0.002	0.028	0.012
1.0	0.000	0.030	0.061	0.121	0.023	0.000	0.026	0.074	0.079	0.001	0.222	0.000	0.014	0.119	0.031
1.5	0.000	0.145	0.064	0.386	0.027	0.000	0.069	0.174	0.158	0.008	0.433	0.000	0.050	0.276	0.040
2.0	0.000	0.461	0.064	0.784	0.027	0.000	0.140	0.323	0.207	0.055	0.596	0.000	0.134	0.490	0.040
Mean *ECM*[a]	0.000	0.071	0.181	0.147	0.174	0.001	0.030	0.102	0.124	0.007	0.185	0.072	0.023	0.145	0.108
Mean ECM_U[b]	0.000	0.001	0.353	0.003	0.370	0.002	0.009	0.083	0.162	0.000	0.091	0.161	0.001	0.098	0.212
Mean ECM_O[c]	0.000	0.160	0.055	0.327	0.022	0.000	0.060	0.147	0.117	0.016	0.327	0.000	0.050	0.228	0.031
$E[\pi_i^{5thprice*}]$	0.000	0.001	0.728	0.003	1.307	4.280	0.012	0.355	1.800	0.000	0.129	2.430	0.001	0.237	2.037

[a]Simple average of *ECM* for each column of results
[b]Simple average of *ECM* for each column of results when an individual underbids, $b_i - v_i < 0$
[c]Simple average of *ECM* for each column of results when an individual overbids, $b_i - v_i > 0$

Table 5
Expected Cost of Misbehaving in BDM Mechanism

b_i - v_i	***Value Distribution***														
	Left-Skewed			Right-Skewed			U-Shaped			Pseudo-Normal			Uniform		
	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8	v_i =2	v_i =5	v_i =8
-2.0	0.003	0.127	0.389	0.196	0.368	0.102	0.387	0.133	0.136	0.031	0.318	0.293	0.200	0.200	0.200
-1.5	0.003	0.088	0.229	0.158	0.194	0.044	0.124	0.073	0.078	0.029	0.193	0.148	0.113	0.113	0.113
-1.0	0.002	0.046	0.105	0.086	0.079	0.014	0.047	0.032	0.036	0.020	0.090	0.057	0.050	0.050	0.050
-0.5	0.001	0.014	0.027	0.024	0.018	0.002	0.010	0.008	0.009	0.007	0.023	0.012	0.013	0.013	0.013
0.0	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
0.5	0.002	0.018	0.024	0.027	0.014	0.001	0.009	0.008	0.010	0.012	0.023	0.007	0.013	0.013	0.013
1.0	0.014	0.079	0.086	0.105	0.046	0.002	0.036	0.032	0.047	0.057	0.090	0.021	0.050	0.050	0.050
1.5	0.044	0.194	0.158	0.229	0.088	0.003	0.078	0.073	0.124	0.148	0.193	0.029	0.113	0.113	0.113
2.0	0.102	0.368	0.196	0.389	0.127	0.003	0.136	0.133	0.387	0.293	0.318	0.031	0.200	0.200	0.200
Mean *ECM*[a]	0.019	0.104	0.135	0.135	0.104	0.019	0.092	0.055	0.092	0.066	0.139	0.066	0.084	0.084	0.084
Mean ECM_U[b]	0.002	0.069	0.188	0.116	0.165	0.041	0.142	0.062	0.065	0.022	0.156	0.128	0.094	0.094	0.094
Mean ECM_O[c]	0.041	0.165	0.116	0.188	0.069	0.002	0.065	0.062	0.142	0.128	0.156	0.022	0.094	0.094	0.094
$E[\pi_i^{BDM*}]$	0.003	0.208	1.529	0.196	1.875	4.669	0.387	1.591	3.388	0.031	0.781	3.031	0.200	1.250	3.200

[a]Simple average of *ECM* for each column of results
[b]Simple average of *ECM* for each column of results when an individual underbids, $b_i - v_i < 0$
[c]Simple average of *ECM* for each column of results when an individual overbids, $b_i - v_i > 0$

v_i = \$8 stands to lose virtually nothing by varying their bid from \$6 to \$10. The reason is that high value bidders are likely to win a ninth price auction regardless of the bid they offer. Except for the LS distribution with v_i = \$2 and NM with v_i = \$2, a ninth-price auction generates higher *ECM* for underbidding as compared to overbidding.

Results for Fifth-Price Auction

Table 4 reports results for the *ECM* for a fifth price auction. For the fifth-price auction, it is difficult to identify clear trends; as it is apparently a mix of the second- and ninth-price auctions. Whether increasing the magnitude of v_i increases or decreases *ECM* depends both on the distribution and on whether an individual over- or under-bids. Conversely, the effect of over- or under-bidding depends on the distribution and on bidder's values. Take for example the UN distribution where increasing v_i tends to increase *ECM* if an individual under-bids; however, when an individual overbids, *ECM* is greater for v_i = \$5 than for v_i = \$2 or v_i = \$8. Additionally, for the UN distribution, overbidding tends to be more costly than underbidding for v_i = \$2 and v_i = \$5 but the opposite is the case for v_i = \$8.

Results for the BDM Mechanism

Table 5 presents the *ECM* for the BDM mechanism. Unlike the second-price and ninth-price auctions, there is no clear relationship between v_i and *ECM*. The uniform distribution provides the starkest example: for a given level of misbehavior, an individual has the same *ECM*, regardless of v_i. If the price distribution is UN, under-bidding by \$2 results in an *ECM* of \$0.20 for v_i = \$2, v_i = \$5, and v_i = \$8. For the symmetric distributions BM and NM, *ECM* is also symmetric in that under-bidding, low-value individuals have the same *ECM* as over-bidding, high-value individuals. For the asymmetric distributions, low-value individuals have a higher *ECM* in the RS distribution than low-value individuals, whereas, in the LS distribution, high-value individuals face a higher *ECM* than low-value individuals.

Overall, results in Table 5 indicate that an NM distribution centered on an individual's value creates the greatest *ECM.* The only exception to this statement is if a practitioner desires greater punishment for over- or under-bidding, in which case the LS or RS distributions might be used. Recall with a BDM that the researcher chooses the price distribution. This finding is striking given that the vast majority of studies using BDM auction have used the UN distribution. Using a NM distribution centered on v_i generates about 70% higher *ECM* than using a U distribution centered on v_i. These findings are also interesting given that applications such as Wertenbroch and Skiera (2002) failed to provide complete distributional information about the price-generating process to participants. As shown in Table 5, different price-generating distributions can create very different incentives for optimal bidding.

Comparison across Mechanisms

Comparing across nth-price auctions, the expected payoffs from participating in an auction are increasing in *n*. This is attributable to the fact that, for a given distribution, an individual stands a higher chance of winning the higher the *n*. Despite this, *ECM* differs, often substantially, across mechanisms. Table 6 summarizes the results. Across all distributions and values, the fifth-price auction tends to generate the highest *ECM* with the BDM coming in second. The ninth-price auction generates the highest *ECM* for low-value bidders, but performs worst for high-value bidders. Conversely, the second-price auction generates the highest *ECM* for high-value bidders, but has the lowest *ECM* for low-value bidders. When the price distribution is centered on an individual's value (e.g., NM distribution with v_i = \$5), the BDM performs well; the only mechanism that routinely does better is the fifth-price auction. Table 6 also shows that for a low-valued individual, *ECM* from the BDM exceeds that from the second price auction for all distributions considered; however, the opposite is true for high-value individuals. In fact, table 6 shows that: a) for low-value bidders, the *ECM* in the second price auction is less than that in all other mechanisms for all assumed distributions, b) for high-value bidders, the *ECM* in the second price auction is higher than that in all other mechanisms for all assumed distributions, c) for low-value bidders, the ECM in the ninth price auction is higher than that in all other mechanisms for all assumed distributions, and d) for high-value bidders, the ECM in the ninth price auction is lower than that in all other mechanisms for all assumed distributions.

Table 6. Comparison of Expected Cost of Misbehaving Across Mechanisms

	Value Distribution					
Auction Mechanism	**Left-Skewed**	**Right-Skewed**	**U-Shaped**	**Pseudo-Normal**	**Uniform**	**Mean Across Distributions**
Mean ECM across all values						
Second-Price	0.075	0.093	0.073	0.076	0.074	0.078
Fifth-Price	0.084	0.107	0.085	0.088	0.092	0.091
Ninth-Price	0.085	0.064	0.076	0.100	0.078	0.080
BDM	0.086	0.086	0.079	0.090	0.084	0.085
Mean ECM for v_i = $2						
Second-Price	0.000	0.006	0.000	0.000	0.000	0.001
Fifth-Price	0.000	0.147	0.030	0.007	0.023	0.041
Ninth-Price	0.041	0.186	0.205	0.175	0.189	0.159
BDM	0.019	0.135	0.092	0.006	0.084	0.067
Mean ECM for v_i = $5						
Second-Price	0.001	0.154	0.003	0.045	0.009	0.042
Fifth-Price	0.071	0.174	0.102	0.185	0.145	0.135
Ninth-Price	0.184	0.006	0.020	0.125	0.043	0.076
BDM	0.104	0.104	0.055	0.139	0.084	0.097
Mean ECM for v_i = $8						
Second-Price	0.225	0.120	0.216	0.181	0.214	0.191
Fifth-Price	0.181	0.001	0.124	0.072	0.108	0.097
Ninth-Price	0.031	0.000	0.001	0.000	0.001	0.007
BDM	0.135	0.019	0.092	0.006	0.084	0.067

8. Discussion and Conclusions

Because experimental auctions create an incentive for individuals to reveal their "true" preferences for a product, they are a potentially useful tool for estimating consumer preferences and WTP for new products and product extensions. Given the high cost of product launch and the low probability of new product success, it is important for marketers to utilize incentive compatible value elicitation mechanisms. Indeed, Ding, Grewal, and Liechty (2005) showed that elicitation mechanisms that properly aligned incentives better predict actual behavior as compared to non-incentive aligned mechanisms.

One of the most common methods used in pre-test marketing research is conjoint analysis. In conjoint applications, utility “part-worths” are estimated from ranking, rating, or choice data. Willingness-to-pay for an attribute is estimated by dividing the attribute’s estimated part-worth by the estimated coefficient on the price variable. Market share simulations are also frequently conducted using the estimated part-worths. Although the advantages of conjoint analysis are well known, one disadvantage is that most conjoint tasks are purely hypothetical, and as such, individuals have little incentive to accurately reveal preferences. Results by Ding, Grewal, and Liechty (2005) and Lusk and Schroeder (2004) indicate that the hypothetical nature of conjoint tasks can indeed be problematic. One way to “incentivize” conjoint analysis is to marry traditional conjoint analysis with experimental auctions. In such an approach, individuals can bid for a conjoint profile (which is a product described by several attributes) and an auction mechanism can be used to determine whether an individual actually makes a purchase. For example, in Ding, Grewal, and Liechty (2005) individuals stated their WTP for 12 different conjoint profiles. One of the profiles was selected at random and a BDM mechanism was used to determine whether an individual bought the randomly selected profile. There is, of course, no reason why the BDM mechanism couldn’t be substituted with any other auction mechanisms, or why the price distribution in the BDM couldn’t be changed in an attempt to increase incentives for truthful responses.

One advantage of experimental auctions, as opposed to traditional conjoint analysis, is that willingness-to-pay measures are obtained for each individual in an auction. In traditional conjoint methods, such as those discussed in Louviere, Hensher, and Swait (2000), willingness-to-pay must be inferred from aggregate econometric estimates.[5] Auctions provide a straightforward way to investigate the heterogeneity in valuations in a population of consumers, and as such, they readily lend themselves to creation of market segments on the basis of the economic value individuals place on a good. Further, by assuming that individuals choose to purchase products that yield the largest difference between a products’ stated price and an individual’s value, Lusk and Schroeder (2006) and Lusk and Shogren (2007) show how WTP values obtained from experimental auctions can be used to create market share simulations as in traditional conjoint analysis. Of course, auction methods are not without criticisms. As mentioned by Jedidi, Jagpal, and Manchanda (2003), auctions may suffer in cases where

[5] Some Bayesian methods are available to provide individual-level estimates; however such models still require an assumption about an error distribution and the functional form for the utility function to yield individual-level valuations, something which is not required for auctions.

willingness-to-pay is not independent of market prices (e.g., subjects use price as a proxy for quality) or in cases where the price-setting mechanism is not made explicit to subjects.

Although marrying conjoint analysis with experimental auctions presents a fruitful avenue for future research, a question that must still be answered is *which* mechanism to employ to elicit valuations. There are a variety of factors to consider when choosing an auction mechanism including the auction setting (field versus laboratory), constraints on the number of goods available for sale, the number of individuals expected to participate in an auction, and time constraints to conduct the auction. In this paper, we suggest that practitioners investigate the shapes of auctions' payoff functions and use the expected cost of deviating from truthful bidding as a diagnostic tool to aid in selecting between mechanisms. Recognizing that the payoff function shape is only one factor to consider in the multi-faceted process of selecting an appropriate mechanism to elicit valuations, our findings suggest several considerations when choosing between mechanisms.

In an incentive compatible auction, incentives for truthful bidding differ for relatively high and low value individuals. As such, some thought must be given regarding which type of individual is of primary interest for the study at hand. Our analysis indicates that when interest is on the top end of the demand curve (i.e., high-value individuals), a second-price auction is likely to provide accurate bids; a finding which does not depend on assumptions regarding the distribution of bidders' values. Thus, if marketers are interested in accurately identifying a market segment with high preferences for a new product, the second-price auction may be preferable. Conversely, if interest is on low-value individuals, a ninth-price auction (or an nth price auction with $n \approx N$) is likely to provide more accurate depictions of true willingness-to-pay than other mechanisms regardless of the distribution of bidders' values. Across all the mechanisms investigated in this study, the fifth price auction (or an auction with $n \approx N/2$) tended to provide the highest punishment from non-truthful bidding when one jointly considers low-, medium-, and high-value bidders. These findings support the conclusions of Shogren et al. (2001), whose empirical results led them to state (p. 420), " . . . there might be an effective mix between the number of subjects (k) and the number of units of an auctioned good (n) that would engage both on-margin and off-margin bidders." It appears, for the parameters used in this study ($N = 10$), that a fifth-price auction offers this "effective mix."

Like the fifth-price auction, the BDM (and thus the random nth-price auction) tends to provide relatively strong incentives for truthful bidding for all individuals regardless of the magnitude of their true WTP. One important implication of our results is that the distribution of prices in the BDM auction can significantly affect incentives for truthful bidding. Importantly, choice of price distribution in the BDM is endogenous to the researcher. Results indicate that utilizing a price-generating mechanism that is normally distributed around an individual's true value will generate the greatest incentives for truthful value revelation. Although conveying a normal price distribution to study participants is more difficult than with a uniform price distribution, effective use of graphics, colored balls, and a bingo cages, for example, can alleviate this difficulty. One difficulty with this conclusion is that an individual's true value is obviously unknown prior to elicitation. However, preliminary analysis could offer some guidance as to the average true value in a sample. Preliminary analysis could also be conducted to identify factors influencing an individual's true values such that the BDM mechanism could be customized for each individual in order to create the greatest incentives for truthful value revelation. For example, stated purchase intention or attitudinal questions might be used to gauge whether an individual has a relatively high or low value. If there is a great deal of uncertainty about individuals' values, even after preliminary analyses, utilizing a uniform price distribution is likely the safest bet as it creates equal incentives for truth telling regardless of whether the distribution is centered on an individual's true value. If there is particular concern about overbidding (underbidding), then a using a price distribution that is left-skewed (right-skewed) would create the greatest costs from overbidding.

Experimental auctions are a potentially valuable pre-test market research tool that can complement existing marketing research methods such as conjoint analysis. This paper presents results that further expose the merits of experimental auctions and provides guidance in selecting between experimental auctions to obtain more accurate estimates of consumer willingness-to-pay for new products.

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