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

Jayson L. Lusk, Corinne Alexander, and Matt Rousu*

**Abstract:** Accurately estimating consumer demand for new products is an arduous task made even more difficult by the fact that individuals tend to overstate the amount they are willing to pay for new goods when asked hypothetical questions. Despite their appeal, marketers have been slow to adopt experimental auctions as a standard tool in pre-test market research. One issue that has slowed adoption of the methodology is the proliferation of auction mechanisms and the lack of clear guidance in choosing between mechanisms. In this paper, we provide insight into the theoretical properties of two incentive compatible value elicitation mechanisms, the BDM and Vickrey $2^{nd}$ price auction, such that practitioners can make more informed decisions in designing experimental auctions to determine consumer willingness-to-pay. In particular, we draw attention to the shapes of the payoff functions and show in a simulation that the two 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. The simulation indicates the $2^{nd}$ price auction punishes deviations from truthful bidding more severely for high value individuals than the BDM mechanism. These results are confirmed by an experimental study, where we find more accurate bidding for high-value individuals in the $2^{nd}$ price auction as compared to the BDM. Our results also indicate that when implementing the BDM mechanism, the greatest incentives for truthful value revelation are created when the random price generator is based on a normal distribution centered on an individual's expected true value.

*Authors are associate professor and assistant professor of agricultural economics at Purdue University and Research Economist, RTI international, respectively.

Contact: Jayson Lusk, Dept. Ag. Econ., 403 W. State Street, Krannert Bldg., W. Lafayette, IN 47907-2056, phone: (765)494-4253, fax: (765)494-9176; e-mail: jlusk@purdue.edu.

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Because of the high failure rate among new products, marketers are continually seeking ways of better forecasting new product success. Traditional approaches to investigating consumer demand and willingness-to-pay (WTP) for new products include focus groups, surveys, market tests, and laboratory pre-test markets. When choosing a method to elicit WTP for a new product or product extensions, a critically important issue to consider is incentive compatibility – i.e., whether an elicitation method provides an incentive for individuals to truthfully reveal their true preferences for a product. Over the past decade, a wealth of evidence has surmounted in the economics literature suggesting that individuals overstate the amount they are WTP in hypothetical settings as compared to when real money is on the line (e.g., Cummings, Harrison, and Rutström). For example, List and Gallet conducted a Meta analysis of 29 studies and 58 valuations and found that, on average, individuals overstated their WTP by a factor of about 3 in hypothetical settings. When attempting to determine consumer demand in order to design optimal pricing schedules, it is clear that non-incentive compatible value elicitation mechanisms will provide biased estimates of WTP, which will lead to inaccurate pricing decisions and sales forecasts.

Hoffman et al. used the incentive compatible fifth-price auction to illustrate the usefulness of experimental auctions in an application to new beef packaging. They concluded (p. 332), "experimental auctions are potentially valuable market measurement tools." Despite this conclusion, very little research has appeared in the marketing literature exploring the viability of experimental auctions as a pre-test market research tool. In one recent exception, Wertenbroch

and Skiera proposed using the incentive compatible Becker, DeGroot, Marschak (BDM) mechanism to elicit consumer WTP at the point of purchase.[1] They illustrated the reliability and validity of the mechanism. Consistent with the extant economics literature, they also showed that WTP from the BDM was significantly lower than WTP elicited from hypothetical price matching or choice exercises. In addition to the BDM used by Wertenbroch and Skiera and the Vickrey-type auction used by Hoffman et al., there are a number of other incentive compatible auctions that could be used to elicit consumer WTP in pretest markets.[2] In fact, a variety of incentive compatible mechanisms, including the BDM and the Vickrey auction, have been widely used in applied economic research to determine consumer WTP for new products (e.g., Buhr et al.; Buzby et al.; Dickinson and Bailey; Fox; Fox et al.; Hayes et al.; Lusk et al. 2001a, 2001b; Lusk, Feldkamp, and Schroeder; Melton et al.; Menkhaus et al.; Noussiar et al., 2002, 2004; Roosen et al.; Shogren, List, and Hayes; Umberger et al.). List (2001, 2002) and Lusk et al. (2001a) show how the BDM and Vickrey auctions can be used in a field setting at the point of purchase.

In a typical incentive compatible experimental auction, subjects bid to obtain a novel good. The highest bidder(s) win the auction and pay a price that is determined exogenously from the individuals' bid. In a $2^{nd}$ price auction, an individual bids against other competitors for a good and the highest bidder wins the auction and pays the $2^{nd}$ highest bid amount. In contrast, in the BDM an individual bids against a random price generator and purchases one unit of a good if their bid is greater than the randomly drawn price. WTP for a new product is often determined

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

[2] Although the BDM is not strictly an auction as it is an individual decision making mechanism, for convenience we refer to the BDM mechanism as an auction because individuals bid against a random number (price) generator instead of other bidders as in a more conventional auction.

by comparing bids for a new good to bids for a pre-existing substitute or 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 active market environment with feedback where subjects exchange real goods and real money.  A further advantage of the method is that exact WTP measures are obtained, which is not the case with discrete choice or conjoint methods (e.g., Louviere, Hensher, and Swait), where WTP must be inferred from econometric estimates.  But perhaps the greatest advantage of experimental auctions is that they create an environment where individuals have an incentive to truthfully reveal their preferences.  This is not to say that individual cannot misrepresent their preferences, or be influenced by other social-psychological factors, but that experimental auctions impose real economic costs on individuals whey they offer bids that deviate from their true values.

Although there is general agreement on the need to employ elicitation mechanisms that are incentive compatible when eliciting WTP, there is currently little guidance as to which mechanism to employ amongst the class of incentive compatible mechanisms.  There are a number of mechanisms that are incentive compatible, but theory gives little guidance as to which incentive compatible auction should be preferred over another.  Thus, choice of auction mechanism often boils down to pragmatic considerations (e.g., see Lusk, 2003) or to properties of auctions that have been determined by comparing valuations across elicitation mechanisms in empirical research (e.g., see Cox, Roberson, and Smith; Kagel, Harstad, and Levin; Lusk, Feldkamp, and Schroeder; Rutström).  Despite the empirical findings that incentive compatible auctions can generate divergent results, no formal theory has yet been advanced to explain *why* there might be systematic deviations from predictions.  This is particularly troubling since the optimal strategy in all such mechanisms is truthful preference revelation.

The purpose of this paper is to provide insight into the theoretical properties of two incentive compatible value elicitation mechanisms (the BDM and Vickrey $2^{nd}$ price auction) such that practitioners can make more informed decisions in designing experimental auctions to determine consumer WTP. In particular, we provide an explanation for why the BDM and $2^{nd}$ price auctions can generate divergent results based on the observation that the two mechanisms differ with respect to the expected cost of deviating from truthful bidding. We show that incentives for truthful bidding can differ across the two mechanisms and even within a mechanism depending on: a) the distribution of competing bidders' values in a $2^{nd}$ price auction, b) the distribution of the random price generator in the BDM, and c) individuals' true values for a good. After demonstrating the theoretical properties of the mechanisms, we provide results from a small-scale induced value experiment, where true values are known, which provides support for the theory. The hope is that by exposing the theoretical underpinnings of experimental auctions, marketers will devote further efforts into exploring the merits of experimental auctions as a marketing research tool.

**Experiment Auctions**

Bidding behavior in BDM and $2^{nd}$ price auctions has been investigated in several induced value experimental studies. Induced value experiments refer to experiments where individuals are assigned a value for a fictitious "item." Individuals are paid the difference between their induced value and the price of an item if they win an auction. 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. and Noussair et al. (forthcoming) investigated whether BDM bids were consistent

with actual values in induced value studies. Both studies concluded the BDM was demand revealing. In the first studies on the subject, Coppinger, Smith, and Titus; and Cox, Roberson, and Smith found that the $2^{nd}$ price auction generated truthful bidding in induced value experiments. Subsequent work by Kagel, Harstad, and Levin and Kagel and Levin found a tendency for subjects to overbid in $2^{nd}$ price auctions. However recent studies by Shogren et al. (2001b), Noussair et al. (forthcoming), and Parkhurst et al. concluded that the $2^{nd}$ price auction is demand revealing.

Although the general consensus is that the BDM and $2^{nd}$ price auction are empirically demand revealing in induced-value studies, the relative accuracy of the mechanisms is still in question. Shogren et al. (2001b) found that although the $2^{nd}$ price auction was demand revealing in the aggregate, it was more accurate for high-value (or "on-margin") bidders than for low-value (or "off-margin") bidders. Noussair, Robin, and Ruffieux (forthcoming) concluded that the $2^{nd}$ price auction generated bids closer to true values than the BDM mechanism all along the demand curve.

A couple of studies have compared homegrown values (those values that individuals bring into an experiment) across competing incentive compatible auctions. Rutström found that BDM bids for chocolates were significantly lower than bids from a $2^{nd}$ price auction. Lusk, Feldkamp, and Schroeder found that $2^{nd}$ price and BDM bids for beef steaks were similar in initial bidding rounds, but that fifth round $2^{nd}$ price auction bids were significantly greater than initial BDM bids. Shogren et al. (2001a) found that the WTP measure of value was significantly less than the willingness-to-accept (WTA) measures of value for both the $2^{nd}$ price auction and BDM in initial bidding rounds; however, over repeated rounds, the disparity between WTP and WTA disappeared with the $2^{nd}$ price auction, but persisted with the BDM. Shogren et al. (2001a)

argued the competitive nature of the 2<sup>nd</sup> price auction promoted more rational bidding as
compared to the BDM, which is an individual decision-making exercise.

**Payoff Functions and the Cost of Misbehaving**

Suppose an individual derives a 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 $\pi_i$ is individual $i$'s 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 that will 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 $b_i = v_i$.

*BDM Payoff Function*

In a 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 $f(p|$

$p < b_i) = \int_{-\infty}^{b_i} \frac{f(p)}{F(b_i)} p\, dp$  - i.e., the mean of the price distribution truncated at $b_i$ from above. The

probability of winning a BDM auction given $b_i$ is simply $F(b_i)$. Thus, the expected payoff for the BDM mechanism is:

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

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


*Vickrey 2nd Price Auction Payoff Function*

In a 2nd price auction, individual $i$ bids on one-unit of a good against $N$ other bidders with values, $v_j$, independently drawn from a distribution with cdf given by $G(v)$ and pdf given by $g(v)$. Assuming that all individuals except individual $i$ bid truthfully (i.e., $b_j = v_j$ for all $j \neq i$) the

expected price conditional on winning given $b_i$ is $\int_{-\infty}^{b_i} (n-1) \left[ \frac{G(v)}{G(b_i)} \right]^{(N-2)} \left[ \frac{g(v)}{G(b_i)} \right] v \, dx$ 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 truncated from above at $b_i$, multiplied by $v$. This result follows from basic order statistics (see Balakrishnan and Cohen). The expected payoff for individual $i$ submitting $b_i$ in a 2nd price auction is

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

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

*Cost of Misbehaving*

For both the BDM and 2<sup>nd</sup> price auction, it is optimal for an individual to submit a bid equal to true value. However, the two mechanisms differ in terms of expected payoff forgone by "misbehaving" or deviating from this optimal. There may be a variety of reasons why an individual may misbehave, but one prominent reason discussed in Harrison (1989, 1991), 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 with the cognitive cost of the individual attempting to determine the exact optimal bid. Let $\pi_i^{k*}$ be individual $i$'s optimal payoff in mechanism $k$ ($k$ = BDM or 2<sup>nd</sup> price) that is achieved when an individual submits $b_i$ equal to $v_i$. The expected cost of misbehaving for mechanism $k$ is given by:

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

*ECM* is simply the expected dollar-loss an individual will incur by making a bid that is not equal to their 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.


**Simulation Study: Effect of Distribution, Value, and Mechanism on Cost of Misbehaving**

In this study, we investigate determinants of *ECM*, to assist researchers in determining how to design experimental auctions. 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.

*Simulation Description*

We carry out simulations by manipulating four variables: 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, which is either the BDM or 2nd price auction. This simulation generates 5x3x9x2 payoff function values which are used to determine the *ECM* under different conditions.

To operationalize the expected payoff functions in equations (2) and (3), 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), bi-modal (BM), pseudo-normal (N), and uniform (U).[3] The parameters that generate each of these Beta distributions are explained in table 1 and the distributions are illustrated in figure 1. It is important to realize that in the BDM, the distribution refers to the distribution of prices drawn from a random number generator (e.g., a bingo cage); whereas, in the 2nd price auction the distribution refers to the distribution of competitors' bidders values 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; however, steps can be taken to form priors about the distribution. For example, the LS distribution identifies a case in a 2nd price auction where most of the individuals have a relatively high value for the good, whereas the RS distribution is associated the exact opposite case. Alternatively, the BM distribution

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[3] When the distribution is uniform, simple analytical solutions are obtainable: the payoff function for the BDM is $(v_i-0.5b_i)*(b_i/N)$ and the payoff function for the 2nd price auction is $(v_i-b_i(N-1)/N)*(b_i/N)^{\wedge}(N-1)$.

describes a situation in a 2$^{nd}$ price auction where there are segments of the population that derive very high and low values from a new good, with few impartial individuals.

The only remaining issue that must be resolved to carry out the simulation is the number of bidders in the 2$^{nd}$ price auction. 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 individuals than in other studies (e.g., Lusk, Feldkamp, and Schroeder had sample sizes of about 15).

**Results of Simulation Study**

*Simulation Results for the 2$^{nd}$ Price Auction*

Table 2 presents the *ECM* for the 2$^{nd}$ price auction simulations. 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 extremely small. For an individual with a true value of $2, the expected payoff from an optimal bid is approximately zero regardless of the value distribution because such an individual has an extremely small probability of winning the auction. As a result, *ECM* is low for all distributions for $v_i = \$2$ and $v_i = \$5$. For example, an individual with $v_i = \$5$ bidding against 10 other bidders whose values are drawn from a BM distribution can submit bids as low as $3 and as high as $7 and only change expected payoff by $0.014. This suggests that the incentives for an individual to bid optimally in a 2$^{nd}$ price auction are 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 regardless of the type of distribution, as an individual's true value increases, the 2$^{nd}$ 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 increase as $v_i$ increases in a $2^{nd}$ price auction.

Third, *ECM* is greater for over-bidding than under-bidding for the LS, BM, and U distributions regardless of $v_i$. For $v_i$ = $2 and $v_i$ = $5, the same result holds for the RS and N 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 occurs when $v_i$ = $8 and the distribution is RS or N. In these cases, the *ECM* of under-bidding is greater than over-bidding. When an individual has a relatively high value, they have a high probability of winning the $2^{nd}$ price auction, and consequently, by under-bidding an individual is very likely to lose an auction that could have been won by bidding true value.

*Simulation Results for the BDM*

Table 3 presents the *ECM* for the BDM mechanism. The last row of table 3 reports maximum expected payoff obtained when $b_i$ = $v_i$. As with table 2, there are several important findings that can be obtained by investigating table 3. Unlike the $2^{nd}$ price auction, 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 U, 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 N, *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 3 indicate that a N 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.

This finding is striking given that the vast majority of studies using the BDM have used the U

distribution. Using a N distribution centered on $v_i$ generates 70% to 80% higher *ECM* than using

a U distribution centered on $v_i$. These findings are also interesting given that applications such as

that in Wertenbroch and Skiera failed to provide complete distributional information about the

price generating process to participants. As shown in table 3, different price generating

distributions can create very different incentives for optimal bidding.


*Simulation Results: 2<sup>nd</sup> Price Auction versus BDM*

The expected payoffs from participating in a BDM are substantially larger than that in a $2^{nd}$ price

auction. In many cases expected maximum payoffs in the BDM are more than double that in the

$2^{nd}$ price auction. This is a result of the fact that for a given distribution, an individual always

stands a higher chance of winning in the BDM than the $2^{nd}$ price auction, so long as $N > 2$.

Despite the fact that expected optimal payoffs are almost universally higher in the BDM than in

the $2^{nd}$ price auction, *ECM* can differ across the two mechanisms. The BDM punishes low-value

individuals much more severely than the $2^{nd}$ price auction. However, the $2^{nd}$ price auction

punishes high-value individuals more severely than the BDM. These results imply that if a

practitioner is interested in the WTP of low-value individuals, then the BDM is preferred to the

$2^{nd}$ price auction as it provides stronger incentives for truthful bidding. However, a more likely case is that interest will be on high-value individuals. These are the individuals that are likely to fall into the market segment most interested in a new product. For such individuals, a $2^{nd}$ price auction will provide stronger incentives for truthful bidding than the BDM.

## Experimental Study

To further investigate these issues, we conducted a small induced-value experiment with 20 student subjects. In the experiment, individuals participated in BDM and $2^{nd}$ price auctions where prices/values were drawn from a U distribution with bounds [1, 40]. Based on the simulation results above and the fact that the distribution is U, the following testable hypotheses can be stated: H1: For high value individuals, the $2^{nd}$ price auction will generate more accurate bids than the BDM; [4] H2: For low value individuals, the BDM will generate more accurate bids than the $2^{nd}$ price auction; H3: High value individuals will submit more accurate bids than low value individuals in a $2^{nd}$ price auction; and H4: The magnitude of an individual's true value is not related to bidding accuracy in the BDM.

### *Experimental Procedures*

Twenty students were recruited from undergraduate economics courses to take part in the study where they had the chance to win a cash prize. Recruited subjects were assigned to one of two experimental treatments. In one treatment, subjects first participated in four rounds of a $2^{nd}$ price auction and then four rounds of the BDM. In a second treatment, subjects first participated in four rounds of the BDM then in four rounds of the $2^{nd}$ price auction. Ten subjects were assigned

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[4] Accuracy here is defined as the absolute difference between an individual's bid and true value - i.e., $|v_i - b_i|$.

to each treatment. This design allows for a within-subject comparison of bids and controls for order effects.

The following outlines the steps in the experiment. In Step 1, participants arrived and received a recording sheet that listed their individual and private induced values for each of the rounds of the experiment. We used the same ten induced values for all bidding rounds and auctions. These values were randomly drawn from a uniform distribution with bounds 1 and 40. The selected induced values were 3, 9, 11, 14, 16, 20, 24, 29, 33, and 38. The induced values were assigned to individuals such that each person had a different induced value in each round; however, the distribution of induced values across individuals was identical in each round. The induced values were described as tokens. Subjects were informed that at the end of the experiment they would participate in a lottery for $30.00, where their chances of winning were directly related to the number of earned tokens. At the end of the experiment, all subjects' (individually labeled) tokens were placed in a bin, and one token was drawn to determine the winner of the $30.00 cash prize. [5]

In Step 2, bidding procedures were explained to participants. Subjects were told that they would earn tokens each round equal to

5)      $v_i - p^*$ if $b_i > p^*$ and

6)      0       if $b_i \leq p^*$,

where $v_i$ is participant $i$'s induced value, $b_i$ is participant $i$'s bid, and $p^*$ is the market price. Following the instructions, participants were allowed to ask any clarification questions. In Step 3, each participant wrote his/her bids on the bid sheet. In Step 4, the monitors collected all of the

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[5] A number of studies have utilized lotteries as payoff mechanisms to induce risk neutrality (e.g., Berg et al.; Smith, 1961). In a 2nd price auction with stochastic payoffs determined via lottery, it is an equilibrium to bid true value, but not necessarily a dominant strategy. We have tested the hypothesis that bids from the 2nd price auction are consistent with demand revelation and cannot reject the null. Our motivation in using a lottery payoff was that it lowered the cost of the experiments.

bids. In Step 5, the monitors determined and announced the market price. For the BDM, the price was drawn from a uniform distribution of 1 through 40 tokens; for the second price auction, the market price was the second highest bid. In Step 6, individuals who bid above the market-clearing price purchased one unit at the market price. In Step 7, payoffs for the round were determined according to equations (5) and (6). Steps 3 through 7 were repeated for four rounds, after which a new mechanism was explained, and then four more bidding rounds were conduced with the new mechanism.

**Results of the Induced Value Experiment**

Aggregate results of the experiments are reported in table 4. Two measures of accuracy are reported, absolute deviations (AD) from true value - $|v_i - b_i|$ and percentage absolute deviations (PAD) from true value - $|v_i - b_i|/v_i$. Regarding Hypothesis 1, AD and PAD are both over 2.5 times greater in the BDM than in the $2^{nd}$ price auction for high value individuals. That is, high value individuals bid closer to true value in the $2^{nd}$ price auction than in the BDM. A parametric t-test and a non-parametric Mann-Whitney test indicate that AD and PAD are both significantly higher ($p < 0.01$ in both cases) for the BDM than the $2^{nd}$ price auction for high value bidders, which lends strong support for H1. Consistent with hypothesis 2, results in table 4 indicate the BDM has a lower AD and PAD than the $2^{nd}$ price auction for low-value bidders – almost half as much in both cases. However, this result is only statistically significant for AD at the $p = 0.09$ level according to a t-test. PAD is not significantly different across the BDM and $2^{nd}$ price auction for low-value individuals according to both parametric and non-parametric tests. The third hypothesis was that an increase in value would lead to an increase in bidding accuracy in the $2^{nd}$ price auction. This result held true for PAD and AD, but was only statistically significant

for PAD ($p < 0.01$). The final hypothesis was that accuracy should be unaffected by value in the BDM. Parametric and non-parametric tests indicate PAD is not significantly different for low- and high-value bidders in the BDM; however, AD was significantly lower for low- than high-value BDM bidders.

Overall, the results in table 4 lend support to the theoretical predictions generated by the simulation study. The lack of statistical significance could be due to low sample size. Another issue could be that the parametric and non-parametric tests carried out on data in table 4 rest on the assumption of independence across observations, which is likely violated. This likely occurs because individuals submitted multiple bids in multiple rounds in both auctions in the experiment. To account for this issue, we further investigated individuals' bidding behavior in the auctions. In particular, for each individual we calculated AD and PAD for the lowest and highest induced value they received in each auction mechanism. Using these statistics, we are able to calculate within-subject differences in AD and PAD across auction mechanisms and high and low values. Overall, findings from this sort of analysis are similar to that obtained using the data in table 4.

First, we find support for H1. On average, AD (PAD) for individuals' highest values in the BDM mechanism were 68.35 (0.08) higher than for individuals' highest values in the 2nd price auction. A within-subject t-test and a Wilcoxn signed-rank test indicate this result is statistically significant at the $p = 0.06$ and 0.05 levels for AD, respectively and at the $p = 0.14$ and 0.05 levels, respectively for PAD. These results indicate that individuals bid more accurately when they received high values in the 2nd price auction as compared to when they received high values in the BDM. H2 states the exact opposite result for low values. The within-subject analysis indicates that although individuals tended to bid more accurately in the

BDM than the 2$^{nd}$ price auction when they received a low value, the result was not statistically significant for AD or PAD.  Increase in individuals' values significantly increased PAD in the second price auction consistent with H3; however the same result for AD was not statistically significant.  Finally, although H4 posits that value will not influence accuracy in the BDM, within-subject changes in AD and PAD were significantly lower when an individual receive a low rather than high value in the BDM.

**Conclusion**

Experimental auctions are a potentially useful tool for estimating consumer demand and WTP for new products and product extensions because they create an incentive for individuals to reveal their true preferences for a product.  Given the high cost of product launch and the low probability of new product success, one would expect that marketers would widely adopt incentive-compatible value elicitation mechanisms such as experimental auctions.  However, experimental auctions are infrequently employed in pre-test marketing research.

Although there are a variety of explanations for the low adoption rate, one prominent reason is that there are a variety of auction mechanisms from which to choose, and marketers are unfamiliar with the theoretical underpinnings of competing mechanisms.  We help resolve this issue by investigating the properties of two of the most popular auction mechanisms, the 2$^{nd}$ price auction and the BDM mechanism.  We explore the incentives for truthful bidding in the BDM and 2$^{nd}$ price auction by calculating the expected cost individuals incur by misrepresenting their true preferences.  Our analysis indicates that when interest is on the top end of the demand curve (i.e., high value individuals), the 2$^{nd}$ price auction is likely to provide more accurate bids than the BDM mechanism, because the 2$^{nd}$ price auction provides punishes high-value

individuals more for misbehavior the BDM. Conversely, if interest is on low-value individuals, the BDM is likely to provide more accurate depictions of true WTP than the $2^{nd}$ price auction. Results from our induced value experimental provide support for the notion that the $2^{nd}$ price auction yields more accurate results than the BDM for high value individuals. Thus, if marketers are interested in identifying a market segment with high demand for a new product, the $2^{nd}$ price auction is likely preferred over the BDM; however, if interest is determining demand for a wide range of consumers with relatively low and medium values for a good, the BDM may be preferable to the $2^{nd}$ price auction.

Another important implication of our results is that the distribution of prices in the BDM mechanism can significantly affect incentives for truthful bidding. Importantly, choice of price distribution is endogenous to the researcher. Simulation results indicate that utilizing a price generating mechanism that is normally distributed around an individual's expected 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, for example, effective use of graphics, colored balls, and a bingo cage 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 give some guidance as to the average true value in a sample. Preliminary analysis could also be conducted to identify factors influencing individual's true values such that the BDM could be tailor-made for each individual to create the greatest incentives for truthful value revelation.

Experimental auctions are a potentially valuable pre-test market research tool that can compliment existing marketing research methods. This paper presents results that further expose

the merits of experimental auctions and provides guidance in designing experimental auctions to obtain more accurate estimates of consumer demand and willingness-to-pay.

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**Table 1**

**Parameters of Beta Distributions Used in Simulation Analysis**

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

# Figure 1

## Probability Density Functions of Value/Price Distributions
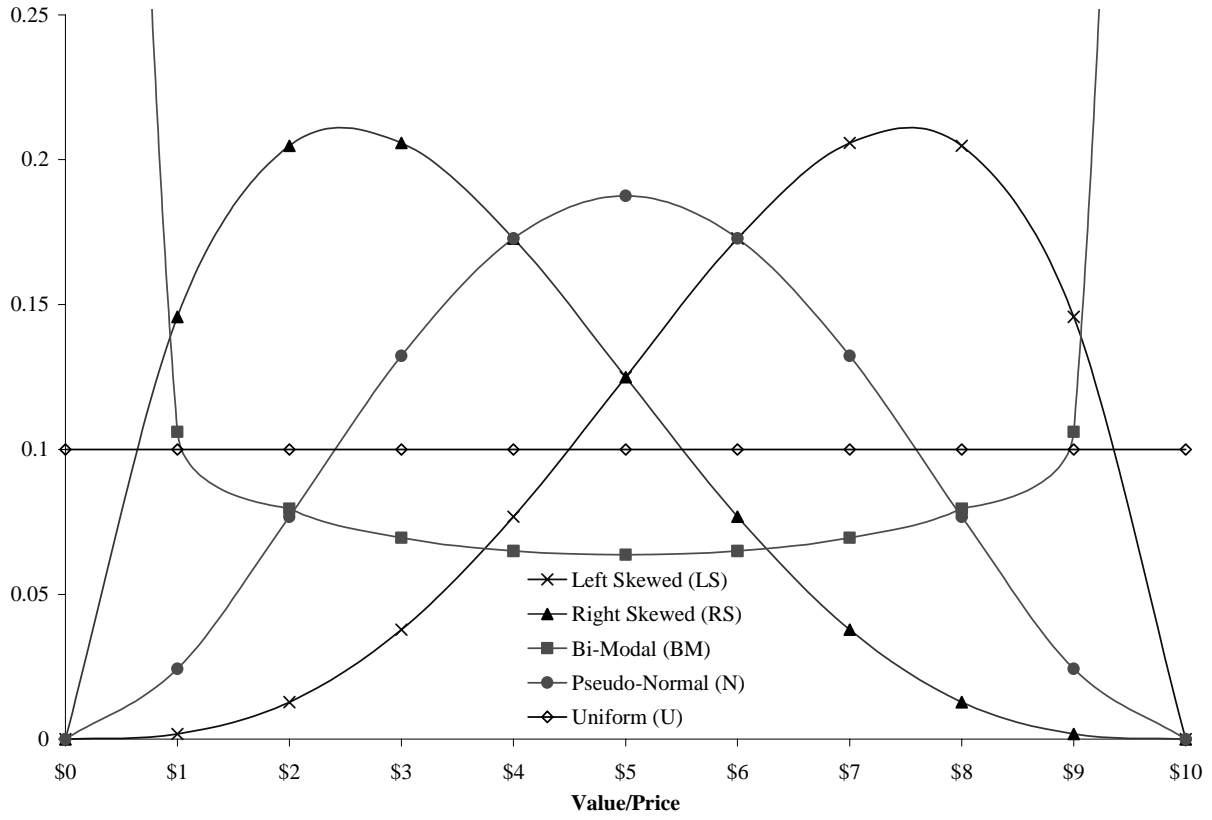
**Table 2**

**Expected Cost of Misbehaving in 2$^{nd}$ Price Auction**

| $b_i - v_i$ | Value Distribution | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Left Skewed | | | Right Skewed | | | Bi-modal | | | 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 |
| $E[\pi_i^{2ndprice*}]$ | 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 |

**Table 3**

**Expected Cost of Misbehaving in BDM**

| $b_i - v_i$ | Value Distribution | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Left Skewed | | | Right Skewed | | | Bi-modal | | | 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 | 0.369 | 0.102 | 0.387 | 0.133 | 0.136 | 0.031 | 0.318 | 0.293 | 0.200 | 0.200 | 0.200 |
| -1.5 | 0.003 | 0.087 | 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 | 0.003 | 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 | 0.026 | 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 | 0.003 | 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 | 0.047 | 0.002 | 0.036 | 0.032 | 0.047 | 0.057 | 0.090 | 0.021 | 0.050 | 0.050 | 0.050 |
| 1.5 | 0.043 | 0.193 | 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 | 0.101 | 0.368 | 0.196 | 0.389 | 0.128 | 0.003 | 0.136 | 0.133 | 0.387 | 0.292 | 0.318 | 0.031 | 0.200 | 0.200 | 0.200 |
| $E[\pi_i^{BDM*}]$ | 0.003 | 0.208 | 1.529 | 0.196 | 1.875 | 4.669 | 0.387 | 1.591 | 3.377 | 0.031 | 0.781 | 3.024 | 0.200 | 1.250 | 3.187 |

**Table 4**

**Accuracy of BDM and Second Price Auction for Low and High Value Bidders in Induced**

**Value Experiments**

| Value | Mean BDM Accuracy | Mean 2nd Price Accuracy |
|---|---|---|
| *Absolute Deviation - $\|v_i\text{-}b_i\|$* | | |
| High Value ($v_i \geq 29$) | 7.708 | 2.792 |
| | (7.178)[a] | (3.623) |
| Low Value ($v_i \leq 11$) | 2.458 | 4.542 |
| | (3.189) | (6.984) |
| | | |
| *Percentage Absolute Deviation - $\|v_i\text{-}b_i\|/v_i$* | | |
| High Value ($v_i \geq 29$) | 0.232 | 0.081 |
| | (0.212) | (0.104) |
| Low Value ($v_i \leq 11$) | 0.451 | 0.714 |
| | (0.806) | (1.283) |

Note: Number of observations in each cell = 24
[a]Numbers in parentheses are standard deviations