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# Auctions versus Posted Price in Experiments: Comparisons of Mean and Marginal Effect

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## ABSTRACT

Economic experiments have been widely used to elicit individuals' evaluation for various commodities and non-market goods. Common elicitation methods include auctions and posted price mechanisms. Experimental auctions are theoretically incentive compatible so are assumed to give an unbiased estimate of individuals' evaluation including willingness to pay (WTP). However, the vast majority of purchasing decisions are not made in auctions but in market settings, such as grocery stores, where consumers make yes/no decisions in response to a set price. In this research, we carefully design an experiment to compare homegrown-value WTP estimates, specifically for honey presented in a variety of jars, between an auction and a posted price elicitation format. This design enables us to make both within- and between-subjects comparisons of the mean WTP and marginal effect estimates. Results from 115 adult consumers indicate that WTP estimates obtained from an auction are approximately 32% - 39% smaller than WTP estimates obtained from a posted price mechanism. We then compare the statistical significance and conclude that auctions require a smaller sample size than posted price mechanisms in order to detect the same preference change. Nevertheless, the signs of marginal effects for different product characteristics are consistent in both mechanisms.

Key words: Auction Experiments; Economic Evaluation; Homegrown Values; Posted Price Markets; Willingness-to-Pay

JEL Codes: D44, D12, C93

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# **Auctions versus Posted Price in Experiments: Comparisons of Mean and Marginal Effect**

## **I. Introduction**

Economists frequently use auctions in experimental economics settings to measure consumers' preference for goods and services (List and Gallet, 2001; Lusk and Shogren 2007; Lusk et al., 2004). From a theoretical perspective, the bids in a well-designed and implemented auction are equivalent to consumers' true willingness to pay (WTP)—the maximum amount they would be willing to spend on a product in a real market environment, since auctions are incentive-compatible. Since a bid obtained from an auction is a point estimate of WTP, auctions are an attractive method as the data they generate is easier to work with econometrically and provide more efficient estimates than the information obtained from other methods such as yes/no decision in a posted prices format. Thus, it has become natural to emphasize auctions as a first-line valuation tool.

Implicit in the decision to use auction is that, while some error in the value elicitation process may be inevitable, the WTP estimates from these auctions have applicability to decisions made in the more common post-price markets, such as those in grocery stores or on Amazon.com, where consumers make yes/no decisions on whether or not to purchase an item at a given 'posted' price. However, typical consumers rarely use auctions as their primary shopping method. Even with training and practice, their decision-making in an auction setting may diverge from the daily purchasing formats they generally use. Thus, an open question is whether consumers behave in an auction the way that is consistent with how they behave in a posted price market.

Some researchers studied the estimated mean WTP disparities in experiments that use auctions versus posted prices and found that auctions in general provide lower mean WTP than posted prices for the same goods (Xie and Gao 2013). Our study contributes to the literature by verifying the existence of and further offering explanations for such WTP estimate discrepancy. Moreover, economists do not only use experiments to elicit consumer WTP for a product or environmental service. Other important outcomes of these experiments include estimations on how WTP changes with certain product attributes, how individuals respond to different treatments, and how demographic variables contribute to WTP differences. For example, many researchers and policymakers are interested in the WTP premium for specific environmental attributes in a product, such as the location (Wu et al., 2015) and growing methods (Loureiro et al., 2003). Surprisingly, little attention has been paid to comparing the marginal effect estimates between these two elicitation mechanisms. In this research, we test the mean WTP and marginal effects of product characteristics using an artefactual field experiment. The experiment provided adult participants the opportunity to purchase different jars of honey using both a sealed-bid, second-price auction and a posted-price, dichotomous-choice mechanism. We avoid drawbacks in the existing literature with careful controls and detect the difference using both within-subject and between-subject tests.

The results suggest that estimated mean WTP in auction is smaller than the posted price mechanism WTP in the range of 32%-39%. We then seek to explain this result by testing different possible explanations. We found no evidence of anchoring effects. We did find evidence suggesting that the cause of low WTP estimates from auctions is due to some characteristic inherent to the auction setting and perhaps associated with consumers' lack of familiarity with auctions. In terms of marginal effects of different product attributes, we find that

the auction and posted price mechanisms provide consistent signs, which indicates that consumer preferences for different product attributes do not vary with the elicitation methods. While the signs of coefficients are consistent, the significance level is much higher in auctions. Therefore, a posted price mechanism requires a larger sample size to detect the same preference change.

## **II. Background**

Researchers and policy-makers are often interested in consumer evaluation for products or services in order to estimate values for welfare, demand elasticity, and other market information. Such information is used to set prices for new products and services and to inform policy decisions and legal proceedings. However, accurately measuring consumer preferences is not an easy task. Many techniques have been adopted to measure WTP for goods that lack an existing well-defined or easily observable market. The many variations on auctions that have been used in laboratory economic experiments are particularly appealing for this purpose since they give the researcher a great deal of control over the data being observed and allow observations of actual decisions involving real financial incentives. In essence, researchers can directly ask an individual “How much are you willing to pay for this item?” Auction methods have been generally eschewed in research on stated preferences associated with environmental valuation as poor indicators of actual WTP (Diamond and Hausman, 1994) since an auction differs from the normal price-taking setting in which consumers react to posted prices (Loomis et al. 1997). In response to such criticisms, a panel convened by the National Oceanic and Atmospheric Administration (NOAA) recommended using a dichotomous-choice format in contingent-

valuation surveys (Arrow et al., 1993).<sup>1</sup> However, auctions have been more widely accepted in experiments for valuing private goods, because these choices are non-hypothetical.

Using posted prices in a laboratory environment should more closely mimic a market setting, such as a grocery store, since participants are price-takers. In this design, participants are asked a yes/no question: “Are you willing to purchase this item at \$A?” Participants will spend \$A to purchase the item if they choose “Yes,” while they will not get the item nor pay anything if they choose “No.” Since this framing of the purchase question resembles decisions consumers make every day about purchasing items at different posted prices, the design is easy for participants to understand. However, a disadvantage is that the experiment does not elicit the exact WTP for each participant – instead it only indicates if WTP is above or below a certain value. Consequently, the mechanism is less statistically efficient and requires large sample sizes to produce the same level of precision as other methods (Loomis et al. 1997) such as auctions.

#### *Comparisons of Posted Prices and Auctions*

Approaches involving incentive-compatible auction mechanisms (e.g., Vickrey, English, Becker-DeGroot-Marschak (BDM), and random  $n^{\text{th}}$  price) are widely used in experimental economics research to elicit values for consumer WTP as they provide a point estimate of WTP for each participant (Vickrey 1961; Becker, DeGroot, and Marschak 1964; Shogren et al. 2001). An auction is considered to be theoretically incentive compatible if the dominant strategy for participants is to bid their true values. Two common auction formats are the Vickrey auction (a second-price sealed-bid auction) and the English auction.

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<sup>1</sup> The dichotomous choice also is referred to as a posted-price, take-it-or-leave-it, and a discrete-referendum design.

In the context of private-value auctions, where each participant knows what the item is worth to her but is uncertain of its value to other participants, both Vickrey and English auctions are theoretically incentive compatible (Vickrey 1961). This study implements a variation of the second-price Vickrey auction that combines the ascending price feature of the English auction with the sealed bids of the Vickrey auction (Bernard 2006; Dillaway et al. 2011).

Economists have also adopted various posted price mechanisms in evaluation studies. For example, double-bounded dichotomous choice models are widely used to elicit consumer WTP for new technologies (Li and McCluskey, 2017), and researchers have studied how to best implement such a mechanism (e.g., Yoo and Yang, 2001). In experimental settings with real monetary incentives, a single-bounded posted price format becomes popular recently (Li et al., 2017; Venkatachalam, 2004). This is mainly because posted price choice activities easy to implement, especially in field experiments that usually take place in real market places surrounded by many distractions.

One increasing stream of literature involves the comparison of Real Choice Experiments (RCE) and auctions. In RCE, participants are presented with combinations of products at different price levels and are asked to choose the one they prefer most. Most studies on this topic found empirical WTP from RCE are significantly higher than WTP from auctions (Lusk and Schroeder 2006; Gracia et al., 2011) . RCE and posted prices are similar in the way that consumers make decisions rather than submitting bids, and no point estimates of WTP can be directly estimated. The price levels presented in RCE are usually chosen from a set of price vectors that were pre-determined based on sales prices in local supermarkets or national retail prices of similar products (Lusk and Schroeder 2006; Gracia et al., 2011). While it might not be an issue for common products in standard size, it would be difficult to determine appropriate

price levels for novel products with additional attributes, such as labeling and packaging. However, introducing more flexible prices in RCE comes with the risk of lower power because a portion of the results would solely be driven by the presence of a very low price. Although in the literature, posted price designs also generally pick price offers from a set of pre-determined prices (Hanemann 1984; Frykblom and Shogren 2000), it is easily extendable, and as discussed later, beneficial, to allow for more flexible price offers. As a result, posted price is especially useful in situations where credible price levels for new products or attributes are hard to obtain.

Despite the extensive literature related to RCE and auctions, fewer studies have compared relative WTP from posted price offers and auctions. Frykblom and Shogren (2000) compared a non-hypothetical dichotomous-choice question to a Vickrey auction using a market good and claimed to have eliminated two potential explanations (strategic behavior and hypothetical bias), leaving anchoring, asymmetric inconsistent preferences, and lack of familiarity with open-ended questions untested. However, the study did not actually find significant difference in resulting WTP estimates of the two methods. Besides, the experiment lacked appropriate training and practice rounds for the participants, which helps the participants to understand the dominant strategy is to bid their true value (Lusk et al., 2004). Moreover, the student participants had to enclose the entire bid in an envelope, which might lead the students to neglect the fact that they would only have to pay the second highest bid and result in underbidding in the auction. Kaas and Ruprecht (2006) proposed a model to explain that with valuation uncertainty, subject bids were lowest in a Vickrey, followed by BDM and stated preference methods. But it was actually not empirically tested since their posted price section was hypothetical. Roosen et al. (2010) explored how BDM compare with a discrete choice mechanism (BMS) that evaluates WTP by measuring the propensity of substitution between two

goods and found that differences in WTP disappear when considering only engaged bidders with non-zero bids. BMS is more similar to RCE than posted price since participants are making a series of choices between two goods with different price vectors.

It is worth noting that a similar question has been discussed in the literature on operations management, especially in the context of “Buy it now” versus auction bids used on eBay. With different specifications on the cost of the auction, the reserve price, the cost to participants, and agent information, “Buy it now” and the auction yield different WTP estimates (Boyer et al., 2014; Wang et al., 2008; Wang 1993). Hammond (2010) empirically tests both auction and posted price online markets for compact discs on two internet selling platforms. A conclusion is that while auctions sell at a higher probability, posting a fixed price sells at a higher price.

#### *Potential Explanations of the WTP Difference*

In the existing literature, several possible reasons on what might have caused the difference in WTP estimates of auction and posted price have been investigated. These candidate explanations include the anchoring effect, the asymmetric inconsistent preferences effect, and the lack of familiarity with auction formats.

The anchoring effect (also known as starting-point bias) occurs when respondents’ valuations are influenced by and biased toward the posted offer in dichotomous choice questions (Tversky and Kahneman 1974; Herriges and Shogren 1996). This anchoring effect could influence both the decisions in the posted price setting and the subsequent auction bids (Ariely et al., 2003). While Frykblom and Shogren (2000) did not observe anchoring effect in posted price decisions and Kriström (1993) observed no anchoring effect in the auction bids, Green et al. (1998) found strong evidence of anchoring on both tasks.

The asymmetric inconsistent preferences effect originates from the “yea-saying” effect in the contingent valuation literature that describes a tendency for some respondents in hypothetical choice settings to choose affirmatively in a dichotomous setting regardless of their true preferences (Couch and Keniston 1960; Ready, Buzby, and Hu 1996). Therefore, it leads to an overestimation of overall WTP in the posted price setting. For instance, Kanninen (1995) concluded that 20% of respondents in the sample were yea-sayers. Ready et al. (1996) found similar evidence with 20–22% of the respondents being yea-sayers in a split sample contingent valuation study for food safety improvements. However, as Frykblom and Shogren (2000) noted “nay-saying” has received little attention and seems to have been generally neglected in the contingent-valuation literature, while this effect would lower WTP from dichotomous choice settings. In the posted price setting with real economic incentives, it is possible that similar effects might still be present. If these effects resulted in difference in WTP estimates between posted price and auction, we could treat the auction bids as the “undisturbed preferences” and test whether the participants deviated significantly to one side from the bids. For example, one inconsistency resulting from “yea-saying” would be when the auction bid is lower than the posted price offer, but the participant accepted the posted price; the inconsistency resulting from “nay-saying” would be when the auction bid is higher than posted price offer, but the participant rejected the price. These two inconsistent preferences would cause WTP discrepancies between posted price and auction if their effects were asymmetric.

Plott (1996) in the Discovered Preference Hypothesis (DPH) casts economic decision-making as a process of discovery that assumes that participants have stable underlying preferences that are consistent with expected utility maximization. If there is appropriate feedback, decision-making converges to expected utility behavior in a series of three steps,

starting with myopic “impulsive” behavior and gradually advancing to behavior that is more systematic as the decision-maker gains additional information through familiarization and feedback. As the NOAA panel pointed out, open-ended questions typically lack realism and is sensitive to trivial characteristics of the scenario presented. In contrast, dichotomous-choice questions better approximate an actual purchasing environment and are easier for respondents to answer accurately Arrow et al. (1993). Although one cannot claim that either posted price or auction reveals the “correct” WTP, posted price is obviously the format that is more familiar, easier to understand and similar to a real-world purchasing decision. Familiarity with auctions is a form of institutional information and choice framing, and many consumers may not be familiar with auction formats because they do not routinely participate in any form of auction. In that case, we would expect to see an experience effect as an auction’s rounds progress.

#### *Contribution to the Literature*

Our study contributes to the literature in several ways. We carefully design an experiment to compare the homegrown-value WTP estimates between an auction and a posted price elicitation format. In addition, we examine possible explanations for such WTP estimate discrepancy. Few studies have compared important findings generated by auctions versus posted price mechanisms other than the mean WTP. However, auctions are not mainly used to measure average WTP for products. Rather, they are often adopted to measure relative WTP for product attributes, information and policy treatment effects, and heterogeneous demographic responses. Therefore, we further extend the research question to comparing the sign and statistical significance of coefficient estimates.

First, we carefully design an experiment that avoids many drawbacks of existing ones in the literature. We only use experienced shoppers as experiment participants since it has been

shown that experience with the good can reduce market anomalies List (2003). Compared to the literature, our experiment includes more extensive training, including written instructions, oral presentations and two training rounds to give participants better understanding on their tasks. In a setting with unfamiliar tasks, extensive training is necessary because even if subjects are told it is in their best interest to bid their “true value,” subtle misconceptions about how the elicitation mechanism works might trigger subjects to default to the strategies associated with familiar auctions (Plott and Zeiler, 2005). Moreover, we argue that for our purposes, running an experiment in a more controlled environment in terms of information and feedback introduces less noise into participants’ decision making process compared to a field setting (Plott 1996). Second, we test if discrepancies exist using both a within-subject and a between-subject design. Compared to the literature where only one kind of comparison is used, combining both within- and between-subject design adds robustness to our results. Third, we introduce more flexible price vectors into the posted price section, since prices vary randomly for each posted price question, we control for the possibility that consumers treat the price offers as quality signal and therefore alleviates valuation being anchored to the price offers. Using flexible price vectors also avoids picking inappropriate price offers in the situation where it is difficult to form fixed price points or appropriate widths between each price point. Fourth, we explicitly test for several possible explanations for the discrepancy and provide our own explanation. Lastly, our participants made choices on otherwise homogeneous honey with different shapes of jars. Therefore, it allows us to easily compare how individuals respond to each jar under both mechanisms. We run regressions based on models commonly used in the literature to examine the signs and statistical significance of the coefficients.

### **III. Experimental Design**

We design a homegrown-value artefactual field experiment in which we offered adult subjects the opportunity to purchase honey presented in a variety of jars. This research was conducted in an experimental economics laboratory at a large university in the Northeastern United States. We recruited 115 adult participants through various sources that included the university's online newspaper, local community meetings, emails to staff members, and the laboratory's website. We endeavored to recruit adult consumers rather than students so that the sample would better represent the community as a whole and to ensure that participants were experienced buyers (Gracia et al., 2011; Chang et al., 2009; List 2003).

Table 1 describes the socio-demographic characteristics of the participants. The average participant age was about 42 years. Most of the participants were female and most of the participants were primary shoppers in their households. Average household income was between \$70,000 and \$80,000 and the average number of years of education was 16. The relatively high education level and income among participants likely reflects the population of a university town.

Fifteen one-hour sessions were held with participants receiving \$20 in cash and/or products for the session (\$5 show up fee and \$15 to be spent during the experiment). Participants were informed that they could keep any portion of the money that they did not spend and that they would be given the opportunity to purchase a jar of honey during the session. Participants received the money and products purchased at the end of the session.

At the beginning of the experiment, the administrator randomly assigned the participants to computer terminals equipped with privacy screens to ensure confidentiality. Participants were asked to read information about the experiments once they were seated (see Review Appendix). A presentation then was given to explain the steps involved and how to use the program. No

communication among participants was permitted, but participants were welcomed to ask questions to the administrator at any time. Data was collected through the use of Excel files that were programmed with Visual Basic with Applications and stored in an Access database.

The experiment involved investigating the effects of labeling and packaging on consumers' WTP for honey products. Specifically, we tested WTP for honey of three origins (local, domestic, and international) that were each distributed to five types of jars that had different shapes but the same volume (12 ounces), making fifteen jar/origin combinations. In the auction, participants bid on all fifteen honey products. In the posted-price rounds, they made purchase decisions for the five jars of U.S. honey only. Therefore, each participant made twenty honey-purchasing decisions in total. In this paper, we limit our comparison of WTP estimates to purchases of U.S. honey because it is most commonly sold in grocery stores and is most familiar to the general public. A set of labeled jars (Jar 1, Jar 2, ..., Jar 5) of honey was placed on the administrator's desk and on the desk of each participant throughout the experiment, and participants were encouraged to examine the appearance of the jars, but not open the jars. Since the three types of honey (U.S., international, local) were indistinguishable in terms of appearance, we just displayed the U.S. honey due to desk space constraints. The sequence of the posted-price experiment and the auction experiment was randomly determined before the session, and the order in which the products were presented was also randomized.

To address the concern of demand reduction, at the end of each session, only one of the twenty decisions made by participants (fifteen in the auction and five in the posted prices) was selected at random to determine which product would be binding and used to calculate cash earnings (Lusk et al., 2004; List and Lucking-Reiley 2000; Messer et al. 2010). This binding decision was selected by having a volunteer draw a labeled ball from a cage containing twenty

balls, each representing one decision. In order to reinforce the understanding of this concept, demonstrations of how the ball would be drawn to determine the binding round were shown to participants prior to them making any decisions. It was also emphasized that no decision was affected by prior or subsequent decisions. As explaining the dominant strategy to participants in homegrown-value experiments is regarded as “best practice” and is widely used, we also informed the participants that it was in their best interest to bid as close to the worth of the item to them as possible (Rutström 1998; Lusk et al., 2004).

In the posted-price experiment, the question to participants was “Are you willing to purchase Jar Y of U.S. honey at \$A?” The price of each product varied randomly for each decision and was distributed uniformly between \$0 and \$15. Participants were informed that clicking “yes” was a decision to purchase the jar of honey at the posted price; clicking “no” meant they would not receive Jar Y nor pay the price.

In the second-price auction, a number representing the participant’s bid for the item was shown on the screen in front of each participant. Once the auction started, this bid increased incrementally at a speed about \$0.10 per second from \$0 to \$15.<sup>2</sup> Participants were asked to click the “withdraw from auction” button when they saw the bid representing the maximum amount they were willing to pay for the product displayed on the screen. When they indicated a desire to withdraw from the auction, a second box appeared that asked them to confirm the number on their screen as their bid. Participants could choose to restart the auction round (incremental ascending increases in the number) from \$0 and bid again or could confirm the bid and submit it. The auction stopped either when all participants’ bids were confirmed or when the

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<sup>2</sup> Since participants started the program by themselves, the participants’ bids were not synchronized making it impossible for other participants to know whether they stopped the program on a low or high bid.

bid reached the pre-set upper limit of \$15. The bids by each participant were stored in a database and the auction then proceeded to a new bidding decision.

To help participants better understand the bidding procedure, two practice rounds were held first. Participants were given \$3 in the practice rounds and were asked to submit bids on a pencil and a ballpoint pen. In the practice auction, the winner and the second highest bidder were announced after each round. It was emphasized to participants that the winner pays only the amount of the second highest bid so it was in their best interest to focus on determining their own value for the item and to bid as closely to that as possible.

After the practice rounds, participants were asked to submit bids on different jars of honey following the same procedure with an initial balance of \$15. This research followed the proposed “best practice” in Harrison et al. (2004) to clearly train and inform the subjects that their dominant strategy is to bid their true value. At the beginning of each new purchasing decision, participants were provided with the list of items already auctioned and bids they submitted for each. After each decision, no feedback was given to participants with regard to the winner or the winning price as a means of reducing market feedback (Corrigan et al. 2011). At the end of the session, participants were asked to fill out a survey about their demographics background and consumer behavior.

The only announcement was the winner of the binding round at the end of the experiment. This was done by having a volunteer draw a ball to determine which of the twenty purchase decisions was binding. Each participant’s screen then displayed a chart showing their decisions and products. Based on this binding decision, the computer program calculated each participant’s earnings and products purchased (if any) and displayed them on that person’s screen to assist them in filling out receipts.

#### IV. Model and Testable Hypotheses

In this section, we describe the model and the hypotheses that we will be testing in the experiment. We proceed by first verifying if WTP estimate difference exists between the two value elicitation methods. We then test if the observed difference (if any) is a result of the inter influence between the posted price and the auction parts. Next, we examine two other behavioral factors that may result in WTP estimate differences. We conclude by comparing the marginal effects offered by the two elicitation methods.

##### *Comparison of Posted Price and Auction*

The series of hypotheses tested in this research are summarized in Table 2. The first hypothesis is that the WTP estimates from the posted-price mechanism equal to those from the second-price auction.

$$H_0: WTP_{\text{Posted\_Price}} = WTP_{\text{Auction}}$$

Where  $WTP_{\text{Posted\_Price}}$  denotes willingness-to-pay estimates obtained from the posted price questions and  $WTP_{\text{Auction}}$  denotes willingness-to-pay estimates derived from the experimental auctions.

The posted price generates binary responses while the auction generates continuous bids. To make the two types of data comparable, the auction data may be transformed to simulated binary responses, or average WTP point estimates can be inferred from posted price responses. For consistency with the literature, we follow the procedure documented in Green et al. (1998) and Frykblom and Shogren (2000) where the auction data is transformed into synthetic binary responses and compared to the actual responses. Let  $b_{ij}$  denote the bid that participant  $i$  submit for good  $j$ , and  $p_{ij}$  denote the posted price offer of participant  $i$  for good  $j$ , and  $\delta_{ij}$  denote whether participant  $i$  responded yes in the posted price section for good  $j$ . Since each participant

responded in both the auction and posted price formats, we can compare their auction responses,  $b_{ij}$  to the binary response that would be consistent with the prices they see in posted price section,  $p_{ij}$ , for the same good. We generate a synthetic dichotomous choice response variable  $\delta'_{ij}$ , where  $\delta'_{ij} = 1$  if  $b_{ij} \geq p_{ij}$ ;  $\delta'_{ij} = 0$  if  $b_{ij} < p_{ij}$ . Here,  $\delta'_{ij}$  can be interpreted as when facing the price offers, what participants' response would be based on the bids they indicated. Theoretically, if the null hypothesis holds, we would not observe a significant difference in the WTP inferred from  $\delta$  and  $\delta'$ .

To test if  $\delta$  and  $\delta'$  significantly differ from each other, we perform both parametric and non-parametric tests. The advantage of a non-parametric test is that no distributional assumption is placed on the variables. Since  $\delta$  and  $\delta'$  are binary variables and since these are considered as paired observations, we use McNemar's non-parametric test (McNemar 1947).

Since non-parametric tests generally have lower power than parametric tests, we also do a parametric test assuming a normal/logistic distribution on the underlying WTP (Frykblom and Shogren 2000). Formally, we assume a consumer's WTP,  $w$ , follows some probability distribution with  $\mu$  as the location parameter and  $\sigma$  as the scale parameter. We denote  $F$  as the cumulative distribution function and  $S$  as the survival (or duration) function. Therefore, for a given posted price offer  $p$ ,  $F(p) = Prob(w \leq p)$ ,  $S(p) = 1 - F(p) = Prob(w > p)$ ,  $f(p) = dF(p)/dp$ . So the survival function, in this case, represents the probability that a "yes" response in the posted price format will continue above a given price. We estimate  $\mu$  and  $\sigma$  by maximizing the log-likelihood function  $L$ , which is written as:

$$L = \sum (\delta_{ij} \log(S(p_{ij})) + (1 - \delta_{ij}) \log(F(p_{ij})))$$

where  $\delta_{ij}$  is equal to 1 if participant  $i$  accepted posted price offer for the  $j$ -th object ( $p_{ij}$ ), and equal to 0 otherwise. The survival function for normal distribution is:

$$S(p_{ij}) = 1 - F(p_{ij}) = 1 - \Phi\left(\frac{p_{ij} - \mu}{\sigma}\right).$$

For logistic distribution, the corresponding function is:

$$S(p_{ij}) = 1 - F(p_{ij}) = \frac{1}{1 + \exp\left(\frac{p_{ij} - \mu}{\sigma}\right)}.$$

The estimated mean for both distributions are  $\mu$ , the estimated variance for normal distribution is  $\sigma^2$ , while for the logistic distribution it is  $\sigma^2\pi^2/3$ .

From this maximum likelihood estimation, we would be able to infer the distribution of WTP that generated the posted price responses. To test if the estimated mean from the two samples are different, we follow the same test as Frykblom and Shogren (2000), which is recommended by Kmenta (1986):

$$Z_{\bar{w}_1 - \bar{w}_2} = (\bar{w}_1 - \bar{w}_2) / \sqrt{\left(\frac{s_1^2}{n_1}\right) + \left(\frac{s_2^2}{n_2}\right)}$$

where  $Z$  is an approximately standard normal variable,  $w_k$  is the estimated mean in offer format  $k$ ,  $s_i^2$  is the estimated sample variance, and  $n_i$  is the sample size.

#### *Possible Task Inter Influences*

Since our experiment consists of different tasks within a subject, we address the most common problem for a within-subject design—the tasks potentially influencing each other. We do this in two ways: first we test if the difference still exists if we only utilize the first task that each participant completed; second we test for anchoring effect to see if the bids in the auction are influenced by posted price offers that were presented to the participant.

#### *Testing for a Difference Using First Task Only*

The intuition is to make comparisons only from data of the first task that a participant did. Specifically, we estimate WTP only from participants who went through the auction first and

compare to posted price WTP estimates from participants who did the posted price first. In this way, we are actually making a between-subject comparison. The procedure used for this test is similar to the one described earlier where we transfer auction data into yes/no responses and compare it to the posted price data. One issue in generating the synthetic yes/no responses is that there does not exist a corresponding relationship between the auction-first group's bids and the posted price-first group's price offers. Therefore, we use a complete combinatorial approach similar to the one suggested in Poe, Giraud and Loomis (2005). For every auction bid (suppose  $n_1$  total observations), we generate a yes/no response according to every posted price offering (suppose  $n_2$  total observations), resulting in  $n_1*n_2$  pairs of observations on bids ( $b$ ), synthetic yes/no ( $\delta'$ ), price offer ( $p$ ) and real yes/no response ( $\delta$ ). Next, we compare  $\delta$  to  $\delta'$  following the procedure discussed before.

#### *Testing for Anchoring Effect*

We randomized the posted price offered for each decision in the experiment to control for possible anchoring of participants' valuation of each item to the posted price. However, posted price offers might still be affecting consumers' value formation process in two ways. First, the WTP estimates from posted price could increase if the participant saw a higher posted price offer for the item (Frykblom and Shogren 2000). Second, the WTP estimates from the auction could be affected by the posted price offers if the subject participated in posted price first (Kriström 1993). We assume that if the underlying valuation of the product is changed by the posted price offer, it is likely reflected in both the posted price part and the auction part, meaning that the presence of the two presentations of anchoring effects are positively related. The design allows us to test for the second type of anchoring effect by a Tobit model that includes posted price offers as an independent variable. Since bids were limited to a range of \$0 to \$15, a two-limit

random-effects Tobit model was appropriate to analyze WTP.<sup>3</sup> The dependent variable is defined based on a latent variable  $y_{ijk}^*$  that cannot always be observed and is specified as

$$(3) \quad y_{ij} = \begin{cases} y_{ij}^* & \text{if } 0 < y_{ij}^* < 15 \\ 0 & \text{if } y_{ij}^* \leq 0 \\ 15 & \text{if } y_{ij}^* \geq 15 \end{cases} .$$

For subject  $i$  and item  $j$ ,  $y_{ij}^*$  is limited to a value between 0 and 15 and depends linearly on  $X_{ij}$  via a parameter (vector),  $\beta$ . The following random-effects Tobit model was used:

$$(4) \quad y_{ij}^* = \alpha + \beta X_{ij} + U_i + u_{ij} = \alpha + \beta_1 \text{Jar type } 2_{ij} + \beta_2 \text{Jar type } 3_{ij} + \beta_3 \text{Jar type } 4_{ij} + \beta_4 \text{Jar type } 5_{ij} + U_i + u_{ij}$$

where  $\alpha$  is the average bid for the entire population,  $U_i$  represents the individual random effects, and  $u_{ij}$  is the error term for individual  $i$  for product  $j$ . We also include a specification with bootstrap standard errors. The variables *Jar type 2* through *Jar type 5* are dummy variables indicating which item was auctioned. The variable *Jar order* is a dummy that included to control for order effects. We define a variable *auction\_first* equals one when the posted price treatment follows the auction and equals zero otherwise.

Under the null hypothesis that the anchoring effect is present, we would expect that when the posted price section is before auction (*Auction\_first=0*), the effect of parameter of  $b$  on  $p$  would be significantly different from 0, we denote this as:  $\beta_{p, \text{Auction\_first}=0} \neq 0$ . Meanwhile, it is expected that when the posted-price section is after auction (*Auction\_first=1*), such an effect should not be observed ( $\beta_{p, \text{Auction\_first}=1} = 0$ ). This hypothesis is listed as Hypothesis 2 in Table 1.

In summary, we test:

$$H_0: \beta_{p, \text{Auction\_first}=0} \neq 0$$

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<sup>3</sup> An OLS model without censoring gives very similar estimates.

$$H_0: \beta_{p, \text{Auction\_first}=1} = 0.$$

### *Testing for Behavioral Factors*

After testing for inter influences between the tasks, we investigate behavioral factors that may result in WTP estimate differences between the two methods. As explained previously, asymmetric inconsistent preferences and the fact that participants are more unfamiliar with auctions may both lead to discrepancies in WTP estimates.

#### *Asymmetric Inconsistent Preferences Hypothesis*

If asymmetric inconsistent preferences were the cause of the WTP discrepancy, we would expect to observe a difference in the following two inconsistencies: 1) when the bid is higher than the price and 2) when the bid is lower than the price. When a participant answers “yes” to a dichotomous choice question even though the price is higher than their bid, we define it as “affirmative inconsistent preference”. In contrast, when a participant answers “no” to a dichotomous choice question even when the price is lower than their bid, we define it as “negative inconsistent preference”. Affirmative inconsistent preference can be denoted as: WTP in posted price offer ( $p$ ) > bid in auction ( $b$ ), meaning when  $\delta' = 0$ ,  $\delta = 1$ . Negative inconsistent preference can be denoted as: WTP in posted price offer ( $p$ ) < bid in auction ( $b$ ), meaning when  $\delta' = 1$ ,  $\delta = 0$ . If the inconsistent preferences cause the WTP discrepancies, we would expect one inconsistency would be more prevalent than the other. We test whether the probability of a affirmative inconsistent preference is larger than the probability of a negative inconsistent preference—specifically, whether  $\Pr(\delta = 1 \mid \delta' = 0) > \Pr(\delta = 0 \mid \delta' = 1)$ . If this hypothesis is rejected, it means participants are not more likely to have affirmative inconsistent behavior than

negative inconsistent behavior, and asymmetric inconsistent preference does not explain any discrepancy.

### *Familiarity Hypothesis*

As compared to answering a posted price question, auction is a mechanism that is relatively unfamiliar to most participants. Even if participants do not receive direct feedback after each round, all information available to a participant may evolve due to additional opportunities for introspection, belief reinforcement, learning, and similar mechanisms. In that case, we would expect to see an experience effect as an auction's rounds progress. We test if *roundnumber* (the number of bidding decisions a participant has made) has an effect on the bids. Under the null,  $\beta_{\text{Auction, RoundNumber}}$  would be significantly different from 0. Specifically:

$$H_0: \beta_{\text{Auction, RoundNumber}} = 0$$

$$H_1: \beta_{\text{Auction, RoundNumber}} \neq 0.$$

### *Comparing Marginal Effects in the Two Methods*

Despite any WTP estimate differences that may exist and the reasons that may cause the differences, in practical research, we are often not only interested in the absolute WTP estimates of a homegrown good, but also care about the marginal effects, or the ability that the estimation method is able to provide relative comparison conclusions on the effects of some particular attributes. When the research question is not about estimating absolute WTP values but instead about testing marginal effects of attributes, it is important to learn if the two mechanisms provide similar results. We compare the marginal effect estimates on jar attributes from the two parts in terms of the signs and significance levels of the coefficients.

## V. Results

### *Descriptive Statistics on Bids and Yes/No choices*

A histogram on the frequency distribution of the bids is displayed in Figure 1. As expected, the number of bids into each price category decreases as the price increases. The mean of the bids is \$2.91 and the standard deviation is 1.97. Figure 2 shows the percentage distributions of posted prices conditioning on whether the posted price was accepted or declined. As expected, number of acceptance decreases as prices go up, and the number of declines increase as price increase. In general, we do not observe fat tails in the distributions

In total there were 45 zero bids in the auction. Out of the 115 participants, 4 people (3.5% of the total participants) bid zero for all five auctions of honey. This seems to be a reasonable proportion of people who would not be interested in purchasing honey at any price. Of these four participants, three also declined the honey in all the posted price questions. So their behavior appears to be generally consistent.

*Hypothesis 1: Test for WTP Difference,  $H_0: WTP_{\text{Posted\_Price}} = WTP_{\text{Auction}}$*

As shown in Panel A of Table 3, for a within-subject comparison, the average of the actual binary response ( $\delta$ ) in posted price is 0.2904; the average of the generated synthetic binary response ( $\delta'$ ) based on bids in the auction and posted price offer is 0.1652. Since McNemar's chi-squared test statistic equals 150.45 and the corresponding p value is less than 0.0001, we reject the null hypothesis.

As discussed earlier, we also do parametric tests assuming the underlying WTP distribution is either normal or logistic (Panel B of Table 3). With a normal distribution, the estimated WTP from auction bids has a mean of 2.4889, while the estimated mean of WTP from

posted price is 4.0587. A Z test rejects the null hypothesis that the two WTP means are equal. With a logistic distribution assumption, results are similar. The estimated mean of WTP is 2.4579 for auction bids and 4.0570 for posted price. The Z test also rejects the null at 1% level. The results suggest that WTP estimate from the auction is approximately 39% lower than that from posted price.

### *Test for Task Inter Influences*

To address potential concerns that a within-subject design involving two tasks might influence each other, we test for the discrepancy using first task only and then test for anchoring effects between the tasks.

*Hypothesis 2.1: Test for Discrepancy using First Tasks Only*,  $H_0: WTP_{\text{Posted\_Price}|\text{Posted\_Price\_First}} = WTP_{\text{Auction}|\text{Auction\_First}}$

We conducted a between-subject comparison using only data from the first task each participant completes. In other words, we generate WTP estimates for auction from participants who did auction first, and generate WTP estimates for posted price from those participants who did posted price first. Since there is no one-to-one corresponding relationship between the bids and posted price offers, we do a complete combinatorial procedure (Poe, Giraud and Loomis, 2005) on bids and price offers to generate a synthetic binary response ( $\delta^{\wedge}$ ) and compare it to the corresponding actual binary response ( $\delta$ ). Again a McNemar's test rejects the null that the probability of accepting is equal.

In a similar fashion, we conducted parametric tests assuming either normal or logistic distribution on the underlying WTP. Under normal distribution assumption, the estimated mean WTP is 3.171 for auction and 4.647 for posted price. Under the assumption of logistic distribution, the estimated mean WTP is 3.137 for auction and 4.603 for posted price. In both

cases, Z test rejects the null that the two estimated means are equal. This indicates that estimated mean WTP from auction is approximately 32% lower than that from posted price.

### *Hypothesis 2.2: Anchoring Effect*

Anchoring effect might happen if participants perceive the posted price as a quality signal of the product and therefore anchor their value of the product to the price offer. We perform a test similar to Kriström (1993) where we examine if the respondents' auction bids are anchored to the posted-price offers when they participated in the posted-price setting first. Meanwhile, their bids should not be affected if the auction was held first. To test  $H_0: \beta_{p, \text{Auction\_first}=0} \neq 0$ , we regressed the bids from sessions in which the posted-price mechanism was conducted first (Table 5). The left panel of Table 5 reports a random effects Tobit model, while the right panel reports the same model with bootstrapped standard errors included. As shown in both panels of Table 5, the posted price in the posted-price mechanism did not affect subsequent bids in the auction. Therefore,  $H_0: \beta_{p, \text{Auction\_first}=0} \neq 0$  is rejected and the anchoring effect appears not to be responsible for differences in WTP.

Similarly, to test  $\beta_{p, \text{Auction\_first}=1} = 0$ , we regressed the bids from sessions in which the posted-price mechanism was conducted first. Again, the left panel of Table 6 reports a random effects Tobit model, while the right panel includes bootstrap standard errors. As both panels demonstrate, posted-price offers do not have an effect on bids when auction was conducted first. Therefore, no anchoring effect is observed.

Therefore, we conclude that WTP estimates from auction significantly differ from WTP estimates from posted price and it is not likely a result of the two tasks influencing each other but rather due to behavioral reasons.

## *Tests for Behavioral Factors*

### *Hypothesis 3.1: Asymmetric Inconsistent Preference Effect*

As mentioned in previous sections, one argument against the accuracy of WTP estimates from posted price markets is that some consumers might respond affirmatively to a posted-price question without actually forming a solid WTP, as opposed to being forced to form a value by open-ended questions such as auctions. This tendency of providing affirmative answers (if exists) would boost WTP estimates in posted price. However, we show that the percentage of affirmative inconsistent preference behavior is not significantly greater than negative inconsistent preference behavior.

We test the hypothesis that the proportion of affirmative inconsistency is greater than the proportion of negative inconsistency. Of the 480 times when WTP estimated from the posted price setting was higher than WTP estimated from the auctions, affirmative inconsistency occurred 89 times. Of the 95 times when WTP under posted prices was lower than under auctions, negative inconsistency happened 17 times. A proportion test of equality does not reject the null hypothesis that the two proportions are equal (p-value of 0.88). Thus, the proportion of affirmative inconsistency is not significantly greater than the proportion of negative inconsistency. Therefore, this hypothesis is rejected and asymmetric inconsistent preferences should not be driving the differences in WTP.

### *Hypothesis 3.2: Lack of Familiarity with Auction Settings*

Participants' institutional information might be affected by their lack of familiarity with auction formats. We test if *roundnumber* (the number of bidding decisions a participant has made) has an effect on the bids by specifically testing whether  $\beta_{\text{Auction, RoundNumber}} = 0$  holds. In order to gain

more insights from the data, the regression in this part involves auction bids for all of the honey products (local, US and international). We test this hypothesis with a Tobit model, adding a set of experimental controls. The experiment controls include three information treatments, origin-information interactions, survey variables on consumer attitude towards honey, and other socio-demographic variables.<sup>4</sup> As shown in Table 7 column 1,  $\beta_{\text{Auction, RoundNumber}}$ , is significantly different from zero with a coefficient estimate of  $-0.039$ . Besides, in a logit model examining the probability that a participant submits a zero bid, we find that a zero bid is more likely to appear as the auction progresses (as shown in column 4, Table 7). Thus, the null hypothesis that  $\beta_{\text{Auction, RoundNumber}} = 0$  is rejected. As the auction rounds progress, participants tend to adjust their behavior based on information gathered through the process.

The underlying reason for the change of WTP in the auctions in successive rounds is not obvious, especially since there was no feedback regarding the price and winners. Meanwhile, it is possible that some participants lost interest and stopped bidding. Thus, we considered if off-margin and on-margin bidders behaved differently. Given the size of the bids, it is reasonable to define “on-margin” bidders as those whose bids are less than \$1 below the second highest bid and the rest as “off-margin” bidders:

On margin:  $\text{Bid} > \text{Second Highest Bid} - \$1$ ;

Off margin:  $\text{Bid} \leq \text{Second Highest Bid} - \$1$ .

Column 2 and 3 in Table 7 show Tobit regression results for on-margin and off-margin bidders respectively with experimental controls. The results are significant and robust to inclusions of demographic and attitude controls. In sum, bids by on-margin bidders increase \$0.024 each round and bids by off-margin bidders decrease \$0.078 each round. Therefore, on-

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<sup>4</sup> For a detailed list of control variables used, reference Wu et al. (2015)

margin bidders seem to show a gradually increasing pattern in their revealed WTP. Note that even though we did 15 rounds of auction, in the end auction is still a relatively unfamiliar task and participants might still be relatively unfamiliar and inexperienced with it. Therefore even the increase in bids of on-margin bidders may not explain the entire discrepancy, it could be a plausible explanation for this discrepancy.

#### *Hypothesis 4: Marginal Effects between Two Methods*

In this part, we compare the marginal effect estimations in the two elicitation mechanisms. Since the auction bids implement a random effects Tobit model and the posted price binary responses use a random effects Logit model, the magnitudes of the variables are not directly comparable. However, the signs and significance levels of the attribute coefficients should be comparable. As demonstrated in Table 8, we examine the sign estimates and significance levels for the jar attributes in the posted price and auction parts. A positive sign in the coefficient would indicate a WTP premium for that attribute and a negative sign indicates the opposite. Significance levels indicate the ability to detect a preference for attributes.

The first three columns show results for auction bids. Compared to the baseline Jar1, participants are willing to pay more for honey packaged in Jar2, Jar4 and Jar5. As shown in the last three columns for the posted price part, with the same number of observations we can only demonstrate that participants are significantly willing to pay more for Jar2, while the rest of the jar attributes are highly insignificant. However, if we focus on the sign estimates in the posted price part, the result suggest that participants are willing to pay more for Jar4 and Jar5, compared to Jar1, which is consistent with the auction. The coefficient is negative but highly insignificant for Jar2, which is also highly insignificant in the auction part. Therefore, even though we obtain less significance in the posted price part, the sign estimates mostly agree with the auction part.

The above analysis suggests that posted price and auction generate similar qualitative marginal effects for attributes, but auctions are more efficient in revealing these underlying preferences.

## **VI. Conclusion**

Experimental auctions are a popular instrument for measuring consumer WTP for various attributes of a commodity or environmental service. A key attractive feature of auction mechanisms is that they provide point estimates of WTP. However, posted price formats are how most consumer choices are made. Inferring consumers' WTP for a posted price market from auction bids can be problematic since consumers generally may have relatively limited experience with auctions and may not behave in a consistent manner in both mechanisms. Therefore, some attention has been paid to comparing the estimated mean WTPs using these two mechanisms. On the other hand, the comparison of other important aspects, such as the estimation of how WTP varies with certain product attributes has not been thoroughly examined in the literature. In this research, we test the mean WTP differs in the two elicitation methods and further offer explanations of such a discrepancy using an artefactual field experiment. Moreover, we compare the signs and significance levels of marginal effects for different product characteristics.

First, in our second price auction, estimates of WTP from bids are significantly less than estimates of WTP for the same product via the posted-price mechanism. We conducted both within-subjects and between-subjects tests and the results are robust. We test several potential explanations related to information and framing effects. The differences in WTP do not appear to be due to either an anchoring effect or asymmetric inconsistent preferences. The results do suggest that the reason for the difference in auctions is that research participants' lack of

familiarity with auctions. Second, we run regressions to test the marginal effects of different product attribute on WTP. The signs of coefficients are consistent in the auction and posted price mechanisms. Third, we find that the significance level is much higher using auctions for each confident.

Our research sheds light on which economic evaluation elicitation format, namely auctions and posted price mechanisms, is more suitable under different circumstances. We show that a WTP estimate difference does exist between the two mechanisms. Participants do demonstrate an adaption process in the auction format. In the meanwhile, the posted price mechanism is more familiar to the general public and participants may focus more on the task itself. This is particularly true in a field setting where the researchers usually recruit participants from busy market places, where attention and time allocated to experiments are generally limited. However, we show that both methods elicit similar signs for the marginal effects of specific product attributes. Thus, either using auctions or posted price mechanisms can provide credible prediction on the marginal effects of important product characteristics. But auctions have clear advantage over posted price in terms of statistical power, which indicates that a larger sample size is required for a posted price mechanism to reveal the preference for specific product attributes. Therefore, it is reasonable to consider using posted price when one's goal is to understand absolute WTP values and to use auctions when one is interested in relative WTP comparisons associated with different attributes.

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Figure 1. Frequency Distribution of Bid Amounts in the Auction

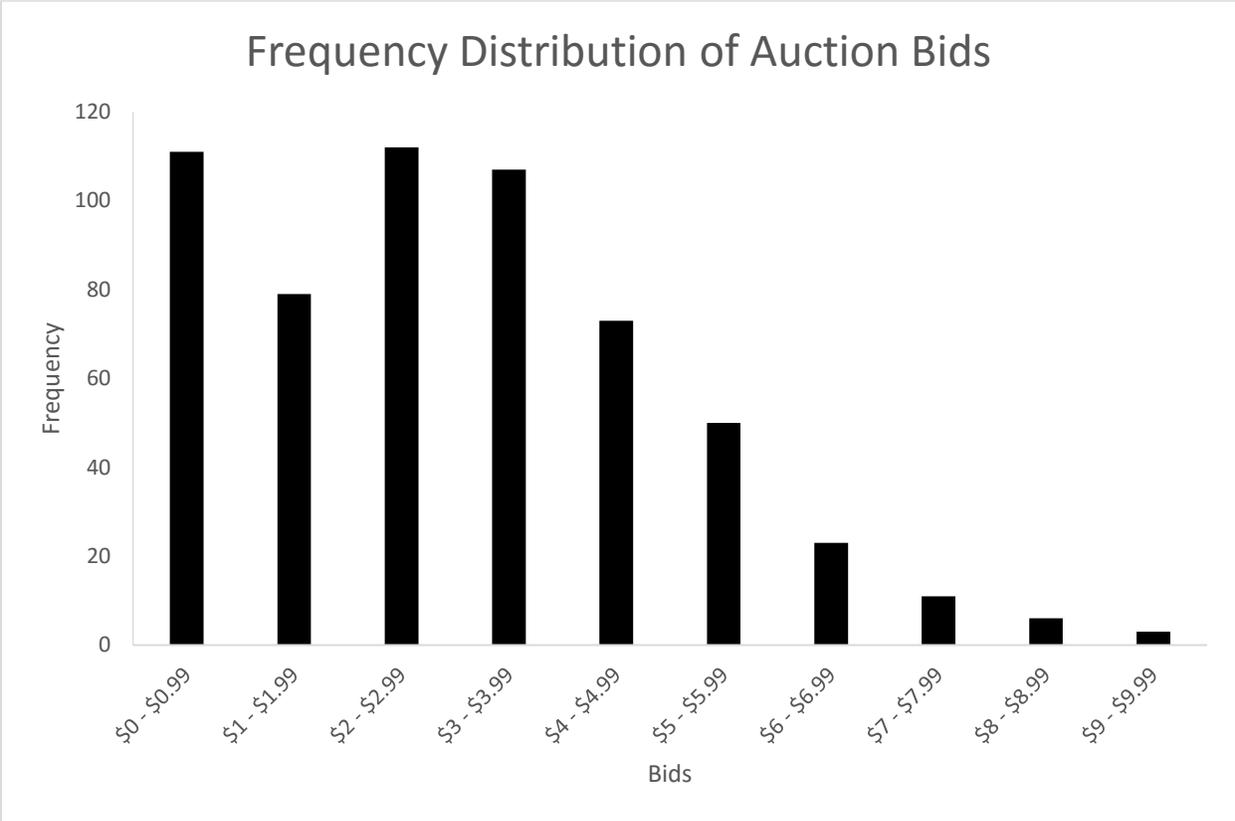


Figure 2. Frequency Distribution of Accepted and Declined Posted Price Offers

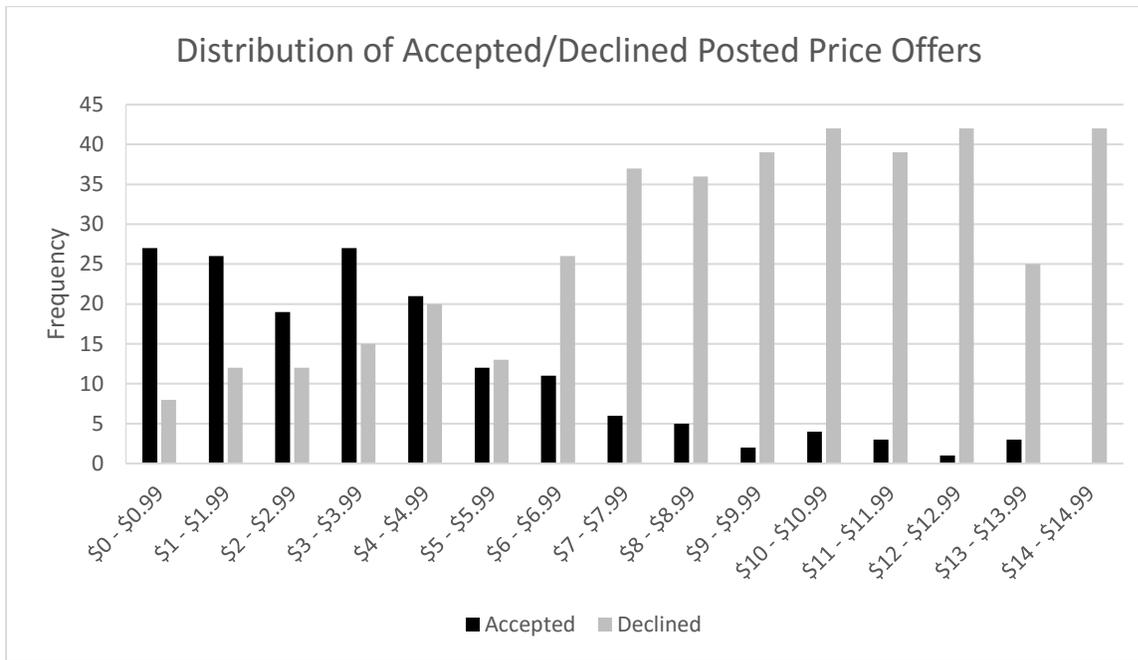


Table 1. Sample Demographic Characteristics

Variable Definition	Mean	Std. Dev.
<i>Gender</i>		
<i>1 = female 0 = male</i>	0.77	0.42
<i>Age (years)</i>	41.93	14.27
<i>Years of Education</i>	16.39	2.85
<i>Household Yearly Income</i>	\$76,086	48,373
<i>Primary Shoppers</i>	0.77	0.42

Table 2. Hypotheses

Question	Hypothesis	Result
1. Is there a difference in WTP between the posted-price mechanism and second-price auction?	$H_0: WTP_{\text{Posted\_Price}} = WTP_{\text{Auction}}$	Reject - There is a difference between measured WTP.
2. Is the difference due to the two tasks influencing each other?		
2.1 Is there a difference only comparing the first task completed?	$H_0: WTP_{\text{Posted\_Price} \text{Posted\_Price\_First}} = WTP_{\text{Auction} \text{Auction\_First}}$	Reject – There is a difference even for the first tasks completed
2.2 Is this difference due to anchoring effect?	$H_0: \beta_{p, \text{Auction\_first}=0} \neq 0$ $H_0: \beta_{p, \text{Auction\_first}=1} = 0$	Fail to Reject - No evidence of anchoring
3. Is the difference due to behavioral factors?		
3.1 Is this difference due to asymmetric inconsistent preferences?	$H_0: \Pr(\text{Accept}=1 \text{ShouldAccept}=0) = \Pr(\text{Accept}=0 \text{ShouldAccept}=1)$	Fail to Reject - no evidence of asymmetric inconsistent preferences
3.2 Is this difference due to a lack of familiarity with an auction setting?	$H_0: \beta_{\text{Auction, RoundNumber}} = 0$ $H_1: \beta_{\text{Auction, RoundNumber}} \neq 0$	Reject - There is evidence that the difference decreases with learning
4. Are the marginal effects comparable?	$H_0: \text{The signs and significance levels are similar}$	The signs are similar, significance levels are higher in auction.

Table 3. Within-subject comparison of estimated WTP from Posted Price and Auction

<i>Panel A: Non-parametric</i>	Mean( $\delta$ ) (std. dev.)	Mean( $\delta'$ ) (std. dev.)	McNemar (p-value)
	0.2904 (0.4544)	0.1652 (0.3717)	150.45 (<0.0001)
<i>Panel B: Parametric Assumption</i>	WTP <sub>Auction</sub> (std. dev.)	WTP <sub>PP</sub> (std. dev.)	Z (p-value)
<i>Normal</i>	2.4889 (2.0898)	4.0587 (4.5021)	7.5838 (<0.0001)
<i>Logistic</i>	2.4579 (1.1698)	4.0570 (2.5562)	7.5199 (<0.0001)

Table 4. Between-subject comparison of estimated WTP from Posted Price and Auction

<i>Panel A: Non-parametric</i>	Mean( $\delta$ ) (std. dev.)	Mean( $\delta'$ ) (std. dev.)	McNemar (p-value)
	0.3396 (0.4736)	0.2192 (0.4137)	14272 (<0.0001)
<i>Panel B: Parametric Assumption</i>	WTP <sub>Auction</sub> (std. dev.)	WTP <sub>PP</sub> (std. dev.)	Z (p-value)
<i>Normal</i>	3.1710 (2.1021)	4.6466 (4.9929)	78.0702 (<0.0001)
<i>Logistic</i>	3.1369 (1.1694)	4.6026 (2.8807)	74.4968 (<0.0001)

Table 5. Test for Anchoring When Posted Price Is before Auction

	Random Effects Tobit			Random Effect Tobit with Bootstrap Std. Err.		
	Marginal Effect	Std. Err	P> z	Marginal Effect	Std. Err	P> z
<i>Price</i>	-.0004	0.001	0.971	-.0004	0.009	0.966
<i>Jar type 2</i>	0.459	0.117	0.000	0.458	0.087	0.000
<i>Jar type 3</i>	-0.044	0.117	0.711	-0.044	0.116	0.707
<i>Jar type 4</i>	0.110	0.117	0.347	0.110	0.109	0.314
<i>Jar type 5</i>	0.342	0.117	0.003	0.342	0.160	0.033
<i>_cons</i>	2.660	0.360	0.000	2.280	0.318	0.000
<i>Wald chi<sup>2</sup></i>	28.33			43.33		
<i>Prob&gt; chi<sup>2</sup></i>	0.000			0.000		
<i>Log likelihood</i>	-322.606			-322.606		
<i>Number of Obs</i>	265			265		
<i>Left-censored observations</i>	31			31		
<i>Uncensored observations</i>	234			234		
<i>Right-censored observations</i>	0			0		

Table 6. Test for Anchoring When Posted Price Is after Auction

	Random Effects Tobit			Random Effect Tobit with Bootstrap Std. Err.		
	Marginal Effect	Std. Err	P> z	Marginal Effect	Std. Err	P> z
<i>Price</i>	0.004	0.012	0.714	0.004	0.009	0.633
<i>Jar type 2</i>	0.303	0.136	0.026	0.303	0.105	0.004
<i>Jar type 3</i>	0.115	0.136	0.397	0.115	0.095	0.226
<i>Jar type 4</i>	0.246	0.137	0.073	0.246	0.151	0.104
<i>Jar type 5</i>	0.361	0.136	0.008	0.361	0.143	0.011
<i>_cons</i>	2.926	0.300	0.000	2.926	0.300	0.000
<i>Wald chi<sup>2</sup></i>	9.39			18.08		
<i>Prob&gt; chi<sup>2</sup></i>	0.094			0.003		
<i>Log likelihood</i>	-452.642			-452.642		
<i>Number of Obs</i>	310			310		
<i>Left-censored observations</i>	14			14		
<i>Uncensored observations</i>	296			296		
<i>Right-censored observations</i>	0			0		

Table 7 The Effect of Round Number

	WTP Bid Amount – Random Effects Tobit			Likelihood of Zero WTP – Random Effects Logit
	All Bidders	On Margin Bidders	Off Margin Bidders	All Bidders
<i>RoundNumber</i>	-0.0393***	0.0237**	-0.0776***	0.0984
<i>Experimental Controls</i>	X	X	X	X
<i>On Margin Bidder</i>	X	X		X
<i>Off-Margin Bidder</i>	X		X	X
<i>Jar type 2</i>	0.421***	0.411***	0.441***	-0.470*
<i>Jar type 3</i>	0.180*	-0.0424	0.130	-0.244
<i>Jar type 4</i>	0.328***	0.202*	0.299***	-0.308
<i>Jar type 5</i>	0.510***	0.537***	0.406***	-0.479
<i>_cons</i>	2.004***	1.658***	2.257***	
<i>Wald chi<sup>2</sup></i>	942.25	772.78	650.34	190.66
<i>Prob&gt; chi<sup>2</sup></i>	0.000	0.000	0.000	0.000
<i>Log likelihood</i>	-2812.153	-1165.610	-1254.617	-543.289
<i>Number of obs</i>	1725	773	952	1725

Notes: \*\*\*, \*\*, \* represent significance at the 1%, 5%, and 10% levels, respectively. Estimates include subject random effects. Experimental Controls include several order effects and information treatments, details can be found in Wu et al. (2015)

Table 8. Marginal Effect Estimation Comparison in Posted Price and Auction

	Auction			Posted Price		
	Coefficient	Std. Err	P> z	Coefficient	Std. Err	P> z
<i>Jar type 2</i>	0.374	0.092	0.000	0.710	0.313	0.023
<i>Jar type 3</i>	0.043	0.092	0.639	-0.054	0.329	0.869
<i>Jar type 4</i>	0.183	0.092	0.048	0.351	0.318	0.270
<i>Jar type 5</i>	0.355	0.092	0.000	0.303	0.319	0.342
<i>_cons</i>	2.643	0.198	0.000	-1.311	0.253	0.000
<i>Wald chi<sup>2</sup></i>	28.06			7.79		
<i>Prob&gt; chi<sup>2</sup></i>	0.000			0.099		
<i>Log likelihood</i>	-786.041			-335.720		
<i>Number of Obs</i>	575			575		
<i>Left-censored observations</i>	45			0		
<i>Uncensored observations</i>	530			575		
<i>Right-censored observations</i>	0			0		

## REVIEWER APPENDIX

### Experiment Instructions: Reverse Order

#### Part A - Experiment Instructions

Welcome to an experiment session in consumer decision making. In the course of this session, you will have opportunities to earn up to \$18 in cash and products. Please read these instructions carefully and ask the administrator if you have questions. Please do not communicate with other participants during the experiment. As stated in the Consent Form, your participation in this experiment is voluntary and you can withdraw from this experiment at any time.

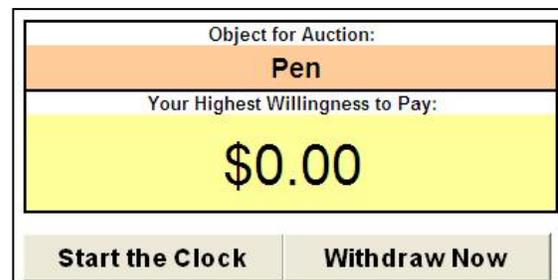
**Part A:** For this part of today's session, you will be given \$15 cash. You are welcome to keep this money and take it home at the conclusion of this session, or you may use this money to purchase a jar of honey. Any money you do not use to buy a jar of honey is yours to keep.

In this session, you will make **20 decisions** about purchasing different **jars of honey**. However, at the end of the session, only **one** of the 20 decisions will be selected. This selected decision will determine which jar of honey is purchased and your final cash earnings. This decision will be determined randomly at the end of the session by having a volunteer draw a ball from a bag containing 20 balls, labeled 1 to 20. Since each of the 20 decisions is represented by one ball, each decision has an equal likelihood of being selected. Thus, you should treat every decision as if it was the one that will be selected.

Your decision will be referred to as a **bid** and your bid will represent the **highest amount of money you would be willing to pay** for each jar of honey. On your desk and in front of the room, there are displayed five different jars labeled by the numbers 1 through 5. All of the jars contain 12 ounces of honey.

You will submit your bid by using the computer program, as shown below. If you wish to bid \$0.00 for the item, simply click the "Withdraw Now" button. If you wish to bid an amount greater than \$0.00, then click the button labeled "Start the Clock" and then your computer will show your bid amount that will gradually increase starting from \$0.00. When your displayed bid reaches the highest amount you would be willing to pay for this jar of honey,

click the "Withdraw from Auction" button. This will stop the clock and a box will then ask you if you like to submit your bid at the current price. If you would like to submit this bid, click "OK".



The screenshot shows a window titled "Object for Auction: Pen". Below the title, it says "Your Highest Willingness to Pay:" followed by a large "\$0.00" in a yellow box. At the bottom, there are two buttons: "Start the Clock" and "Withdraw Now".



The screenshot shows a dialog box titled "Submit Bid" with a close button (X) in the top right corner. The text inside says "Submit bid at the current price? (Cancel restarts your bidding at zero.)". At the bottom, there are two buttons: "OK" and "Cancel".

If not, click “Cancel”. If you click “Cancel”, your bid amount will be re-set \$0.00 and the bid will again continue to increase until you click the “Withdraw from Auction” button.

Once all participants have submitted their bids, the administrator will rank them from highest to lowest and sell the item to the person who submitted the **highest bid**. The price that this person pays will be equal to the **second highest bid** that was submitted for this item. To better understand how this works consider the following hypothetical example in which four participants each \$1.50 as the **initial balance** and submitted the following bids for an item:

<u>Bid A</u>	<u>Bid B</u>	<u>Bid C</u>	<u>Bid D</u>
\$1.00	\$0.25	\$0.50	\$1.25

After receiving these four bids, the administrator ranks them from the highest to the lowest, as shown below:

<u>Bid D</u>	<u>Bid A</u>	<u>Bid C</u>	<u>Bid B</u>
\$1.25	\$1.00	\$0.50	\$0.25

In this case, the participant with the highest bid (Participant D) would purchase the item, but would pay a price equivalent to the second highest bid (\$1.00). Thus, Participant D would receive the item and \$0.50 cash (\$1.50 - \$1.00). The other participants who did not purchase the item would receive their initial balance of \$1.50.

Note that in this auction, it is in your best interest to submit a bid equal to the highest amount you would be willing to pay for each item, because if you purchase the item, you will pay a price equal to the second highest bid, not necessarily of your bid.

To give you experience with how this auction will work, you will first make a couple of decisions for non-honey products. The first item is a Ticonderoga Pencil. The second item is a Zebra Z-Grip Ball Point Pen. For each of these products you will be given an additional \$1.50 and each item will be selected and be used to determine earnings.

### **Part B - Experiment Instructions**

This part will again use an auction and will operate in a similar manner to Part A, except that your decision is now for 15 different jars of honey. You will be given \$15.00 for these decisions. In the auction, you can submit any bid between \$0.00 and \$15.00. As described in Part A, only one of the 20 jars of honey (15 jars in Part B and 5 jars in Part C) will be selected randomly at the end of the session for purchase and will be used to determine your cash earnings.

In this part of the experiment, you will submit bids on three types of honey that differ based on its production location. These are labeled: Local, US, and International.

**Local honey** comes from the local region around Newark, Delaware.

**US honey** was produced in the United States.

**International honey** was produced outside of the United States.

Each of these three types of honey is in five different jars, labeled 1 to 5.

**Part C - Experiment Instructions**

In this part, you will again be making decisions about purchasing jars of honey. However, instead making your decision using an auction, you will now make your purchase decision based on a posted price. For these final five decisions, you will be given a **posted price** for each jar of honey. This honey was produced in the United States. The posted prices for each of these jars of honey will vary and range from \$0 to \$15. The posted price that you can purchase each jar of honey is shown on your computer spreadsheet (see the hypothetical example below). For these decisions, you will then need to determine whether you want to purchase this jar of honey for that price.

<b>Would you purchase one Jar 1 of US honey for the following posted price?</b>			
	<b>Price:</b>	\$12.00	
	<input type="button" value="Yes"/>		<input type="button" value="No"/>

**If you want to purchase this honey at this posted price**, then click the “Yes” button. By answering “Yes”, you are indicating that you would pay this price for this jar of honey. Therefore, if this decision is selected you will purchase this jar of honey and your cash earnings will be \$15 minus the price.

**If you do not want to purchase this honey at this posted price**, then click the “No” button. By answering “No”, you are indicating that you would not pay this price for this jar of honey. Therefore, if this decision is selected, your cash earnings would be \$15.

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