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DO AUCTIONS UNDERESTIMATE CONSUMER WTP? AN ARTEFACTUAL FIELD EXPERIMENT

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ABSTRACT

Auction experiments are commonly used to elicit consumer values for a wide range of items and services. These auctions are theoretically incentive compatible so are assumed to give an unbiased estimate of consumers' willingness to pay (WTP). However, the vast majority of consumer decisions are made not in auctions but in posted-price settings, such as grocery stores. This study tests whether the two mechanisms yield similar WTP estimates by comparing WTP for honey from a second-price Vickrey auction and the WTP from a posted-price dichotomous-choice mechanism in a within-subject, homegrown-value setting. Results from 115 adult consumers indicate that estimates of WTP generated by an auction are approximately 50% smaller than WTP estimates generated by a posted-price mechanism. We test several potential explanations for this difference in behavior and find no evidence of anchoring or yea-saying effects. The evidence does suggest that the framing of choice in an auction format and a lack of familiarity with auctions are the most plausible explanation for this downward bias.

Keywords: Consumer Demand; Willingness-to-Pay; Auction Experiments; Posted Price Mechanism; Homegrown Values

JEL Classification: D44, D12, C93

I. Introduction

Economists have frequently used auction in experimental economics settings to measure consumers' values for goods and services (Hayes et al. 1995; Lusk and Shogren 2007; Lusk, Feldkamp, and Schroeder 2004). Ideally, the studies measure consumers' true willingness to pay (WTP)—the maximum amount they would be willing to spend when faced with a purchase decision in a traditional market setting. In actual practice, however, consumers make such decisions not as auction bids but in a posted-priced setting where consumers observe the price and decide whether to purchase the item. A key assumption of the studies that used auctions is that the bids in a well designed and implemented auction are equivalent to consumers' maximum WTP in a posted-price setting because the auctions typically are incentive-compatible and demand-revealing. While some error and noise in the valuation process may be inevitable, researchers have assumed that an effective auction design and proper training of participants will reveal their true WTP and that the resulting distribution of auction bids should be representative of the distribution of posted-price WTP for the same good. Since the information obtained from auction bids is a point estimate of WTP, it has been an attractive method as it provides a seemingly more precise estimate than the information obtained from posted prices and typically is much easier to work with econometrically. Thus, it has become natural to emphasize auctions and use them as a first-line valuation tool.

There has been a great deal of research comparing various auction mechanisms and design decisions using both induced-value and homegrown-value experiments, but there has been surprisingly little investigation into the central supposition that the WTP estimates that come from auction bidding data accurately represent how consumers behave when faced with a posted-price decision. We tested this question explicitly using a within-subject design in an artefactual field experiment that gave adult consumers the opportunity to purchase jars of honey using a sealed-bid, second-price auction and a posted-price, dichotomous-choice mechanism. The results suggest that WTP in the posted-price mechanism exceeds WTP in the auction by upwards of 50%.

We considered this result within the context of a basic behavior model of value and strategy discovery–the Discovered Preference Hypothesis (Plott 1996). We used ordering effects and within-subject-difference comparisons to test several hypotheses about the source of this discrepancy between the two settings. We found no evidence of anchoring on the posted price in the auction or of a yea-saying tendency in the dichotomous-choice setting, further pointing to the cause of low WTP estimates from auctions to some characteristic inherent to the auction setting, perhaps associated with consumers' lack of familiarity with auctions.

II. Background

Researchers and decision-makers are often interested in how much consumers are willing to pay for products or services in order to estimate values for welfare, demand elasticity, market share, and other market information. Such information is used in setting prices for new products and services and informs policy decisions and legal proceedings. Accurately measuring an individual consumer's true WTP, however, 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 X?" 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).[1] However, this recommendation seems to have been lost in the literature related to measuring WTP for private goods.

Using posted prices in a laboratory environment would 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 $X?" Participants must spend $X for the item if they choose "Yes" and pay nothing 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 exact WTP for each participant. 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 experimental auctions.

Experimental Auctions

Approaches involving incentive-compatible auction mechanisms (e.g., Vickrey, English, Becker-DeGroot-Marschak (BDM), and random n^{th} price) are widely used in experimental economics

[1] The dichotomous choice also is referred to as a posted-price, take-it-or-leave-it, and a discrete-referendum design.

research to elicit accurate 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). However, how WTP estimates from experimental auctions compare to estimates from an incentive-compatible posted-price setting remains an open question (Frykblom and Shogren 2000). 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. In a Vickrey auction, participants confidentially state their bids, and the auction administrator ranks the bids from highest to lowest. The highest bidder wins the auction and receives the item after paying the price set by the second highest bid. In an English auction, the administrator announces the price for the item in ascending order. Participants withdraw from the auction when they view the announced price as exceeding their maximum WTP. The last person left in the auction wins the item and pays the price at which the last competitor withdrew.

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 and bidding one's true value is the dominant strategy (Vickrey 1961). However, in empirical experimental settings, these auction formats suffer from various drawbacks. Multiple studies have shown consistent overbidding in Vickrey auctions that used induced values (e.g., Kagel, Harstad, and Levin 1987; Kagel and Levin 1993; Harstad 2000; Cooper and Fang 2008). English auctions suffer less from overbidding (e.g., Kagel, Harstad, and Levin 1987; Harstad 2000; Cooper and Fang 2008), but market feedback is difficult to control and participants' bids can be affiliated (Lusk 2003). Although Lusk, Feldkamp, and Schroeder (2004) showed that English auction and BDM mechanism auctions provide similar between-subject estimates of WTP, market feedback can still affect bids in many ways. With market feedback, off-margin bidders might realize that their chances of winning are low and the auction thus might not be incentive compatible due to the low cost of misbehaving (Shogren et al. 2001). Even when price feedback is provided only after each round in a multiple round auction, bids can become affiliated, which would raise a series of problems (Corrigan et al. 2012; Corrigan and Rousu 2011). 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).

Comparisons of Posted Prices and Auctions

Despite the extensive literature related to both posted prices and auctions, few studies have compared relative WTP from the two mechanisms. Frykblom and Shogren (2000) compared a nonhypothetical 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, yea-saying, 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 comparison was between subjects and the experiment involved student participants choosing whether to buy a book that was related to their majors. Kaas and Ruprecht (2006) found evidence that subject bids were lower in a Vickrey auction with value uncertainty than in auctions based on the BDM and stated preference methods. But their explanation for those results is problematic because it relies on the degree of risk-aversion among participants, which should be equivalent in all of the tested formats. A recent study by Berry, Fischer, and Guiteras (2012) compared a BDM auction with a posted-price mechanism and found that bids in the BDM were smaller than the estimated WTP revealed by the posted-price mechanism. Like the model used in Frykblom and Shogren (2000), this experiment used compounds as a unit (extended-family households in rural Africa) and the comparison was between subjects.

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 (e.g., Wang 1993; Boyer, Brorsen, and Zhang 2013; Grebe, Ivanova-Stenzel, and Kröger 2010; Wang, Montgomery, and Srinivasan 2008).

To our knowledge, there has been no empirical study comparing behavior from the two formats using a within-subject design and appropriate experimental controls. Thus, this study is novel in so far that it compares within-subject WTP estimates from a second-price private-value auction to estimates of WTP in a posted-price design. Our experiment allows us to avoid heterogeneity among subjects and potential learning effects and makes the comparison more plausible. We show that WTP estimates from commonly used auction mechanisms are significantly less than WTP estimates from posted-price mechanisms.

III. Motivation

To conceptualize response differences between second-price auctions and posted prices, one considers participant behavioral anomalies as errors relative to standard preference theory as expounded in the Discovered Preference Hypothesis (DPH) (Plott 1996). This approach 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. Braga and Starmer (2005) identified an implicit division in Plott's description of DPH between "institution" preferences (preferences regarding strategies to achieve goals in the decision environment) and "value" learning (more basic preferences about things like basic tastes, risk, and consumption baskets in unfamiliar states of the world). Notably, DPH implies that the utility of money is stable (Van de Kuilen 2009) and is well adapted into a random utility analysis framework in which distribution of the utility error term evolves with information and feedback from the decision environment (Kingsley and Brown 2010).

Auctions used in WTP economic experiments used for value elicitation have typically provided very little in the way of direct feedback regarding participants' choices until after all of the choices have been made. In such an environment where there is very little information concerning value outcomes, it is reasonable to suppose that participants who are making decisions in the impulsive mode could be sensitive to information provided through framing of the decision. We propose several hypotheses along this line to explore potential causes of behavioral discrepancies between second-price auctions and posted prices.

Formally, suppose that each participant i considering item j in choice opportunity k has the following utility:

$$u_{i,j,k} = \alpha_{i,j} + \varepsilon_{i,j,k}.$$

Note that $\alpha_{i,j}$ is constant across all decision opportunities for each item and participant. No restrictions are placed on $\varepsilon_{i,j,k}$ in terms of distribution or mean. However, we posit that the distribution can be affected at the time of the decision by information provided in the choice-opportunity framing. Therefore, the participant has a prior error distribution that enters the research setting, $\varepsilon_{i,j}$, and an error distribution for each choice opportunity that is conditional on the information provisioned from both the current decision and from feedback from any prior decisions with $j < k$:

$$\varepsilon_{i,j,k} = \varepsilon_{i,j}|\Omega_{i,k}$$

where $\Omega_{i,k}$ represents all information available to a participant for decision k. According to DPH, as $\Omega_{i,k}$ increases with information from prior decisions, $\varepsilon_{i,j,k}$, will go to zero and the participant will play a strategy that is consistent with $u = \alpha_{i,j}$ with certainty.

If participants are risk-averse, the uncertainty in values suggests that they will demand a risk premium in their responses, but the premium would be uniform for both posted prices and auctions. Thus, risk-aversion should affect the strategies in both mechanisms equally and not affect the results of a within-subject, homegrown-value experiment. Therefore, risk-neutrality is assumed so that the usual equilibrium strategies hold. In the second-price auction for participant i considering good j in offering k, the equilibrium strategy will be to bid the expected value conditional on information gained at the time of offering:

$$bid_{i,j,k} = E\left(u_{i,j,k}\middle|\Omega_{i,k}\right).$$

For posted prices, the participant is expected to accept the price ($accept = 1$) when the offer, $pp\_offer_{i,j,k}$, does not exceed their conditional expected value and otherwise to reject the price ($accept = 0$):

$$accept_{i,j,k} = \begin{cases} 1 \; if \; pp\_offer_{i,j,k} \le E\left(u_{i,j,k}\middle|\Omega_{i,k}\right) \\ 0 \; if \; pp\_offer_{i,j,k} > E\left(u_{i,j,k}\middle|\Omega_{i,k}\right) \end{cases}.$$

Note that this model accommodates both institutional and value uncertainty. We can assume that the players are aware of equilibrium strategies but may rationally adopt a strategy that is off the equilibrium if $\Omega_{i,k}$ contains beliefs and/or information about the institutional setting that systematically shifts $\varepsilon_{i,j,k}$. Therefore, for our purposes under this paradigm, investigating value response anomalies is equivalent to considering the conditional effect of information on the error term. Specifically, we test five hypotheses about behavior in auction and posted-price settings.

Hypotheses

The series of hypotheses tested in this research are summarized in Table 1. The first hypothesis is that WTP estimates from the posted-price mechanism equal those from the second-price auction.

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

If this hypothesis is rejected ($WTP_{Posted\_Price} \neq WTP_{Auction}$), we then seek to determine whether the result is due to biased statistical estimations or behavioral factors. When the inconsistency is due to different statistical procedures, it should disappear when a single procedure is applied to both mechanisms. Assuming that participants' bids, $bid_{i,j,k}$, accurately reflect true WTP, the participants should accept ($ShouldAccept_{i,j,k}$ = 1) the price in the posted-price setting if the offer, $pp\_offer_{i,j,k}$, does not exceed their bids and should not accept the price ($ShouldAccept_{ijk}$ = 0) otherwise:

$$ShouldAccept_{i,j,k} = \begin{cases} 1 \ if \ pp\_offer_{i,j,k} \leq bid_{i,j,k} \\ 0 \ if \ pp\_offer_{i,j,k} > bid_{i,j,k} \end{cases}.$$

Since $ShouldAccept_{i,j,k}$ and the posted-price results, $accept_{i,j,k}$, are both binary, the same statistical approach can be applied to calculate WTP. If participants' behaviors are consistent and any difference in WTP is a result of the estimation method used, the confidence intervals (CIs) for *ShouldAccept* in the posted-price setting should be significantly different from the CIs in the auction. Specifically, two questions under hypothesis 2 are tested:

H_0: $WTP_{ShouldAccept} \neq WTP_{Auction.}$

H_0: $WTP_{ShouldAccept} = WTP_{Posted\_Price}$.

If those hypotheses are rejected, differences and the WTP estimates are not due to statistical error. What behavioral factors could cause differences? Previous studies suggest several potential factors: the anchoring effect, yea-saying, and lack of familiarity with auction mechanisms.

Anchoring Effect

The anchoring effect (also known as starting-point bias) occurs when respondents' values can be influenced by and biased toward the posted offer (e.g., the price asked for an item) in dichotomous-choice questions (Tversky and Kahneman 1974; Herriges and Shogren 1996). While Green et al. (1998) found strong evidence of anchoring, Kriström (1993) observed no such effect when comparing responses from respondents who answered dichotomous-choice questions before answering open-ended questions to responses from respondents who answered only open-ended questions. However, both studies involved WTP for public goods. Other effects, such as symbolic bidding and yea-saying, could have played a role.

In the terms presented, anchoring of bids to posted-price offers would result in $E(\varepsilon_{i,j})$ differing from $E(\varepsilon_{i,j} \mid p_{i,j,k})$. In that case, posted-price offers would affect bids in the auction when respondents participated in the posted-price mechanism *before* participating in the auction but should not have an effect if they participated in the posted-price mechanism *after* participating in the auction. Specifically, bids in posted-price mechanisms for posted prices *before* and *after* the auction would be regressed (Hypothesis 3, Table 1):

H_0: $\beta_{PP\_after\_Auction=0,\ PP\_offer} \neq 0$

H_0:$\beta_{PP\_after\_Auction=1,\ PP\_offer} = 0$.

Yea-saying Effect

The yea-saying effect describes a tendency for some respondents in hypothetical choice settings with no real payments, such as those in the contingent valuation literature, to choose affirmatively in a dichotomous setting regardless of their true preferences (Couch and Keniston 1960; Ready, Buzby and Hu 1996). For instance, Kanninen (1995) described a statistical approach and concluded that 20% of respondents in the sample were yea-sayers. Ready, Buzby, and Hu (1996) found similar evidence with 20–22% of the respondents being yea-sayers in a split sample contingent valuation study for food safety improvements.[2]

Perhaps yea-saying or something similar is behind overstated WTP estimates in posted-price settings even when the decision involves direct financial payments. Researchers have argued that the higher WTP estimates generated from closed-ended questions are due to a greater proportion of yea-sayers and that open-ended questions force yea-sayers to express true values and thus are a more accurate method (Ready, Buzby, and Hu 1996). We test whether the probability of a yea-saying error is larger than the probability of a nay-saying error—whether Pr(*Accept* =1 | *ShouldAccept* = 0) is greater than Pr(*Accept* = 0 | *ShouldAccept* = 1). Further, we test whether the disparity in WTP between posted prices and auctions is smaller when respondents experience the auction *first*: $\text{WTP}_{\text{A\_First,Posted\_Price}} - \text{WTP}_{\text{A\_First, Auction}}$ is less than $\text{WTP}_{\text{PP\_First, Posted\_Price}} - \text{WTP}_{\text{PP\_First, Auction}}$ (Hypothesis 4, Table 1).

Lack of Familiarity with Auction Formats

As the NOAA panel pointed out, a format of open-ended-questions in hypothetical questions lacks realism and is sensitive to trivial characteristics of the scenario presented. In contrast,

[2] As Frykblom and Shogren (2000) note nay-saying has received little attention and seems to have been neglected in the contingent-valuation literature.

dichotomous-choice questions better approximate an actual purchasing environment and are easier for respondents to answer accurately (Arrow et al. 1993). 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, especially if feedback is provided about the outcome of the auction. However, even when participants do not receive direct feedback after each round, $\Omega_{i,k}$ (all information available to a participant) may evolve due to additional opportunities for introspection, belief reinforcement, learning, and other similar mechanisms. Thus Hypothesis 5 in Table 1 tests whether $E(\varepsilon_{i,j}|\Omega_{i,k}) = E(\varepsilon_{i,j}|\Omega_{i,k+h})$ for any h and k.

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

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

IV. Experimental Design

We tested the five hypotheses using a within-subject, homegrown-value artefactual field experiment in which we offered adult subjects the opportunity to purchase jars of honey. This research was conducted in an experimental economics laboratory at a large university in the northeastern United States. We recruited 115 adult participants from the local community through various sources that included the university's online newspaper, local church 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 all participants were experienced buyers (e.g., Gracia, Loureiro, and Nayga 2011; Chang, Lusk, and Norwood 2009; List 2003).

Table 2 describes the socio-demographic characteristics of the participants. The average participant age was about 42 years. Most of the participants were female, which corresponds with the fact that 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 between participants was permitted, but participants were welcomed to ask questions of 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 posted-price rounds, they made purchase decisions for the five jars of U.S. honey only. 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 U.S. honey was placed on the administrator's desk and on the desk of each participant, and participants were encouraged to examine the jars.[3] 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 controlled.

At the end of each session, 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 distributed and used to calculate cash earnings (Hayes et al. 1995; Lusk, Feldkamp, and Schroeder 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. Demonstrations of how the ball would be drawn to determine the binding round were given to participants prior to their making any decisions. The instructions also explained that no decision was affected by prior or subsequent decisions and that it was in the best interest of participants to bid as close to the worth of the item to them as possible.[4]

In the posted-price experiment, the question to participants was "Are you willing to purchase Jar Y of U.S. honey at $X?" The price of the item 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 and that the cost of the jar would be deducted from

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[3] We also offered four information treatments that related to international and local honey in a between-subject design. Those treatments did not affect the results discussed here and are not included in this analysis. They are available from the authors upon request.

[4] Explaining the dominant strategy to participants in homegrown-value experiments is regarded as "best practice" and is widely used (e.g., Rutström, 1998; Lusk, Feldkamp, and Schroeder 2004).

the money they would receive at the end of the experiment; clicking “no” meant they would not receive Jar Y and would be paid $15 at the end of the experiment session.

In the second-price auction, a number representing a bid for the item was shown on the screen in front of each participant. Once the auction started, this bid increased incrementally from $0 to $15.[5] 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 market price 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 (Kanter et al., 2009). Participants were given $3 in the practice rounds and were asked to submit bids on a pencil and a ballpoint pen. The range of bids was restricted to between $0.00 and $1.50 for each item. 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 honey following the same procedure but with an initial balance of $15. At the beginning of each new purchasing

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[5] Since each participant started the program 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.

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., 2012).

The only announcement was the winner of the binding round at the end of the experiment. This was done by having a volunteer draw one ball which determined which of the twenty purchase decisions would be binding and 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. At the end of the session, participants were asked to fill out a survey about their demographics background and consumer behavior.

V. Results

Since bids were limited to a range of \$0 to \$15, a two-limit random-effects Tobit model was appropriate to analyze WTP. The dependent variable is a latent variable, y_{ij}^*, and is specified as

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

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), β. The following random-effects Tobit model was used:

$$y_{ij}^* = \alpha + \beta X_{ij} + U_i + u_{ij}$$

$$= \alpha + \beta_1 PP\_after\_Auction_{ij} + \beta_2 Reverse_{ij}$$

$$+ \beta_3 jar2_{ij} + \beta_4 jar3_{ij} + \beta_5 jar4_{ij} + \beta_6 jar5_{ij} + U_i + u_{ij}$$

where α is the average bid for the entire population, Ui represents the individual random effects, and u_{ij} is the error term of individual i for product j. The variables *jar2* through *jar5* are dummy variables indicating what jar was auctioned. The variable *PP_after_Auction* and *Reverse* are dummies controlling for order effects. *PP_after_Auction* equals one when the posted-price experiment follows the auction and equals zero otherwise; *Reverse* equals one when the posted-price experiment is conducted first and zero otherwise. The 'primary order' in each case is the posted-price experiment occurring *after* the auction.

For the data from posted prices, the dependent variable *accept* is binary. We denote the probability of subject *i* accepting the posted price for product *j* as $\pi(X_{ij})$ where X_{ij} is the explanatory vector. Then,

$$logit(X_{ij}) = \ln\left(\frac{\pi(X_{ij})}{\left(1 - \pi(X_{ij})\right)}\right)$$

$$= \beta_0 + \beta_1 PP\_offer_{ij} + \beta_2 PP\_after\_Auction_{ij}$$
$$+ \beta_3 Reverse_{ij} + \beta_4 jar2_{ij} + \beta_5 jar3_{ij} + \beta_6 jar4_{ij} + \beta_7 jar5_{ij}$$
$$+ U_i + u_{ij}$$

where PP_offer_{ij} is the posted-price offer by individual *i* on item *j*. As before, the variables *jar2* through *jar5* are dummies representing each jar, *PP_after_Auction* equals one when the posted-price mechanism comes after the auction and *Reverse* equals one when the posted-price mechanism comes first. After estimating the logit, we can easily calculate the probability of accepting the posted-price offer given a vector of **x** using the inverse function[6]:

$$\pi(\mathrm{x}) = \frac{1}{(1+e^{-\left(\begin{array}{c}\beta_0+\beta_1 PP_{offer_{ij}}+\beta_2 PP_{after_{Auction_{ij}}}+\beta_3 Reverse_{ij}+ \\ \beta_4 jar2_{ij}+\beta_5 jar3_{ij}+\beta_6 jar4_{ij}+\beta_7 jar5_{ij}+U_i+u_{ij}\end{array}\right)})}.$$

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[6] For discussions on Logistic Regression, see Agresti, 2002.

Based on the estimates from the logit model (see Table 4), we calculated WTP point estimates and 95% confidence intervals using a Krinsky-Robb parametric bootstrap following the WTP procedure in STATA (Hole 2007).

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

Table 3 shows the results from the Tobit model. *PP_after_Auction* is significant; consumers' bids are $0.74 higher when the posted-price experiment follows the auction. The constant term suggests that participants' WTP for a jar of honey is $2.37 with a confidence interval of [1.76, 2.98] when the posted price occurred before the auction and reverse order not in use.

Table 4 displays the results from the logit regression when we treat accepting the posted-price offer (*accept*) as the dependent variable. Variable *PP_offer* is significant at the 1% level; thus, when holding the other effects constant, an increase of $1 in the posted price will decrease the logit estimator of accepting the item by 0.71. The odds ratio of accepting the item is exp(–0.71) = 0.49 times the odds ratio if the cost did not increase $1. Thus, the odds ratio of accepting the item decreases 51% when the posted price increases by $1.

Following the logit regression, the WTP procedure in STATA (Hole 2007) provides us with 95% confidence intervals for the WTP estimates. Variable *PP_offer* was used as the cost coefficient and *_cons* as the attribute. To elicit the confidence intervals, we chose the Krinsky-Robb parametric bootstrap method.[7] The estimates of WTP and their confidence intervals from both the auction and the posted-price mechanisms are summarized in Table 5. Consumers' WTP is significantly greater in the posted-price mechanism than in the auctions, and we see no overlap in the tails. The estimates of WTP from the auctions are about $1.50 smaller, which is about 50% of the estimates of WTP from posted prices.

[7] See the discussion of the methods in Hole (2007).

Hypothesis 2: Test for Statistical Estimation Bias

As previously explained, differences in WTP could come from using different estimating approaches. We generated a dummy variable, *ShouldAccept*, that equals one if the bid exceeds the posted price and equals zero otherwise (Table 6). Theoretically, *ShouldAccept* represents the result of posted-price questions when the bids are the participants' true WTP. However, both the paired t-test and the nonparametric Wilcoxon signed-rank test rejected the null hypothesis that *ShouldAccept* equals *Accept* at the 1% level.

To demonstrate this further, we viewed *ShouldAccept* as the result of posted-price questions when a consumer's WTP in the posted-price mechanism and the auction were consistent. The logit regression results are presented in Table 7. Again using the WTP procedure in STATA (Hole 2007), we calculated WTP and confidence intervals. Those results are summarized in Table 8, along with results from posted prices and auctions. If variations in estimates of WTP result from different estimation methods instead of behavioral factors, the following hypotheses should be rejected.

H_0: $WTP_{ShouldAccept} \neq WTP_{Auction}$

H_0: $WTP_{ShouldAccept} = WTP_{Posted\_Price}$

As shown in Table 8, the first hypothesis is rejected. There is a small overlap in the tails for the second hypothesis. However, using 95% confidence intervals to compare differences provides conservative results and small interval overlaps do not necessarily imply any statistical significance, so the second hypothesis also should be rejected (Payton, Greenstone, and Schenker 2003).[8] Therefore, the smaller estimates of WTP observed in the auction are not a result of the

[8] The authors concluded that using 83% or 84% for the intervals would generate a test approximately at the 5% level when the standard errors were about equal. In addition, using 95% confidence intervals would give very conservative results based on both theoretical results for large samples and simulation results for a variety of sample sizes.

statistical approach; instead, they likely arise from behavioral factors associated with the auction setting.

Tests for Behavioral Factors

Recall that the anchoring effect, the yea-saying effect, and lack of familiarity could be the primary explanations for differences in WTP between posted prices and auctions. We test each explanation following the methods previously discussed in Section III.

Hypothesis 3: Anchoring Effect

If the anchoring effect exists, respondents' auction bids would be anchored to the posted-price offers when they participated in the posted-price setting first. Their bids should not be affected if the auction was held first. To test H_0: $\beta_{PP\_after\_Auction=0,PP\_offer} \neq 0$, we regressed the bids from sessions in which the posted-price mechanism was conducted first (Table 9). As shown in Table 9, participation in the posted-price mechanism did not affect subsequent bids in the auction. Therefore, H_0: $\beta_{PP\_after\_Auction=0,PP\_offer} \neq 0$ is rejected and the anchoring effect appears not to be responsible for differences in WTP.

Similarly, to test H_0:$\beta_{PP\_after\_Auction=1,PP\_offer} = 0$, we regressed the bids from sessions in which the posted-price mechanism was conducted first. As Table 10 demonstrates, posted-price offers do not have an effect on bids when auction was conducted first. Regardless of which is conducted first, therefore, no anchoring effect is observed. This result is consistent with the one from Berry, Fischer, and Guiteras (2012), which compared the BDM auction with posted prices.

Hypothesis 4: Yea-saying Effect

As previously mentioned, some traditional evidence on yea-saying found contradictory responses generated by open-ended and closed-ended questions. An important assumption underlying these studies is that WTP estimated from an auction is the true value. A major argument is that yea-sayers respond “yes” to a posted-price question without actually forming a value while being forced to form a value by open-ended questions and sometimes state a value that is smaller than the posted price they accepted.

For the moment, assume that the argument regarding yea-saying is valid. In that case, two results should be observed: (1) the proportion of yea-saying should be larger than the proportion of nay-saying; and (2) participating in the auction first would give individuals opportunities to formulate values and thus mitigate yea-saying. Therefore, the disparity in WTP between posted prices and auctions should be smaller when the auction is conducted first.

Our results support neither hypothesis. Of the 480 times when WTP estimated from the posted price setting was higher than WTP estimated from the auctions, yea-saying occurred 89 times; of the 95 times when WTP under posted prices was lower than under auctions, nay-saying 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 yea-saying is not significantly greater than the proportion of nay-saying. Splitting the responses by the mechanism order and calculating WTP disparities for both orders suggest that there is no significant decrease in disparity when participants go through the auction first (Table 11). Therefore, we find no evidence to support the hypothesis that auctions facilitate value formation by participants.

These results also show that the proportion of nay-saying is greater than yea-saying when the auction is conducted first and that the opposite occurs when the posted-price experiment is conducted first.[9] There is a relative increase in the proportion of nay-saying and decrease in the proportion of yea-saying when reversing the order of the mechanisms.[10] Based on these results, both proposed hypotheses are rejected and yea-saying should not be driving the differences in WTP.

Hypothesis 5: Lack of Familiarity with Auction Settings

Participants' institutional information might be affected by their lack of familiarity with auction formats. In that case, $E(\varepsilon_{i,j}|\Omega_{i,k}) = E(\varepsilon_{i,j}|\Omega_{i,k+h})$ would hold for any h and k generally and specifically when $\beta_{\text{Auction, RoundNumber}} = 0$ is tested. The result from a Tobit model that includes auction bids for all of the honey products, $\beta_{\text{Auction, RoundNumber}}$, is significantly different from zero with a coefficient estimate of –0.039 and p-value of 0.000. 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 decrease in difference between WTP in the auctions and posted price settings in successive rounds is not obvious, especially since there was no feedback regarding the price and winners in any of the choice settings. Thus, we considered whether off-margin bidders could have had an influence even though very little market feedback was given. Given the size of the bids, it is reasonable to define "on-margin" bidders as those whose bids are greater than the market price minus $1 and the rest as "off-margin" bidders:

On margin: Bid > Market Price – $1;

Off margin: Bid ≤ Market Price – $1.

[9] When the auction is conducted first, there is a greater proportion of nay-saying (13 out of 55) than of yea-saying (35 out of 255) at the 10% level (p-value = 0.065). When the posted-price mechanism is conducted first, there is a greater proportion of yea-saying (54 out of 225) than of nay-saying (4 out of 40) at the 5% level (p-value = 0.048).
[10] When the auction is done first, the increase in nay-saying is significant at the 10% level while the decrease in yea-saying is significant at the 1% level.

The Tobit regression results suggest that bids by off-margin bidders decrease \$0.079 each round and bids by on-margin bidders increase \$0.025 each round, both of which are significant at the 1% level. Therefore, on-margin bidders seem to follow the Discovered Preference Hypothesis and gradually identify their WTP while off-margin bidders base their WTP value on various information sources even though very little market feedback is provided.

VI. Conclusion

Second-price auctions have become popular instruments for measuring consumer WTP for various attributes of a good. A key attractive feature of auction mechanisms is that they provide point estimates of WTP, even though posted-price formats are how most consumer choices are made. Motivated by the Discovered Preference Hypothesis (DPH) (Plott 1996), we empirically test several hypotheses concerning the accuracy of second-price auctions in measuring WTP for a food product by comparing auction-generated estimates with estimates from a posted-price setting. Estimates of WTP from auction bids are significantly less than estimates of WTP for the same product via the posted-price mechanism. This result is robust to different modeling specifications. We test several potential explanations for those results related to information and framing effects. The differences in WTP do not appear to be due to variations in statistical methods, the anchoring effect, or the yea-saying effect. The results do suggest that the reason for the difference in auctions is that research participants' lack of familiarity with auctions. Further research would be useful in more precisely identifying informational factors that drive down WTP values in auction formats and determining whether the valuations decrease over time as predicted by Discovered Preference Hypothesis (Plott, 1996) discussed in Section III.

The primary implication of this research is that relatively low estimates of WTP from auctions suggest a possible flaw in auction-based value-elicitation mechanisms. If the DPH is a valid approach for understanding this phenomenon, a natural conclusion is that participants in such auction experiments will require more training prior to bidding and more feedback regarding their bidding decisions. However, additional feedback could influence participants' perceived values inordinately (i.e., feedback could increase the error from anchoring on auction results or increase the misbehavior of off-margin bidders). An alternative would be to rely more on dichotomous-choice designs. However, that option would demand much larger (and more expensive) samples to achieve the same level of statistical power. Future studies also could focus more on the cause of the inconsistency in the WTP estimates and consider other potential explanations.

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Table 1. Hypotheses

Question	Hypothesis	Result
Is there a difference in WTP between the posted-price mechanism and second-price auction?	H_0: $WTP_{Posted\_Price} = WTP_{Auction}$	Reject - There is a difference between measured WTP.
Is this difference robust to statistical specification?	H_0: $WTP_{ShouldAccept} \neq WTP_{Auction}$ H_0: $WTP_{ShouldAccept} = WTP_{Posted\_Price}$	Fail to Reject - The difference is robust to specification.
(3) Is this difference due to anchoring effect?	H_0: $\beta_{PP\_after\_Auction=0,PP\_offer} \neq 0$ H_0: $\beta_{PP\_after\_Auction=1,PP\_offer} = 0$	Fail to Reject - No evidence of anchoring
(4) Is this difference due to yea-saying?	H_0: $(Accept=1 \mid ShouldAccept=0)$ $= Pr(Accept=0 \mid ShouldAccept=1)$ H_0: $WTP_{A\_First,Posted\_Price} – WTP_{A\_First, Auction}$ $= WTP_{PP\_First, Posted\_Price} - WTP_{PP\_First, Auction}$	Fail to Reject - no evidence of yea-saying
(5) Is this difference due to a lack of familiarity with an auction setting?	H_0: $\beta_{Auction, RoundNumber} = 0$ H_1: $\beta_{Auction, RoundNumber} \neq 0$	Reject - There is evidence that the difference decreases with learning

2. Sample Demographic Characteristics

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

3. Two-limit Tobit results, WTP for honey

	Marginal Effect	Std. Err	P>|z|
PP_after_Auction	0.744	0.375	0.047
Reverse Order	-0.307	0.379	0.419
jar2	0.374	0.092	0.000
jar3	0.043	0.092	0.639
jar4	0.183	0.092	0.048
jar5	0.355	0.092	0.000
_cons	2.369	0.313	0.000
Wald chi^2	32.36		
Prob> chi^2	0.000		
Log likelihood	-783.884		
Left-censored observations	45		
Uncensored observations	530		
Right-censored observations	0		

4. Logit Model results

	Marginal Effect	Std. Err	P>|z|
PP_offer	-0.705	0.086	0.000
PP_after_Auction	-0.572	0.528	0.279
Reverse Order	-0.726	0.538	0.177
jar2	0.779	0.489	0.111
jar3	-0.307	0.499	0.538
jar4	0.046	0.490	0.926
jar5	0.181	0.479	0.705
_cons	3.431	0.691	0.000
Wald chi^2	68.69		
Prob> chi^2	0.000		
Log likelihood	-208.275		

5. Calculated WTP from Posted Price and Auction

	WTP estimates and 95% C.I.		
	WTP estimate	95% CI lower bound	95% CI upper bound
Posted price (from logit and wtp)	4.866	3.222	6.358
Auction (from Tobit)	2.369	1.755	2.983

6. Paired T-test and Wilcoxon Signed Rank Test of *ShouldAccept=Accept*

T-test	Mean	Std. Err.	95% CI
ShouldAccept	0.165	0.019	0.135, 0.196
Accept	0.290	0.016	0.253, 0.328
Diff	0.125	0.017	0.092, 0.159
t-statistic	7.305		
p-value	0.000		

Signed Rank	z statistic	p-value
	-6.993	0.000

7. Logit Model results of *ShouldAccept*

	Marginal Effect	Std. Err	P>|z|
PP_offer	-2.704	0.940	0.004
PP_after_Auction	2.523	1.560	0.106
Reverse Order	-1.120	1.328	0.399
jar2	0.901	1.303	0.490
jar3	0.343	1.338	0.798
jar4	-0.084	1.195	0.944
jar5	-0.007	1.243	0.995
_cons	5.838	2.546	0.022
Wald chi^2	8.51		
Prob> chi^2	0.290		
Log likelihood	-100.958		

Table 8. Compare WTP from Posted Price, Auction, and *ShouldAccept*

	WTP estimates and 95% C.I.		
	WTP estimate	95% CI lower bound	95% CI upper bound
Posted-price results	4.866	3.222	6.358
Auction results	2.369	1.755	2.983
Result from ShouldAccept	2.159	0.805	3.377

Table 9. Test for Anchoring When Posted Price Is before Auction

	Marginal Effect	Std. Err	P>|z|
PP_offer	–.0004	0.001	0.971
Reverse Order	-1.023	0.589	0.082
jar2	0.459	0.117	0.000
jar3	-0.044	0.117	0.710
jar4	0.110	0.117	0.346
jar5	0.342	0.117	0.003
_cons	2.660	0.360	0.000
Wald chi^2	31.32		
Prob> chi^2	0.000		
Log likelihood	-321.034		
Left-censored observations	31		
Uncensored observations	234		
Right-censored observations	0		

10. Test for Anchoring When Posted Price Is after Auction

	Marginal Effect	Std. Err	P>|z|
PP_offer	0.004	0.012	0.717
Reverse Order	0.269	0.497	0.589
jar2	0.303	0.136	0.026
jar3	0.115	0.136	0.397
jar4	0.246	0.137	0.073
jar5	0.361	0.136	0.008
_cons	2.804	0.357	0.000
Wald chi^2	9.68		
Prob> chi^2	0.139		
Log likelihood	-452.496		
Left-censored observations	14		
Uncensored observations	296		
Right-censored observations	0		

Table 11. Comparing WTP Disparities of Posted-Price/Auction Order Effects

Posted Price *after* Auction	WTP estimate	95% CI lower bound	95% CI upper bound
Posted Price	4.296	2.637	5.955
Auction	2.837	2.159	3.514
Disparity 1	1.459	0.478	2.441
Posted Price *before* Auction	WTP estimate	95% CI lower bound	95% CI upper bound
Posted Price	4.632	2.673	6.590
Auction	2.658	1.970	3.345
Disparity 2	1.974	0.703	3.245

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". 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:

Bid A	**Bid B**	**Bid C**	**Bid D**
$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:

Bid D	**Bid A**	**Bid C**	**Bid B**
$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, Participate 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, <u>it is in your best interest to submit a bid equal to the highest amount you would be willing to pay for each item</u>, 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

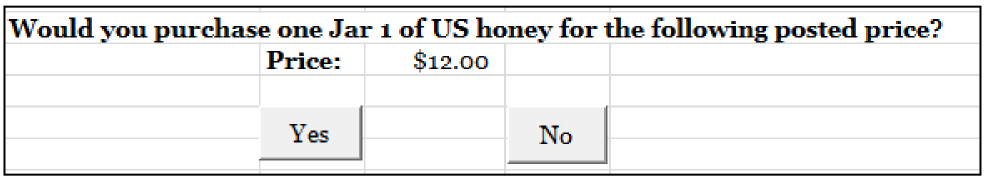
This part will again use an auction and will operate in a similar manner to Part A, except that your decision is now for 15 different jars of honey. You will be given $15.00 for these decisions. In the auction, you can submit any bid between $0.00 and $15.00. As described in Part A, only one of the 20 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.



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 <u>not</u> 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.