Comparing Open-Ended Choice Experiments and Experimental Auctions: An Application to Golden Rice

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Abstract

We use two different experimental valuation methods to estimate consumer demand for genetically-modified golden rice. The first is an open-ended choice experiment (OECE) where participants name the quantities of golden rice and conventional rice demanded at

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each of several price combinations, one of which will be randomly chosen as binding. This allows us to estimate market demand by aggregating demand across participants. This estimate of market demand also allows us to estimate own-price elasticity and consumer surplus for golden rice. Comparing willingness-to-pay (WTP) estimates from the OECE with those from a uniform-price auction, we find that OECE WTP estimates exhibit less affiliation across rounds, and the effects of positive and negative information under the OECE are more consistent with prior expectations and existing studies. We also find that while auction WTP estimates more than double across five rounds, OECE WTP estimates are stable across rounds and are always roughly equal to those from the final auction round.

Running Head: Open-Ended Choice Experiments and Experimental Auctions

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The most common experimental valuation methods in the agricultural economics literature today are experimental auctions (e.g. Corrigan and Rousu 2006) and non-hypothetical choice experiments (e.g. Alfnes et al. 2006). Researchers have used experimental auctions to estimate consumer willingness to pay (WTP) for new products and product traits for at least 25 years (Hoffman et al. 1993). Assuming the researcher uses a demand-revealing auction mechanism like the Vickrey (1961) or the Becker-DeGroot-Marschak (BDM) (1964) auction, bids provide a direct measure of auction participants' WTP for the good for sale. Taking the difference between bids submitted for a conventional good and a good possessing some new quality improvement allows the researcher to easily estimate participants' WTP for this novel trait.

While interpreting auction results is straightforward, explaining the auction mechanism to participants is not necessarily so. In the overwhelming majority of retail transactions taking place in the field, consumers are presented with a fixed price at which they can buy one or more units of the good for sale. This is particularly true in the supermarket environment, where Americans buy most of their food. By contrast, experimental auctions participants are presented with a fixed quantity and asked to name the highest price they would be willing to pay. The novelty of the name-your-reservation-price exercise is then compounded by the introduction of an unfamiliar auction mechanism.

On the other hand participants in choice experiments (CEs) are presented with two or more goods and asked to choose the one they most prefer. Exercises like these are more similar to familiar retail environments and therefore should seem straightforward to participants. CEs also have a sound theoretical basis given that they combine Lancaster's (1966) characteristics theory of value and McFadden's (1974) random utility theory. Hypothetical CEs have long been used in the marketing and environmental valuation literatures. More recently, agricultural economists have begun using non-hypothetical CEs to value private goods (e.g. Lusk and Schroeder 2004). Most CEs offer a polychotomous choice where participants choose to purchase at most one unit of one of the goods presented.

A third valuation method that incorporates many of the advantages of both experimental auctions and CEs is the non-hypothetical "open-ended choice experiment" (OECE) (e.g. Maynard, Hartell, and Hao 2004). As with more conventional CEs, participants in an OECE are presented with multiple goods for sale at different prices. And as with experimental auctions, participants provide open-ended responses. That is, they can choose to purchase as many units of the goods for sale as they wish. Unlike the name-your-reservation-price exercise in an experimental auction, the name-your-quantity exercise in an OECE is familiar to consumers who engage in a similar exercise every time they purchase food at a supermarket. By soliciting count data instead of binary data, the OECE allows the researcher to collect a richer dataset for a given sample size.

In this study we use both an experimental auction and an OECE to estimate the value Filipino consumers place on genetically-modified "golden rice." In particular we compare the results of a uniform-price Vickrey auction with four units supplied with those from an OECE that can best be thought of as a refinement of existing OECE methodologies.[1] We conducted our experiments in the Philippines, where rice is a staple food consumed by all Filipinos regardless of age, income, or other characteristics. The latest version of golden rice has been approved for trial plantings in India and the Philippines (*New Scientist* 2005). However, the introduction of genetically-modified foods has met with mixed consumer reactions (Lusk et al. 2005). Therefore, we are interested in estimating Asian consumers' WTP for golden rice and how it is affected by positive and negative information about genetic modification. The dataset used in this study is, to our knowledge, the first to use non-hypothetical empirical valuation techniques to estimate consumer WTP for golden rice and the first of any kind focusing on Asian consumers' WTP for golden rice.

The remainder of the article is organized as follows. The next two sections review the literature on golden rice and the effects of information on experimental auction bids, respectively. We then present a more detailed discussion of the OECE and how it relates to the existing auction and CE literature. This is followed by a description of our experimental design. We then demonstrate how OECE data can be used to estimate demand, own-price elasticity, and consumer surplus. This is followed by an application to golden rice as well as a comparison of value estimates from the OECE and the uniform-price auction.

Golden Rice

The second generation of genetically-modified (GM) crops include those that are bred for attributes desired by consumers rather than producers (Rousu et al. 2005). "Golden rice," which has been genetically engineered to contain a higher level of vitamin A, is a prime example. It is aimed at combating vitamin A deficiency (VAD) in developing countries where rice is the main staple (Nielsen and Anderson 2005). VAD can cause temporary or permanent vision impairment and increased mortality, especially among children and pregnant or lactating women.

Scientists at the Philippine-based International Rice Research Institute are currently working on verifying and improving golden rice gene constructs and incorporating them into popular rice varieties. Although golden rice is still in the development stage, it is already a source of controversy. Supporters consider it a solution to vitamin A deficiency, while critics denounce it as a public relations ploy and consider it useless for the poor (Zimmermann and Qaim 2004).

During the last decade governments and aid agencies have experimented with various policies for reducing VAD (e.g. food fortification, supplementation, and dietary education programs). Because rice is the dominant staple in Asia, golden rice has several advantages as a vitamin A intervention strategy: (1) golden rice could be distributed through existing channels for modern rice varieties; (2) golden rice could deliver vitamin A without the institutional, industrial, and logistical infrastructure required for supplementation and fortification; (3) if culturally acceptable and agronomically sound, golden rice has the potential to provide widespread relief; and (4) most importantly, golden rice could sustainably address VAD with minimum additional expense beyond the sunk costs of development and would require only modest additional investments to achieve greater geographic coverage (Robertson, Unnevehr, and Dawe 2002).

Zimmermann and Qaim's (2004) scenario calculations demonstrate that golden rice will mitigate blindness and premature death in the Philippines, with social benefits ranging between $16 million and $88 million per year. One unresolved issue, however, is consumer acceptance of golden rice (Robertson, Unnevehr, and Dawe 2002). Zimmermann and Qaim (2004) point out that quality improvements generally increase consumer demand, but this presupposes that consumers recognize and appreciate the quality improvement.

Hossain and Onyango (2004) find that consumers' acceptance of GM foods is driven primarily by their perceptions of risk, benefit, and safety of the technology. Bredahl (2001) finds that consumers do not distinguish between risks and benefits of the technology itself and risks and benefits of the resulting products. Because consumers generally have little first-hand experience with GM foods, they are using attitudes toward the technology to form opinions about GM food products.

Anderson, Jackson, and Nielsen (2005) use a global computable general equilibrium trade model to estimate welfare gains from the introduction of golden rice. Assuming golden rice captures a 45% market share in Asia, the authors estimate that its introduction would lead to a $17.4 billion annual welfare gain, with 73% of that gain coming from increased productivity among unskilled Asian workers.

The only previous empirical valuation study focusing on golden rice uses the hypothetical contingent valuation method to estimate WTP among a random sample of Mississippi households (Lusk 2003). Lusk finds that 62% of survey respondents given cheap talk information to counter hypothetical bias were willing to pay a \$0.10 per-pound premium for golden rice. The author estimates that, on average, these respondents would be willing to pay \$0.87 per pound for golden rice, a \$0.12 premium over the \$0.75 reference price for white rice.

Information Effects

Participants in experimental auctions are often provided with information regarding the goods for sale. Several experimental auction studies have evaluated the effect that positive or negative information can have on participants' WTP for GM food products. For example Tegene et al. (2003) examined the effects of positive, negative, and two-sided (conflicting) information about biotechnology on WTP for three different food products. The authors found that participants who received only negative information bid on average between 35 and 38% less for GM-labeled foods than for foods without the GM label. On the other hand participants who received only positive information bid on average at most 4% less for GM-labeled foods. Participants who received both positive and negative information bid on average between 16 and 29% less for GM-labeled foods, suggesting that consumers place greater weight on negative information than on positive information. This is consistent with the findings of earlier studies such as Fox, Hayes, and Shogren (2002),who found that WTP for irradiated foods is affected by information in the same way.

Lusk et al. (2004) found that information on the environmental, health, and social benefits of genetic modification significantly decreased the amount of compensation participants demanded in order to consume GM food in four out of the five locations where the study was conducted.

Rousu et al. (2005) examined the effect of marketing information and labeling on consumers' WTP for cigarettes containing genetically-modified tobacco. They found that among participants not provided with marketing information, those bidding on GM cigarettes explicitly labeled as such are willing to pay significantly less than those bidding on identical cigarettes with no GM label. However, among participants who do receive marketing information, the presence or absence of a GM label has no impact on WTP for the GM cigarettes. This implies that the positive information reduces the discount consumers place on genetic modification.

More recently, Huffman et al. (2007) studied how prior information affects the interpretation of new information. They found that individuals who came into the experiment with informed prior beliefs about genetic modification discounted GM-labeled food products more heavily than participants with uninformed prior beliefs. The authors note that the behavior of informed participants suggests that their prior information was somewhat negative. When presented in the experiment with information about biotechnology, uninformed participants discounted GM-labeled products the most heavily when given negative information. The discount placed on GM-labeled products was smaller for participants given either positive information or both positive and negative information, although there was no statistically significant difference between the bidding behavior of these last two groups.

Open-ended Choice Experiments

Hypothetical OECEs have a long history in the marketing literature. For example Gabor, Granger, and Sowter (1970) created "hypothetical shop situations" where they presented participants with product pairs at different prices and asked them to indicate which product they would purchase and how many units. The authors used data from area stores to show that participants' behavior in hypothetical shop situations is broadly similar to that of consumers in actual markets. More recently, Pilon (1998) asked participants to choose among five beer brands and then among several different package sizes and finally to indicate the desired number of packages. The author used this hypothetical data to calculate own-price and cross-price elasticity of demand. Louviere, Hensher, and Swait's (2000) text on stated choice methodology includes a chapter on analyzing data from "marketing case studies" like those described above.

Choice experiments and questions eliciting quantity demanded from participants with different travel costs have also been used extensively in the environmental valuation literature (e.g. Herriges and Kling 1999; Bennett and Blamey 2001). Other authors have adapted contingent valuation methods developed by environmental economists, applying them to the valuation of newly-introduced consumer goods (e.g. Loureiro and Bugbee 2005; Nayga, Woodward, and Aiew 2006).

Agricultural economists have recently begun estimating the value of private goods using non-hypothetical CEs, complementing the non-hypothetical auction experiments long used in this literature. Lusk and Schroeder (2004) compare results from hypothetical and non-hypothetical CEs where participants are allowed to buy a single unit of one of five grades of beefsteak. They find that the hypothetical CE significantly overstates purchase probability and thus total WTP. Lusk and Schroeder (2006) go on to compare results from a non-hypothetical CE with those from five demand-revealing auction experiments and find that WTP estimates from the CE are greater than those of name-your-price auctions. Assuming participants have unit demand, the authors use CE data to construct "inverse cumulative density functions of WTP," observing that the cumulative density functions "can be interpreted as demand curves assuming each individual only consumes one unit and ... no other steak alternative exists to purchase" (p. 15). The authors also discuss how simulated pairwise comparisons could be used to calculate elasticity. Alfnes et al. (2006) introduce several interesting refinements of Lusk and Schroeder's (2004) technique.

Masters and Sanogo (2002) and Sanogo and Masters (2002) endowed CE participants with 400g of a branded infant formula, then offered them the chance to exchange it for increasingly larger quantities of an unbranded formula, with the understanding that one of these choice scenarios would be randomly selected as binding. The authors argue that this iterative CE is easier to explain and implement than a Vickrey auction.

Most similar to the methods we present in this article, Maynard et al. (2004) develop a non-hypothetical CE where participants can purchase any nonnegative quantity of any of five types of beefsteak. Participants were presented with just one set of prices and asked to allocate a $20 budget across the five steaks, with change given in frozen hamburger patties. The authors argue that CEs where participants can indicate any nonnegative quantity demanded may produce more reliable WTP estimates than CEs where they can purchase at most one unit, observing that "diminishing marginal utility suggests that WTP for the first unit will exceed average WTP per household purchase occasion" (p. 319).

Our methodology differs from that of Maynard et al. (2004) in three important ways. First, participants indicate their quantity demanded at several price combinations with the understanding that one of these will be randomly determined to be binding. By separating what participants pay if they buy an item from the quantity that they indicate, this design preserves the demand-revealing properties of widely used auction mechanisms (e.g. Vickrey, BDM, random *n*th-price) but in a market environment more familiar to participants.[2] This design also allows us to estimate an individual participant's WTP for a single unit of the novel product as the highest price at which he/she indicates a quantity demanded of at least one.[3] As we will demonstrate in section 6, this allows us to directly compare results from an OECE and an experimental auction.

Second, we fix the price of the substitute product at its price outside of the experimental marketplace (i.e. its field price). Experimental auction practitioners increasingly recognize the role field alternatives play in experimental valuation. For example Harrison, Harstad, and Rutström (2004) present evidence suggesting that experimental auction participants take into account field alternatives when formulating bids. Researchers can incorporate field substitutes into experimental auctions by endowing participants with a substitute good and allowing them to bid to upgrade to the good possessing the trait of interest. Alternatively, researchers can announce that the field substitute will be for sale at the end of the auction at its field price.

CEs incorporate field substitutes by offering conventional and novel goods side by side. Indeed, one of the strengths of CEs is that varying the price of both conventional and novel goods across choice opportunities allows researchers to estimate cross-price elasticities. One weakness of the OECE proposed here is that because the substitute good is always available at its field price, researchers can only estimate the own-price elasticity for the novel good. However, there may also be a benefit from fixing the price of the substitute good at its field price. If products available outside of the experiment are offered at prices different from their field prices, this may have unintended effects on demand. For example consider the case where a participant is offered the choice between two goods and a "none of these" option. Even if purchasing either good would yield positive surplus, the participant may choose "none of these" if he believes that the good that offers the greatest surplus could be purchased in the field at a lower price. This would have the effect of understating demand for the favored good. Removing the "none of these" option introduces a different problem since it may force the participant into a transaction yielding negative surplus, thus overstating demand.

In our study participants were offered an array of potentially binding prices for 500g packages of golden rice (ranging from ₱5 to ₱25 in ₱2 increments) and were told that 500g packages of conventional rice would always be available at the ₱15 field price.[4] Participants then indicated the quantity of each type of rice they would like to buy for each of the eleven price combinations, with the understanding that only one of the price combinations would be randomly chosen as binding (see figure 1 for a sample bid form). By explicitly informing participants that the conventional alternative will be available at its field price, we eliminate possible confounding influences of selling field goods at prices different from their field price.[5] However, because we do not vary the price of the field substitute, we cannot calculate cross-price elasticities like Pilon (1998).

Third, in order to mimic an actual shopping environment as closely as possible, we placed no restrictions on the amount of money that participants must spend during the experiment. Instead, participants received the following instructions:

> Keep in mind that you are allowed to indicate that you want zero units at any or all of the price combinations listed. Also keep in mind that you shouldn't feel limited by the ₱200 show-up fee that you have earned. You may choose to spend more than ₱200, but you will need to provide the additional money yourself.

Estimating WTP, Consumer Demand, Own-price Elasticity, and Consumer Surplus

Because each participant indicates the quantity of the novel good demanded at an array of prices, the OECE allows the researcher to estimate individuals' WTP for a single unit of the good as the highest price at which they indicate a positive quantity. Censoring will be an issue for participants who indicate a positive quantity at the highest price. However, provided that fewer than half of WTP estimates are censored, median WTP estimates will not be affected. Conducting a pretest should allow the researcher to choose an OECE price range that minimizes the censoring problem.

Because participants can request any non-negative quantity at a given price level, the researcher can estimate individual participants' entire demand curves, not just their WTP for a single unit. To aggregate consumer demand across participants, the researcher sums individual demand at each price. A more formal estimate of the quantity of the novel good demanded by each participant as a function of own price can be estimated using a random-effects Poisson regression (Hausman, Hall, and Griliches 1984). This specification takes into account the panel and count nature of the data while also allowing for the overdispersion common in this type of demand study. Start by assuming that:

$$\Pr\left(q_{ij}=m\right)=f\left(m,p_j,u_i\right), \tag{1}$$

where q_{ij} is the quantity demanded by participant *i* when facing price $p_j\in\left\{p_1,\ldots,p_J\right\}$, *m* is a nonnegative integer, and u_i is an individual-specific effect. Assuming q_{ij} is drawn from a Poisson distribution:

$$\Pr\left(q_{ij}=m\right)=\frac{e^{-\lambda_{ij}}\lambda_{ij}^{m}}{m!}, \tag{1}$$

where $\lambda_{ij}=\exp\left(\beta_0+\beta_1 p_j+u_i\right)$. Recognizing that the individual-specific effects are not correlated with the exogenously set price p_j, the conditional joint probability is:

(2) $$\Pr\left(q_{i1},\ldots,q_{iJ} \mid u_i\right)=\prod_{j=1}^{J}\Pr\left(q_{ij} \mid u_i\right).$$

Assuming that $U_i = \exp\left(u_i\right)$ is drawn from a normalized gamma distribution with mean 1 and variance α, the unconditional joint probability is found by integrating (3) with respect to U_i. The resulting function is a negative binomial model where $E\left(q_{ij}\right)=\lambda_{ij}$ and $V\left(q_{ij}\right)=\lambda_{ij}\left(1+\alpha\lambda_{ij}\right)$. The variance-mean ratio for this model is $1+\alpha\lambda_{ij}$, allowing for overdispersion. Indeed, testing whether α is significantly different from zero is a test for overdispersion.[6]

Under this demand specification own-price elasticity is estimated as:

(3) $$\hat{\eta}=\frac{\partial E\left(q_{ij}\right)}{\partial p_j}\frac{p_j}{E\left(q_{ij}\right)}=\hat{\beta}_1 p_j.$$

One of the benefits of the random-effects Poisson demand specification is that it allows for the own-price elasticity to vary as a function of price.

Compensating variation measures the reduction in income necessary to hold utility constant after a price decrease. Given that prior to the introduction of a new product, that product cannot be obtained at any price, its introduction can be thought of as a reduction in its price from infinity to some finite value. This in mind, compensating variation is the theoretically-correct measure of welfare change following the introduction of a new product or trait and can be represented as the area under the new product's Hicksian demand curve and above its new price. Unfortunately, Hicksian demand is unobservable. Much easier to estimate is consumer surplus or the area under the Marshallian demand curve and above the new product's price.

Under random-effects Poisson demand specification, the researcher estimates consumer surplus at p_j as:

$$
\begin{aligned}
CS &= \int_{p_j}^{\infty} \exp\left(\beta_0 + \beta_1 p\right) dp, \\
&= \left.\frac{\exp\left(\beta_0 + \beta_1 p\right)}{\beta_1}\right|_{p=p_j}^{p\to\infty}, \qquad (4) \\
&= -\frac{\exp\left(\beta_0 + \beta_1 p_j\right)}{\beta_1}.
\end{aligned}
$$

Confidence intervals around this *CS* estimate can be derived using a parametric bootstrapping technique (Krinsky and Robb 1986).

Experimental Design

We use a 2 x 4 factorial experimental design with two valuation mechanisms (uniform-price auction and OECE) and four types of information about GM products: no information and positive, negative, and two-sided information. Hence, we have eight groups of subjects. All experimental sessions were conducted from late November to mid-December 2006, with each of the uniform-price auction treatments consisting of 25 participants and the OECE treatments consisting of 15 participants. Uniform-price auction participants received a ₱100 participation fee. OECE participants received a ₱200 participation fee because that experiment was roughly twice as long. All subjects were students at the University of the Philippines Los Baños.

The uniform-price auction had five steps:

Step 1: On arrival at the lab site, participants were given an ID number and a packet containing a payment coupon, consent form, experimental instructions, questionnaire, and (when appropriate) information sheets. They were asked to read and sign the consent form and payment coupon, read together with the monitor the brief instructions for the experiment, and complete a questionnaire about their demographic characteristics and level of awareness about genetic modification and GM food products.

Step 2: Participants engaged in a series of practice rounds to familiarize themselves with the auction mechanism. Participants were shown a chocolate bar and then asked to submit a sealed bid for it with the understanding that if this round were chosen as binding, the four highest bidders would buy the chocolate bar at a price equal to the fifth-highest bid. At the end of the round, the monitor posted the five highest bids along with the four highest bidders' ID numbers. This same procedure was repeated four more times, and a binding round was randomly selected after the fifth round. The actual uniform-price auction followed.

Step 3: Participants were told that conventional rice could be purchased at a local store for about ₱15 per 500g. They were also shown a sample bag (500g) of the golden rice.[7] They were told that the golden rice was genetically-modified to produce provitamin A and that other than its golden color, the bag of rice had the same size, weight, and taste as conventional rice.

Step 4: After reading the information sheets (when appropriate), participants submitted a sealed bid for the golden rice. At the end of the round, the monitor posted the five highest bids along with the four highest bidders' ID numbers. This same procedure was repeated four more times, and a binding round was randomly selected after the fifth round.

Step 5: Winners were given a claim certificate for 500g of golden rice and ₱100 less the cost of rice purchased and were instructed to pick up their golden rice on a future date announced by the monitor (after all the experiments had been conducted). Participants were asked not to discuss the study with anyone.

The OECE had five steps:

Step 1: Same as the uniform-price auction.

Step 2: Participants engaged in a series of practice rounds to familiarize themselves with the valuation mechanism. Participants were shown a large chocolate bar and a small chocolate bar and were presented with three possible price combinations for the two candy bars. They were then asked to indicate how many units of each candy bar that they would like to purchase at each price combination. They were also informed that one of the price combinations would later be randomly drawn to determine the binding price combination for the round. All of the quantities indicated by all participants under the randomly selected binding price combination were posted at the front of the room. This same procedure was repeated four more times, and a binding round was randomly selected after the fifth round. The actual OECE followed.

Step 3: Same as the uniform-price auction.

Step 4: After reading the information sheets, participants were presented with eleven possible price combinations. The price of golden rice ranged from ₱5 to ₱25 in ₱2 increments. Conventional rice was always available for ₱15, the same price at which it could be purchased outside of the experiment. For each of the price combinations, participants were asked to indicate the quantity of each variety of rice (i.e. the number of bags) that they wished to purchase, understanding that one of the price combinations would later be randomly drawn to determine the binding price.[8] The binding price combination was then determined, and the quantities all participants indicated for both types of rice at that price combination were posted at the front of the room. This same procedure was repeated four more times, and a binding round was randomly selected after the fifth round.

Step 5: All participants who made purchases during the experiment were given a claim certificate for rice and ₱200 less the total cost of rice purchased. They were instructed to pick up their golden rice on a future date announced by the monitor (after all of the experiments had been conducted). Participants were asked not to discuss the study with anyone.[9]

Empirical Results

Table 1 summarizes socioeconomic characteristics for the 60 participants who took part in the OECE and the 100 who took part in the uniform-price auction. The two samples differ significantly in terms of gender, class year, frequency of buying rice, age, and household size.

Estimating consumer demand, own-price elasticity, and consumer surplus from the OECE

When performing this kind of demand analysis, it is important to consider the timeframe in which we define demand. This will depend in large part on the shopping behavior of participants. In our study participants were Filipino university students. Like Filipinos in general, Filipino students tend to buy enough food supply in a given shopping trip for one week. We therefore interpret our data as estimates of weekly rice demand. For instance when the price of golden rice was ₱15, we found that the average participant's weekly demand is 1.8 kg, equivalent to an annual demand of 94 kg. This is in line with recent estimates of annual per capita rice demand in the Philippines, which range from 111 kg (FNRI 2003) to 118 kg (Malabanan 2007).

An alternative interpretation is that our estimates represent demand when facing a one-time opportunity to buy golden rice. Given that rice has a shelf-life of at least a year, under this interpretation our results could better be thought of as estimates of annual demand constrained by the quantity that participants can easily store. To determine whether participants are buying for a week or a year, the researcher could repeat the experiment a week later using the same participants to see whether their demand decreases substantially.[10]

This problem is likely to be most pronounced at relatively low prices. For instance in this study, we sold golden rice for as little as ₱5 per 500g bag—one-third of the field price of conventional rice. At such a low price it is possible that participants would buy rice not just for their own family's consumption but also to give away to friends and possibly for resale.

This problem is not insurmountable, though. Because experimental valuation studies typically focus on value-added versions of a generic field substitute (e.g. Rousu and Corrigan 2008), the most relevant prices will be those *higher* than the field price of the conventional good.

In order to avoid bias introduced by participants stocking up on low-price goods, the researcher may choose to estimate demand based only on prices greater than or equal to the field price of the conventional substitute(s) (in this experiment ₱15). However, it may still be advisable to present participants with prices lower than this field price in order to avoid signaling that the focus good is more valuable than its substitutes.

Issues of timeframe and storability are easier to deal with when valuing perishable goods. For instance cooked rice or fresh produce will have a shelf life of roughly a week. With these goods the researcher can more confidently interpret OECE results as estimates of weekly demand. This in mind, the OECE may be best suited to estimating the value of perishable goods.

In the analysis that follows, we assume that at any given price combination, participants wish to purchase only the quantity of golden rice that their household will consume in the span of one week (i.e. there is no stocking up at low prices, and participants do not buy rice in order to resell it or to give it to people outside of their household).

Table 2 reports the aggregated quantity demanded from the OECE for each good at each price combination, while table 3 reports summary statistics for individual quantities of golden rice demanded.[11] As expected, the quantity of golden rice demanded falls as the price increases. We included conventional rice in this study primarily as an explicit reminder of outside substitutes. Because of its easy availability outside of the experimental market, we make no claims that the numbers reported in table 2 accurately reflect demand for conventional rice given the introduction of golden rice.

As described in section 4, we estimate the quantity of golden rice demanded by each participant as a function of the price of golden rice using a random-effects Poisson regression. The second column of table 4 presents the results of this analysis for all information treatments combined. Both beta coefficients have the expected sign and are highly statistically significant. Figure 2 shows both the observed demand (aggregated across the 60 participants) and the estimated demand associated with the results of the random-effects Poisson regression (scaled up by 60).[12]

The estimate of α is also significantly different from zero, confirming that a model that allows for the variance of q_{ij} to exceed the mean is warranted.

To test whether participants behave differently when facing prices below the ₱15 field price (e.g. hording rice for the future or purchasing large quantities to share with friends), we report the results of two additional regressions. The first estimates the quantity demanded by participant *i* facing price *j* as:

(6) $$E\left(q_{ij}\right) = \exp\left(\beta_0 + \beta_1 p_j + \beta_2\left(D_{low} \times p_j\right) + u_i\right),$$

where D_{low} is a dummy equal to one if the price of golden rice is less than ₱15. This specification allows for a distinct change in price responsiveness when golden rice costs less than conventional rice. The estimate of β_2 presented in the third column of table 4 is not significantly different from zero (p = 0.32) and therefore provides no evidence that participants' behavior changes markedly at low prices. The second alternative regression limits observations to those when the price of golden rice is greater than or equal to ₱15. The results reported in the fourth column of table 4 are extremely similar to those reported in the second column, which again provides no evidence that participants' behavior changes markedly at low prices.

We estimate own-price elasticity as described in equation (4). For example when p_j equals the ₱15 field price of its conventional substitute, $\hat{\eta} = -2.03$ using the data from all information treatments, suggesting that a 1% increase in the price of golden rice would lead to roughly a 2% decrease in quantity demanded. A 95% confidence interval about this estimate is [-2.14, -1.92], which is estimated by multiplying p_j by $\left(\hat{\beta}_1 \pm 1.96\hat{\sigma}_1\right)$, where $\hat{\sigma}_1$ is the standard error from the second column of table 4. Own-price elasticity estimates associated with a selection of golden-rice prices used in the experiment are reported in table 5. Note that, as expected, own-price elasticity increases in absolute-value terms as the price rises. That is, participants become more price-sensitive as the price of golden rice rises relative to the price of the conventional substitute.

Next, we estimate consumer surplus as defined in equation (5). Assuming again that golden rice sells for ₱15, the average participant would derive an estimated ₱22 worth of additional consumer surplus from the introduction of golden rice based on the results from all treatments. We use a parametric bootstrapping technique to generate a 95% confidence interval around *CS* of [₱17, ₱27]. Specifically, we drew 10,000 realizations of β_0 and β_1 from a multivariate normal distribution with a variance-covariance matrix and mean vector taken from the regression whose results are presented in the second column of table 4. For each of these draws, we calculated an estimate of *CS*. The reported confidence interval was generated by ranking these 10,000 estimates and deleting the highest and lowest 250. Table 5 reports selected consumer surplus estimates associated with the regression results from the second column of table 4.

While techniques exist for calculating compensating variation directly (e.g. Hausman 1981), Willig (1976) shows that compensating variation and consumer surplus should only differ substantially when income effects are very large or when the budget share of the good in question is large. In particular Willig shows that the proportion by which compensating variation exceeds consumer surplus can be written as:

$$(7) \qquad \frac{CV - CS}{CS} \approx \frac{\xi CS}{2y},$$

where y is income and ξ is the income elasticity of demand. In our study the average participant's monthly income from all sources was ₱4083. Using this conservative measure of income, equation (7) suggests that in order for *CV* and *CS* to differ by more than 1% in the case where p_j =₱15, ξ would need to be greater than 3.70. This seems unlikely given that Seale, Regmi, and Bernstein (2003) find that income elasticities for food products typically range from 0.10 to 1.16.

Comparison of the Uniform-price Auction and the OECE

In this section we compare the performance of the OECE to that of a conventional uniform-price auction. We begin by testing whether positive and negative information about genetic modification has the expected impact on WTP estimates under both valuation methods. We then consider whether WTP estimates from both methods are influenced by posted market information in repeated rounds. In all cases WTP in the OECE is identified as the highest price at which a participant indicated a positive quantity demanded. Because mean WTP estimates are influenced by censoring in the OECE, the following analysis focuses on median WTP estimates.

Tegene et al. (2003) find that when participants are faced with conflicting positive and negative information, they put more weight on negative information and consequently decrease their WTP values. Table 6 presents mean and median WTP estimates from the fourth round of the OECE and uniform-price auction. Median WTP estimates from the OECE are consistent with the WTP ordering suggested by the existing literature (i.e. $WTP_{Positive} > WTP_{No\ info} > WTP_{Two-sided} > WTP_{Negative}$). WTP estimates from the auction, on the other hand, are inconsistent with this literature in that both mean and median WTP estimates from the two-sided-information treatment are less than those from the negative-information treatment.

In order to control for socioeconomic differences among participants presented with a given valuation method, table 7 reports the results of a random-effects analysis of WTP conditioned on demographic characteristics, information treatment, round effects (represented as dummy variables), and posted market information from the previous round. We control for censoring at ₽25 in the OECE treatments by using random-effects tobit estimation. Consistent with the results of the unconditional analysis presented in table 6, our regression results show that in the auction treatments positive information has no statistically significant effect on WTP and two-sided information has a larger negative effect on WTP than negative information. These results conflict with the findings of the extant literature. Information effects from the OECE, on the other hand, have the expected signs and relative magnitudes. While there are many possible interpretations of these results, our conjecture is that because the market environment in choice experiments is more familiar to participants, these studies might be expected to produce more reliable results than less familiar auctions. It is possible that if our auction sample had been larger (e.g. Tegene et al. 2003) or had auction participants received more rounds of training (e.g. Fox, Hayes, and Shogren 2002), the information effects would have been more consistent with the extant auction literature.

Several studies have found that when winning bids are posted after each auction round, auction bids tend to increase across rounds. While some researchers argue that this may be the result of market information from early rounds biasing participants' bidding behavior in later rounds (e.g. Corrigan and Rousu 2006), others argue this increase in bids is benign as it indicates that participants are learning that bidding truthfully is indeed in their best interest (e.g. List and Shogren 1999). It may be the case that both arguments are correct. For instance participants may initially (and erroneously) believe that they can earn a larger consumer surplus by underbidding. Over successive rounds they learn that underbidding is not in their self interest, and this learning is accelerated when posted prices are high.

Table 8 presents summary statistics for five rounds (across all information treatments) from the uniform-price auction and the OECE. Both mean and median WTP increase across rounds in the auction; however, median WTP remains essentially constant across rounds in the OECE. After each auction round, the monitor posted the ID numbers and bids of the four highest bidders along with the fifth-highest bid. After each OECE round, the monitor posted the desired quantities of golden rice and regular rice at the binding price combination for all the participants. Focusing again on the regression results presented in table 7, round effects were highly significant in the auction, as were the effects of posted prices. This suggests both a general tendency for bids to increase across rounds, and that bids in later rounds are influenced by prices posted after earlier rounds. There is no evidence of either round effects or bias from posted market information in the OECE.

There are several possible explanations for why posted market information would not affect participants' behavior in the OECE. (1) Because there is no "winning" associated with choice experiments, the top-dog effect (Shogren and Hayes 1997) can be ruled out. If the tendency for auction bids to increase across rounds is driven primarily by participants' desire to be among the top bidders (as opposed to the utility participants expect to derive from the product itself), this would suggest that CEs provide more reliable value estimates. (2) Because participants are more familiar with the market environment in choice experiments, they may immediately recognize that responding truthfully is in their best interest (unlike experimental auctions where several rounds of training may be required to learn that the market is demand revealing). This is supported by the apparent convergence between OECE and auction median WTP estimates by round 5. Note that in the auction, median WTP estimates double over the course of five rounds, bringing them in line with the nearly constant median WTP estimates from the OECE.[13] This explanation would also suggest that CEs of all types may provide more reliable value estimates. This result is particularly relevant in applications where researchers are unable to conduct repeated rounds (for example due to time constraints in the field). (3) Because participants were presented with more information in the OECE treatments, they may not have been able to process it all in the limited time between rounds. With the data from this study, we are not able to say definitively which of these explanations is the most likely, although this is an interesting avenue for future research.

Conclusions

In this study we introduce an open-ended choice experiment that asks consumers to make decisions parallel to those that they routinely make in the field and which allows researchers to estimate WTP and demand for new products or product traits while controlling for the existence of field substitutes. The OECE's greatest strength relative to experimental auctions or conventional choice experiments is that it allows researchers to estimate a participant's entire demand curve and thereby meaningfully aggregate across participants to estimate market demand. However, the OECE as presented here is limited to estimating demand for one novel good, whereas other CE designs can be used to estimate the value of multiple new goods (e.g. Alfnes et al. 2006). And because we choose not to vary the price of the field substitute sold, we cannot estimate cross-price elasticity (e.g. Lusk and Schroeder 2004).

In this article we also compare bidding behavior and information effects in repeated rounds of uniform-price auctions and OECEs. Specifically, we analyze bidding behavior in terms of posted market information and round effects. We also examine the effects of positive and negative information on WTP. Our findings generally suggest that: (1) there is no evidence of affiliation or round effects with the OECE, and (2) the OECE produced estimates of information effects on WTP that are more consistent with existing auction studies (e.g. Tegene et al. 2003; Lusk et al. 2004; Rousu et al. 2005; Huffman et al. 2007).

Regarding the absence of affiliation or round effects, this may suggest that less effort is required to familiarize participants with the OECE than with the uniform-price auction. For example table 8 shows that while both mean and median WTP estimates doubled across the five auction rounds, mean and median WTP estimates are virtually unchanged across the five OECE rounds and are always roughly equal to estimates from the final auction round. However, these results could also be partly attributed to the OECE's information revelation properties. OECE participants were presented with a great deal of information after each round. The difficulty of processing all of this information may have led them to base their actions solely on their own value estimates without incorporating the valuations of other participants. Further, since there is no "winning" bid in the OECE, participants could not adjust their valuation toward the posted information (i.e. the winning bids). More research would be required to answer this question.

Regarding the consistency of information effects, our results suggest that WTP estimates from the OECE may be more reliable than those from the uniform-price auction. However, it is also possible that our auction results are anomalous due in part to our relatively small sample size and/or our relatively small number of rounds. Repeating our auction treatments with a larger sample and with more rounds (e.g. 10 rounds) of bidding instead of five may well produce results more in line with the extant information literature.

Our findings lend support to the wider use of the OECE in estimating information effects on consumers' acceptance of new products or product traits. Future research might try to compare the OECE with other valuation methods to test the robustness of the OECE results in this study. The timeframe implicit in OECE demand estimates also deserves greater attention when dealing with a nonperishable good like rice. Repeating a study like this one at regular intervals with the same set of participants would help to determine whether demand is determined by the shelf life of the good or (as we have assumed in this study) the frequency with which participants typically buy that good. Finally, the impact of the choice of price combinations on demand estimates should be investigated, particularly in light of increasing awareness of the role that anchoring plays in the formation of WTP (e.g. Nunes and Boatwright 2004).

[1] Henceforth we will refer the uniform-price auction with four units supplied simply as a "uniform-price auction."

[2] See the Appendix for a formal proof that the OECE is demand-revealing.

[3] As discussed below, WTP inferred for an OECE is censored from above by the highest given price.

[4] Here, ₱ represents Philippine pesos. At the time this research was conducted, $1 = ₱50.

[5] An alternative approach would be to simply tell participants the price at which they could purchase the field substitute outside the experiment. However, under this framework the transaction costs of purchasing the substitutes in the field are unknown to the researcher. If the field substitute and the focus good are sold side by side in an OECE, the researcher can safely assume that the transaction costs are the same for purchasing either good.

[6] For a more detailed discussion of the random-effects Poisson model, see Cameron and Trivedi (1998).

[7] Participants in all treatments were actually shown conventional rice colored yellow to look like golden rice. When this experiment was conducted, golden rice had been approved for test planting in the Philippines but was not available for consumption. Therefore, it was impossible to estimate non-hypothetical WTP values without presenting participants with what they thought at the time was golden rice. Winning participants were asked to return to pick up any rice that they had agreed to buy after all data had been collected. At that point the monitor explained why golden rice was not actually available and refunded any money that they had paid for golden rice.

[8] As Shogren, List, and Hayes (2000) find and Alfnes (2007) shows formally, WTP for a novel good in an experimental setting may be influenced by "preference learning" where participants are primarily interested in purchasing the product not for its one-time consumption value but in order to determine how it can be incorporated into their preference set. Preference learning may also impact demand for the first unit of a novel good in an OECE, although whether it would influence demand for subsequent units is unclear.

[9] All experimental instructions can be found in Corrigan et al. (forthcoming).

[10] We thank an anonymous reviewer for this suggestion.

[11] Friedman and Sunder (1994) suggest that participants may behave erratically in the last round of an experiment. Therefore, here and throughout the paper we report results from the fourth of five rounds. In all cases results from the fifth round are qualitatively similar.

[12] Note that the random-effects Poisson demand specification implicitly assumes a vertical asymptote of zero. This may not be appropriate for staple goods without field substitutes. In these cases buyers may be willing to pay exorbitantly high prices in order to maintain a subsistence-level of consumption.

[13] Using a nonparametric Fisher's exact test, we reject the null hypothesis that round 1 bids for the two valuation methods are drawn from a sample with the same median ($p < 0.01$). We cannot reject that null hypothesis for round 5 bids ($p = 0.42$).

Appendix

The proof closely follows Becker, DeGroot, and Marschak (1964). Start by defining $x_i^*\left(p_x, p_y, m_i\right)$ as the quantity of good *x* demanded that maximizes participant *i*'s utility $u\left(x, y, m_i\right)$ given the price of good x p_x, the price of good y p_y, and income m_i. Similarly, let $y_i^*\left(p_x, p_y, m_i\right)$ maximize $u\left(x, y, m_i\right)$ given p_x, p_y, and m_i.

By definition of $x_i^*\left(\cdot\right)$ and $y_i^*\left(\cdot\right)$, it is in participant *i*'s best interest to indicate $\left[x_i^*\left(p_x^j, p_y, m_i\right), y_i^*\left(p_x^j, p_y, m_i\right)\right]$ in response to the price combination $\left[p_x^j, p_y\right]$ $\in\left\{\left[p_x^1, p_y\right], \ldots, \left[p_x^J, p_y\right]\right\}$, assuming that good *x* is not available outside of the experimental auction, good *y* is available at price p_y, and it is common knowledge that the binding price combination will later be chosen at random from a known distribution.

Now, suppose that in response to price combination $\left[p_x^j, p_y\right]$, participant *i* chooses to indicate a quantity demanded $\tilde{x}_i\left(\cdot\right) \neq x_i^*\left(\cdot\right)$. By definition of $x_i^*\left(\cdot\right)$, $u\left(\tilde{x}_i, y^*, m_i\right) \leq u\left(x_i^*, y^*, m_i\right)$. Thus, for a given price combination $\left[p_x^j, p_y\right]$, truthfully indicating $x_i^*\left(\cdot\right)$ weakly dominates (truthtelling strictly dominates if we assume that $x_i^*\left(\cdot\right)$ is the unique quantity that maximizes $u\left(\cdot\right)$).

Finally, given that $x_i^*\left(\cdot\right)$ is, by definition, the Marshallian demand for good *x*, participant *i*'s best response at every price combination $\left[p_x^j, p_y\right]$ is to reveal his true Marshallian quantity demanded.

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Table 1. Participants' Socioeconomic Characteristics

Variable	Categories	Uniform-price auction (N = 100)		OECE (N = 60)	
		Mean	Std. dev.	Mean	Std. dev.
Age		19.0	0.4	19.6	1.9
Household size		5.5	2.3	3.4	2.7
Family income[a]		6.55	5.4	6.0	5.5
Gender	Male	20%		40%	
	Female	80%		60%	
Year classification	Freshman/Sophomore	0%		7%	
	Junior/Senior	100%		93%	
Frequency of buying rice	Seldom	65%		40%	
	At least monthly	35%		60%	
Level of awareness about golden rice	Informed	70%		78%	
	Uniformed	30%		22%	
Opinion on safety of golden rice	Safe	55%		63%	
	Not Safe	45%		37%	

[a] Family income was reported in seventeen ₱10,000 intervals: [less than 9,999], [10,000-19,999],…,[170,000 and higher].

Table 2. Aggregate Quantities of Golden Rice and Conventional Rice Demanded

Golden rice		Conventional rice	
Price (Philippine pesos)	Quantity demanded (500g bags)	Price (Philippine pesos)	Quantity demanded (500g bags)
5	727	15	130
7	473	15	143
9	378	15	136
11	301	15	142
13	233	15	146
15	206	15	140
17	118	15	209
19	88	15	226
21	73	15	240
23	64	15	254
25	57	15	252

Table 3. **Summary Statistics for Individual Quantities of Golden Rice Demanded**

Price	Mean	Median	Standard deviation	Minimum	Maximum
5	12.0	12	7.9	0	20
7	7.9	9	5.2	0	15
9	6.3	6	4.0	0	11
11	4.9	4.5	3.4	0	9
13	3.8	3.5	2.7	0	7
15	3.5	3	2.8	0	16
17	2.0	2	1.9	0	5
19	1.6	1	1.7	0	5
21	1.3	1	1.5	0	4
23	1.1	0	1.5	0	4
25	0.9	0	1.5	0	4

Table 4. Results from the Random-effects Poisson Regression

Variable	Coefficient estimates		
	All prices	All prices with cross term	Only prices ≥ ₱15
Constant	3.10**	3.15**	3.14**
	(0.11)[a]	(0.12)	(0.27)
p_j	-0.14**	-0.14**	-0.14**
	(0.00)	(0.00)	(0.01)
$D_{low} \times p_j$	—	-0.01	—
		(0.01)	
α	0.61**	0.61**	0.94**
	(0.11)	(0.11)	(0.20)
Observations	660	660	360
Log likelihood	-1210	-1209	-527

[a] Standard errors in parentheses.

* Statistically significant at the 0.05 level.

** Statistically significant at the 0.01 level.

Table 5. Own-price Elasticity and Consumer Surplus Estimates at Selected Prices

Price	Own-price elasticity	Consumer surplus
5	-0.68	84
	[-0.71, -0.64][a]	[69, 102]
11	-1.49	37
	[-1.57, -1.41]	[30, 46]
15	-2.03	22
	[-2.14, -1.92]	[17, 27]
19	-2.30	13
	[-2.70, -2.43]	[10, 16]
25	-3.38	6
	[-3.56, -3.20]	[4, 7]

[a] 95% confidence interval in parentheses.

Table 6. Mean and Median Bids under the Uniform-price Auction and OECE by Information Type

	Information treatment			
	No information	Positive	Negative	Two-sided
WTP (OECE)				
Mean	20	23	16	18
Median	21	25	15	17
Standard deviation	4.6	2.9	7.8	5.4
WTP (fifth-price)				
Mean	25	33	15	12
Median	25.5	30	18	12.5
Standard deviation	9.4	26.6	7.0	5.8

Table 7. Regression Results on WTP (with Affiliation Effect)

Variables	Uniform-price auction		OECE	
	Coefficient	t value	Coefficient	z value
Intercept (no information)	-2.74	-0.12	34.67	15.35 ***
Positive information	0.46	0.11	1.81	2.84 ***
Negative information	-7.21	-2.16 **	-6.11	-9.93 ***
Two-sided information	-10.37	-2.80 ***	-5.28	-9.28 ***
Round 3	1.44	1.34	0.13	0.26
Round 4	4.90	4.15 ***	0.48	0.88
Round 5	4.58	3.08 ***	0.46	0.94
Market information[a]	0.24	3.86 ***	-0.08	-1.05
Gender	-8.73	-3.41 ***	-0.54	-1.11
Age	1.29	1.07 *	-0.35	-3.53 ***
Classification of year in college	-3.92	-0.69	-7.46	-7.87 ***
Household size	0.16	0.33	-0.11	-1.33
Family income	-0.18	-0.75	-0.22	-6.35 ***
Frequency of buying rice	-5.30	-2.16 **	-2.34	-5.43 ***
Level of awareness about golden rice	2.05	0.79	0.97	1.90 *
Bidder opinion on safety of golden rice	-0.53	-0.21	-0.04	-0.07

Log Likelihood: -1408.80 Log Likelihood: -575.39

[a] Prior fifth-highest price or the average quantity demanded depending on treatment.

* Statistically significant at the 10 percent level.

** Statistically significant at the 5 percent level.

*** Statistically significant at the 1 percent level.

Table 8. WTP Summary Statistics from All Rounds for the Uniform-price Auction and OECE

	Round				
	1	2	3	4	5
WTP (OECE)					
Mean	19	19	19	20	20
Median	21	21	20	21	21
Standard deviation	6.1	5.9	6.1	5.9	5.8
WTP (uniform-price auction)					
Mean	10	14	17	21	23
Median	10	11.5	15	18	20
Standard deviation	6.9	10.2	12.8	16.9	17.4

	Desired units of golden rice	Desired units of conventional rice
Golden rice price ₽5; Conventional price ₽15		
Golden rice price ₽7; Conventional price ₽15		
Golden rice price ₽9; Conventional price ₽15		
Golden rice price ₽11; Conventional price ₽15		
Golden rice price ₽13; Conventional price ₽15		
Golden rice price ₽15; Conventional price ₽15		
Golden rice price ₽17; Conventional price ₽15		
Golden rice price ₽19; Conventional price ₽15		
Golden rice price ₽21;		

Conventional price ₱15		
Golden rice price ₱23; Conventional price ₱15		
Golden rice price ₱25; Conventional price ₱15		

Figure 1. Sample bid form

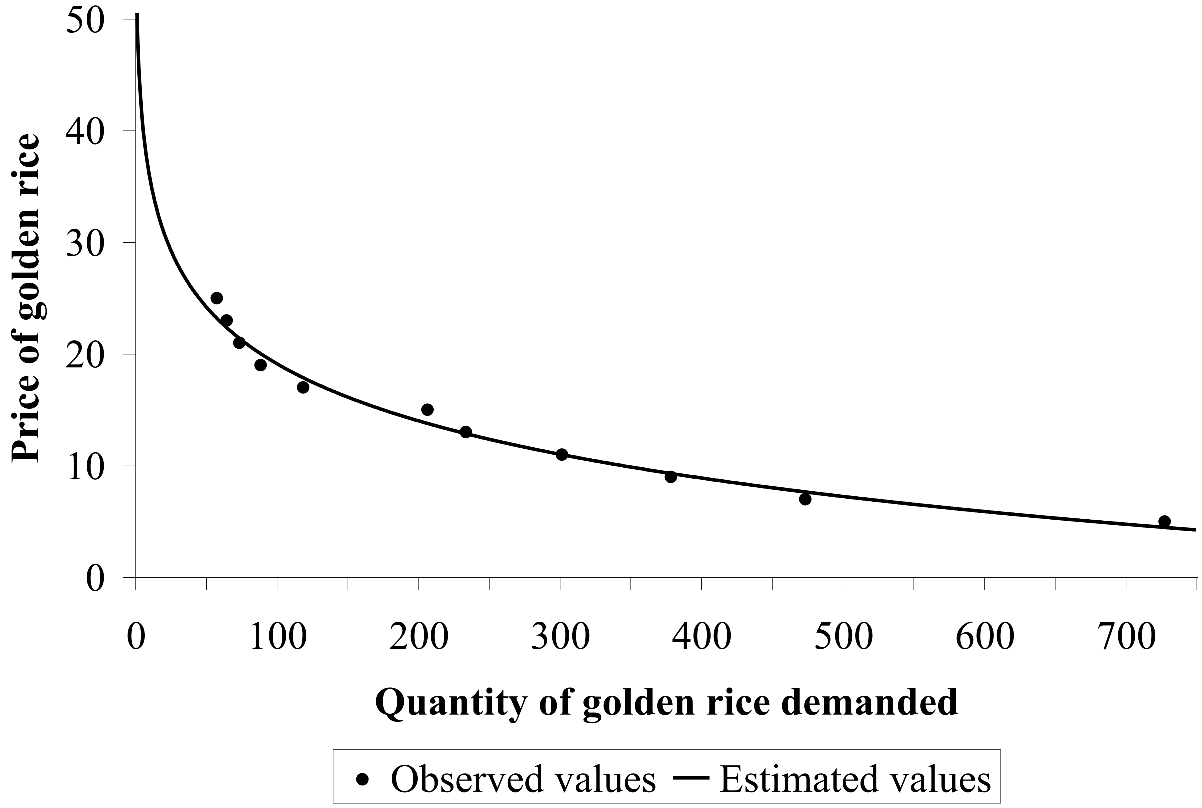

Figure 2. Observed versus estimated demand from all treatments