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The Reverse Auction:
A New Approach to Experimental Auction Valuation

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Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California, July 23-26, 2006

Abstract: I propose an alternative approach to auction valuation in which participants indicate the quantity they wish to buy at a series of prices, with the understanding that one will be randomly chosen as the binding price. This technique allows researchers to estimate entire demand curves as well as own-price elasticities. (*JEL:* C91, C93, D44)

Keywords: Experimental Auctions, Price Elasticity of Demand, Reverse Auction

Introduction

In the overwhelming majority of retail transactions taking place in the field, potential 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 and restaurant environments where Americans buy most of their food. By contrast, in experimental auctions aimed at estimating the value of new products or product traits participants are presented with a fixed quantity and are asked to name the highest price they would be willing to pay. This runs counter to a well established strand of the environmental valuation literature showing that participants find naming their own price difficult (Freeman 2003). The novelty of the name-your-price exercise is then further compounded by the introduction of an unfamiliar demand-revealing auction mechanism.

In this paper I propose an alternative approach to laboratory and field auction valuation in which participants are instead asked to name the quantity they wish to buy at a series of different prices, with the understanding that one of these prices will be randomly chosen as the binding market price. By separating what participants pay if they win the auction from the quantity they indicate, this "reverse auction" preserves the demand-revealing properties of other widely used auction mechanisms (e.g., Vickrey, Becker-DeGroot-Marschak, random *n*th-price), but in a market environment far more familiar to participants. I also report the results of a pilot study where I use this new approach to estimate the demand and own-price elasticity for fair trade chocolate bars.

In addition to the greater familiarity of the name-your-quantity exercise, the reverse auction has a number of other benefits. First, the reverse auction format allows the researcher to incorporate outside substitutes in an intuitive and non-arbitrary way.

For example, suppose a researcher is interested in estimating the premium consumers are willing to pay for the organic designation as applied to farm-raised salmon. In this situation, the outside substitute is clearly conventional farm-raised salmon, a product participants could purchase at a supermarket for $*X* per pound. In a reverse auction, the researcher can easily sell the novel organic product alongside its conventional counterpart. Specifically, participants would be offered an array of prices for the organic salmon (say, $*V*, $*W*, $*X*, $*Y*, and $*Z*) and would be told that the conventional salmon always sells for $*X* per pound. For each of the five price combinations, participants would then indicate the quantity of each type of salmon they would like to buy with the understanding that only one of the price combinations would be randomly chosen as binding. This incorporation of field substitutes addresses a longstanding criticism of experimental auction valuation (Harrison 1992). Corrigan (2005) shows that WTP bids submitted in a laboratory auction setting are significantly influenced by participants' beliefs regarding the relative difficulty of buying or selling the good outside of the experimental market, suggesting that laboratory auctions are not hermetically sealed markets and underscoring the importance of the incorporation of outside substitutes into experimental auction methodology.

Second, because participants can request any non-negative quantity at a given price level, the reverse auction allows the researcher to estimate individual participants' entire demand curves, not just their willingness to pay for a single unit. While this is also possible using demand-revealing multiunit auctions such as the Groves-Clark auction mechanism (Clarke 1971, Groves 1973), List and Lucking-Reiley (2000) observe that such auctions are demand revealing "only in cases where every bidder's demand curve is either flat or downward sloping" (p. 962). This is not a concern with the reverse auction assuming that the experimenter has enough units of the good on hand to meet every participant's demand. This condition would be easiest to meet, of course, in auction experiments where just one individual participates at a time such as the "in-store valuation" auctions pioneered by Lusk et al. (2001).

Third, aggregating individual demand curves across participants allows the researcher to meaningfully estimate market demand. This is not possible using conventional auction methods where all we observe is participants' willingness to pay for a single unit. Using conventional auction methods, aggregation across participants would necessarily ignore the value participants place on subsequent units.

Finally, and most importantly, the aggregated market demand curve allows the researcher to estimate own-price elasticity of demand, a core economic concept that has been virtually ignored in the experimental auction literature. While Rousu, Beach, and Corrigan (2006) attempt to estimate inverse elasticities using data from a conventional name-your-price auction experiment, to my knowledge no experimental auction study has estimated own-price elasticity of demand.

In the next section I will discuss the design of an experiment that uses the reverse auction to estimate demand curves for fair trade chocolate bars in a laboratory environment. This is followed by a discussion of empirical estimates of own-price elasticity of demand.

Experimental Design

Four groups of fourteen or fifteen Principles of Economics students took part in this study, for a total of 58 participants. The experimental auction had five steps:

Step one. Participants arrived and were assigned by a monitor to one of fifteen computer workstations in a computer classroom. These workstations were situated so that it was not easy for one participant to see other participants' computer screens.

Step two. A monitor provided participants with both web-based and oral instructions on the workings of the reverse auction mechanism.[1] This introduction included an example and a quiz on the auction format.

Step three. A monitor provided participants with detailed written and oral descriptions of both products up for auction. Participants also received a small sample (~4 grams) of the fair trade chocolate in order to mitigate bidding behavior motivated primarily by "preference learning." Shogren, List, and Hayes (2000) show that between 61% and 92% of willingness to pay to upgrade to a superior good can be attributed to preference learning, not consumption value.

Step four. In the real auction that followed, participants were presented with a menu of price combinations. The price of the fair trade chocolate bar ranged from $0.50 to $2.50 in twenty-cent increments. A conventional chocolate bar of similar quality was always available for $1.50, roughly the same price at which it could be purchased outside of the experiment.[2] For each of these eleven price combinations, participants indicated

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[1] The web-based instructions and the auction used in this study can be viewed at http://www.openwater.ca/auction/.

[2] The auction instructions indicated that both chocolate bars were "of similar quality." In a small pilot study ($N = 29$), participants sampled both chocolate bars in a blind tasting without any indication that one bar was fair trade. Participants then submitted WTP bids in a second-price auction. Mean WTP for the two bars differed by just 2¢, not a statistically significant difference ($p = 0.57$ using a Wilcoxon sign-rank test and 0.85 using a paired t-test).

the quantity of each type of chocolate bar they wished to purchase, understanding that one of the price combinations would later be randomly drawn to determine the binding price.

Step five. A monitor determined the binding price pair by drawing a number from a jar. Participants were then dismissed one-by-one, at which point they were paid $10 for participating in the study and any transactions agreed to were carried out.

I should note that this type of name-your-quantity exercise is not unprecedented in the economics literature. Kahneman, Knetsch, and Thaler (1990) gave potential buyers bid forms with a series of prices and asked each participant to indicate "I will buy" or "I will not buy" at each potential price. However, these authors' design differed from the design I present here in two important ways. First, participants were able to purchase at most one unit, which does not allow the researcher to meaningfully aggregate quantity demanded across participants (thus making it impossible to estimate elasticity). Second, a group of potential sellers also completed a similar exercise, and the binding price was the price that cleared the market. Because of this reliance on sellers as well as buyers, this design would not be useful for conducting field auctions with one participant at a time (Lusk et al. 2001).

Empirical Results

Table 1 reports the aggregated quantity demanded for each good at each price combination. As expected, the quantity of fair trade chocolate bars demanded falls as the price of those bars increases. Interestingly, while the quantity of conventional chocolate bars demanded is positively correlated with the price of fair trade chocolate bars for prices greater than or equal to the \$1.50 outside price of those bars ($p < 0.01$), there is no significant correlation between the two for prices below the outside market price ($p = 0.08$).

While there are any number of demand specifications that would allow for the estimation of own-price elasticity for the fair trade chocolate, here I will consider the double-log specification and a simple flexible functional form. Turning first to the double-log specification, I estimate the quantity of fair trade chocolate bars demanded aggregated across participants as a function of the price of fair trade chocolate using the following demand equation:

(1) $$\ln Q_{FT} = \beta_0 + \beta_1 \ln P_{FT} + \varepsilon .$$

Under this specification, the (constant) own-price elasticity of demand is estimated as

(2) $$\hat{\eta} = \frac{\partial \ln Q_{FT}}{\partial \ln P_{FT}} = \hat{\beta}_1 .$$

Using ordinary least squares to estimate equation (1) yields $\hat{\eta} = \hat{\beta}_1 = -2.33$ ($p < 0.01$). The results of this regression are presented in table 2.

I also consider a simple flexible functional form. A flexible functional form is one that can approximate a given twice-differentiable function to the second order at any arbitrary point. The following quadratic specification is the most straightforward of these flexible demand specifications:

(3) $$Q_{FT} = \beta_0 + \beta_1 P_{FT} + \beta_2 \frac{P_{FT}^2}{2} + \varepsilon .$$

Under this specification, own-price elasticity of demand is a function of price and is estimated as

(4) $$\hat{\eta} = \frac{\partial Q_{FT}}{\partial P_{FT}} \frac{P_{FT}}{Q_{FT}} = \left(\hat{\beta}_1 + \hat{\beta}_2 P_{FT}\right) \frac{P_{FT}}{\hat{\beta}_0 + \hat{\beta}_1 P_{FT} + \hat{\beta}_2 \frac{P_{FT}^2}{2}}.$$

Using ordinary least squares to estimate equation (3) yields the results presented in table 3. Using equation (4) I can then estimate η about any P_{FT}. For example, setting $P_{FT} = \$1.50$ (i.e., the outside market price of the substitute conventional chocolate bar) $\hat{\eta} = -4.53$. Using a bootstrapping technique to generate a confidence interval around $\hat{\eta}$ yields a 95% confidence interval of (-6.73, -3.34). Specifically, I drew 10,000 realizations of β_0, β_1, and β_2 from a multivariate normal distribution with a variance-covariance matrix and mean vector taken from the OLS estimation whose results are presented in table 3. For each of these draws, I calculated an estimate of $\hat{\eta}$. The reported confidence interval was generated by ranking these 10,000 $\hat{\eta}$ estimates and deleting the highest and lowest 250 (Krinsky and Robb, 1986).

Figure 1 depicts the estimated demand curves associated with the double-log and quadratic demand specifications. While visual inspection suggests that both demand specifications seem to fit well, as a more formal test I have calculated $\bar{R}^2$ for equation (1) and quasi $\bar{R}^2$ for equation (3). Quasi $\bar{R}^2$ allows for fit comparisons of equations with different functional forms for the dependent variable. Calculating quasi $\bar{R}^2$ involves first transforming the predicted values of one of the dependent variables into the functional form of the other, then computing the necessary residuals using these new predicted values (Greene 2000). In this case I have transformed the estimates of Q_{FT} from equation (3) into estimates of $\ln Q_{FT}$, which can be directly compared with the results from regressing equation (1). Quasi $\bar{R}^2$ for the quadratic specification equals 0.703, while $\overline{R}^2$ for the double-log specification equals 0.947, suggesting that the double-log specification offers better fit.

Conclusions

The reverse auction design presented in this paper represents a useful addition to the experimental auction practitioner's toolkit. While it is not meant to replace the name-your-price auction mechanisms now ubiquitous in the literature, this name-your-quantity mechanism offers a useful complement. In many cases, though, the reverse auction may be preferable to conventional auctions both because naming a quantity is a much more familiar exercise for participants, and because the reverse auction allows researchers to estimate the entire demand curves and, therefore, own-price elasticity of demand.

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Table 1. Results of the reverse auction for fair trade and conventional chocolate bars.

Fair trade chocolate		Conventional chocolate	
Price	Quantity demanded	Price	Quantity demanded
$0.50	168	$1.50	10
$0.70	118	$1.50	8
$0.90	83	$1.50	9
$1.10	51	$1.50	8
$1.30	35	$1.50	7
$1.50	30	$1.50	11
$1.70	17	$1.50	12
$1.90	11	$1.50	17
$2.10	8	$1.50	18
$2.30	7	$1.50	18
$2.50	4	$1.50	19

Table 2. Regression results for the double-log demand specification

Variable	Coefficient estimate
Constant	3.95** (0.10)[a]
$\ln P_{FT}$	-2.33** (0.17)
$\bar{R}^2$	0.947

[a] Standard errors in parentheses.
** Statistically significant at the 0.01 level.

Table 3. Regression results for the quadratic demand specification

Variable	Coefficient estimate
Constant	269.71** (14.47)[a]
P_{FT}	-255.62** (21.43)
$P_{FT}^2/2$	122.32** (14.04)
$\overline{R}^2$	0.976
Quasi $\overline{R}^2$	0.703

[a] Standard errors in parentheses.
** Statistically significant at the 0.01 level.

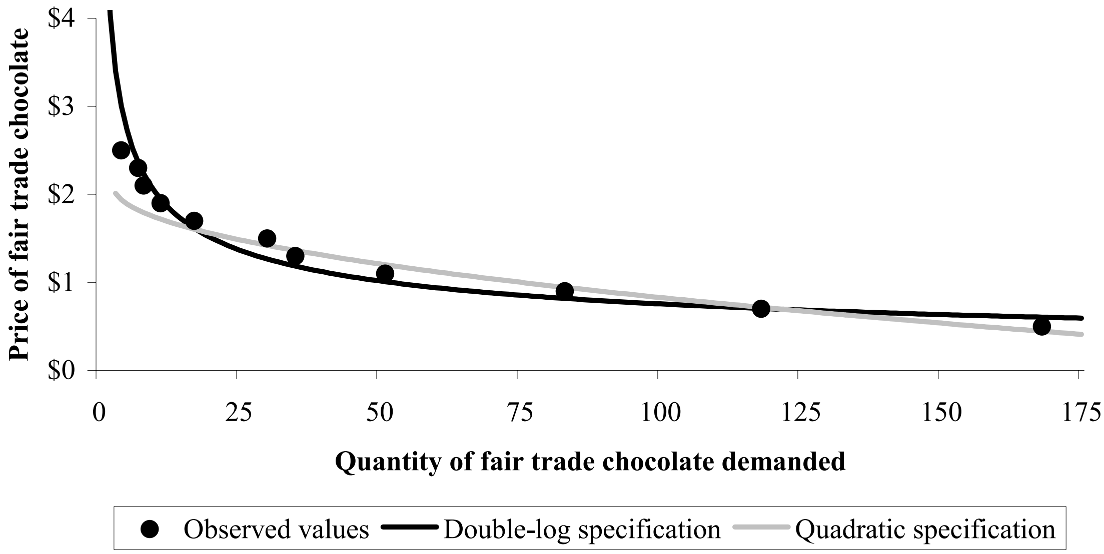

Figure 1. Estimated demand curves for the double-log and quadratic demand specifications