



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

**Purchase Intention Effects in Experimental Auctions and Real Choice
Experiments: A Case with both Novel and Non-novel goods**

Preliminary
Updated 2013/06/022

Jing Xie
jxie@ufl.edu
University of Florida

Zhifeng Gao
zfgao@ufl.edu
University of Florida

Lisa House
lahouse@ufl.edu
University of Florida

*Selected Paper prepared for presentation at the Agricultural & Applied
Economics Association's 2013 AAEA & CAES Joint Annual Meeting, Washington,
DC, August 4-6, 2013.*

*Copyright 2013 by Jing Xie, Zhifeng Gao, and Lisa House. All rights reserved.
Readers may make verbatim copies of this document for non-commercial purposes by any
means, provided this copyright notice appears on all such copies.*

Abstract:

This article examines consumers' preference for three types of orange juice in China. Two non-hypothetical experiments, Real Choice Experiments and Experimental Auctions were used in the study. We found that WTP estimates from real choice experiment are significantly higher than auction bids, which is consistent with what Lusk and Schroeder (2006) and Gracia, Loureiro, and Nayga (2011) found in their paper. In addition, we found that purchase intention only has significantly effects on consumers' behavior in Experimental Auction, but not in Real Choice Experiments, and this purchase intention only has effects on non-novel food, but not novel food.

Keywords:

Consumer preferences, choice experiment, experimental auction, purchase intention

1. Introduction

The inconsistency in product valuations between hypothetical and non-hypothetical experiments has been examined thoroughly in the literature. Hypothetical experiments are those experiments and survey that ask respondents/subjects to respond to the questions with hypothetical scenarios. Traditional choice experiments and contingent valuation methods are very common hypothetical experiments that popular in food marketing studies to estimate consumers' WTP for certain attribute or product. In contrast, non-hypothetical experiments are those experiments with real purchase transactions. A wealth of evidence has indicated that individuals tend to over-state the amount of money they are willing to pay in the state preference survey comparing to the elicitation experiments with real money purchase, so called hypothetical bias.

Researchers in Economics and market behaviors have proposed many ways to reduce hypothetical bias. One way is to change the survey design such as using cheap talk, or add some questions in the hypothetical experiment to get more information about consumers' real attitudes. Johannesson, Liljas, and Johannesson (1998) compared the results from the dichotomous choice (DC) contingent valuation approach with and without real purchase decisions. The results show that the hypothetical yes responses overestimate the real yes responses and that the hypothetical absolutely sure yes responses underestimate the real yes responses. Another way is to combine the hypothetical experiment with non-hypothetical experiment to obtain the calibration factors of the hypothetical bias (Fox, Shogren, Hayes, and Kliebenstein 1998; Johannesson, Liljas, and Johansson 1998; Norwood and Lusk 2011); more often, researchers use non-hypothetical experiment directly in order to avoid hypothetical bias (Carlsson and Martinsson 2001; Cameron *et al.* 2002; Chang, Lusk and Norwood 2009; Lusk, Fields and Prevett 2008; Johansson-Stenman and Svedsäter 2008; Loomis *et al.* 2009). For example, Change, Lusk and Norwood (2009) compared the ability of three preference elicitation methods (hypothetical choices, non-

hypothetical choices, and non-hypothetical rankings) and found that non-hypothetical elicitation approaches, especially the non-hypothetical ranking methods, outperformed the hypothetical choice experiment in predicting retail sales.

Real choice experiment and experiment auction are two popular non-hypothetical experiments. The fundamental difference between hypothetical experiment and non-hypothetical experiment is that non-hypothetical experiment involves real purchasing transaction in the experiment, therefore respondents may be less likely to exaggerate their true WTP value in the experiment.

While economic theory suggests that all of these non-hypothetical incentive compatible valuation methods should give equivalent outcomes in estimating consumers' willingness to pay (WTP), Lusk and Schroeder (2006) and Gracia, Loureiro, and Nayga (2011) have found disparities between experimental auction (EA) and real choice experiments (RCE).

Lusk and Schroeder (2006) compared experimental auction and real choice experiment. They study consumers' preference for genetic steak, guaranteed tender steak, natural steak, and USDA Choice steak using two non-hypothetical experiments, EA and RCE. They compared the estimated demand elasticities from each method and confirmed that the disparity existed between EA and RCE—the auction bids were lower than the choice prices, and the demand elasticities calculated from each experiment were also inconsistent with each other.

Continuing with Lusk and Schroeder (2006)'s research, Gracia, Loureiro and Nayga (2011) compared the same experiments—EA and RCE. They used storable product (ham) with animal welfare labels in order to decrease possible temporal bias in shopping associated with the use of fresh product. And the subjects in their EA only bid one to avoid bid affiliation problems. Besides all the differences this article did in the experiments, they found the same results as Lusk and Schroeder (2006) did, that is the auction bids were lower than the WTP price estimated in the choice data.

Both of the studies show that auctions bids were significantly lower than the WTP estimated from RCE. These articles have discussed that this disparity might come from the

differences in the mechanism between EA and RCE, however, they didn't specified where exactly the differences came from, nor did any tests of it. Since all of these non-hypothetical experiments are widely used, it is important to compare the WTP valued elicited from them. If the disparity does exist, how and why it exists and which one is better are critical for researchers who want to accurately estimate the real market behaviors. In this article, we are not focusing on explain why these two experiments might give us different results as Xie and Gao (2013) did, but trying to test if purchase intention has different impacts on respondents' behavior in these two experiments.

Purchase intention may affect the study results of consumers' WTP. Lusk and Fox (2003) compared results from laboratory and field valuation experiments, and found that field valuations were greater than laboratory valuations. One possible reason is that consumers has higher purchase intention in the grocery store rather than in the lab, therefore the estimated WTP value is higher if the experiment is conducted in/ or in front of the grocery store.

In addition, whether the target product in the experiment is novel or non-novel food would also matter. If the product is novel food that consumers are not familiar with, even though they may still have purchase intention to buy that categories of the product, their willingness to buy this certain new product may not be affected by their purchase intention. For example, in China most consumers are not familiar with Nor-From-Concentrated orange juice, even if consumers may have purchase intention to buy a bottle of orange juice in that day, purchase intention may not be a strong determinates on how much they are willing to pay for it in the experiments.

Moreover, purchase intention may have different effect in EA and RCE because the mechanisms of these two experiments are so different. For example, price plays quite different roles in RCE and EA when eliciting consumers' WTP value. In EA, the bidding process—"how much are you willing to pay" draws consumers' full attention to the price. In the choice experiment, however, participants are facing the choices with price and non-price attributes at the same time. As a result, in EA consumers are focusing on price levels and more likely to bid or choose a lower price while participants in RCE are more likely to consider all the attribute levels at the same time and accept a higher price choice. Compared to EA, the price attribute is no longer the main focus but is part of a group along with other

non-price attributes in RCE, thus participants in RCE may not consider “how much I want to pay” first, but “which one I like the most.” Therefore consumers with less purchase intention may behave differently compared to consumers with strong purchase intention in EA rather than that in RCE.

In this article, we determine the impact of purchase intentions on WTP estimates in both EA and RCE. We want to test if the purchase intention has different impacts in these two experiments, and whether the impacts are different on novel food and non-novel food. This article is structured as follows. Section 2 describes the experimental design for each method. Section 3 illustrates the estimation model of each elicitation value mechanism. Section 4 reports the results derived from each method. The last section is the conclusion.

2. Experimental Design

General experimental design

To test consistency of the results among three methods, we carefully designed RCE and EA to be comparable. We kept the feature of different experiments as similar as possible by using the same products and setting price attribute ranges as close as possible. Moreover, we recruited the experiment participants randomly enough so that their demographic characteristics are statistically indifferent across all the groups.

Experiment subjects were recruited in front of local grocery stores in Changsha, China in 2012. The preferences of residents in Changsha cannot represent the preferences of whole residents in China; however, the focus of this study is the difference among three experiments. As long as we could control demographic statistics equivalence among those different experiments, conducting experiments in multiple cities is not a necessity. Subjects were offered ¥20 (about three us dollars) to participate in an “orange juice preference experiment.” All participants claimed to eat orange juice at least occasionally. Each participant attended only one of the three experiments. They were asked to indicate their preference for different type of orange juice—100% Not-from-concentrate (NFC) orange juice, a 100% Frozen Concentrated Orange Juice (FCOJ), and a 10% Orange Juice Drink (OJD). The 100% NFC orange juice is fairly new product in the China market and not available everywhere in normal grocery store yet, and so far, only a local brand and several imported brand (including Florida’s Nature from the United States) produce this type of

orange juice. In real market, the product size of NFC orange juice is usually larger than FCOJ and OJD, but in experiments we keep the size of products the same across choices (500ml) since it is easy for respondents to compare and choose. By including new product in our experiment could help us understand that how consumers react differently between new products and products they are very familiar with (such as FCOJ and OJD).

The information of each type of orange juice was introduced to participants in the experiment (Appendix). After they read the information, they took about 10 to 20 minutes to do the experiment and complete the survey on socioeconomic and demographic characteristics as well as their orange juice shopping and eating behavior.

In the last section of the survey, we also asked some questions about their price bargaining attitudes and previous price bargaining behaviors in order to measure the aggressiveness of the price behavior. Xie and Gao (2013) found that consumers' heterogeneous aggressive level in price bargaining can significantly affect their behaviors in these two experiments, therefore in this analysis, several measurement that capture the aggressive level in price bargaining are also included in the estimation as independent variables following Lee (2000). In the questionnaire, respondents were asked how much they will bargain back when a product and a price tag were given. This question is presented in Table 1. Two products were chosen to measure consumers' aggressiveness in price bargaining, one is a cheap product, a white cotton T-shirt, and the other one is a relatively expensive product, a desktop computer. They were told that they were allowed to bargain the price, and asked how much they would bargain back.

EA design

Among all the auction methods, we choose Becker, DeGroot, Marshak (BDM) experiment. BDM is a common and easy method for eliciting the willingness to pay. Under the BDM, an individual reports a bid for an item; the item's price is then randomly drawn (respondents do not know the price range). If the bid is above the price, the individual receives the good and pays the drawn price. If the bid is below the price, the individual does not receive the good and pays nothing. The incentive of truth-telling in this mechanism is that truth-telling is a dominant strategy and therefore it is independent of risk attitudes and whether the individual is an expected utility maximizer.

Many studies show that the BDM is incentive compatible for non-random goods

(Davis and Holt 1993; Rutström 1998; Irwin *et al.* 1998; Noussiar, Robin, and Ruffieux 2004; Shogren *et al.* 2001). And BDM is the easiest experiment auction to conduct since the respondents are randomly picked in front of a grocery store gate and it is hard to gather them together at the same time. Another reason we used BDM instead of other auction mechanism is that BDM is very easy to understand by participants. It is an individual decision-making mechanism instead of group decisions. Lusk and Schroeder (2006) mention that the auction mechanisms such as second price auction are unfamiliar to most individuals, and Plott and Zeiler (2005) also show that without significant training and experience, misperceptions could affect the valuation methods. Comparing to 2nd price or random nth price auction, BDM is easier for participant to understand and conduct, and they don't have to worry about other individuals' preference and bidding prices. Lusk, Alexander, and Rousu (2007) discuss a potential problem for BDM: the bids of people with relatively high values tend to have less deviation than that of people with relatively low value. But this problem would be occurred if the sample size is fairly large, and easily understandable process of BDM could do us a favor in reducing the misperception bias. The auctions were conducted according to the following steps:

Step 1. Subjects were asked to read the products information and experiment instruction carefully.

Step 2. Subjects wrote down the most they are willing to pay for each type of orange juice. If they don't want to purchase a certain type of product, they can fill ¥0 for this product.

Step 3. After subjects finish the survey, we randomly drew a type of orange juice as the binding product.

Step 4. Subject randomly drew a number from a bowl as a "secret market price" for the binding orange juice. When his/her bid for the binding orange juice was equal or higher than the price from the bowl, he/she purchased the orange for the market price; when the bid price was lower than the market price, subject couldn't purchase the product.

RCE design

We designed our choice sets with two attributes: price and product types. The attribute levels are reported in Table 3, and an example of a choice set is provided in Table 4. The

average price levels of the orange juice products were chosen to be consistent with prices in local grocery stores. To determine which choice sets to present to respondents, we used “brand” experiment design in which each type of orange juice was treated as a factor and was varied at four price levels. This design generated in total $4^3=64$ full factorial choice sets. From this full factorial we selected 10 saturated choice sets by using SAS, and the D-efficiency is 81.91%.

At the very beginning, subjects were instructed the process of RCE step by step. To ensure the elicitation mechanism is theoretically incentive compatible, respondents were told that after finishing the survey, they will randomly draw a number through 1 to 10 to determine the binding shopping scenario and purchase the product they chose in that scenario. If they choose “none of them,” they will leave without purchasing any orange juice. Respondents were explicitly informed that actual payment would occur for the binding scenarios and they should evaluate each scenario carefully, as each scenario had equally chance of being binding.

3. Model and Specification

The auction bids are continuous while the choices in RCE are discrete. To make the result comparable, we convert the results from RCE to continuous measurement—WTP values, so that we can compare them to the average bids from EA data.

Experimental Auction Bids using Multivariate Tobit Model

To study the relationship between experimental auction bids and participants’ purchase intention, a Tobit model is usually used because auction bids are left censored at zero. The Tobit model is specified as follows:

$$(1) \text{ If } Bid_i^* > 0, Bid_i = Bid_i^* = \alpha_0 + \alpha_1 X + \varepsilon_i$$

$$\text{If } Bid_i^* \leq 0, Bid_i = 0$$

The latent dependent variable for product i is Bid_i^* and the observed dependent variable for product i is Bid_i . X is the demographic variables including gender, income, and number of children in the household.

Since respondents bid for three different types of orange juice, we can construct three Tobit model to estimate consumers’ purchase intention and other demographic effects on their bidding behavior independently. However, the error terms of these three equations

can be correlated with each other. Therefore, using Seemingly Unrelated Regressions (SUR) to estimate these three Tobit model simultaneously could improve the efficiency of the estimates.

The Seemingly unrelated regressions (SUR) was proposed by Zellner (1962). A SUR system involves n observations on each of K dependent variables (K equations). When SUR is constructed with several Tobit model, this type of SUR is so called Multivariate Tobit Model. This model is following:

$$(1) \begin{cases} \text{If } Bid_i > 0, Bid_i = Bid_i^* = \alpha_0 + \alpha_1 X + \varepsilon_i \\ \text{If } Bid_i \leq 0, Bid_i = 0 \end{cases} \quad i = 1, \dots, K$$

where

$$\varepsilon = [\varepsilon'_1, \varepsilon'_2, \dots, \varepsilon'_K]'$$

and

$$E[\varepsilon | X_1, X_2, \dots, X_K] = 0$$

$$E[\varepsilon \varepsilon' | X_1, X_2, \dots, X_K] = \Omega$$

WTP value from RCE

RCE is based on random utility theory (Hanemann 1984; Hanley *et al.* 1998; Hanley, Wright, and Adamowicz 1998). To determine the WTP values for each orange juice product from the RCE allowing for heterogeneity in valuations, we use random parameter logit model. The utility level of the i th product for the n th respondent can be written as:

$$(2) U_{ni} = V_{ni} + \varepsilon_{ni} = \alpha_{ni} + \beta_i p_i + \mu_i T + \gamma_i X \times T + \varepsilon_{ni}.$$

where V_{ni} is the deterministic and ε_{ni} is the stochastic portion of utility, p_i is the price in the choice set, α_{ni} is the intrinsic preference of respondent that captures all the non-price attributes of product i , T vector is the type of orange juice in this choice i , and X is the vector of demographic variables that include gender, income, number of children in the household, and β_i is the marginal utility of price. In this analysis, we use the “none of these products” as the base in the regression, thus the estimation of WTP value is not marginal WTP but total WTP for each product. The coefficients of this random utility function and WTP values can be estimated by Multinomial Logit (MNL) Model.

Under the assumption that ε_{ni} is *iid* with an extreme value distribution, the probability of consumer n choosing alternative i is estimated by the multinomial logit (MNL) model:

$$(3) \text{Prob}(y_n = i|\beta) = \frac{\exp(\alpha_{ni} + \beta_i p_i + \mu_i T + \gamma_i X \times T)}{\sum_{j=1}^J \exp(\alpha_{nj} + \beta_j p_j + \mu_j T + \gamma_j X \times T)} \quad \text{for } i = 1, \dots, J$$

$$(4) L = \prod_{n=1}^N \prod_{i=1}^J \text{Prob}(y_n = i)^{y_{ni}}$$

where $y_{ni} = 1$ if alternative i is chosen by the n^{th} individual, and $y_{ni} = 0$ otherwise.

Consumers' WTP for a certain type of product k versus the base “none of these products,” is calculated as the negative value of the ratio of the coefficient of all the independent variables that include “ k ” (both k and other interaction terms that include k) to the price coefficient.

4. Results

Participants in the experiment were recruited in June, 2012 in local grocery stores in Changsha, China. Participants were offered ¥20 (about \$3) to compensate their time consuming in the experiment. Each participant attended (were randomly assigned) only one of the three experiments. In total, 203 individuals agreed to participate in the experiments, and 183 of them (90.1%) have completed the experiments. Among these individuals, 107 completed the RCE and 76 completed the EA. The null hypothesis of equality of means for demographic variables such as gender, age, and household income in the RCE and EA, cannot be rejected at any standard significance level, ensuring that the discrepancies, if it exists, are not coming from the demographic differences across experiments.

We collected respondents' demographic information such as their age, gender, household monthly income, number of children in the family, and their purchase intentions for orange juice on that day in the grocery store. In addition, consumers' aggressiveness in price bargaining was also measured by series questions following Lee (2000).

Purchase intention effect in EA

The description statistics of auction bids are reported in Table 6. The average bids for NFC orange juice was around ¥11.9, higher than the average bids than FC orange juice (¥8.1), and way higher than the average bids for OJD (¥3.6). And different products had different proportion of zero bids. There are around 6% zero bids for NFC orange juice and OJD, but only 2% zero bids for FCJ orange juice.

Purchase intention effect in RCE

WTP values from two experiments

The calculated WTP values from all the three experiments are reported in Table 7. The first column reports the WTP value for three types of orange juice from RCE data. In RCE, using RPL we estimated the WTP values for NFC orange juice, FCOJ, and OJD are ¥20.3, ¥16.3, and ¥7.9 respectively. However, these numbers dramatically dropped to ¥11.9, ¥8.1, and ¥3.6 in EA, respectively. In most cases, estimates of WTP values in RCE are higher than auction bids in EA. This result is consistent with what Lusk and Schroeder (2006) and Gracia, Loureiro, and Nayga (2011) found in their studies that estimates of WTP from RCE data were significantly higher than bidding value from EA data.

5. Conclusion

Our study conducted and compared the estimate WTP values from two different incentive compatible experiments, RCE and EA. And we also analyzed the individuals' aggressiveness levels in PB in the experiments and compared the WTP values by aggressiveness groups. We found that 1) WTP values from RCE data were higher than average bids from EA, which is consistent with the results in Lusk and Schroeder (2006) and Gracia, Loureiro, and Nayga (2011); 2) by grouping respondents into low aggressive, middle aggressive, and highly aggressive groups, we found that WTP values were significantly lower in highly aggressive groups; 3) moreover, the gaps of WTP values between low and highly aggressive group in EA is higher than the gaps in RCE, indicating that highly aggressive people in EA showing more aggressiveness than the highly aggressive people in RCE. Our task in this study is not to confirm which experiment is the best to reveal consumers' WTP, but to illustrate that the different mechanism of experiments could trigger consumers behavior differently.

References:

1. Cameron, T., G. Poe, R. Ethier, and T. Schulze. 2002. Alternative Non-Market Value-Elicitation Methods: Are the Underlying Preferences the Same? *Journal of Environmental Economics and Management* 44: 391–425.
2. Carlsson, F., and P. Martinsson. 2001. Do Hypothetical and Actual Marginal Willingness to Pay Differ in Choice Experiments? *Journal of Environmental Economics and Management* 41: 179–192.
3. Chang, J. B., J. L. Lusk, and F. B. Norwood. 2009. "How Closely do Hypothetical Surveys and Laboratory Experiments Predict Field Behavior?" *American Journal of Agricultural Economics* 91 (2): 518-534.
4. Davis, D. D. and C. A. Holt. 1993. *Experimental Economics* Princeton Univ Press.
5. Fishbein, M., and Ajzen, I. 1975. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.
6. Gracia, A., M. L. Loureiro, and R. M. Nayga Jr. 2011. "Are Valuations from Nonhypothetical Choice Experiments Different from those of Experimental Auctions?" *American Journal of Agricultural Economics* 93 (5): 1358-1373.
7. Hanemann, M., 1984. Discrete choice models of consumer demand. *Econometrica* 52: 541-561
8. Hanley, N., Wright, R., Adamowicz, W., 1998. Using choice experiments to value the environment. *Environmental and Resource Economics* 11: 413-428.
9. Irwin, J.R., G.H. McClelland, M. McKee, W.D. Schulze, and N.E. Norden. 1998. "Payoff Dominance vs. Cognitive Transparency in Decision Making." *Economic Inquiry* 36: 272-85.
10. Johansson-Stenman, O. and H. Svedsater. 2008. "Measuring Hypothetical Bias in Choice Experiments: The Importance of Cognitive Consistency." *The B.E. Journal of Economic Analysis & Policy* 8 (1): 1898.
11. Lee, D.Y. 2000. "Retail Bargaining Behavior of American and Chinese Customers." *European Journal of Marketing*, 34:190-206.
12. Loomis, J., P. Bell, H. Cooney, and C. Asmus. 2009. A Comparison of Actual and Hypothetical Willingness to Pay of Parents and
13. Non-Parents for Protecting Infant Health: The Case of Nitrates in Drinking Water. *Journal of Agricultural and Applied Economics* 41(3): 697–712.

14. Lusk, J. L., C. Alexander, and M. Rousu. 2007. "Designing Experimental Auctions for Marketing Research: The Effect of Values, Distributions, and Mechanisms on Incentives for Truthful Bidding." *Review of Marketing Science* 5 (1): 1-30.
15. Lusk, J., D. Fields, and W. Prevett. 2008. An Incentive Compatible Conjoint Ranking Mechanism. *American Journal of Agricultural Economics* 90(1): 487–498.
16. Lusk, J. L. and T. C. Schroeder. 2006. "Auction Bids and Shopping Choices." *The BE Journal of Economic Analysis & Policy*.
17. Noussair, C., S. Robin and B. Ruffieux. 2004. "Do Consumers Really Refuse To Buy Genetically Modified Food?" *Economic Journal* 114:102-121.
18. Plott C. R. and Zeiler, K. (2005) "The Willingness to Pay-Willingness to Accept Gap, the "Endowment Effect," Subject Misconceptions, and Experimental Procedures for Eliciting Valuations" *The American Economic Review* 95(3): 530-545
19. David Revelt & Kenneth Train, 1998. "Mixed Logit With Repeated Choices: Households' Choices of Appliance Efficiency Level," *The Review of Economics and Statistics*, MIT Press, 80(4): 647-657.
20. Rutström, E.E. "Home-Grown Values and Incentive Compatible Auction Design." *International Journal of Game Theory* 27(1998):427-41.
21. Shogren, J.F., Cho, S., Koo, C., List, J., Park, C., Polo, P., Wilhelmi, R. (2001). "Auction mechanisms and the measurement of WTP and WTA." *Resource and Energy Economics* 23: 97-109.
22. Train, K. 2003. "Discrete Choice Methods with Simulation," Online economics textbooks, SUNY-Oswego, Department of Economics, number emetr2.

Appendix A:

Information about three types of orange juice or organic drink:

1) Not-From-Concentrate (NFC) orange juice: Is orange juice processed and pasteurized by flash heating immediately after squeezing the fruit without removing the water content from the juice. No additional water or other ingredients are added in 100% NFC orange juice. There are only a few NFC orange juice products in the Chinese market such as Paisengbai NFC orange juice and some imported brands such as NFC orange juice from Florida and Australia. Now the price of a bottle of 250ml 100% NFC orange juice ranges from ¥5 to ¥12.

2) Frozen Concentrated Orange Juice (FCOJ): Is orange juice obtained from concentrated juice (COJ) that is reconstituted with water. FCOJ is orange juice made by removing, through evaporation, the water from the orange juice of fresh, ripe oranges that have been squeezed in extraction machines. No other ingredients are added in 100% FCOJ except for the same amount of water that was evaporated. So far, FCOJ has the biggest market share in China. For example, Huiyuan 100% FCOJ, Farmer's Orchard 100% FCOJ, and Great Lake 100% FCOJ are very common in the market. The price for a bottle of 450ml 100% FCOJ ranges from ¥4 to ¥8.

3) Orange Juice drink (OJD): Is sweetened beverage that is made of diluted fruit juice containing no less than 10% orange juice with other ingredient such as sweetener added. OJD is also very popular in the orange juice drink market. You can find OJD in the market very easily. Minute Maid, Uni President, and Master Kong are the common brands which carry orange juice drinks. The price for a bottle of 450ml OJD ranges from ¥1 to ¥5.

Tables:**Table 1. Measure aggressiveness in price bargaining questions**

Suppose you want to buy the following products. If bargaining is possible, please indicate the price level that closest to your bargaining price:

Aggressive_1: A simple cotton T-shirt, price ¥20	1) ¥10	2) ¥13	3) ¥15	4) ¥17	5) ¥20
Aggressive_2 A regular desk computer with all the common features you need, price ¥4000	1) ¥3000	2) ¥3300	3) ¥3500	4) ¥3700	5) ¥4000

Table 2 Attributes for choice experimental design

Product	Price levels
NFC orange juice, 500ml	¥17, ¥21, ¥25, and ¥29
FCOJ, 500ml	¥6, ¥8, ¥10, and ¥12
OJD, 500ml	¥2, ¥2.5, ¥3, and ¥3.5

Table 3 Examples of RCE and EA questions

RCE	In these 4 choices, I would choose... A. A bottle of 500ml 100% NFC orange juice, ¥21 B. A bottle of 500ml 100% FC orange juice, ¥8 C. A bottle of 500ml 100% OJD, ¥3 D. None of them
EA	For the following product, please fill the most you are willing to pay. A bottle of 500ml 100% NFCOJ ¥ _____

Table 4: Variable definitions on consumer specific characteristics and statistics

Variable	Unit	Definition
Age	Year	Age of Respondents in Years
Gender	Dummy	Female=1 Male=0
Income	Scale	Monthly household income Scale from 1: ¥ 500-1,000 to 12: over ¥ 15,000
# of Children	Persons	How many children under 18 in the household
Ranking	Scale	Ranking these three product 1: best 2: middle 3: worst
Intention	Dummy	Have intention to buy=1 No intention to buy=0
Aggressive_1¹	Scale	Bargaining aggressiveness for cheap product: 1-5 1 is the most aggressive 5 is the least aggressive
Aggressive_2²	Scale	Bargaining aggressiveness for cheap product: 1-5 1 is the most aggressive 5 is the least aggressive

Table 5: Basic Descriptive Statistics of Consumer Specific Characteristics

	EA data		RCE data	
	Mean	Standard deviation	Mean	Standard deviation
Age	33.289	15.005	33.908	12.604
Gender	0.767	0.425	0.908	0.289
Income	8.028	2.337	7.750	2.318
# of Children	0.570	0.674	0.829	0.750
Ranking				
NFC	2.084	0.802	2.013	0.835
FC	1.897	0.776	1.816	0.720
OJD	2.018	0.869	2.145	0.854
Intention	0.168	0.376	0.237	0.425
Aggressive_1	2.748	1.117	2.947	1.307
Aggressive_2	2.346	1.206	2.289	.984
Number of obs.	107		76	

¹ The question to measure consumers' aggressiveness in price bargaining is presented in Table 1

² The question to measure consumers' aggressiveness in price bargaining is presented in Table 1

Table 6 Purchase Intention

Purchase Intention	RCE		EA	
	Frequency	Percent	Frequency	Percent
Yes	18	23.68%	18	16.82%
No	44	57.89%	68	63.55%
Not sure	14	18.42%	21	19.63%
Total	76	100%	107	100%

Table 7 Description statistics for the auction bids

	Alternatives	Values
Mean	NFC orange juice	11.850
	FC orange juice	8.089
	OJD	3.556
Median	NFC orange juice	10
	FC orange juice	8
	OJD	3
Standard deviation	NFC orange juice	7.394
	FC orange juice	3.698
	OJD	1.825
Percentage of zero bid	NFC orange juice	7.5%
	FC orange juice	1.9%
	OJD	6.5%

Table 8 Multivariate Tobit Model

		Coefficient	Std. Err.	z	P> z	[95% Conf. Interval]	
100% Not-From-Concentrated Orange Juice							
	Age	-0.048	0.027	-1.770	0.076	[-0.102,	0.005]
	Gender	0.061	0.922	0.070	0.947	[-1.745,	1.868]
	Income	0.736	0.169	4.340	0.000	[0.404,	1.068]
	# of Children	1.036	0.621	1.670	0.095	[-0.181,	2.254]
	Intention	-1.018	1.070	-0.950	0.341	[-3.116,	1.079]
	Ranking	-3.275	0.431	-7.600	0.000	[-4.119,	-2.430]
	Aggressive_1	-0.116	0.399	-0.290	0.771	[-0.898,	0.666]
	Aggressive_2	1.633	0.379	4.310	0.000	[0.891,	2.375]
	Constant	10.176	2.284	4.460	0.000	[5.699,	14.652]
100% Frozen Concentrated Orange Juice							
	Age	-0.004	0.013	-0.280	0.780	[-0.030,	0.022]
	Gender	-1.612	0.453	-3.560	0.000	[-2.499,	-0.725]
	Income	0.427	0.083	5.170	0.000	[0.265,	0.589]
	# of Children	0.242	0.303	0.800	0.423	[-0.351,	0.836]
	Intention	-1.664	0.522	-3.190	0.001	[-2.687,	-0.640]
	Ranking	0.046	0.222	0.210	0.834	[-0.389,	0.482]
	Aggressive_1	0.101	0.197	0.510	0.607	[-0.284,	0.487]
	Aggressive_2	0.990	0.184	5.370	0.000	[0.628,	1.351]
	Constant	3.450	1.082	3.190	0.001	[1.329,	5.571]
10% Orange Juice Drink							
	Age	-0.025	0.007	-3.720	0.000	[-0.038,	-0.012]
	Gender	0.130	0.238	0.550	0.585	[-0.336,	0.596]
	Income	-0.061	0.043	-1.400	0.162	[-0.146,	0.024]
	# of Children	-0.275	0.152	-1.800	0.071	[-0.573,	0.024]
	Intention	0.752	0.273	2.760	0.006	[0.217,	1.286]
	Ranking	-0.408	0.118	-3.470	0.001	[-0.639,	-0.178]
	Aggressive_1	0.270	0.104	2.610	0.009	[0.067,	0.473]
	Aggressive_2	0.066	0.096	0.690	0.487	[-0.121,	0.254]
	Constant	4.691	0.588	7.980	0.000	[3.538,	5.844]
Number of Obs.			321.000				
Wald chi2(24)			237.500				
Log likelihood			-2428.694				

Table 9 MNL Model

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
Price	-0.258	0.024	-10.730	0.000	[-0.305, -0.211]
NFC	9.597	1.824	5.260	0.000	[6.023, 13.171]
FC	8.332	1.498	5.560	0.000	[5.396, 11.268]
OJD	5.253	1.518	3.460	0.001	[2.278, 8.228]
Interactive Terms					
NFC*Age	-0.019	0.017	-1.120	0.263	[-0.053, 0.015]
NFC*Income	-0.228	0.116	-1.960	0.050	[-0.455, 0.000]
NFC*Gender	-0.563	0.725	-0.780	0.437	[-1.983, 0.857]
NFC*# Child	0.483	0.334	1.440	0.149	[-0.172, 1.137]
NFC*Intention	-1.019	0.527	-1.930	0.053	[-2.053, 0.015]
NFC*Ranking	-1.156	0.218	-5.310	0.000	[-1.582, -0.729]
NFC*Aggressive_1	-0.487	0.210	-2.320	0.020	[-0.900, -0.075]
NFC*Aggressive_2	1.286	0.292	4.410	0.000	[0.714, 1.859]
FC*Age	-0.024	0.014	-1.700	0.090	[-0.051, 0.004]
FC*Income	-0.384	0.100	-3.860	0.000	[-0.579, -0.189]
FC*Gender	-0.340	0.600	-0.570	0.571	[-1.515, 0.835]
FC*# Child	0.178	0.294	0.610	0.543	[-0.397, 0.754]
FC*Intention	-0.282	0.418	-0.670	0.500	[-1.102, 0.538]
FC*Ranking	-0.094	0.158	-0.600	0.551	[-0.403, 0.215]
FC*Aggressive_1	0.016	0.172	0.090	0.926	[-0.322, 0.354]
FC*Aggressive_2	0.600	0.245	2.440	0.014	[0.119, 1.080]
OJD*Age	-0.004	0.014	-0.260	0.796	[-0.031, 0.024]
OJD*Income	-0.207	0.101	-2.060	0.039	[-0.405, -0.010]
OJD*Gender	0.981	0.631	1.560	0.120	[-0.255, 2.217]
OJD*# Child	0.350	0.299	1.170	0.242	[-0.235, 0.935]
OJD*Intention	-0.073	0.426	-0.170	0.863	[-0.908, 0.762]
OJD*Ranking	-1.005	0.135	-7.460	0.000	[-1.269, -0.741]
OJD*Aggressive_1	-0.268	0.175	-1.530	0.126	[-0.612, 0.075]
OJD*Aggressive_2	0.576	0.249	2.320	0.020	[0.089, 1.063]
Number of Obs.	76*4*10				
LR chi(28)	913.34		Prob> chi2= 0		
Pseudo R2	0.292				

Table 10 Compare WTP from EA and RCE

WTP	RCE	EA
NFC orange juice	23.311 ^a (6.555)	11.630 ^a (3.714)
FCOJ	21.641 (4.420)	8.065 (1.697)
OJD	11.869 (4.377)	3.508 (0.811)
No. of obs.	76*10 ^b	107

Note: ^a Mean and standard errors of WTP in RCE were determined Delta method.

^b Number of observations is 760 (=76 individuals ×10 choices of each individual)