BARTER MARKETS

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August 2007

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ABSTRACT

We propose a new data collection mechanism (barter markets), as an alternative to conjoint analysis, that allows for information diffusion among respondents, as an accelerated method to capture real life learning and measurement of consumer's partworths for product features. An empirical study that compares the barter method and choice-based conjoint demonstrates very superior out-of-sample predictive performance, both immediately (as is commonly done) and on a two-week later validation task, based on data collected from a barter market.

We also show evidence that respondents indeed learn from those who are familiar with the product suggesting those cases, and for what people, the barter market is likely to be superior to traditional conjoint measurement methods. However, in the spirit of "no free lunch", as the barter mechanism is "new to the world", we found that subjects did find the task more taxing (in various ways) suggesting a potential tradeoff between consumer resource allocation (at the time of the task) and (managerial) predictive accuracy.

INTRODUCTION

Hauser and Rao (2004), in their summary of conjoint analysis and discussion of important future research opportunities, noted: “Conjoint analysis is based on measurements and information that respondents have about product features and does not happen instantaneously. Thus, we expect further development of methods that combine the diffusion of information among consumers with models of how consumers will choose based on that information.” We propose a new and alternative data collection mechanism in this paper, *barter markets*, to address this issue. Our preliminary empirical exploration suggests that barter markets can provide increased respondent learning and subsequent partworths that are more reflective of a consumer’s underlying utilities both in short-term choices and in longer term hold-out validation tasks, a finding of high potential managerial importance.

Conjoint analysis is a rigorous methodology designed to uncover individuals’ true preferences (Carroll and Green 1995) that has been applied to many contexts in marketing, including new product development (e.g., Kohli and Mahajan 1991), pricing (e.g., Mahajan, Green, and Goldberg 1982), and segmentation and positioning (e.g., Green and Kreiger 1991; 1992). That it has become one of the marketing methods most widely adopted by practitioners underscores its immense contribution to marketing theory and practice (e.g., Bradlow, Hu, and Ho 2004; Cattin and Wittink 1982; Wittink and Cattin 1989; Wittink, Vriens, and Burhenne 1994).

Since its introduction to marketing (Green and Rao 1971), researchers have focused on two areas to improve conjoint analysis’s external validity, namely, data collection formats (such as adaptive conjoint designs, Johnson 1991; Toubia et al. 2003) and estimation methods (Hauser and Rao 2004). Whereas various state-of-the-art estimation methods have been proposed, tested (Carroll and Green 1995), and compared (e.g., Toubia et al. 2003), the question of which data collection format is the best "remains one of strongly-held beliefs and open debates" (Hauser and Rao 2004).

One promising direction for improving data quality is to use "market data". Researchers have long believed that preferences revealed at the marketplace have numerous advantages (Hauser and Rao 2004) such as, among others, they capture information diffusion. The key roadblock that has constrained the use of marketplace data in conjoint analysis is the fact that the number of observations per individual from real marketplaces tends to be very small and "they suffer from sample selection bias when the set of existing products represents an efficient frontier of the product space" (Hauser and Rao 2004). Conventional conjoint approaches (such as choice-based) expose participants to many possible combinations of products and likely capture a more complete picture of the preference structure, whereas data extracted from the marketplace may have limited variations and may not allow researchers to infer how a person will revise his or her purchasing behavior if the product offerings change.

To overcome this obstacle, we propose a laboratory-based market institution, barter markets, that enables us to capture rich revealed preferences. Lab-based markets, unlike the markets in the field, give experimenters control over the products presented in the market through various efficient designs (e.g., fractional factorial designs, Lenk et al. 1996), which alleviates the key concern of sample selection bias. Lab-based markets, however, must also extract as much information as possible while maintaining realistic aspects of a market. The proposed barter markets satisfy these objectives.

To test the benefits of barter markets, we conducted a random assignment between-subjects contrast experiment where we compared barter markets with choice-based conjoint. We found that the model with barter data predicts substantially better (out-of-sample) than that using only conjoint data in two holdout tasks, and we show that subjects "learn" during the barter market task from others who have more experience on the subject.

We organize the rest of the paper as follows. First, we propose a lab-based method, barter markets, to measure consumer preferences via a realistic market learning environment. Next, we present an experiment in which we implement both a conventional choice-based conjoint and the proposed barter method. We then report a summary of our analyses and results, focusing on changes in partworths, improved prediction, and evidence of learning due to the barter market mechanism. Finally, we discuss general findings, limitations, and future research opportunities.

BARTER MARKET DESIGN

In this section, we first describe our design implementation in detail, and then discuss some desirable properties of barter markets in general.

General Design

The barter market is implemented as a collection of independent product trading markets, each market with several individuals, over a web-interface, which allows for dynamic customization of the study based on each subject's responses and outcomes as they evolve. We describe below one possible implementation of barter markets, which we used in the empirical study reported here. Alternative implementations (and how one would choose between them for any particular empirical application) are possible and are discussed in the last section of this paper.

We depict the barter market design graphically in Figure 1. The specific process is as follows: (1) markets are formed by randomly assigning a specific number of participants to a group (market), all markets will operate independently of each other. In each market, the characteristics of every participant (e.g., relevant expertise) are made public to allow for differential information sharing/learning, one of our primary substantive interests and of importance for barter market design.[1] The following instructions describe one such market; (2) each participant in the same market will be endowed with a different product profile, plus a certain amount of cash. Every participant observes all product profiles endowed to other participants in the same market; (3) each participant compares her endowed product profile with those endowed to others, and determines whether she prefers more a product currently owned by another participant. If yes, she then makes an *offer* to the other party to exchange the two products, and furthermore states a specific amount of cash she is willing to give to the other party if that party accepts the offer (thus the name barter market); (4) the market then pauses until all participants in the same market have completed making offers (or decided not to make any offers); (5) each participant is shown the offers made to her by other participants in the same market, and she then decides which offers she will accept or reject; (6) the market then pauses further until all participants in the same market have completed responding to offers; (7) the computer interface then randomly pairs two participants in

[1] As an example, if we find that at least one knowledgeable participant must be in a barter market for learning and accurate partworth estimation to occur, then one would want to assign people using a stratified rather than random assignment mechanism.

the same market (say, A and B), and then randomly picks one possible barter (A → B or B→A) to determine the outcome for the pair. If no offer is made, or an offer is made but rejected (steps (4)-(5)) in this randomly picked possible barter, both persons keep their endowed products and the endowed cash. On the other hand, if an offer is made and accepted, they will switch products, and their cash balance will be adjusted based on the cash amount stated in the offer; (8) each participant is shown the complete information – offers made, responses to offers, and final product, for everybody in the same market; (9) steps (2) to (8) (this is defined as one round) are repeated with a new set of product profiles for this market, until all rounds have been completed; and (10) finally the computer will randomly pick a round, and the product and cash a participant owns at the end of that round (based on step (7)) will be given to the participant. We note that this is announced to the participants at the beginning of the barter market and can be considered a form of incentive alignment recently documented in the marketing literature (Ding et. al., 2005; Ding 2007).

Insert Figure 1 about here

In the case where the product is expensive, a lottery mechanism may be used to determine which participant will end up receiving the final product and cash (which is what we employed in the empirical study in this paper due to the realistic but expensive nature of the product).

Several parameters of the barter market design should be determined by the researcher/practitioner, based on their specific situation. For instance, the *number of* *rounds* as well as the *number of individuals* in each market should be a reflection of the total product profiles to be used (i.e., as determined by the number of attributes and levels). For example, if an efficient design requires 72 profiles[2], the barter market could be structured as either 18 rounds with 4 individuals in each market, or 12 rounds with 6 individuals in each market (as examples). On one hand, the bigger the market (more individuals) the greater the potential is that a participant can learn from other individuals. On the other hand, a participant will also have less information per individual, if the total number of profiles is held constant. Finally, although we suggested to pair subjects in determining the outcome (see step (7)), an odd number of participants is perfectly fine. (e.g., one individual can be randomly chosen to keep his/her endowed profile and cash at a given round.)

General Properties

The barter market has some unique advantages that are worth noting. First, it allows information diffusion among the participants in the same market. Each individual will observe barter offers made by others, as well as the responses to these offers. Such information conveys how valuable other individuals perceive the various features in the product, not unlike word-of-mouth information (Godes and Mayzlin 2004) in real life. Thus, in some sense, barter markets combine choice-based methods, dynamic experimentation, and word-of-mouth methods all-in-one. Furthermore, since the profiles of individuals in the same market are public information, a person can weigh each

[2] Determining efficient designs for barter markets is an open research question. In this research, we utilize efficient design methods for choice-based conjoint and distribute these products across the barter market rounds.

person's valuation differently, based on their profile (such as their expertise on the subject).

Second, the nature of the barter market enables us to obtain *abundant* information about (pairwise) comparisons (note the emphasis on plural and this is where the efficiency comes in) among different products, which conforms to the essence of conjoint analysis. That is, instead of having one observation per question with J options as in a standard pick 1 out of *J* conjoint design where it is assumed that the respondent picks the alternative with the highest utility, a barter market will provide information on a potential maximum of 2*(*J*-1) observations from an individual (*J*-1 offers made/not made to others, and *J*-1 responses to offers made to him/her).[3] Thus, barter markets generate two types of data that can be used for preference measurement. The first type is the bids submitted by participants. From the viewpoint of a bidder, a pairwise comparison can be made between two products in a potential exchange. The second form of data is responses to the bids received; pairwise comparisons can be made from this information as well.

Third, because participants can specify an additional amount of money for each bid submitted, the barter mechanism gives experimenters new information that would not be available from conventional conjoint analysis. Specifically, the price (with a cash premium) is continuous and endogenously chosen by each subject for each offer, whereas in a conventional conjoint task, the price is discrete. Furthermore, the price across offers may span a wider range than the price specified by an experimenter in a conventional conjoint. We might call this feature *participant-controlled adaptive design*, because the

[3] In future research, it would be of interest to combine barter data with Bayesian methods for detection of which pairs of information the respondent pays attention to, akin to the latent choice rule research of Gilbride and Allenby (2004).

new profiles (bids, for which additional money represents an adjustment to the original price) are generated dynamically by participants, not the experimenter. We believe this is a potentially big benefit of barter markets.

Fourth, the barters occur among the participants in the marketplace (both buyers and sellers are participants), so participants do not simply react to an experimenter's questions. This format gives participants more control over the process, which may lead to their high involvement.

AN EMPIRICAL APPLICATION

In order to validate the barter method empirically, we conducted a between-subjects contrast experiment between the barter method and a benchmark choice-based conjoint approach. We used the following criteria to select the product for our experiment: (1) The potential study subjects (university students) must be a key target segment of the product/service; (2) The potential study subjects must be reasonably familiar with the product/service category and be interested in purchasing such a product/service at the right price; and (3) This should be a category where a subject can benefit from other people's opinion about what features should be purchased and at what price.

The first two criteria are essential for any realistic study, while the third criterion is used to allow us to test for the degree of information diffusion built into the barter market. We interviewed a small sample of potential subjects using one-on-one interviews, open-ended surveys, and follow-up interviews to select a product category; *beach vacations* came out as their top choice (this may due to the season and the university student population as the study was conducted in June). To ensure we use a beach that (1) students in this university are interested in going to, and (2) there is sufficient heterogeneity in familiarity about this beach, we did an additional preliminary survey of target subjects on what beaches they are familiar with and are interested in going to. Ocean City, Maryland emerged as the best candidate beach and is thus used in this study. Details of the pre-surveys are available upon request.

Experimental Design

To determine the appropriate attributes and levels for the beach vacation packages, we conducted extensive web research and two focus groups. As a result of these qualitative studies, our packages include the following attributes: hotel, restaurant, entertainment, and the expected temperature and visitor type during the time the vacation will take place. In particular, we selected six real Ocean City, Maryland hotels (Beach Walk, Carousel, Castle in the Sand, Lighthouse Club, Park Place, and Princess Bayside Beach), four real restaurants of varying kinds that span the type at Ocean City, Maryland (Bonfire, Castaways, Phillips Crab House, Seacrets Bar and Grille), six different types/places of entertainment (Baja Amusements, Carousel Ice Skating Rink, Garvin's Comedy Club, H2O Under 21 Dance Club, Jolly Roger Amusement Park, and Planet Maze and Laser Storm), three types of visitors that will be dominant during the time that the vacation package is to be taking place (high school grads, college students, young professionals), and three average outdoor temperatures (88°F, 81°F, and 74°F). Finally, we also included three levels of price ($700, $600, and $500) for the conjoint study; remember the barter auction utilizes cash (price) as part of the barter. A detailed description of each alternative (e.g., Carousel Hotel) was provided to participants and they had the ability to access this information anytime during the study by clicking a special link to *Product Overview*. The fact that these features were determined by web research, interviews, and focus groups, and subjects utilized the product overviews alleviated our concerns about this specific product's use.

The experiment was a between subjects-design with two conditions. In the first condition, subjects first completed a conventional choice-based conjoint (with 18 4-tuples of products as described below), followed by a <u>first</u> holdout task (where a subject selects his/her most preferred vacation package from a list of 10 different packages), and finally a brief survey. Subjects assigned to the second condition participated in a barter market instead of choice-based conjoint, but the remaining two tasks are identical to that in the first condition. All subjects also completed a "delayed" second holdout task (2 weeks after the lab study) from any computer with an internet connection containing 10 different product profiles than the first holdout task to provide a "clean" longer-term assessment. Participants' self-stated familiarity about the Ocean City, Maryland beach (collected in advance of the barter market) are public information and available to everybody in the same market.

To ensure the objectivity and external validity of the study, we used SAS experimental design macros to determine the number and the actual profiles of the various beach profiles for the two experiments. Given the number of attributes and their corresponding levels, a 72-profile design is deemed to be most efficient. We therefore generated 72 different profiles and divided them into 18 sets with 4 profiles in each set. Each set is used for one choice question in choice-based conjoint and one round in the barter market. Albeit, as described earlier and in the future research section, the optimal barter market design needs further study; however, our choice of equating rounds in the barter market to 4-tuples in the conjoint task does reduce confounding and provide us some control.

The instructions provided for choice-based conjoint was standard, asking subjects to choose their most preferred beach vacation from a set of four for 18 rounds. The instructions for the barter method closely followed the theoretical design (previous section). In particular, during each round of the barter, a subject was endowed with a vacation package, plus $300 cash that he/she can use for barter purposes. Every subject was paid $8 for participation, and had the potential to "win" a beach vacation. In particular, subjects were told that an actual vacation package would be awarded to one subject that is randomly selected from the entire pool of subjects. If this subject is assigned to condition 1 (choice-based conjoint), he/she will receive the vacation package he/she selected in one of the two holdout tasks (randomly picking one), plus the difference between $900 and the price associated with that vacation package. If this subject is assigned to condition 2 (barter market), a coin flip will determine whether the barter market or holdout task will be used to determine the actual prize. If the holdout task is chosen, we first randomly pick one of the two holdout tasks and he/she will receive whatever he/she selected in that task and the difference between $900 and the price of that package. If barter task is chosen, one of the 18 rounds of barter will be randomly selected, and the subject will receive whatever package he/she has at the end of that barter round, plus the cash balance in that round.

The barter method (and this study) was implemented through a web-interface using PHP (a programming language used for server side applications) and MySQL database, on a Linux server. With this implementation, the barter method (study) can be conducted on any computer that has internet connections. The specific code is available from the authors upon request.

Experimental Procedure

A total of 122 undergraduate students at a major U.S. university participated in the study in a campus computer lab. 66 of them were randomly assigned into the choice-based conjoint condition, and 56 to the barter market condition. All subjects completed the choice-based conjoint (barter), first holdout task, and survey in the lab. They were then told that they would receive an email in 2 weeks that contains the link to the second holdout task. They must complete the second holdout task in order to qualify for the prize. All, except 6 subjects (3 in each condition) completed the second holdout task. One winner was randomly selected upon the completion of the second holdout task and rewarded based on the rules and her choice made during the study.

ANALYSIS

We first provide an overview of the data collected from the experiment (Table 1), because of the unique and new nature of the barter task as compared to the conjoint task. From the choice-based conjoint, 66 subjects completed all 18 choice tasks, yielding 1188 (= 66 × 18) observations. In the barter task, we observed a large amount of variation in the number of bids submitted (mean = 30.30, std. dev. = 8.94), across barter markets, with a range from 11 to 54. For submitted bids, most include some cash premium but the amount varies widely, from \$1 to \$300 with an average of \$138.60 (std. dev. = \$83.66). In the barter market, bids submitted from the bidder's perspective will results in bids received from the seller perspective. Of the average number of bids, 30.30, about half of them (16 out of 30.30) were deemed acceptable by their recipients. These descriptive data on the number of bids and completion rates, at a minimum, suggest that subjects are very involved in the barter market. We have other measures comparing this to the choice-based conjoint reported later.

Insert Table 1 about here

<u>Heuristic Description</u>

To aid readability, we describe the following simplified barter market as an example. As we noted previously, we can draw two types of information from the barter trade market: bids submitted (and bids not submitted) and bids received (i.e., accepted and rejected). We illustrate an example in Figure 2 in which we include four subjects (1, 2, 3, and 4) and each subject's corresponding profile number (e.g., subject 1 randomly receives profile 1, subject 2 randomly receives profile 2, etc). In this example, subject 1 submitted two bids: one to subject 2 with a cash premium $\$X_{12}$ and the other to subject 4 with a cash premium $\$X_{14}$. Similarly, subject 2 submitted a bid to subject 4 with a cash premium $\$X_{24}$, and subject 3 submitted a bid to subject 4 with a cash premium $\$X_{34}$.

Insert Figure 2 about here

The relative preference between two profiles in a barter market can be formally defined as follows: For submitted bids, a pairwise comparison between the two parties in a potential exchange provides the relative preference. For example, because subject 1 submitted an offer to subject 2 of $\$X_{12}$, subject 1's utility from holding profile 1 with $\$X_{12}$ is less than his or her utility from holding profile 2, and furthermore we can utilize the cash amount offered as an attribute of that comparison. As we show in Table 1, there were a total of 1697 bids submitted across 18 barter market rounds. For bids not submitted, a pairwise comparison between the two parties *not* in a potential exchange reveals the relative preferences. For example, subject 1 did not submit a bid to subject 3, which implies that his or her utility of holding profile 1 is greater than or equal to his or her utility of holding profile 3 (at any possible cash exchange value). Otherwise, subject 1 would have submitted a bid to subject 3. This inference about the bids not submitted yields an additional 1327 observations (note that the total number of potential exchanges in our barter market is 3024, 56 subjects × 18 barter rounds × 3 potential exchanges per barter round). Note that our approach does not impose any structural assumptions on the behavior in the barter market yet is consistent with utility maximization of choices.

For bids received, each subject decides whether the bid is acceptable. For example, subject 4 received three bids: one from subject 1 for $\$X_{14}$, one from subject 2 for $\$X_{24}$, and one from subject 3 for $\$X_{34}$. On the basis of these received bids, subject 4 compares the utility of each bid with his or her utility of holding his or her own profile (plus the associated cash). Similar to the submitted bid framework, we obtained 903 and 794 observations from the accepted and rejected bids, respectively.

<u>Estimation Procedure</u>

To provide the most relevant apples-to-apples comparison between the conventional choice-based conjoint and barter markets, we used state-of-art models and estimation methods to assess individual subjects' preferences and out-of-sample predictions. To analyze the choice data from the choice-based conjoint (four profiles) and barter markets (two profiles in a potential exchange with a cash premium), we use a random-effects hierarchical Bayesian multinomial logit model, similar to the model specified by Allenby, Arora, and Ginter (1998) and Ding, Grewal, and Liechty (2005). The probability that the *i*-th subject chooses the *k*-th alternative from the *j*-th choice set is given by

$$p_{ij}^{k} = \frac{\exp\left\{\beta_i^T x_{ij}^k\right\}}{\sum_l \exp\left\{\beta_i^T x_{ij}^l\right\}},$$

where x_{ij}^k describes the *k*-th vacation package evaluated by the *i*-th subject from the *j*-th choice set, and β_i is a vector of partworths for the *i*-th subject. We assume a hierarchical shrinkage specification for the individual partworths, where a priori, $\beta_i \sim N\left(\overline{\beta}, \Lambda\right)$.

This specification allows for individual-level partworth estimates β_i but still permits estimation of the aggregate or average partworth $\overline{\beta}$, as well as of the amount of heterogeneity for each partworth Λ. In line with the literature (Ding, Grewal, and Liechty 2005), we use a simplified version of the model and assume that Λ is a diagonal matrix. Furthermore, we assume diffuse conjugate priors for $\overline{\beta}$ and Λ to ensure proper posteriors but also allow the data to primarily govern the inferences.

We tested a range of prior values to ensure that the reported results are invariant to the degree of non-informativeness of the prior specification. In addition, we assessed the convergence properties of the Markov Chain Monte Carlo analysis (using multiple chains from overdispersed starting values, Gelman and Rubin 1992) to ensure that the algorithm converged to the target density, as induced by the model specification, before we made marginal summaries of the posterior density.

Results

We include the parameter estimates in Table 2.[4] To align our barter results (that uses dollars offered on a continuous scale) with conventional choice-based conjoint partworths, we note that we used actual prices (with a cash premium in the barter market) to estimate the models rather than dummy variables that are common. We start by presenting a comparative analysis of the results from the conjoint and barter models.

Our first observation regarding the model results relates to the number of significant parameters for the two models. The high number of statistically significant parameter estimates in both models indicates a needed level of discrimination amongst the attribute levels. Whereas this could be an artifact of levels that are spaced too far apart (Wittink et al. 1990), our predictive results suggest that this is not the case.

Insert Table 2 about here

Further comparative results are: (1) there is a great level of similarity in parameter estimates for the attributes hotels, outside temperature, and entertainment between the two models; (2) parameter estimates of restaurant and other visitor types are quite

[4] For the barter market, we implemented two models to test the predictive power of the barter market data. As a benchmark model, Model 1 uses both data from bids submitted and received. We assume a paired comparison between the two packages in a potential exchanges, plus dollar amounts for model estimation. We also assume independence of various packages in each barter task. Model 2 uses the data from bids submitted, and not submitted, and received. Model 2, whose results are available from the authors upon request, does not show any improvement in terms of model performance (both in terms of in-sample and out-of-sample predictions). Thus, we report the results of Model 1 for the barter market.

different[5]; and (3) the price coefficient is "interesting". Subjects appear to be more price sensitive in the barter market than the choice-based conjoint. This finding provides strong face validity for the barter market, because a key reason for low out-of-sample predictability of standard conjoint tasks (as shown in extant literature) is the underestimation of price sensitivity (Ding, Grewal, and Liechty 2005).

Finally, we examine the predictive performance for two holdout tasks (one on the same day and the other after two weeks) from both approaches. As Green and Srinivasan (1990) note, out-of-sample prediction provides true validation for conjoint methodology and should serve as the best yardstick to judge whether the proposed barter market institution adds value to conventional conjoint analysis. In Figure 3, we provide the out-of-sample predictions; the baseline in a naïve random selection strawman model is 10% (i.e., a subject randomly selects 1 of 10 choices). We also note that compared to the more traditional immediate holdout task, our second holdout task will provide a more realistic test of the validity of the barter method.

As shown in Figure 3, the barter market leads to significantly better predictive performance: the percent of matches between the actual choice and the top predicted option are 32% for the first holdout task (the same day) and 30% for the second holdout task (two weeks later) under the barter market, versus 19% and 17% under the choice conjoint, respectively. This result provides strong empirical evidence for the validity and managerial usefulness of the proposed barter method in understanding consumer preferences for products; and furthermore, the magnitude of this effect is not one of pure statistical artifact, rather one of sufficient magnitude likely to be of managerial relevance.

[5] The difference observed in these attribute partworths is neither 'good' nor 'bad', but simply reflects that it is unlikely that identical processes are going on in the choice and barter tasks. The increased predictive ability of the barter tasks suggests that they may be more reflective of the true preferences.

Insert Figure 3 about here

Besides showing that barter markets can provide improved out-of-sample predictions (as Figure 3 shows), we were also substantively interested in understanding some of the "whys". Hence, we conducted a further analysis using the survey data collected at the time of the study to try and uncover a possible set of reasons. In particular, we ran an analysis to understand which individual-level and group-level variables are drivers of successful holdout prediction under the barter market. To be consistent with the methodological frameworks of the estimation procedures in this paper, these analyses were conducted in a fully Bayesian way (Rossi and Allenby 2003). In particular, we took every $t = 10^{th}$ draw from the MCMC sampler – known as thinning (at $t = 10$ the MCMC draws were essentially zero auto-correlated), and computed a logistic regression at each iteration with dependent variable whether the prediction was correct (determined via stochastic simulation from the posterior predictive distribution of the outcomes) and the survey-based independent variables described below:

1. <u>One's familiarity</u>: Based on the self-stated familiarity (on a scale from 1 to 5, with 1 being extremely unfamiliar and 5 being extremely familiar) about the Ocean City, Maryland beach, we dichotomize the variable: 0 if the self-stated familiarity is 1 or 2 (i.e., low familiarity), and 1 otherwise.
2. <u>Number of familiar people</u>: Based on the one's familiarity noted above, we count the *number* of other people in one's barter market whose value for the

familiarity variable is 1. Thus, this independent variable reflects *group knowledge* in one's barter auction.[6]

3. Willingness to learn: In the survey, we asked the question "Do you seek other people's opinion when you decide which beach you want to visit?" (on a scale from 1 to 5, with 1 being not at all and 5 being all the time). Similarly we dichotomize this variable: 0 if the value is 1 or 2, and 1 otherwise.

We then computed average parameter estimates and standard errors across those values estimated for each MCMC iteration. Our results, presented in detail in Table 3, indicate that all three independent variables are significant drivers of correct prediction in the barter market.

Insert Table 3 about here

From these results, we note that an a priori increase in one's own familiarity with the product, the number of people in one's group who are familiar with, and one's willingness to learn all lead to an increased accuracy of hold-out predictions. Furthermore, the fact that one's willingness to learn coefficient is greatest, and that the number of other "experts" in one's group is of similar magnitude (both larger than a priori familiarity) suggests a substantial amount of learning from others in barter markets. Certainly, other learning process measures and further study are needed to assess the generality of this finding.

[6] We checked other operationalizations such as at least one familiar person, the total of the familiarity scores of the other barter market participants, and the maximum score of other participants. The results were robust to these alternative specifications.

Finally, we conducted one last set of comparative analyses to assess subjects' liking of, willingness to participate in, ease of comprehension, and time taken for the choice-based versus barter task (Tables 4 and 5). We did not observe statistically significant differences in means between the two methods for the first three variables (Table 5), but barter markets do take much longer to complete (Table 4).

Insert Tables 4 and 5 about here

We note, however, that taking more time for the barter market is not necessarily a bad thing as it demonstrates significant engagement of the approach; albeit, one could run a longer and potentially more predictive conjoint study in the same *equal* amount of time. Needless to say, these measures indicate possible trade-off implications where the researcher/practitioner may have to trade off consumer engagement and effort during measurement with the increased predictive accuracy that is a result of the barter market. Our expectations are that as the barter market mechanism gains in popularity, these trade-off disparities may become less salient.

DISCUSSION

To address the issue and demonstrate the value of information diffusion in preference measurement, we propose a new data collection mechanism that we termed 'barter markets', describe its implementation and a test of its performance, and find that the model generates superb out-of-sample forecasting compared with the results from a traditional choice-based conjoint task.

The proposed barter method is easy to implement, provides abundant market-based behavioral information, and requires relatively little additional effort from researchers. Feedback from the participants in our experiment indicates that participants were very involved; some even stated "We had fun!", yet after-experiment survey data suggests that trade-offs may be necessary.

As mentioned above, our implementation of a barter market is but one of many possible, and other variations of barter markets exist such as: (1) barter offers can be to products that are *less* desirable, with a demand for a certain amount of cash to be paid to the individual who suggests the offer (in other words, trade-down markets); (2) some of the individuals in the same market may be endowed with the same product profiles; this may be less efficient in implementation, however, a participant can conceivably learn more about a value of a specific profile if he/she has more than one observation for that product; (3) increasing or decreasing the number of persons assigned to a group – more increases potential learning but could lead easily to information overload (Kahn 1998; Lehmann 1998), and (4) allow for multiple trades (across people or within rounds) – this would increase both flexibility (a good thing) and complexity (potentially a drawback) on a task already believed to be somewhat complex.

We believe that this research is just an introduction to barter markets; there are many fruitful directions for further research. First, it will be extremely interesting to examine the conditions under which consumer learning happens. For example, the number of participants in a market may be a significant driver. Second, it will be interesting to examine under what general context barter markets will be superior to choice-based conjoint. We documented one such example with beach vacations, but it is conceivable (and one of our main hypotheses here) that little learning will happen if the product/service is well understood and familiar to everybody in a given market. Third, alternative ways are needed to interpret barter data. We now interpret it as a series of pairwise comparisons. It is possible to interpret any offer as a choice from three options, the original product plus the cash, the target product, and no product. The very fact that an offer is made indicates that the individual has positive utility for the target product. Such interpretation will allow us to infer willingness to pay, although in the current context with such substantial value in each package, such interpretation is unlikely to yield any additional useful information. But this may be quite relevant to other contexts or implementations. Fourth, subjects were endowed with a product from the start, and the barter process required them to give up what they already had. As a result, loss aversion (Camerer 2005) may induce participants to behave somewhat differently from their conventional choice behavior or make them less likely to try new things. It will be interesting to investigate such effects and these initial results suggest the practical importance of doing so. Fifth, our current format allows subjects to revise one attribute of the product (price), but it is possible to allow subjects to change other attributes as well during a barter market. For example, a participant could first upgrade one attribute that he/she thinks is valuable to potential buyers (given his/her current configuration), and then make a barter with the revised profile. Such subject-driven adaptive design could provide a very efficient way to uncover preferences.

More broadly, barter markets can be considered as the first foray into using market-based mechanisms for uncovering individual's preferences. Such mechanisms can be categorized based on (1) participants' role (who are the buyers and sellers and how many are in the market at a given time), and whether the experimenter will serve an active role (either buyer or seller) in the market; and (2) the number of product each seller offers and the heterogeneity of these products within a seller and across sellers. Market-based mechanisms offer several advantages including, but not limited to, diffusion of information among participants. We believe alternative market-based mechanisms should be studied and compared to standard mechanisms (such as choice-based conjoint), and a set of guidelines can then be developed as to which mechanism is most appropriate for a given situation.

Table 1: Data Description

	Total	Mean	Std. Dev.
<u>Choice-Based Conjoint</u>			
Number of choices made	1188	18	0
<u>Barter Market</u>			
Number of bids submitted	1697	30.30	8.94
Cash premium in bids submitted ($)		138.60	83.66
Number of bids received	1697	30.30	6.52
Number of bids accepted	903	16.13	5.11
Number of bids rejected	794	14.18	4.86

Table 2: Parameter Estimates

	Choice-Based Conjoint		Barter Market	
	Post. Mean	Heterogeneity	Post. Mean	Heterogeneity
Hotel				
Beach Walk Hotel: Base	0.00	--	0.00	--
Carousel Resorts	**0.18**	0.19	**0.10**	0.21
Castle in the Sand	**0.21**	0.43	**0.23**	1.86
Lighthouse Club Hotel	0.03	0.11	**0.18**	0.22
Park Place Hotel	**0.24**	0.13	**0.29**	1.48
Princess Bayside Beach Hotel	**0.17**	0.32	0.06	1.60
Restaurant				
Bonfire Restaurant: Base	0.00	--	0.00	--
Castaways	**0.23**	0.24	**-0.13**	1.93
Philips Crab House	-0.06	0.84	**-0.19**	2.26
Seacrets Bar and Grille	0.15	0.92	-0.09	1.39
Temperature				
88°F	0.01	1.24	0.07	2.31
81°F	**0.13**	0.21	**0.12**	1.63
74°F: Base	0.00	--	0.00	--
Entertainment				
Baja Amusements: Base	0.00	--	0.00	--
Carousel Ice Skating Rink	0.02	0.54	0.02	1.38
Garvin's Comedy Club	**0.30**	0.59	**0.27**	1.51
H2O Dance Club	**0.34**	0.22	**0.29**	2.07
Jolly Roger Amusement Park	**0.18**	0.22	**0.25**	0.30
Planet Maze and Laser Storm	**0.34**	0.22	**0.28**	0.46
Visitor Type				
High School Grads	-0.04	0.46	-0.12	1.08
College Students	-0.03	0.15	**0.09**	0.52
Young Professionals: Base	0.00	--	0.00	--
Price				
$700	**-0.21**	0.47	--	--
$600	-0.10	0.19	--	--
$500: Base	0.00	--	--	--
Offers made (received) / 100	--	--	**-0.76**	1.09

Note: Bold indicates that zero lies outside of the 95% posterior interval.

Table 3: Effects of Familiarity and Learning

	Holdout Tasks 1 & 2	Holdout Task 1 only	Holdout Task 2 only
Intercept	**0.81**	**0.62**	**1.01**
One's familiarity	**0.12**	**0.13**	**0.10**
Number of familiar (knowledgeable) people	**0.17**	**0.32**	0.03
Willingness to learn	**0.31**	**0.34**	**0.29**

Note: Bold indicates that the parameter coefficient is significant at the 1% significant level.

Table 4: Time Taken for the Task

	Choice-Based Conjoint		Barter Market	
	Mean	Std. Dev.	Mean	Std. Dev.
Total	427.58	197.16	786.38	225.50
Time to make offers	--	--	514.27	180.61
Time to evaluate offers received	--	--	272.11	77.42
Per task	23.75	25.50	27.85	10.54
Time to make offers	--	--	18.56	8.73
Time to evaluate offers received	--	--	9.29	3.02

Table 5: Comparative Process Measures for Conjoint and Barter Tasks

	Choice-Based Conjoint		Barter Market	
	Mean	Std. Dev.	Mean	Std. Dev.
Do you like the study you just completed?	3.83	0.83	3.39	0.76
Will you be willing to participate in similar studies in the future?	4.35	0.85	4.16	0.93
Is it easy for you to understand and complete the tasks?	4.67	0.62	3.88	1.05

Figure 1: The Barter Market

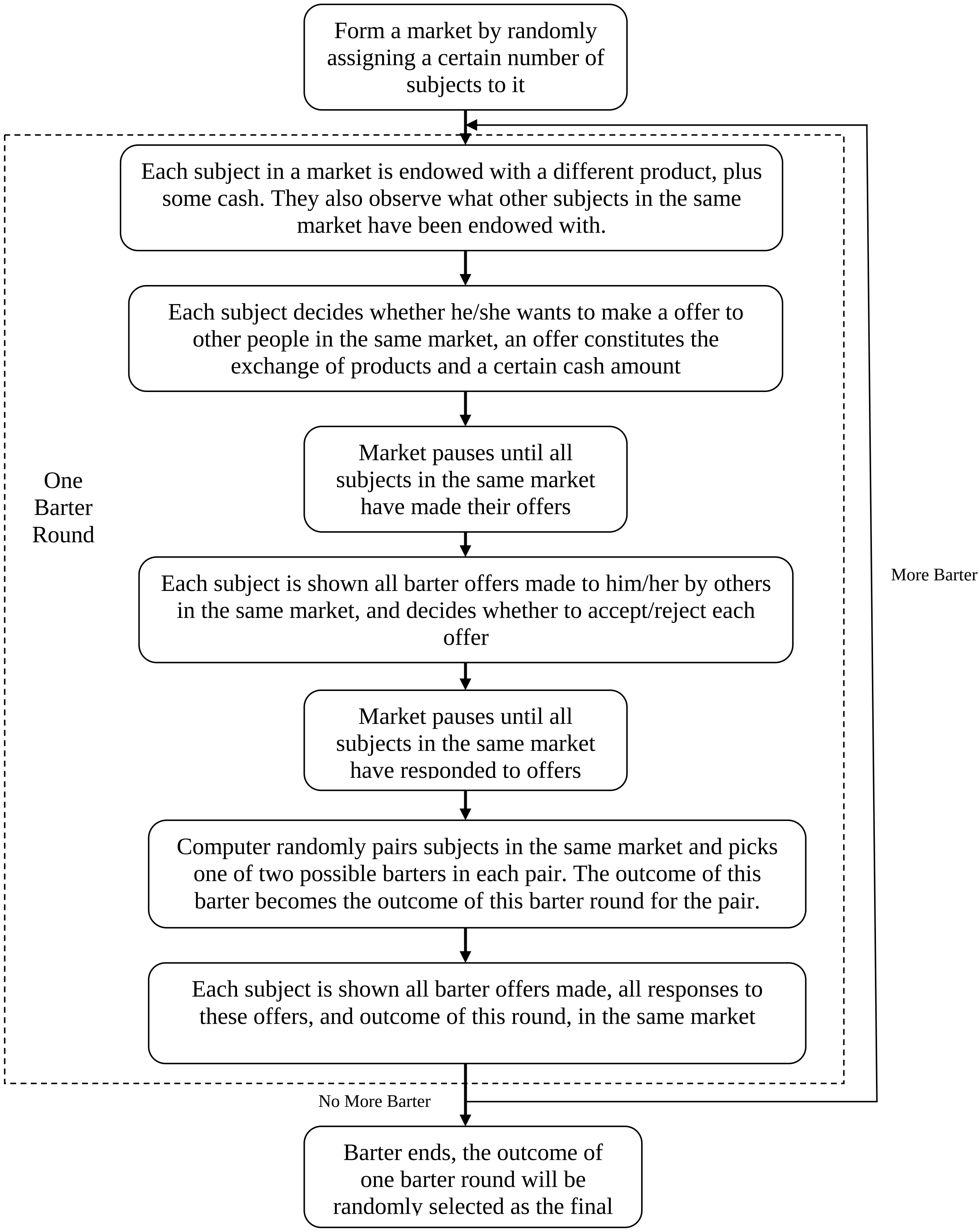


Figure 2: Information Drawn from the Barter Market

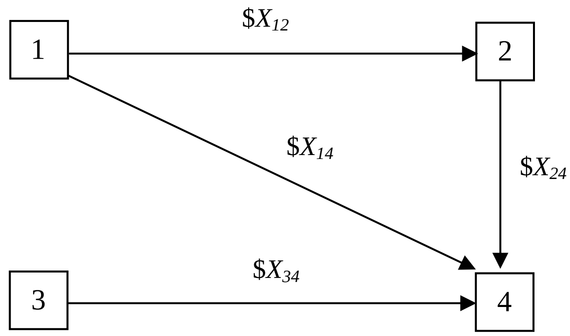
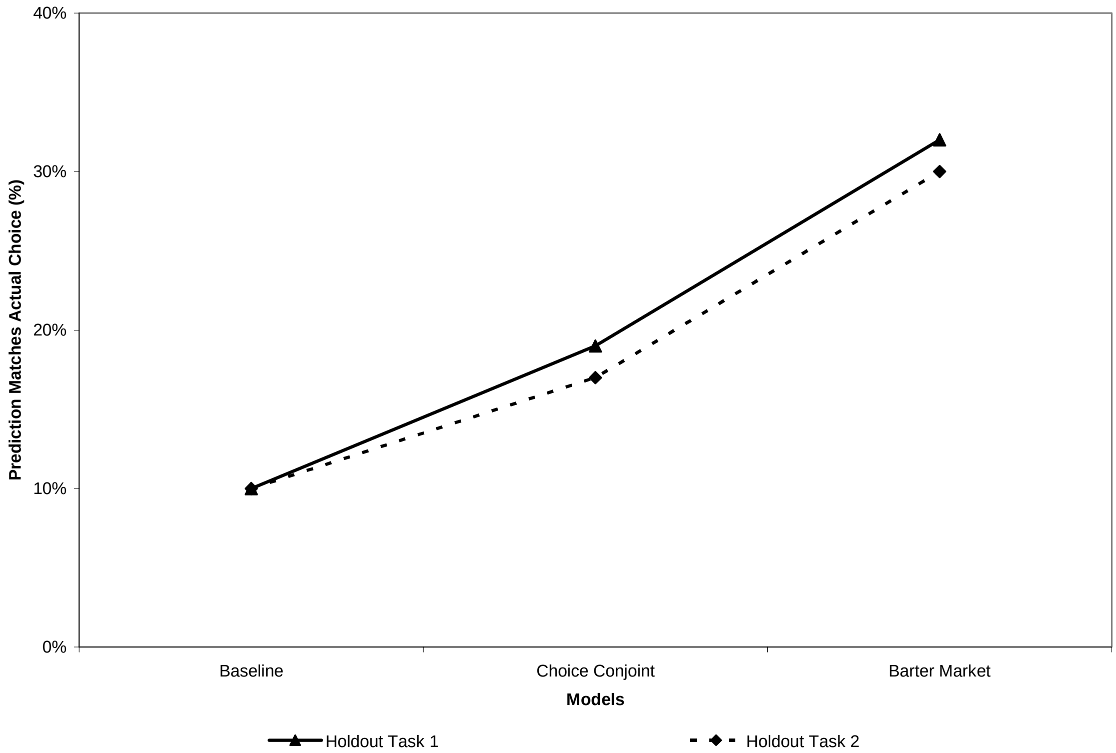


Figure 3: Predictive Performance for the External Validity Tasks



REFERENCES

Allenby, Greg M., Neeraj Arora, and James L. Ginter (1998), “On the Heterogeneity of Demand,” *Journal of Marketing Research*, 35 (3), 384-389.

Bradlow, Eric T., Ye Hu, and Teck-Hua Ho (2004), “A Learning-Based Model for Imputing Missing Levels in Partial Conjoint Profiles,” *Journal of Marketing Research,* 41 (4) 369-381.

Camerer, Colin F. (2005), “Three Cheers—Psychological, Theoretical, Empirical—for Loss Aversion,” *Journal of Marketing Research*, 42 (2), 129-33.

Carroll, J. Douglas and Paul E. Green (1995), “Psychometric Methods in Marketing Research: Part I, Conjoint Analysis,” *Journal of Marketing Research*, 32 (4), 385-391.

Cattin, Philippe and Dick R. Wittink (1982), “Commercial Use of Conjoint Analysis: A Survey,” *Journal of Marketing*, 46 (3), 44-53.

Ding, Min, Rajdeep Grewal, and John Liechty (2005), “Incentive Aligned Conjoint Analysis,” *Journal of Marketing Research*, 42 (1), 67-82.

Ding, Min (2007), “An Incentive Aligned Mechanism for Conjoint Analysis,” *Journal of Marketing Research*, 44(2), 214-223.

Gelman, Andrew and Donald B. Rubin (1992), “Inference from Iterative Simulation Using Multiple Sequences,” *Statistical Science*, 7 (4), 457-472.

Gilbride, Timothy J. and and Greg M. Allenby (2004), ”A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules,” *Marketing Science*, 23 (3), 391-406.

Godes, David and Dina Mayzlin (2004), “Using Online Conversations to Study Word-of-Mouth Communication,” *Marketing Science*, 23 (4), 545–560.

Green, Paul E. and Abba M. Krieger (1991), “Segmenting Markets with Conjoint Analysis,” *Journal of Marketing*, 55 (4), 20-31.

Green, Paul E. and Abba M. Krieger (1992), “An Application of Product Positioning Model to Pharmaceutical Products,” *Marketing Science*, 11 (2), 117-132.

Green, Paul E. and Vithala R. Rao (1971), “Conjoint Measurement for Quantifying Judgmental Data,” *Journal of Marketing Research,* 8 (3), 355-363.

Green, Paul E. and V. Srinivasan (1990), “Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice,” *Journal of Marketing*, 54 (4), 3-19.

Hauser, John R. and Vithala R. Rao (2004), "Conjoint Analysis, Related Modeling, and Applications" in *Advances in Marketing Research: Progress and Prospects*, Jerry Wind, ed. Kluwer Academic Publishers.

Johnson, Richard M. (1991), "Comment on "Adaptive Conjoint Analysis: Some Caveats and Suggestions," Journal of Marketing Research, 28 (2), 223–225.

Kahn, Barbara E. (1998), "Dynamic Relationships with Customers: High-Variety Strategies," *Journal of the Academy Marketing Science*, 26 (1), 45-53.

Kohli, Rajiv and Vijay Mahajan (1991), "A Reservation-Price Model for Optimal Pricing of Multiattribute Products in Conjoint Analysis," *Journal of Marketing Research*, 28 (3), 347-354.

Lehmann, Donald R. (1998), "Customer Reactions to Variety: Too Much of a Good Thing?," *Journal of the Academy Marketing Science*, 26 (1), 62-65.

Lenk, Peter J., Wayne S. DeSarbo, Paul E. Green, and Martin R. Young (1996), "Hierarchical Bayes Conjoint Analysis: Recovery of Partworth Heterogeneity from Reduced Experimental Designs," *Marketing Science*, 15 (2), 173-191.

Mahajan, Vijay, Paul E. Green, and S.M. Goldberg (1982), "A Conjoint Model for Measuring Self- and Cross-Price/Demand Relationships," *Journal of Marketing Research*, 19 (3), 334-342.

Rossi, Peter E. and Greg M. Allenby (2003), "Bayesian Statistics and Marketing," *Marketing Science*, 22 (3), 304-328.

Toubia, Olivier, Duncan Simester, John R. Hauser and Ely Dahan, (2003), "Fast Polyhedral Adaptive Conjoint Estimation," *Marketing Science*, 22 (3), 273–303.

Wittink, Dick R. and Philippe Cattin (1989), "Commercial Use of Conjoint Analysis: An Update," *Journal of Marketing*, 53 (3), 91-96.

Wittink, Dick R., Marco Vriens, and Wim Burhenne (1994), "Commercial Use of Conjoint Analysis in Europe: Results and Critical Reflections," *International Journal of Research in Marketing*, 11 (1), 41-52.

Wittink, Dick R., Lakshman Krishnamurthi, and David J. Reibstein (1990), "The Effect of Differences in the Number of Attribute Levels on Conjoint Results", *Marketing Letters*, Volume 1, Number 2, 113-123.