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Barter Markets for Conjoint Analysis

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We propose a new alternative preference measurement method, barter conjoint, to contrast with traditional choice-based conjoint (CBC) approaches. Barter conjoint collects a substantially larger amount of data compared to CBC and allows for information diffusion among respondents. We conducted two empirical studies that compare CBC (with and without incentive alignment) and barter conjoint. The studies employed a total of three product categories, each with two validation tasks (one follows immediately and one conducted two weeks later). Our results confirmed prior research that incentive alignment, in general, substantially improves out-of-sample predictive performance of CBC. Furthermore, we found barter conjoint performs substantially better than the incentive-aligned CBC. However, in the spirit of "no free lunch," barter conjoint is more taxing (in various ways) than CBC, suggesting a potential trade-off between consumer resource allocation (at the time of the task) and (managerial) predictive accuracy downstream. Given that this is the first study on barter conjoint, we discuss various limitations of the current implementation and fruitful directions for future research.

Key words: marketing; new products; design of experiments; utility preference; conjoint analysis; mechanism design
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Introduction

Conjoint analysis is a rigorous methodology designed to uncover individuals' 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 et al. 1982), and segmentation and positioning (e.g., Green and Krieger 1991, 1992) to name just a few. 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 et al. 2004, Cattin and Wittink 1982, Wittink and Cattin 1989, Wittink et al. 1994).

Since its introduction to marketing (Green and Rao 1971), researchers have focused on two areas to improve the external validity of conjoint analysis, namely, data collection formats (such as adaptive conjoint designs, Johnson 1991, Toubia et al. 2003, and incentive-aligned data collection, Ding et al. 2005, Ding 2007) and estimation methods (Hauser and Rao 2004, Lenk et al. 1996, Liechty et al. 2005). 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, p. 148).

One promising direction for obtaining better data is to simply collect more data from each individual. This is an old idea that has been largely discarded by researchers and practitioners in the past due to participants' tendency to "wear-out." The consensus has been that it is hard to get participants motivated once they have responded to a certain number of questions. The recent developments in incentive-aligned conjoint analysis (Ding et al. 2005, Ding 2007), however, open the door to reexamine this direction. Although participants in conventional (hypothetical) conjoint have a fixed payoff regardless of how they respond, the welfare (utilities) of participants in incentive-aligned conjoint depends on whether they truthfully respond (with effort) to every question. As a result, we hypothesize that the ceiling of fatigue under incentive-aligned conjoint will be much higher than that under conventional conjoint, and it is thus worthy of conjoint researchers to reexamine this direction for improving data quality.

Another promising direction for obtaining better data is to improve the quality of the data, as is best illustrated by a quote from Hauser and Rao (2004, p. 159), "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."

Following these two directions, we propose a new alternative preference measurement method, *barter conjoint*. Relative to the state-of-the-art choice-based conjoint (CBC), barter conjoint collects a substantially larger amount of data from each individual and allows for the diffusion of information among participants in a very natural (but admittedly not yet observed in the market) way.

To test the benefits of barter conjoint, we conducted two random assignment between-subjects contrast experiments where we compared CBC and barter conjoint. To test the generalizability of the potential insights, the two studies include a total of three tasks (beach vacation, cruise ship trip, and camcorder), each with two validation tasks (one follows immediately and one conducted two weeks later). We found that barter conjoint performs substantially better than incentive-aligned CBC in out-of-sample prediction, providing the first empirical research support for its superiority, compared to the de facto standard CBC. Our results also confirmed prior research (Ding et al. 2005, Ding 2007) that incentive alignment substantially improves out-of-sample predictive performance for CBC. This provides further evidence that conjoint analysis should ideally be implemented with incentive alignment.

We organize the rest of this paper as follows. First, we propose a lab-based market, barter conjoint, to measure consumer preferences via a realistic market environment tool. We then present two experiments in which we implement CBC and barter conjoint, followed by a summary of our analyses and results. Finally, we discuss general findings, limitations, and future research opportunities.

Barter Conjoint Design

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

General Design

Barter is an exchange system that has existed from the beginning of civilization, and organized barter was originated in the 1950s in the United States (Cresti 2005). Recent estimates indicate that 8 out of 10 corporations engage in some type of barters (American Association of Advertising Agencies 2003) and, in North America alone, about a half-million firms and businesses barter (*BarterNews* 2003). The extant literature studies barter as a mechanism for liquidity, i.e., a way to facilitate trade under adverse conditions (Hammond 1990, Verzariu 2000). Both the theoretical and empirical literature has focused on describing various barter markets and explaining the existence of such practice (Cresti 2005). To the best of our knowledge, however, there has not been any work on designing barter markets to be used in an experimental setting. The barter conjoint proposed here thus follows the basic definition of barter markets and is novel in its application to preference measurement; however, we do not make claims of efficiency in our design choices.

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

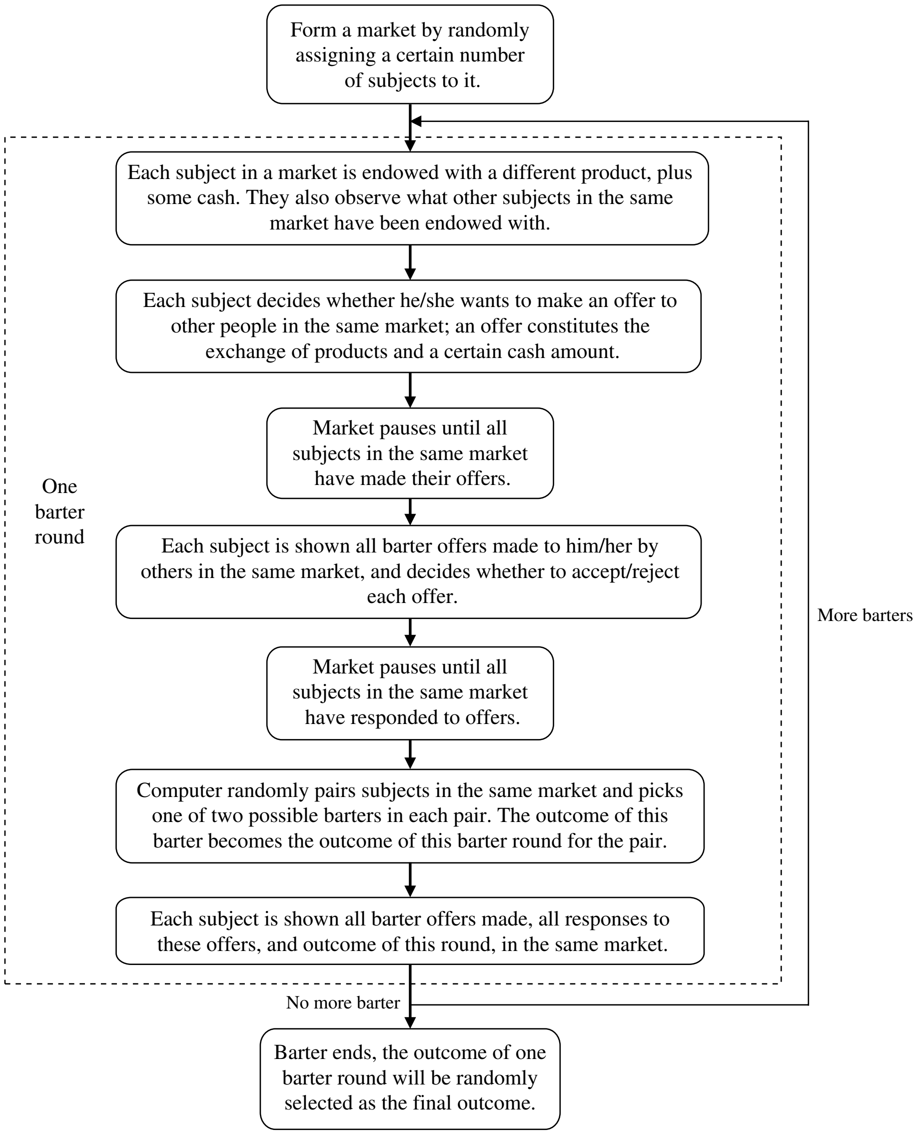
We depict the barter market design graphically in Figure 1, and key terms are defined in Table 1. The specific process is as follows:

Step 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. The following describes one such market (Steps 2–8 are defined as one *round*).

Step 2. Each participant in the same market will be endowed with a different product profile, plus a certain amount of cash (e.g., a constant amount in every round and it does not carry over from round to round). Every participant observes all product profiles endowed to the other participants in the same market; all interactions among the participants in the same market are conducted over Internet-connected computers and they do not communicate with each other directly.

Step 3. Each participant compares her endowed product profile with those endowed to others, and determines whether she prefers a product currently owned by another participant to her product profile. 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); a participant can make such offers simultaneously to every other participant if so desired,

Figure 1 The Barter Conjoint



and each offer can include an amount of cash no larger than the total of their endowed money; the endowed money will not be carried over from round to round.[1]

Step 4. The market pauses until all participants in the same market have completed making offers (or decided not to make any offers).

Step 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, if any.

Step 6. The market pauses further until all participants in the same market have completed responding to offers.

Step 7. The computer interface randomly pairs two participants in the same market (say, A and B), and then randomly picks one possible barter ($A \rightarrow B$ or $B \rightarrow A$) to determine the outcome for the pair. This is done for everybody in the barter market. If no offer is made, or an offer is made but rejected (Steps 4 and 5) in this randomly picked possible barter, both persons keep their endowed products and cash. On the other hand, if an offer is made and accepted, they will exchange products, and their cash balance will be adjusted based on the cash amount stated in the offer.

Step 8. Each participant is shown the complete round information (offers made, responses to offers, and final product) for everybody in the same market.

Step 9. Steps 2–8 (this is defined as one *round*) are repeated with a new set of product profiles (that are different from previous sets) for this market until all rounds have been completed.

Step 10. Finally, the computer will randomly pick a round, and the product and cash a participant owns at

[1] The basic idea has parallels with the Pessemier et al. (1971) dollar metric graded paired-preference data. We thank the associate editor for pointing this out.

Table 1 Barter Conjoint Terms

Term	Definition	Implementations in the empirical studies
Barter	An exchange mechanism where two individuals exchange their current possessions, plus an additional amount of cash from one person to the other to facilitate the exchange	Two participants exchange the endowed beach vacation package (or Bahamas cruise or camcorders) with each other, potentially with a cash amount paid from one to the other
Market	A self-contained barter environment where people in the same environment can barter with each other, but not with people in other environments	Same
Number of individuals	Number of people in the same barter market	Four individuals
Round	A complete barter process from start to end, it may involve multiple iterations of exchanges	One iteration is allowed in each round
Number of rounds	Number of such complete barter processes to be used in a specific barter conjoint	18 rounds for Ocean City, Maryland, 12 rounds for Bahamas cruise, and 9 rounds for camcorders
Set of products	Contains the products that will be endowed to the individuals during a round in a barter market	Four profiles in each set
Offer	A binding proposal from one individual in the market to another individual in the same market to exchange the products, usually including the promise of paying an additional amount of cash if the other individual agrees to the exchange	Same
Evaluation	The decision whether to accept or reject an offer made to oneself	Same
Public information	Information of the individuals in the same barter market that are available to everybody else in the same market	Offers made, evaluations of offers received, current product owned, personal knowledge about the product category (e.g., technology products) and the focal product (e.g., camcorder)

the end of that round (based on Step 7) will be given to the participant (participants know this; hence, they are incentive aligned).

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 studies in this paper due to the realistic but expensive nature of the products).

Several parameters of the barter market design should be determined by researchers/practitioners 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 conjoint could be structured as either 18 rounds with four individuals in each market, or 12 rounds with six individuals in each market (as examples). On the one hand, the bigger the market (more individuals), the greater the potential there 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 pairing 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 its endowed profile and cash at a given round).

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

General Properties

The barter conjoint has some unique advantages that are worth noting. First, it allows information diffusion amongst the participants in the same market. Each individual observes barter offers made by others, as well as the responses to these offers. Such information could convey how valuable other individuals perceive the various features in the product to be, even though they are not stated in an attribute-specific manner as in real life word-of-mouth information (Godes and Mayzlin 2004). Because the profiles (characteristics) of individuals in the same market are public information, a person can weigh each person's valuation differently based on their profiles (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 K options, as in a standard pick 1 out of K conjoint, where it is assumed that the respondent picks the alternative with the highest utility, a barter market provides information on up to $2 \times (K-1)$ observations from an individual ($K-1$ offers made and not made to others, and $K-1$ responses to offers made to him or her).[3] Thus, barter conjoint generates two types of data that can be used for preference measurement. The first type is the offers *submitted* (or not 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 offers received; pairwise comparisons can be made from this information as well. Furthermore, pairwise comparisons can be *inferred* across the offers made, across the offers made and not made, and across the offers received, which will be discussed later.

Third, because participants can specify an additional amount of money for each offer 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. One might call this feature a *participant-controlled adaptive design*, because the new profiles (offers, 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 conjoint.

Fourth, 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 (which we assess along with other features in our empirical application provided next).

Empirical Applications

To validate barter conjoint as a practical tool, it is important to demonstrate empirically that it can outperform the de facto state-of-the-art CBC in out-of-sample prediction. We describe below two empirical studies designed to serve this purpose. There are only two differences between the two studies, and we will thus discuss them together to avoid repetition. The first difference is product category used: Study 1 used one product category, a weekend trip to Ocean City, Maryland (beach); and Study 2 used two product categories (Bahamas cruise and camcorder). The second difference is experimental conditions employed: In Study 1, we conducted a random assignment between-subjects contrast experiment where we compared two conditions, hypothetical CBC and barter conjoint. In Study 2, we had incentive-aligned CBC in addition to the two conditions used in Study 1.

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

Experimental Contexts

To potentially provide empirical generalizations within our limited resources, we decided to validate the method in diverse contexts. We used the following criteria to select the product/service for our experiments: (1) the potential study subjects (university students) should be a target segment of the product/service; (2) the potential study subjects must be interested in purchasing such a product/service at the right price (and the market is not saturated); and (3) this should be a category where a subject can potentially benefit from other people's opinions about what features should be purchased and at what price.

The first two criteria are essential for any realistic study, whereas the third criterion is used to allow us to better showcase any potential benefits of barter conjoint. We used one-on-one interviews, open-ended surveys, and follow-up interviews of potential participants to select the product categories. To ensure that we used the appropriate features (conjoint attributes) in the study and to avoid subjectivity, we decided to use features that are currently being used by real established merchants in their respective categories if possible, and that were vetted by individuals from the target participant pool.

To determine the appropriate attributes and levels for the beach vacation packages in Study 1, we conducted extensive Web research and two focus groups. As a result of these qualitative studies, our beach 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, Castaway's, Phillips Crab House, and 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, and 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 CBC study; remember the barter conjoint 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 that subjects utilized the product overviews, alleviated our major concerns about this specific product's use.

To determine the appropriate attributes and levels for a cruise trip to the Bahamas in Study 2, we copied the design of Carnival Cruise Line's 4-day Bahamas cruise as of February 2008. Two attributes are related to the room on the cruise ship: view (ocean or interior) and deck (1 to 4). One attribute is about the time of the trip to be taken (April, April to May, April to June). An additional three attributes are the activities that they can do at port calls in the Bahamas: the first is activities at Freeport (island tour, snorkel, kayak, beach party), the second is guided tours at Nassau (Ardastra Gardens and City, Atlantis and Harbor, glass-bottom boat, and historical highlights), and the third is wet activities at Nassau (beach snorkeling, catamaran snorkel, stingray adventure, and two-tank dive). All features here are selected from those offered by Carnival Cruise Lines for this trip. Finally, we also included four levels of price ($629, $679, $729, and $779) to be used for CBC that are consistent with the prices at Carnival Cruise for this trip with different activities.

To determine the appropriate attributes and levels for a camcorder in Study 2, we adopted the key features suggested by the "Camcorder Advisor" at Sony's website, designed to facilitate the purchasing decision for camcorder buyers. As a result, we included storage format (MiniDV, DVD, and hard-drive), LCD screen size (2.4 inch and 3.2 inch), optical zoom (10×, 20×, and 40×), camera resolution (1 Mp and 3 Mp), and low-light sensitivity (1 Lux, 3 Lux, and 6 Lux). Finally, we added three levels of price ($399, $469, and $539) that are consistent with the price range of these camcorders.

To ensure the objectivity and external validity of the study, we used SAS experimental design macros to determine the number of and the actual profiles of the various beach trips, cruises, and camcorder profiles for the two studies. Given the number of attributes and their corresponding levels, a 72-profile design, a 48-profile design, and a 36-profile design are deemed to be 100% *D*-efficient for the Ocean City, Maryland trip, Bahamas cruise, and camcorder, respectively. We therefore generated 72 different profiles for the trip to Ocean City, Maryland and divided them into 18 sets with four profiles in each set. Similarly, we generated 12 sets of four profiles for the Bahamas cruise, and 9 sets of four profiles for camcorders.

Experimental Conditions

One main objective of the empirical application is to contrast the performance of barter conjoint with CBC. In Study 1, we implemented two conditions, a conventional (hypothetical) CBC and barter conjoint, in the context of a beach trip to Ocean City, Maryland. Given the recent literature that has shown incentive-aligned CBC has performance superior to conventional (hypothetical) CBC, we added a third condition (incentive-aligned CBC) in Study 2.[4]

Participants in the hypothetical CBC and (in Study 2) incentive-aligned CBC complete the same tasks; the only difference is how they are paid. We describe below the CBC conditions in Study 2; the CBC condition in Study 1 is identical to the hypothetical CBC in Study 2 except the context is a beach trip to Ocean City, Maryland. For both conditions in Study 2, they first complete the CBC for the Bahamas cruise (with 12 four-tuples of trips as described earlier), followed by a holdout task for the Bahamas cruise (where a participant selects his or her most-preferred vacation package from a list of 10 different trips), and then complete the corresponding CBC (9 four-tuples) and a holdout task for camcorders (select 1 from 10 different camcorders), and finally a brief survey.

The implementation of barter conjoint are identical in the two studies; again, we will only describe the process in Study 2 here (given it has two product categories). Participants assigned to the barter conjoint condition participated in a barter market instead of CBC for the Bahamas cruise and camcorder (the specific profiles in a barter round are the same as the profiles used in the corresponding CBC), but the two holdout tasks are identical to that in the two CBC conditions. All participants also completed two "delayed" holdout tasks, one for the Bahamas cruise and one for the camcorder (two weeks after the lab study), from any computer with an Internet connection to provide a "clean" longer-term (strong validation) assessment. Each task contains 10 different product profiles than those used in the holdout tasks that they completed in the lab. The instructions for the barter conjoint closely followed the theoretical design described earlier. Participants' self-stated knowledge about the product category and focal product (Ocean City, Maryland, tropical vacation destination and the Bahamas, and electronic products and camcorders), collected in the very beginning of each study, are public information and are available to everybody in the same barter market. In particular, during each round of the barter for the Ocean City, Maryland trip (Bahamas cruise, or camcorders), a subject was endowed with a specific Ocean City, Maryland trip (Bahamas Cruise, or camcorder), plus $300 cash that can be used for barter purposes.[5]

[4] In Study 2, the participants assigned to both CBC conditions, after identifying the most-preferred profile from each choice set, were also asked to further identify the second and third most-preferred profile in each set. These data were not used in this paper.

[5] The cash amount of $300 is chosen because it is substantially higher than the ranges of price differences used in the CBC conditions in all three contexts. This alleviates potential ceiling effects of the barter offers.

Incentive Alignment

Every subject was paid $8 for participation in Study 1 (and $15 in Study 2 due to the longer duration), and had the potential to "win" a prize. The prize in Study 1 consisted of a specific Ocean City, Maryland trip, and a certain amount of cash that was determined by the trip in the prize. In Study 2, the prize consisted of a specific Bahamas cruise, a specific camcorder, and a certain amount of cash that was determined by the Bahamas cruise and camcorder in the prize. In each study, participants were told that one such prize would be awarded to one participant who is randomly selected from the entire pool of participants.

For participants in the hypothetical CBC condition, participants in Study 2 were told that, if chosen as a winner, they would be given the specific Bahamas cruise that they selected in one of the two *holdout tasks* (randomly picking one), and similarly for camcorder, plus the difference between $1,500 and the prices associated with these specific Bahamas cruise and camcorder choices. In Study 1, the same process is followed except it is a trip to Ocean City, Maryland, and the total cash is $900 instead of $1,500.

For participants in the incentive-aligned CBC condition in Study 2, they were told that, if chosen as a winner, first a coin will be flipped to decide whether their responses in CBC *or* the holdout tasks will be used. If CBC is selected, 1 question from their 12 questions will randomly be picked for the Bahamas cruise and 1 question from their 9 questions for the camcorders. They would then receive the option that they stated as most preferred. If the coin flip selects the holdout tasks, the prize will be determined based on the same rules described above for hypothetical CBC. In this manner, the participants are incentive aligned throughout the entire task, as opposed to the hypothetical condition where it is for the holdout task only.

For participants in the barter conjoint condition in both studies, subjects are told that first a coin will be flipped to decide whether their responses in barter conjoint or the holdout tasks will be used. If barter task is chosen in Study 2, 1 of the 12 rounds of the Bahamas cruise barter will be randomly selected, and the subject will receive whatever package he or she has at the end of that barter round, similarly for camcorder, plus the sum of the cash balances from these two rounds. The same process is used in Study 1 to determine the actual Ocean City, Maryland trip and the cash balance. If the holdout task is chosen, the prize will be determined based on the same rules described above for hypothetical CBC. The incentive alignment mechanism for the incentive-aligned CBC and barter are theoretically identical to that used in Ding et al. (2005).

Web Implementation

Both studies were implemented through a Web interface, with the codes (in PHP, available from the authors upon request) and data (in MySQL) stored on a remote server (on Linux). With this implementation, these studies can be conducted on any computer that has an Internet connection. This Web-based implementation is required for barter conjoint, because it involves dynamic updating of the study based on other participants' responses in previous rounds.

Experimental Procedure

In Study 1, 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 CBC condition, and 56 to the barter conjoint condition. All subjects completed the CBC (barter), first holdout task, and survey in the lab. They were then told that they would receive an e-mail in two 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 but six subjects (three 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.

In Study 2, a total of 169 students (different from those participated in Study 1) at the same U.S. university participated in the study in a campus computer lab; 53 of them were randomly assigned into the hypothetical CBC condition, 56 to incentive-aligned CBC, and 60 to the barter conjoint condition. All subjects completed CBC (barter) and the first holdout task for the Bahamas cruise, followed by the same tasks for the camcorder, and finally, a short survey. Two weeks later, they received an e-mail that contained a link to the second holdout tasks for the Bahamas cruise and camcorder. They must complete the second holdout tasks in order to qualify for the prize. All but four subjects (three in hypothetical CBC and one in incentive-aligned CBC) completed the second holdout tasks. One winner was randomly selected upon the completion of the second holdout task and rewarded (a Bahamas cruise and a camcorder) based on the aforementioned rules and his choices made during the study.

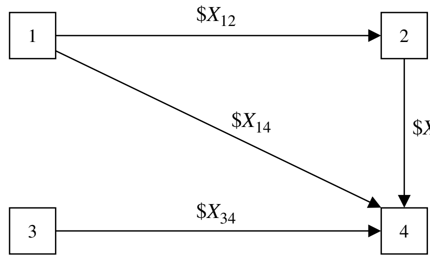
Data and Estimation Method

Given the unique nature of barter conjoint, we first discuss how the barter data are converted to a format that is amenable for statistical analysis. We then describe the estimation procedure used for analyzing both CBC and barter conjoint data.

Data Conversion

To aid readability, we describe the following simplified barter market to illustrate the types of data

Figure 2 **Information Drawn from the Barter Conjoint**



that can be distilled from barter conjoint, followed by the actual number of such data points inferred in Study 2. Figure 2 includes four subjects (1, 2, 3, and 4), and each subject's corresponding profile number (e.g., subject 1 receives profile 1, subject 2 receives profile 2, etc). In this example, subject 1 submitted two offers: 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 an offer to subject 4 with a cash premium $\$X_{24}$, and subject 3 submitted an offer to subject 4 with a cash premium $\$X_{34}$. Subject 4 did not make offers to any participant in this barter market.

The relative preference between two profiles in a barter market can be formally defined as follows. For offers made, 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 for $\$X_{12}$, subject 1's utility from holding profile 1 with $\$X_{12}$ is less than its utility from holding profile 2, and furthermore we can utilize the cash amount offered as an attribute of that comparison. In Study 2, there were a total of 1,025 (664) offers made across 12 (9) barter market rounds for the Bahamas cruise (camcorder). For offers not made, a pairwise comparison between the two parties *not* in a potential exchange reveals the relative preferences. For example, subject 1 did *not* submit an offer to subject 3, which implies that subject 1's utility of holding profile 1 is greater than or equal to its utility of holding profile 3 (at any possible cash exchange value). Otherwise, subject 1 would have submitted an offer to subject 3. This inference about the offers not made in Study 2 yields 1,135 (956) observations for the Bahamas cruise (camcorder) (note that the total number of potential exchanges in our barter market is 2,160 (1,620) for the Bahamas cruise (camcorder), 60 subjects times 12 (9) barter rounds times 3 potential exchanges per barter round). Note that our approach does not impose any structural assumptions on the behavior of participants (which can be viewed as both positive and negative, but at least an area for future research) in the barter market, yet is consistent with utility maximization of choices.

For offers received, each subject decides whether the offer is acceptable. For example, subject 4 received three offers: 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 offers received, subject 4 compares the utility of each offer with its utility of holding its own profile (plus the associated cash). Identical to the submitted offers, we obtained 1,025 and 664 observations for the Bahamas cruise and camcorders, respectively, in Study 2.

In addition, pairwise comparisons can be *inferred* across the offers made, across the offers made and not made, and across the offers received. In particular, a pairwise comparison between offers made provides their relative preference. For example, as subject 1 submitted two offers (one to subject 2 for $\$X_{12}$ and the other to subject 4 for $\$X_{14}$), subject 1's utility from holding profile 2 can be compared with its utility from holding profile 4 based on the cash premiums of $\$X_{12}$ and $\$X_{14}$. If $\$X_{12}$ is greater than $\$X_{14}$, subject 1 prefers profile 2 to profile 4 because subject 1 is willing to pay more for profile 2 than profile 4. In a similar vein, pairwise comparisons between offers made and offers not made provide their relative preference. For example, because subject 1 submitted two offers (one to subject 2 for $\$X_{12}$ and the other to subject 4 for $\$X_{14}$) but not to subject 3, subject 1's utility from holding profile 2 (4) can be compared with its utility from holding profile 3. Subject 1 prefers profile 2 (4) to profile 3 because subject 1 is willing to pay a cash premium of $\$X_{12}$ ($\$X_{14}$) to profile 2 (4), but no cash premium for profile 3. Finally, a pairwise comparison between offers received also provides the relative preference from the perspective of a seller who compares offers received. These three different types of inferences (across offers made, across offers made and not made, and across offers received) yielded 599, 852, and 274 (356, 616, and 135), respectively, additional observations for the Bahamas cruise (camcorder) in Study 2. The data in Study 1 with a beach trip to Ocean City, Maryland is as follows: (1) offers made (1,697), (2) offers not made (1,327), (3) offers received (1,697), (4) across the offers made (1,072), (5) across the offers made and not made (1,250), and (6) across the offers received (468).

Estimation Procedure

To provide the most relevant apples-to-apples comparison among various preference measurement methods, we used recently developed models and estimation methods to assess individual subjects' preferences and derive out-of-sample predictions. We use a random-effects hierarchical Bayesian multinomial logit model, similar to the model specified by Allenby et al. (1998), Ding et al. (2005), and Park et al. (2008). Specifically, the probability that the *i*th subject chooses the kth alternative from the jth choice set[6] is given by

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

where x_{ij}^k describes the kth alternative evaluated by the ith subject from the jth choice set, and β_i is a vector of partworths for the ith subject. We assume a hierarchical shrinkage specification for the individual partworths, where a priori $\beta_i \sim N(\bar{\beta}, \Lambda)$.

This specification allows for individual-level partworth estimates β_i, but still permits estimation of the aggregate or average partworth $\bar{\beta}$, as well as of the amount of heterogeneity for each partworth via Λ. In line with the literature (Ding et al. 2005), we use a simplified version of the model and assume that Λ is a diagonal matrix.[7] Furthermore, we assume diffuse conjugate priors for $\bar{\beta}$ 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 noninformativeness 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

In this section, we first present the parameter estimates from different conditions in the two studies, followed by the comparisons of predictive performance between barter conjoint and benchmark CBC (hypothetical or incentive-aligned). 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. Finally, we address the issue of robustness and cost of barter conjoint by studying two subsets of barter data, one subset equated with CBC on the data amount and the other equated with CBC in the amount of time participants spent.

[6] The choice set of an individual contains each four-tuple under CBC. In barter conjoint, a pairwise comparison is used between the two products (plus cash involved) in a potential exchange, e.g., offers made and not made, offers received, across the offers made, across the offers made and not made, and across the offers received.

[7] In line with the literature (Ding et al. 2005), we did not find substantial difference in predictive performance between the two models (with a diagonal and nondiagonal matrix). We report the results with a diagonal matrix, which led to slightly better out-of-sample predictive performance.

Parameter Estimates

We include the parameter estimates for the Ocean City, Maryland trip (Study 1), Bahamas cruise, and camcorders (Study 2) in Tables 2, 3, and 4, respectively. To align our results from barter conjoint (which uses dollars offered on a continuous scale) with CBC, 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 in conjoint methods.[8]

Our first observation regarding the model results relates to the number of significant parameters across conditions (methods) and product categories, in both studies. The high number of statistically significant parameter estimates indicates a needed level of discrimination amongst the attribute levels (i.e., subjects do not perceive the products as identical). 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.

Although the features significant under one method are often significant under other methods, the magnitude of parameter estimates of many features are quite different. 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.

Predictive Performances

We now examine the predictive performance of barter conjoint, relative to CBC, for the two holdout tasks (one on the same day and the other after two weeks) for the Ocean City, Maryland beach trip (Study 1), Bahamas cruise, and camcorders (Study 2). In Table 5, we provide the out-of-sample predictions; the baseline of 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 methods.

In Study 1, the barter conjoint leads to significantly better predictive performance: the percent of matches between the actual choice and the top predicted option are 33% for the first holdout task (the same day) and 31% for the second holdout task (two weeks later) under the barter market, versus 19% and 17% under the CBC, respectively. This improvement in prediction over the hypothetical CBC is significant at the 1% level in both cases.

Given the recent literature that has documented the superior performance of incentive-aligned conjoint, Study 2 included an incentive-aligned CBC, in

[8] We tried both (actual prices and dummy variables) for price in estimation, but did not find any meaningful difference.

Table 2 Parameter Estimates for Ocean City Beach

	Hypothetical CBC		Barter conjoint	
	Post. mean	Heterogeneity	Post. mean	Heterogeneity
Hotel				
Beach Walk Hotel: Base	0.00	—	0.00	—
Carousel Resorts	**0.21**	0.22	**0.11**	0.24
Castle in the Sand	**0.24**	0.41	**0.28**	1.26
Lighthouse Club hotel	0.04	0.13	**0.15**	0.22
Park Place Hotel	**0.29**	0.16	**0.39**	1.18
Princess Bayside Beach Hotel	**0.16**	0.38	0.06	1.20
Restaurant				
Bonfire Restaurant: Base	0.00	—	0.00	—
Castaways	**0.25**	0.34	−**0.12**	1.43
Philips Crab House	−0.05	0.72	−**0.20**	2.16
Seacrets Bar and Grille	0.15	0.90	−0.09	1.19
Temperature				
88 °F	0.02	1.20	0.06	1.82
81 °F	**0.13**	0.31	**0.19**	1.43
74 °F: Base	0.00	—	0.00	—
Entertainment				
Baja Amusements: Base	0.00	—	0.00	—
Carousel Ice Skating Rink	0.03	0.44	0.02	1.34
Garvin's Comedy Club	**0.31**	0.57	**0.25**	1.41
H2O Dance Club	**0.38**	0.22	**0.27**	1.87
Jolly Roger Amusement Park	**0.21**	0.25	**0.20**	0.32
Planet Maze and Laser Storm	**0.35**	0.23	**0.28**	0.41
Visitor type				
High school grads	−0.04	0.40	−0.12	0.78
College students	−0.03	0.25	**0.10**	0.32
Young professionals: Base	0.00	—	0.00	—
Price or cash ($)/100	−0.12	0.21	−**0.62**	0.79

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

addition to the two conditions in Study 1, so we could verify whether barter conjoint can offer additional benefits over this recent advance in conjoint research. In all four cases (two holdout tasks (immediate and delayed) times two contexts (Bahamas cruise and camcorder)) in Study 2, we found that barter conjoint predicts significantly better than the incentive-aligned CBC. The improvement in prediction over the incentive-aligned CBC is significant at the 1% level in all four cases. 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, but rather one of sufficient magnitude likely to be of managerial relevance.

We also compared the predictive performance of incentive-aligned CBC against hypothetical CBC in Study 2. We found that the incentive-aligned method outperforms the corresponding hypothetical method in three cases (all differences are significant at the 1% level), and is identical in the other one (delayed holdout task for camcorders). These results confirm the evidence in extant literature that incentive-aligned CBC is superior compared to conventional hypothetical CBC.

Robustness of Predictive Performance: Data Equating and Time Equating

The results in both studies demonstrated the superior performance of barter conjoint, relative to both conventional (hypothetical) CBC and incentive-aligned CBC. Given that this is the first barter conjoint studied in the literature, it will be helpful to test the robustness of the improved predictive performance. The approach we took is to test the performance of two subsets of barter conjoint data.[9]

The first subset of barter data was constructed to exactly mirror the CBC design and has exactly the same number of *observations*. To do this, we infer each participant's most-preferred profile in a barter round as the profile she made the highest offer to, or the profile she was assigned to if no offer was made. This subset of barter data, consisting of participants' most preferred profiles in each round, are identical to CBC data, both in terms of the information evaluated in

[9] We thank the review team for making this suggestion.

Table 3 Parameter Estimates for Bahamas Cruise

	Hypothetical CBC		Incentive-aligned CBC		Barter conjoint	
	Post. mean	Heterogeneity	Post. mean	Heterogeneity	Post. mean	Heterogeneity
Room view						
Interior: Base	0.00	—	0.00	—	0.00	—
Ocean view	**1.64**	1.47	**1.37**	1.02	**1.23**	1.03
Deck						
Deck 1: Base	0.00	—	0.00	—	0.00	—
Deck 2	0.02	0.18	0.22	0.19	0.09	0.47
Deck 3	0.20	0.12	0.32	0.12	**0.36**	0.14
Deck 4	**0.43**	0.13	0.34	0.17	**0.39**	0.56
Time of travel						
April: Base	0.00	—	0.00	—	0.00	—
April or May	**1.12**	0.57	**2.11**	0.87	**1.36**	1.33
April, May, or June	**1.57**	1.33	**3.19**	1.64	**2.00**	1.50
Freeport						
Island tour: Base	0.00	—	0.00	—	0.00	—
Snorkel tour	0.24	0.19	0.30	0.16	0.02	0.57
Kayak and nature	0.41	0.81	0.06	1.66	0.24	0.91
Junkanoo Beach	**0.58**	1.44	0.35	1.33	0.06	1.11
Nassau (morning)						
Ardastra and city: Base	0.00	—	0.00	—	0.00	—
Atlantis and harbor	0.18	1.18	**0.70**	0.92	**0.79**	0.96
Glass-bottom boat	−0.34	0.31	**0.45**	0.17	−0.17	1.07
Historical highlights	−**0.93**	0.16	−**0.52**	0.42	−**0.47**	0.86
Nassau (afternoon)						
Treasure snorkeling: Base	0.00	—	0.00	—	0.00	—
Catamaran snorkel	−0.01	0.24	0.16	0.36	0.07	0.76
Stingray and beach	**2.30**	0.99	**4.33**	0.51	**1.89**	0.14
Two-tank dive	−**2.94**	0.14	−**4.81**	0.38	−**1.98**	0.96
Price or cash ($)/100	−**0.31**	0.57	−**0.64**	0.91	−**0.42**	0.14

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

each task (choice set or barter round) and the number of data points. We call this data-equated barter conjoint. Because barter conjoint is incentive-aligned, we expect that this data-equated subset will perform as well as the incentive-aligned CBC, and better than the hypothetical CBC.

The second subset of barter data was constructed such that the average time it took for participants to provide this subset of data is the same as the time it took for CBC participants to complete their task.[10] We call this time-equated barter conjoint. Clearly, there are many ways to select a time-equated subset; we selected one-third of the rounds in each experiment and included all types of pairwise comparisons. Because this subset contains more data than the first subset, we would expect that this time-equated subset will perform somewhat better than the incentive-aligned CBC, and certainly better than the hypothetical CBC. However, it is a fair comparison because it does equalize for time.

The predictive performances of these two types of subsets for the three product categories are included in Table 5. We focus our discussion on Study 2 because it has both incentive and hypothetical CBC conditions. As expected, the data-equated subset performs very similarly to the incentive-aligned CBC, and like incentive-aligned CBC, they are significantly better than hypothetical CBC in three cases and identical in the remaining one. Furthermore, the time-equated subset performs better than the incentive-aligned CBC, significantly better in two cases and identical in the remaining two cases. This pattern was observed in Study 1 as well, where both data-equated and time-equated subsets outperform the hypothetical CBC.

The fact that the data-equated barter subset performs identically to incentive-aligned CBC should be interpreted that the barter data has *at least* the same "quality" as the incentive-aligned CBC. The reason is that this subset of data are inferred from barter offers with added assumptions (see above), whereas the incentive-aligned CBC are directly stated by participants. The results from our time-equated barter subset show that the improvement in barter conjoint

[10] On average, the CBC (time-equated barter) took 428 (437) seconds in a beach trip to Ocean City, Maryland in Study 1, 247 (233) seconds in Bahamas cruise, and 113 (117) seconds in camcorder in Study 2.

Table 4 Parameter Estimates for Camcorder

	Hypothetical CBC		Incentive-aligned CBC		Barter conjoint	
	Post. mean	Heterogeneity	Post. mean	Heterogeneity	Post. mean	Heterogeneity
Format						
Mini DV: Base	0.00	—	0.00	—	0.00	—
DVD	**1.23**	2.25	**0.89**	2.03	**0.55**	0.90
Hard drive	0.86	3.59	0.49	1.92	**1.09**	1.63
LCD screen						
2.4 inch: Base	0.00	—	0.00	—	0.00	—
3.2 inch	**0.60**	0.64	**0.70**	0.46	**0.65**	0.84
Optical zoom						
10×: Base	0.00	—	0.00	—	0.00	—
20×	**1.15**	0.17	**0.94**	0.13	**0.97**	0.32
40×	**1.84**	0.66	**1.36**	0.76	**1.66**	0.92
Camera resolution						
1 MP: Base	0.00	—	0.00	—	0.00	—
3 MP	**1.82**	1.02	**1.46**	1.23	**1.12**	1.05
Low light						
1 Lux: Base	0.00	—	0.00	—	0.00	—
3 Lux	0.16	0.66	**0.49**	0.12	−0.12	0.79
6 Lux	0.06	0.60	0.20	0.48	−0.40	1.48
Price or cash ($)/100	−**0.69**	2.47	−**1.20**	2.03	−**0.58**	0.48

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

performance does not seem to require added "cost" in terms of time.

Discussion

We propose a new alternative preference measurement method, barter conjoint, in an attempt to improve the predictive performance of the de facto CBC. Barter conjoint attempts to achieve this objective by collecting a substantially larger amount of data without demanding too much additional effort from participants, as well as potentially improving the quality of data by allowing information diffusion among subjects during preference measurement.

In two empirical studies designed to validate the performance of barter conjoint, we find that (1) barter conjoint outperforms both incentive-aligned and hypothetical CBC; and (2) incentive alignment substantially improves the performance of CBC, adding to the extant literature (Ding et al. 2005, Ding 2007) on the importance of incentive alignment. The empirical results suggest that practitioners could consider using barter conjoint for their practical applications, or, at a minimum, they should use incentive-aligned CBC.

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 indicated that participants were very involved (mean = 4.38, std. dev. = 0.88 based on a 1–5 scale, with 5 being the highest involvement level);

Table 5 Predictive Performance for the External Validity Tasks

	CBC (%)		Barter conjoint (%)		
	Hypothetical	Incentive-aligned	Data-equated	Time-equated	Full data
Ocean City beach					
Immediate	19	—	23[b]	27[b]	33[b]
Delayed	17	—	20[b]	24[b]	31[b]
Bahamas cruise					
Immediate	30	39[a]	37[b]	37[b]	42[b, c]
Delayed	24	35[a]	36[b]	38[b,c]	41[b, c]
Camcorder					
Immediate	29	33[a]	33[b]	35[b]	40[b, c]
Delayed	32	32	31	37[b, c]	41[b, c]

[a], [b], and [c] indicate that the difference in predictive performance between hypothetical conjoint and incentive-aligned conjoint, between hypothetical conjoint and (data-equated, time-equated, full) barter conjoint, and between incentive-aligned conjoint and (data-equated, time-equated, full) barter conjoint, respectively, is significant at the 1% level based on the two-samples t-test.

some even stated, "We had fun!" Note, however, that the encouraging results from the two empirical studies should be interpreted as an indication that barter conjoint deserves attention from academics and practitioners alike, and should not be interpreted that barter conjoint dominates CBC in general (the latter statement will need validation from substantially more evidence from many future applications—both experimental and field based).

Having stated that, barter conjoint is a completely new concept and merits additional discussion. We will first discuss potential variations of the barter conjoint implemented in this paper, followed by a detailed discussion of limitations and directions for future research.

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, negative offers in 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 or 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 conjoint; there are many fruitful directions for further research. We next present a partial list, loosely organized into four groups of future ideas: (1) cognitive aspects of design; (2) design extension; (3) estimation; and (4) alternative validation metrics.

On the cognitive side, the current design raises the issue of endowment and loss-aversion effects. Subjects were endowed with a product, plus a certain amount of cash, from the start. It will be interesting to study the endowment effect in barter conjoint, especially for high-price product/service categories. Similarly, the effect of cash amount endowed for barter needs to be examined. Participants' behavior may change based on how much money they are endowed with. In addition, the barter process required subjects 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.

The barter method can also benefit from further (and alternative) tests. 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 or she thinks is valuable to potential buyers (given his or 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 consumer preferences. Also, participants in barter are not salient about the absolute price level of the product because they are endowed with the initial product, this problem can be remedied if participants are asked to purchase the starting product. 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. Barter conjoint incurs an additional cost compared to CBC. Although it does not necessarily take that much longer than CBC to complete and the time-equated barter still outperforms CBC, barter conjoint does require synchronized implementation (participants in the same barter market must do it simultaneously). The upside of this is that it might make completing the study more interesting for participants (similar to online games). The plus and minus of this requirement needs to be better understood for practitioners. Finally, participants in the CBC in Study 2 provided their second best and third best for each choice task, in addition to the first best. We have treated the first best in this task as equivalent to the conventional CBC implementation, where participants simply pick the best (as in Study 1). This is an assumption consistent with that made by conjoint firms such as Sawtooth, but it deserves a rigorous future investigation.

Another direction is the estimation. 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 profile, such interpretation is unlikely to yield any additional useful information. However, this may be quite relevant to other contexts or implementations. Also, in our interpretation of barter data, we have assumed participants do not try to infer other participants' type from round to round, and act strategically (e.g., person A might strategically offer \$10 to person B if A believes B will accept the offer at \$10, when in effect the valuation difference for A is \$20). It will be interesting to investigate to what extent this actually happens, and if it does, the best way to interpret such data. Finally, the current estimation method does not model any dynamic effect in preferences (time-varying partworths), and we believe a thorough examination of how preference evolves in barter conjoint will be fruitful (e.g., Liechty et al. 2005). One related possibility is to weigh the data from later rounds more heavily.

Last, but certainly not least, we acknowledge that performance in a holdout task is only one way to judge the value of a new method. Another metric is to examine the outcome of its recommendation in real-life product segmentation and positioning applications. If possible, real market metrics, such as operation profits, margins, and market share, should be used to validate any preference measurement methods. This is certainly beyond the scope of an academic paper, but users of barter conjoint need to keep this in mind. In addition, it will also be interesting to test the barter method in a context such as auction markets (e.g., eBay).

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 products 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 CBC), and a set of guidelines can then be developed as to which mechanism is most appropriate for a given situation.

In sum, we have proposed and validated barter conjoint, one alternative preference measurement method, in this paper. We hope this paper will offer practitioners another useful tool in understanding consumers' preferences and as stimulations for research in developing alternative preference measurement methods, especially either in the form of market or game.

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