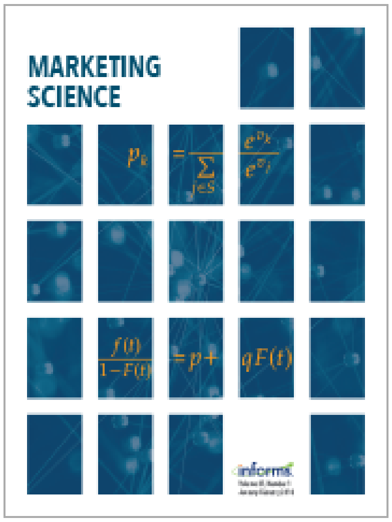

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Predicting Joint Choice Using Individual Data

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Choice decisions in the marketplace are often made by a collection of individuals or a group. Examples include purchase decisions involving families and organizations. A particularly unique aspect of a joint choice is that the group's preference is very likely to diverge from preferences of the individuals that constitute the group. For a marketing researcher, the biggest hurdle in measuring group preference is that it is often infeasible or cost prohibitive to collect data at the group level. Our objective in this research is to propose a novel methodology to estimate joint preference without the need to collect joint data from the group members. Our methodology makes use of both stated and inferred preference measures, and merges experimental design, statistical modeling, and utility aggregation theories to capture the psychological processes of preference revision and concession that lead to the joint preference. Results based on a study involving a cell phone purchase for 214 parent-teen dyads demonstrate predictive validity of our proposed method.

Key words: joint decision making; preference revision; utility aggregation; Bayesian
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Introduction

Choice decisions in the marketplace are often made by a collection of individuals or a group. Examples include families and organizations. A particularly unique aspect of a joint choice is that the group's preference is very likely to diverge from preferences of the individuals that constitute the group (Corfman 1991, Davis 1973). Although marketing scholars have done well in developing preference models at the level of an individual, limited research (e.g., Corfman and Lehmann 1987, Krishnamurthi 1988, Menasco and Curry 1989, Arora and Allenby 1999, Aribarg et al. 2002, Arora 2006) has studied preferences of a group. The use of preference of the primary decision maker as the surrogate for a group's preference appears to be a common practice in the industry. For marketing researchers, the biggest hurdle in measuring group preference is the infeasibility and high cost of data collection at the group level. In a business-to-business context involving the purchase of MRI equipment by a hospital, for example, it is virtually impossible to get a doctor, a nurse, and a purchase manager in the same room to assess their joint preference. Similarly, in a business-to-consumer context, joint choice data from a parent and a teen for the purchase of a shared durable good are quite difficult and expensive to obtain.

Accurate assessment of joint preference is important because individual preference is unlikely to predict market shares with great fidelity. This is particularly true when individuals in the group have high influence on different attributes and there is no clear-cut primary decision maker or user. Therefore, the practical challenges in estimating joint preference raise an important research question: Is it possible to estimate joint preference without requiring individuals to convene as a group to provide joint choice data? Our objective in this research is to propose a novel methodology to estimate joint preference without the need to collect joint data from the group members. The methodology merges experimental design, statistical modeling, and utility aggregation theories to capture the psychological processes of preference revision and concession that lead to the joint preference. In contrast to Aribarg et al. (2002), which mandates choice data collection at the dyadic level, our goal in this paper is to predict joint choice using data collected only from the individuals. By removing the big hurdle of joint choice data collection, the methodology makes accurate assessment of joint preference a lot more feasible.

Several aspects of our proposed methodology are noteworthy. First, we estimate individual sensitivity to the other member's preference—or preference revision—using an experimental approach. This is accomplished by careful manipulation of the other member's preference. Because member preferences within a group may or may not be congruent, we formally recognize and model the systematic effect of preference congruence on joint preference. Second, common approaches to measure individual preference are either *stated* or *inferred* (e.g., based on choice data and models). We merge both approaches to assess revised preference by exposing each member to the designed stated preference of the other member, and estimating the extent of his or her preference revision using choice data. Third, the give-and-take that is natural in a joint choice context—or preference concession—is captured by investigating a variety of theory-based utility aggregation models (e.g., Harsanyi 1955). Finally, joint choices for each group are determined by using a hierarchical Bayes choice model coupled with an appropriate utility aggregation model.

Although our proposed ideas in this paper are likely to work effectively in both business-to-business and business-to-consumer contexts, we chose the latter to conduct our empirical testing. This was guided primarily by our intention to compare the predictive performance of our approach to conventional approaches, which involve the estimation of joint preference using joint choice data (Arora and Allenby 1999). We are able to obtain such joint choice data much more easily in a business-to-consumer context. The business-to-consumer context we selected involves choice of cell phones for a teen. Pretests revealed that parents played a significant role in this dyadic choice decision. Therefore, a study with 214 parent-teen dyads was used to test the proposed model. Our results show the viability of our proposed method in obtaining revised preference from each dyad member. We also find that the most effective way to aggregate group members' utilities (which are based on their revised preferences) is to use a weighted Harsanyi (1955) aggregation model. Overall, our study demonstrates that it is certainly feasible to predict joint choices that reflect group preferences by using only individual data obtained separately from each group member. Empirical findings show that our method, which accounts for both preference revision and concession, leads to better predictive performance than using data from either parents or teens alone.

For the reported study, empirical evidence suggests substantial preference incongruence between parent and teen preferences. In general, teens appear to demand higher functionality on cell phone attributes such as a camera upgrade and loudspeaker; attributes such as a low price and GPS support service are more preferred by parents. By experimentally manipulating the other member's preference, we uncover a revision pattern that sheds fresh insight into how preferences shift. Both parents and teens appear to revise their preferences, and the preference shifts vary significantly across cell phone attributes. We demonstrate significant gains in the ability to predict joint choice when preference revision is properly accounted for. Preference concession also adds to our ability to predict joint choice. Our findings suggest that in the absence of any additional information, an equally weighted Harsanyi (1955) model that aggregates members' revised preference may be appropriate. The predictive results based on our proposed methodology clearly dominate an approach that relies on members' initial preference and ignores the important phenomenon of preference revision inherent in any joint choice context. Our predictive tests also point to the significant disadvantage of the common practice of relying on the primary user's preference as a surrogate for the group's preference. Finally, while in our context we observe matched data from each member in the dyad, we show that it is possible to extend our approach to the unmatched case where only one member from each dyad provides the data. The proposed methodology therefore offers significant promise in the business-to-business context where collection of joint data is known to be difficult.

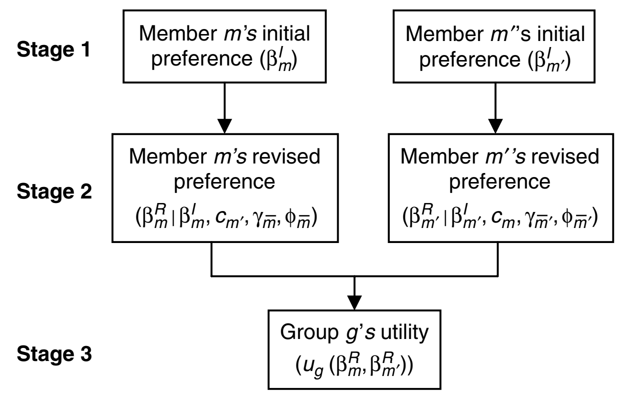
This paper begins with a section that presents our modeling framework and theoretical underpinnings of our overall approach. This is followed by the section that describes our experimental design and data collection procedure. Our model estimation results and predictive tests are included in the empirical section. We end with two possible extensions of our approach and a discussion section that highlights the value of the proposed approach, and our limitations and opportunities for future research.

Modeling Framework and Theory

Following Aribarg et al. (2002), we construct our modeling framework[1] to capture three key elements of a group's preference: individual members' initial preference, revision, and concession. We describe our framework (shown in Figure 1) for a situation in which two members (say, member m and member m') jointly make a decision to choose a product. We assume that each member belongs to a class of individuals with distinct preferences that are identifiable a priori. Examples of such classes in business-to-business settings are doctors and nurses. In business-to-consumer settings, the classes may include husbands, wives, and teens. At the beginning, each member is assumed to possess initial preferences for the attributes of a target product (initial preference stage). However, upon learning about the other member's preferences for the attributes, members m and m' may revise their

[1] Our model should be viewed as a paramorphic representation of the preference revision and concession process. The basic model structure could be expanded to a multistage process where the number of stages is likely related to decision importance.

Figure 1 Modeling Framework



preferences for these attributes (preference revision stage). At the end, to make a joint choice, each member may also have to concede to each other if their revised preferences do not converge (preference concession stage). Next, we describe in detail how we model the three stages outlined above.

Stage 1: Initial Preference

Let subscripts j, k, m, m', and g denote choice alternative j, attribute level k, member m, member m', and group g. Let $u_{mj}^I = V_{mj}^I + \varepsilon_{mj}^I$ and $u_{m'j}^I = V_{m'j}^I + \varepsilon_{m'j}^I$ be the initial utilities of members m and m', respectively, for alternative j. The deterministic parts of the utilities, V_{mj}^I and $V_{m'j}^I$, can be written as

$$V_{mj}^I = \sum_k x_{jk}\beta_{mk}^I \quad \text{and} \quad V_{m'j}^I = \sum_k x_{jk}\beta_{m'k}^I, \tag{1}$$

where x_{jk} indicate the specification of attribute level k in choice alternative j that a member evaluates. The elements β_{mk}^I and $\beta_{m'k}^I$ capture the initial preference of members m and m', respectively, for attribute level k. In a typical joint choice context, individual choice is not observed and initial preferences are therefore not estimable. In our setup, individual data are available, thus permitting us to obtain member specific parameter estimates. Member-specific errors are assumed to be independent and identically distributed type 1 extreme value (McFadden 1979) with parameters $(0, 1)$. We capture heterogeneity in initial preferences across respondents by the random effects specifications $\beta_m^I \sim \text{Normal}(\bar{\beta}_m, B_m)$ and $\beta_{m'}^I \sim \text{Normal}(\bar{\beta}_{m'}, B_{m'})$. Preferences are expected to vary within the class to which a member belongs and also between classes.

The individual initial preferences (β_{mk}^I and $\beta_{m'k}^I$) above are model-based. Stated measures of preference are also widely used in marketing (Srinivasan and Park 1997). A simple way to assess stated preference (s_{mk}) is by asking member m to classify each attribute level into the three categories of "must have," "nice to have," and "don't need" (Yee et al. 2006, Hauser et al. 2006). These three levels of stated preference for attribute level k, when viewed collectively for members m and m', provide a measure of preference incongruence (Table 1). From the standpoint of member m, the preference incongruence (c_{mk}) has nine levels that break down into the three distinct categories: preference congruence (along the diagonal), type 1 incongruence (below the diagonal), and type 2 incongruence (above the diagonal). Type 1 incongruence implies that member m' wants the attribute level more than m and type 2 implies that member m wants it more than m'.

Table 1 Preference Incongruence

	Member m'		
Member m	Must have	Nice to have	Don't need
Must have	Positive congruence		Extreme incongruence
Nice to have			
Don't need	Extreme incongruence		Negative congruence

Stage 2: Preference Revision

As seen in Figure 1, upon learning the other member's preferences each member (m and m') may revise his or her preference. Let $u_{mj}^R = V_{mj}^R + \varepsilon_{mj}^R$ and $u_{m'j}^R = V_{m'j}^R + \varepsilon_{m'j}^R$ be the revised utilities of members m and m', respectively, for alternative j. The deterministic parts of the utilities, V_{mj}^R and $V_{m'j}^R$, are

$$V_{mj}^R = \sum_k x_{jk}\beta_{mk}^R \quad \text{and} \quad V_{m'j}^R = \sum_k x_{jk}\beta_{m'k}^R, \tag{2}$$

where β_{mk}^R and $\beta_{m'k}^R$ are the revised preferences of members m and m', respectively, for attribute level k. Once again, in a typical joint choice context, individual choices are not observable and revised preference estimates are therefore not estimable. However, in our setup, individual data that help estimate member-specific revised preferences are available, thus permitting us to obtain member-specific parameter estimates. Member-specific errors are assumed to be independent and identically distributed type 1 extreme value $(0, 1)$.

Member-specific preference shifts, by attribute, are modeled as follows:

$$\begin{aligned} \beta_{mk}^R &= \beta_{mk}^I + \phi_{\bar{m}k}\sum_{l=1}^{9}\gamma_{\bar{m}l}c_{m'kl} \quad \text{and} \\ \beta_{m'k}^R &= \beta_{m'k}^I + \phi_{\bar{m}'k}\sum_{l=1}^{9}\gamma_{\bar{m}'l}c_{mkl}. \end{aligned} \tag{3}$$

Focusing on the first part of Equation (3), the revised preference of member m contains two parts: his or her initial preference β_{mk}^I and preference shift $\phi_{\bar{m}k}\sum_{l=1}^{9}\gamma_{\bar{m}l}c_{m'kl}$. Next, we explain individual components of the preference shift part of Equation (3).

Preference Incongruence ($c_{m'kl}$). For attribute level k, $c_{m'k}$ is a (9×1) vector (see Table 1) with elements 0 or 1 such that $\sum_{l=1}^{9} c_{m'kl} = 1$, reflecting the congruence in stated preferences between member m and his or her partner m'. Previous literature provides evidence that a member's preference revision depends on his or her own initial preferences (Chandrashekaran et al. 1996, Myers and Lamm 1976, Rao and Steckel 1991) as well as preference of the other. Viewed via our framework, this implies that a must-have/must-have preference for a given dyad is likely to impact a member's preference revision differently than a must-have/nice-to-have or a must-have/don't-need preference. A particular challenge in this context is that while member m is likely to be well aware of his or her own preferences (s_{mk}) he or she may have limited or no knowledge of others' preferences ($s_{m'k}$). Logistically, and from a cost standpoint, it may be infeasible to collect dyadic data to accurately assess preference revision likely to result because of incongruence. Our solution proposes experimental manipulation of the stated preference of member $m'(s_{m'})$ to uncover systematic shifts in preferences of member m. To determine how a given member m responds to preference incongruence between members, we expose member m to a careful design of stated initial preference of member m', and vice versa. Details on the experimental design are provided in the empirical section. By experimentally manipulating the stated initial preference of member m', our goal is to estimate the preference revision parameter ($\gamma_{\bar{m}}$) for member m. We also do the converse—manipulate the stated initial preference of member m to estimate the preference revision parameter ($\gamma_{\bar{m}'}$) for member m'.

Preference Revision Parameter ($\gamma_{\bar{m}l}$). The parameter $\gamma_{\bar{m}l}$ in Equation (3) captures member m's preference revision because of preference incongruence. Equation (3) implicitly assumes that preference revision of a given member is contingent on initial preference differences between members. It permits unequal $\gamma_{\bar{m}l}$ for $\forall\, l$—the magnitude and direction of preference revision is expected to be different for each one of the nine cells in Table 1. Analogously, parameter $\gamma_{\bar{m}'l}$, which appears in the second part of Equation (3), captures the degree of preference revision of m' caused by preference incongruence. Because of context-specific factors (e.g., who is the primary user, who is paying, relative knowledge, etc.) we expect $\gamma_{\bar{m}l}$ to be different from $\gamma_{\bar{m}'l}$. That is, we allow preference revision of members to be asymmetric. Furthermore, because stated initial preference—and therefore attribute congruence—does not vary within an individual, preference revision parameters (γ) are homogeneous across respondents that belong to a given class. We use subscripts $\bar{m}$ and $\bar{m}'$ to indicate that these revision parameters are estimated at the aggregate level across respondents. We allow the revision parameters to vary between classes.

As stated earlier, from the standpoint of member m, preference incongruence (c_{mk}) breaks down into the three distinct categories: preference congruence (along the diagonal), type 1 incongruence (below the diagonal), and type 2 incongruence (above the diagonal). Type 1 incongruence implies that member m' wants the attribute more and type 2 implies that member m wants it more. The preference revision parameters (γ) corresponding to incongruence above the diagonal are expected to be positive and those below the diagonal are expected to be negative. These off-diagonal elements of γ are also expected to follow an ordinal structure. In Table 1 consider the simple case when the preference of member m' for an attribute is very high (i.e., must have). Contingent on the must-have preference of m', we expect his counterpart member m to revise preference more when member m's stated initial preference is don't need (extreme incongruence), as compared to when member m's stated initial preference is nice to have (mild incongruence). Analogously, if the preference of member m' for an attribute is very low (i.e., don't need), we expect member m to revise member m's preference more when member m's stated initial preference is must have (extreme incongruence), as compared to when member m's stated initial preference is nice to have (mild incongruence).

Elements along the diagonal in Table 1 suggest preference congruence. Although we expect no preference revision when the dyadic stated preference is nice to have/nice to have, findings involving group polarization (Myers and Lamm 1976, Rao and Steckel 1991) suggest that preferences tend to become more extreme in the presence of congruence. We therefore expect a positive sign for the γ parameter when preferences are positively congruent (must have/must have) and a negative sign when they are negatively congruent (don't need/don't need). That is, attributes that are very desirable for both members become even more desirable and those that are very undesirable for both become even more undesirable.

Preference Shift Varies by Attribute ($\phi_{\bar{m}}$). To account for possible differences in the degree of preference revision across attribute levels (Arora and Allenby 1999, Aribarg et al. 2002) we introduce attribute-level–specific multipliers $\phi_{\bar{m}k}$ for member m. The first element of this parameter vector ($\phi_{\bar{m}1}$) is set to be equal to one for the purpose of identification. Similarly, parameter $\phi_{\bar{m}'k}$ captures attribute-specific differences in preference revision for member m'. Similar to preference revision parameters (γ), attribute-level–specific multipliers (ϕ) are homogeneous across respondents that belong to a given class.

It is important to draw the distinction between the actual and manipulated stated preference in our framework. While the manipulated stated preference is controlled by the experimenter, actual stated preference is being measured. The purpose of injecting manipulated stated preference into our framework is to assess the revision parameters ($\gamma_{\bar{m}}$ and $\gamma_{\bar{m}'}$). The measured or actual stated preference is also a critical piece because it allows us to determine the actual preference incongruence that exists within a dyad. Using Equation (3), conditional on revision parameters (γ) and the actual preference incongruence that is being measured, it is straightforward to obtain the revised preference for each member in a group predictively. Formally, we denote $c^*_{m'kl}$ and c^*_{mkl} as the incongruence based on actual stated initial preferences associated with both members. The actual revised preference for a given members m and m' can be obtained as follows:

$$\beta^R_{mk} = \beta^I_{mk} + \phi_{\bar{m}k} \sum_{l=1}^{9} \gamma_{\bar{m}l} c^*_{m'kl} \quad \text{and} \quad \beta^R_{m'k} = \beta^I_{m'k} + \phi_{\bar{m}'k} \sum_{l=1}^{9} \gamma_{\bar{m}'l} c^*_{mkl}. \tag{4}$$

A nice property of our modeling framework is that although preference revision parameters ($\gamma_{\bar{m}}$ and $\gamma_{\bar{m}'}$) are homogeneous within a class, member-specific preferences (β^R_m and $\beta^R_{m'}$) are heterogeneous.

Two special cases of the proposed model structure in Equation (3) are worth noting. First,

$$\beta^R_{mk} = \beta^I_{mk} + \phi_{\bar{m}k} \sum_{l=1}^{3} \gamma_{\bar{m}l} s_{m'kl} \quad \text{and} \quad \beta^R_{m'k} = \beta^I_{m'k} + \phi_{\bar{m}'k} \sum_{l=1}^{3} \gamma_{\bar{m}'l} s_{mkl}. \tag{5}$$

The difference between Equations (5) and (3) is that the latter assumes that preference shift is caused by the other member's stated preference, whereas the former assumes that it is incongruence in stated preference that better captures preference revision. Equation (5) requires fewer ($l = 3$ versus 9) preference revision parameters than Equation (3). Second,

$$\beta^R_{mk} = \beta^I_{mk} + \sum_{l=1}^{9} \gamma_{\bar{m}l} c_{m'kl} \quad \text{and} \quad \beta^R_{m'k} = \beta^I_{m'k} + \sum_{l=1}^{9} \gamma_{\bar{m}'l} c_{mkl}. \tag{6}$$

The difference between Equations (6) and (3) is that the latter assumes that preference revision is constant across attributes ($\phi_{\bar{m}k} = 1$ for $\forall k$). Equation (6) requires fewer model parameters than Equation (3). We will test both the special cases empirically.

Stage 3: Concession and Utility Aggregation

Despite preference revision, it is likely that member preferences do not perfectly converge, and consequently, their utilities do not give rise to the same choice outcomes. Prior research in economics and decision theory (e.g., Arrow 1951, Harsanyi 1955, Keeney 1976, Keeney and Raiffa 1993) has extensively examined properties of different normative models to aggregate utilities of group members to derive their group choice in a cooperative setting. Social welfare problems in economics (e.g., Small and Rosen 1981) also fall under this broader class of utility aggregation problems. The well-known Arrow's impossibility theorem asserts that it is impossible for a group, even with only two members, to find a procedure to aggregate members' ordinal utilities to obtain group ordinal utilities that satisfy a set of seemingly innocuous assumptions (Arrow 1951). Working with cardinal utilities (i.e., von Neumann-Morgenstern utilities) instead of ordinal utilities, Harsanyi (1955, 1978) presents a set of axioms under which a group utility can be derived as an equally weighted additive function of the utilities of individual members comprising the group. Keeney (1976) also shows that a group utility derived from an additive function of members' cardinal utilities is in fact consistent with a set of assumptions analogous to those originally proposed by Arrow.

Harsanyi Model (Additive Aggregation). The Harsanyi model (Diamond 1973; Harsanyi 1955, 1975; Keeney and Raiffa 1993, pp. 295–297; Sen 1970), which takes an additive form, is derived based on the social welfare viewpoint and follows four axioms: (1) individual preferences satisfy the Marschak's postulates (1954) of the von Neumann-Morgenstern utility theory (1944),[2] (2) group preferences satisfy the Marschak's postulates of the von Neumann-Morgenstern utility theory, (3) group utilities can be written as an increasing function of individual expected utilities, and (4) interpersonal comparability of individual utilities (i.e., utilities are interpersonally calibrated with respect both to unit/scale and to origin). The interpersonal comparability axiom has been a topic of discussion in later research, although according to Harsanyi (1978), it is required only for the equal-weight result to hold.

[2] Marschack's postulates include (1) the relation of preference establishes a complete and transitive ordering among all alternatives; (2) preference continuity (if alternative P is preferred to R, while Q takes position in between them, then there exists a mixture of P and R with appropriate probabilities such as to be exactly indifferent to Q); (3) sufficient number of nonindifferent alternatives; and (4) equivalence of mixture of equivalent alternatives (if alternatives Q and R are indifferent, a given probability mixture of P and Q is indifferent to a similar mixture of P and R).

To achieve interpersonal comparability, previous research normalizes each group member's utility before aggregating them to derive the group utility (Eliashberg et al. 1986, Green and Krieger 1985, Keeney and Raiffa 1993). That is, for each member his or her highest and lowest utility is set to be equal to one and zero, respectively. Such normalization becomes necessary because utilities are commonly obtained using either gambling tasks or ranking and rating conjoint experiments. In contrast, we use a choice-based conjoint experiment and a multinomial logit choice model in our study where the utilities are already normalized (see Train 2003, pp. 27–29, for a discussion). For both members m and m', we set the utility of an arbitrary product option to zero. This is true for any discrete-choice experiment where attributes are dummy coded. Also, the utilities of all product options are scaled by the scale parameter (it equals one, as indicated earlier) of the extreme value distribution so that the variance of the unobserved portion for both m and m' is equal to $\pi^2/6$. The utilities derived from choice models are therefore already normalized—calibrated to have the same origin and scale—to be comparable across members. However, unlike the 0–1 normalization, the lowest and highest utilities for each member based on the logit choice model are not constrained to be the same (i.e., set to be zero and one, respectively). Also, an origin is fixed by setting the utility of an arbitrary product option to be zero. For ease of interpretation, it is not uncommon for that arbitrary product option to also be the least desirable (e.g., lowest functionality and highest price).

A plausible argument against interpersonal comparability of members' utilities is that normalized utilities, albeit comparable from the scaling perspective, may not be comparable from the psychological perspective (Brock 1980, Harsanyi 1955). Specifically, the normalization procedure assumes that members in a group have—or at least compare their preferences with each other as if they have—the same utility of zero for the baseline alternative, which may not necessarily be warranted. However, there is evidence that the Harsanyi model using normalized utilities works well as long as there is some degree of agreement between group members or, in other words, preferences of group members are positively correlated (Dawes and Corrigan 1974). Viewed in light of our context, given that preference revision is expected to facilitate the convergence of group members' preferences, we expect the Harsanyi model to provide better prediction of joint choice outcomes when revised, instead of initial, preferences are used as the basis for aggregation.

Weights can also be incorporated into the Harsanyi model. In fact, some previous research in marketing has proposed different ways to estimate these weights as a result of aggregating members' initial preferences (Arora and Allenby 1999, Krisnamurthi 1988) or revised preferences (Aribarg et al. 2002). As a result, we specify the utility associated with group g alternative j derived from the weighted Harsanyi model as follows. The chosen alternative is expected to maximize the following utility function:

$$u_{gj}(u^R_m, u^R_{m'}) = w_m u^R_{mj} + w_{m'} u^R_{m'j}, \tag{7}$$

where the terms w_m and $w_{m'}$ capture the decision weights associated with members m and m'; $w_m + w_{m'} = 1$. The weights w_m and $w_{m'}$ reflect relative degree of concession between members m and m'; $w_m > w_{m'}$ suggests relatively lower concession by member m.

An emerging stream of literature proposes that individuals may not make a choice decision that maximizes their utility, but one that minimizes their anticipated regret (Chorus et al. 2008, Inman et al. 1997, Simonson 1992). A choice that maximizes compensatory utility may lead to postpurchase regret if one has to accept an inferior level of an attribute for a superior level of another attribute. It is plausible that the chooser later wishes not to be stuck with the inferior attribute level. Translating such a notion into a group setup, members of a group may avoid choosing an alternative that leads to maximum regret for a particular member. Motivated by the notion of anticipated regret, we also test such an aggregation model that takes into account an analogous notion of regret among group members.

Rawls Model (Maximin Aggregation). The Rawls model (Rawls 1971, 1974) evaluates each group outcome based on its utility to the group member who likes it the least. Motivated by the theory of justice, the Rawls model is the most egalitarian form of utility aggregation because it attempts to maximize the utility of the most disadvantaged member: the one who has to give up his or her utility the most for the group to reach the group choice outcome. The benefit of making such a decision is that the group can make sure that none of the group members has to suffer too much pain in making a joint choice, and as a result, the group is likely to maintain strong relationships among group members.

Similar to the Harsanyi model, the Rawls model also requires interpersonally comparable utilities. Previous research has shown that 0–1 normalized utilities work well with the Harsanyi but not with the Rawls model (Gupta and Kohli 1990). In this research, we empirically examine whether the use of normalized utilities derived from a logit choice model can improve predictive performance of the Rawls model. Formally, we specify the utility associated with group g alternative j derived from the Rawls model as

$$u_{gj}(u^R_m, u^R_{m'}) = \min(u^R_{mj}, u^R_{m'j}). \tag{8}$$

Table 2 Summary of Study Design

Phase	Task: Parent	Task: Teen	Objective
1	Stated preference task to classify each attribute into "must have," "nice to have," and "don't need."	Stated preference task to classify each attribute into "must have," "nice to have," and "don't need."	To obtain the actual stated initial preferences and estimate the actual inferred initial preferences for cell phone attributes for each member.
	A choice-based conjoint task given to parent.	A choice-based conjoint task given to teen.	
	Manipulation: Stated teen's preference shown to parent.	Manipulation: Stated parent's preference shown to teen.	To manipulate preference congruence/incongruence for each attribute at the dyadic level and then estimate preference revision parameters (γ) for each member.
	A choice-based conjoint task given to parent.	A choice-based conjoint task given to teen.	
2	A choice-based conjoint task and predictive holdouts to be filled out by parent and teen together.		To obtain group preferences for cell phone attributes. The holdouts were used to conduct predictive tests. Data in this phase were obtained for the sole purpose of model validation.

Given the specification of the aggregate (joint) utility from Equations (7) and (8), the group choice is predicted to be the one that maximizes the joint utility of the group members. In our Bayesian framework, we account for uncertainty in parameter estimates by using the entire posterior distributions of parameter estimates in conducting the predictive performance comparison of the two utility aggregation models.

Previous research in marketing has also tested different aggregation models (Curry et al. 1991; Eliashberg et al. 1986; Gupta and Kohli 1990; Neslin and Greenhalgh 1983, 1986). Our paper differs from previous research on several dimensions. First, we test utility aggregation models in the context of joint decisions for family purchases, not buyer-seller negotiations. Second, we test aggregation models based on utilities that are based on revised, and not initial, preferences. This helps develop a better process level understanding of joint choice phenomena and likely improves prediction quality. Third, we measure preferences based on individual and group conjoint choice tasks, instead of gambling (Eliashberg et al. 1986) or conjoint ranking tasks (Neslin and Greenhalgh 1983, 1986).

Experimental Design and Data Collection

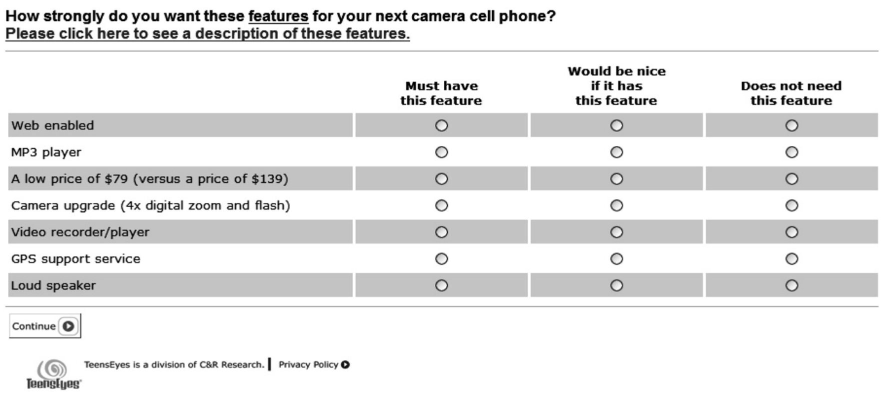
Experimental Design

To test the proposed methodology, we designed and implemented a study involving cell phone purchases for teenagers. We chose this context because existing research (Geser 2006) suggested that this is a joint choice context with significant parental involvement. Included in our study are seven cell phone attributes: an MP3 player, video recorder/player, Web-enabled functionality, GPS support service, loudspeaker, camera upgrade (4× digital zoom and flash), and price. We chose these attributes based on multiple consumer reviews on cell phones such as Cell Phone Buying Guide by CNET (http://reviews.cnet.com/cell-phone-buying-guide/) and Important Features of Cell Phones by *Consumer Reports* (http://www.consumerreports.org/; January 2006 report). Each nonprice attribute takes two levels of "yes" and "no," where "no" is set to be the baseline level. There are two levels for price, \$79 and \$139, where the higher price of \$139 is set to be the baseline.

The study had two phases involving individual and joint tasks, and respondents completed both phases online (the study design is summarized in Table 2). Phase 1 involves individual tasks. Our goal in this phase was to obtain each member's initial and then revised preferences for the seven attributes. Two separate measures for initial preference were obtained: stated and inferred (i.e., model-based). The former was obtained by asking respondents to classify each attribute into one of three categories of "must have," "nice to have," and "don't need" as shown in Figure 2.

Then we asked each individual to complete 13 choice tasks, each involving a triple, which were used to estimate his or her inferred initial preference. The use of triples is motivated by (1) prior research (Roberts and Lattin 1997), which suggests that consumers tend not to engage in a compensatory decision process (an assumption implicit in our logit specification) when faced with a larger number of options; and (2) a significant gain in design efficiency (Huber and Zwerina 1996) as the number of alternatives increased from two to three. Design efficiency gain was much smaller when the number of alternatives increased from three to four. A blocked design involving four sets of such 13 triples was created using SAS OPTEX. Respondents were randomly allocated to one of the four sets. When performing these

Figure 2 Measuring Stated Initial Preference



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choice tasks, members were instructed to make choice decisions based strictly on their own preferences. For example, the teens were instructed: "When answering the questions, please consider your own opinion only. Please do not take into account anyone else's (like your parents') likes and dislikes."

Next, we were interested in capturing preference revision as a result of incongruence in initial preferences between members and, subsequently, estimating members' revised preferences. To accomplish this goal, we presented to each respondent the hypothetical (i.e., manipulated) stated initial preference of his or her counterpart. An example for a given teen is shown in Figure 3. To ensure adequate variation in the manipulated stated preference across respondents, the following design strategy was used. Stated preference for each one of the seven attributes could take three different values of "must have," "nice to have," and "don't need." For the 2,187 ($=3^7$) possible cases, we randomly generated a design with two restrictions: (1) the manipulated preference presented to each respondent contains at least one attribute that falls under each one of the three possible categories of "must have," "nice to have," and "don't need," and (2) to maximize design efficiency, there are no repetitive cases across respondents.

We also embedded a mechanism in the study to ensure that each respondent indeed paid attention to and understood the manipulated preference of his or her counterpart. Specifically, he or she was asked to drag each one of the seven attributes into the three possible bins of "must have," "nice to have," and "don't need" as a manipulation check. If the respondent failed to correctly classify the seven attributes, he or she was shown the above screen (Figure 3) again. The manipulation was followed by conjoint choice tasks involving a new set of 13 triples. We used these data to assess how and to what extent the respondent revised his or her preference given his or her counterpart's stated preference. While considering each choice set, the respondent was shown the manipulated preference of the other member as a reminder. When performing the choice tasks, respondents were also instructed to consider their family member's opinions as well as their own. For example, the teens were asked, "Please consider your parents' likes and dislikes, based on the information we showed you on the previous screen and above, along with your own." A typical choice task is shown in Figure 4.

In phase 2 involving joint tasks (see Table 2), our primary goal was to obtain joint preference. We included this phase strictly to validate our proposed model. Before performing choice tasks in this phase, members in each dyad were first asked to discuss their likes and dislikes with regard to cell phone features included in the study. This was done to facilitate an exchange of true preference and the resulting preference revision is therefore based on the true member preferences. In contrast to phase 1, where member preferences were manipulated to estimate preference revision patterns, in phase 2, members are expected to truly revise their preferences. In effect, our experimental approach and the model in using phase 1 data attempts to mimic the true preference revision that occurs in phase 2. Members were then instructed to jointly select an alternative from each of the 15 conjoint choice sets, each of which consists of three alternatives. Specifically, they were asked, "Which one of these cell phones do both of you like the best? That is, which one are both of you most likely to choose as [teen's name]'s next cell phone?" We used choice data from the 10 choice tasks to directly estimate joint preference parameters β_g (see Arora and Allenby 1999). We used these parameter estimates as a benchmark against which we compared the predictive performance of our proposed method. The remaining five holdout joint choices were used for out-of-sample predictive performance tests.

Finally, we also obtained information on a variety of measures pertaining to cell phone usage, knowledge, and experience during the two phases of the study. Respondents also indicated the importance of

Figure 3 Manipulation of Stated Initial Preference

Now, please imagine that we talked to your mom about buying a new camera cell phone for you. Let's assume that:

Your mom feels that your next cell phone must have:

Loud speaker
Camera upgrade (4x digital zoom and Flash)

Your mom feels it would be nice if your next cell phone had:

MP3 player
Video recorder/player
GPS support

Your mom feels your next cell phone does not need to have:

$79
Web enabled

Please read over this information carefully since you will need it in the next few questions.

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each attribute on a 1–5 scale and how much relative influence they would have in making a purchase decision of a cell phone for the teen. Demographic information, such as respondent age, gender, and ethnicity, was also collected at the end.

Data Collection

Data were collected with the help of C&R Research by using their TeensEyes nationwide panel for teenagers between the ages of 14 and 18 years. Teenagers who own or plan to get a cell phone were recruited for the study. The study began with phase 1 (Table 2) for the teens. At the end of this phase, the teens were asked to provide their parents' e-mail addresses if they would be interested in participating in the study. The parents were then contacted to provide phase 1 data. Upon completion of phase 1, the parents were asked to provide data for phase 2 by providing joint data with their teens. A quota sample ensured an equal number of male and female teens. In addition, we also established a minimum of 10% of the total sample for the five age groups of 14, 15, 16, 17, and 18 years old.

The questionnaire was pretested on 57 parent-teen dyads. On the basis of the pretest, several questions and instructions in the survey were simplified and

Figure 4 Conjoint Choice Task Used to Obtain Revised Preference

As a reminder, here is that information again. Your mom feels that your next camera cell phone:

MUST HAVE:	NICE TO HAVE:	DOES NOT NEED TO HAVE:
Loud speaker Camera upgrade (4x digital zoom and Flash)	MP3 player Video recorder/player GPS support	$79 Web enabled

Which one of these camera cell phones do you think both you and your mom would like the best? That is, which one are both of you most likely to choose as your next cell phone?

Please consider your mom's likes and dislikes, based on the information we showed you on the previous screen and above, along with your own.

• $79 • MP3 player • Video recorder/player • No Web enabled • GPS support • No loud speaker • Camera upgrade (4x digital zoom and Flash)	• $139 • No MP3 player • No video recorder/player • No Web enabled • No GPS support • No loud speaker • Camera upgrade (4x digital zoom and Flash)	• $79 • MP3 player • No video recorder/player • Web enabled • No GPS support • Loud speaker • Camera upgrade (4x digital zoom and Flash)

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rewritten. Our sample goal was 200 dyads. Given our plan to collect joint data in phase 2 for the purpose of model validation, we oversampled 354 teens to get data for phase 1. Parents of 225 of these teens agreed to participate in the study. Data from 11 dyads were not usable, resulting in a sample size of 214 dyads. Participating teens received TeensEyes points as an incentive, and parents were entered into a sweepstakes where they could win one of five $25 Amazon.com gift certificates.

Empirical Analysis

Sample Profile

We begin with summary statistics for the sample. The average age of the teens was 15.8 years old and 52.8% of teens were female. The modal income of the families participating in the study was $50,000–$75,000. Approximately 90% of the teens currently own a cell phone. Teens participating in the study perceived themselves as more knowledgeable about cell phone features (means for parents = 2.44 and teens = 3.15, using 1–5 scale; $p < 0.01$). Teens also talk with people about new cell phone features more than their parents do (means for parents = 2.15 and teens = 2.55, using 1–5 scale; $p < 0.01$).

Stated Initial Preferences and Incongruence in Stated Initial Preferences

Both parents and teens were asked to classify the attributes into the three bins of "must have," "nice to have," and "don't need." As seen in Table 3, the majority of the parents (51.9%) classified the low price as a must-have feature, and the Web-enabled feature was dominantly viewed as a don't-need feature (48.1%). The remaining five features were viewed as nice to have by a majority of the parents. Across all attributes, substantial heterogeneity in preferences of parents exists. On the other hand, data from teens reflect their desire for more cell phone features than their parents. A majority of the teens indicated low price (54.7%), an MP3 player (46.7%), and a camera upgrade (48.6%) as must-have features. The remaining four features were seen as nice to have by the majority of the teens. Across all attributes with the exception of GPS support, the percentage of teens checking the must-have option is higher than that of parents. Similar to parents, teens also exhibit substantial heterogeneity in preference for attributes.

There is also compelling evidence for preference incongruence across all attributes. We illustrate this by focusing our attention on the GPS attribute in Table 4(a). Approximately 46% of the dyads exhibit preference incongruence. These correspond to the off-diagonal entries in Table 4(a). As seen from the lower triangular elements of the table, preference of GPS among parents is lower than that of their teens for about 22% of the dyads. The upper triangular elements reveal that the opposite is true for approximately 24% of the dyads. The incidence of preference incongruence is 46% for the GPS attribute, and the corresponding percentages for price, an MP3 player, a video recorder/player, Web-enabled functionality, a loudspeaker, and a camera upgrade, respectively, are 43%, 51%, 57%, 54%, 58%, and 57%.

Although the incongruence results are instructive, recall that our methodology relies on manipulating the preference of a member's counterpart to estimate the revision parameters (γ). Using GPS as an illustration, Table 4(b) provides summary statistics that point to the effectiveness of the design we used. Specifically, all nine cells need to be sufficiently populated to ensure adequate variation in preference congruence across respondents thus enabling us to precisely estimate revision parameters (Equations (3) and (6)). Having only a few or no observations in a given cell adversely affects our ability to accurately estimate the revision parameter for that cell. Overall, our restricted random design appears to do an adequate job of populating all nine cells. This pattern holds across all seven attributes.

Table 3 Stated Initial Preference

	Must have		Nice to have		Don't need	
	Teens	Parents	Teens	Parents	Teens	Parents
$79 (lower price)	117 (54.7%)	111 (51.9%)	84 (39.3%)	85 (39.7%)	13 (6.1%)	18 (8.4%)
MP3 player	100 (46.7%)	48 (22.4%)	93 (43.5%)	108 (50.5%)	21 (9.8%)	58 (27.1%)
Video recorder/player	81 (37.9%)	31 (14.5%)	105 (49.1%)	104 (48.6%)	28 (13.1%)	79 (36.9%)
Web-enabled	63 (29.4%)	35 (16.4%)	105 (49.1%)	76 (35.5%)	46 (21.5%)	103 (48.1%)
GPS support	49 (22.9%)	58 (27.1%)	105 (49.1%)	91 (42.5%)	60 (28.0%)	65 (30.4%)
Loudspeaker	69 (32.2%)	30 (14.0%)	105 (49.1%)	95 (44.4%)	40 (18.7%)	89 (41.6%)
Camera upgrade	104 (48.6%)	58 (27.1%)	97 (45.3%)	109 (50.9%)	13 (6.1%)	47 (22.0%)

Model Estimation

To estimate initial preference and preference revision parameters and subsequently obtain expected revised preferences, we tested four possible models as shown in Table 5. We estimated each of these models using the Metropolis-Hastings algorithm (Chib and Greenberg 1999, Arora et al. 1998). From the total of 10,000 draws, we used every 10th draw from the last 5,000 to obtain parameter estimates, test the hypotheses of interest, and conduct predictive performance tests. To perform a hypothesis or predictive performance test,

Table 4(a) Actual Preference Congruence: GPS

	Teen actual			
GPS support service	Must have	Nice to have	Don't need	Total
Parent actual				
Must have	27 (12.6%)	24 (11.2%)	7 (3.3%)	58 (27.1%)
Nice to have	15 (7.0%)	56 (26.2%)	20 (9.3%)	91 (42.5%)
Don't need	7 (3.3%)	25 (11.7%)	33 (15.4%)	65 (30.4%)
Total	49 (22.9%)	105 (49.1%)	60 (28.0%)	214 (100.0%)

Table 4(b) Manipulated Preference Congruence: GPS

	Teen manipulated			
GPS support service	Must have	Nice to have	Don't need	Total
Parent actual				
Must have	22 (10.3%)	21 (9.8%)	15 (7.0%)	58 (27.1%)
Nice to have	22 (10.3%)	30 (14.0%)	39 (18.2%)	91 (42.5%)
Don't need	14 (6.5%)	26 (12.1%)	25 (11.7%)	65 (30.4%)
Total	58 (27.1%)	77 (36.0%)	79 (36.9%)	214 (100.0%)

we report the probability of a certain parameter (fit statistic) greater or smaller than another parameter (fit statistic). Consistent with Bayesian hypothesis testing involving Markov chain Monte Carlo estimation, a probability is computed by counting the number of draws that satisfy a certain hypothesis or predictive criterion. Time-series plots and convergence statistics suggested by Gelman and Rubin (1992) were used to ensure convergence of the sampling chains.

Model A corresponds to Equation (5) with the added constraint that the revision parameters are the same across all attributes ($\phi_{\bar{m}k} = 1$ for $\forall k$). It views preference revision as a function of the other member's stated preference. Model C is the same as model A except that it allows revision parameters to be attribute specific. Model B corresponds to Equation (6), which views preference revision as a function of dyadic incongruence with the added constraint that the revision parameters are the same across all attributes ($\phi_{\bar{m}k} = 1$ for $\forall k$). Model D is the same as model B except that it allows revision parameters to be attribute specific (Equation (3)). Based on log-marginal density (Newton and Raftery 1994) and deviance information criteria (Gelman et al. 2004), model D provides the best fit to the data (as shown in boldface). Analyses reported in the remainder of the paper therefore correspond to model D, our best-fitting model.

Table 5 Model Comparison for Revision Estimates

			Fit statistics	
Model	Preference shift based on dyadic incongruence	Attribute-specific multiplier	Log-marginal density (LMD)	Deviance information criteria (DIC)
Model A	No	No	−6,242.13	14,330.11
Model B	Yes	No	−6,215.79	14,283.22
Model C	No	Yes	−6,227.27	14,305.94
Model D	**Yes**	**Yes**	**−6,204.46**	**14,282.70**

Table 6 Parameter Estimates for Initial Preference and Revision Multiplier

	Initial preference ($\bar{\beta}$)		Heterogeneity ($\sqrt{B_{kk}}$)		Revision multiplier (ϕ)	
Attributes	Teens	Parents	Teens	Parents	Teens	Parents
Price (a low price $79 vs. $139)	1.194 (0.078)	1.885 (0.146)	1.107 (0.062)	1.744 (0.118)	1.000 n/a	1.000 n/a
MP3 player	1.594 (0.099)	1.569 (0.133)	1.320 (0.078)	1.563 (0.115)	1.418 (0.253)	1.191 (0.267)
Video recorder/player	0.864 (0.069)	0.875 (0.086)	0.796 (0.053)	0.844 (0.075)	0.694 (0.143)	0.868 (0.215)
Web-enabled functionality	0.763 (0.078)	0.620 (0.111)	0.966 (0.065)	1.095 (0.089)	0.927 (0.203)	0.765 (0.200)
GPS support service	0.706 (0.075)	1.186 (0.121)	0.816 (0.054)	1.479 (0.105)	0.941 (0.154)	0.835 (0.182)
Loudspeaker	0.526 (0.064)	0.321 (0.068)	0.631 (0.053)	0.684 (0.061)	0.844 (0.174)	0.505 (0.166)
Camera upgrade	1.171 (0.085)	1.075 (0.118)	1.065 (0.060)	1.244 (0.104)	0.932 (0.167)	1.240 (0.199)

Parameter Estimates

Table 6 reports the aggregate parameter estimates (posterior means and standard deviations) for model D, the best-fitting model. The aggregate parameter estimates for initial preference ($\bar{\beta}$) have face validity. All else equal, both parents and teenagers prefer a cell phone with a lower price, an MP3 player, a video recorder/player, Web-enabled functionality, GPS support service, a loudspeaker, and a camera upgrade. However, there are differences in preferences between parents and teens. For example, teens, on average, have lower preferences for cheaper price and GPS support service than their parents and stronger preferences for a camera upgrade and loudspeaker (probabilities > 0.95). The square roots of the diagonal elements of the covariance matrix ($\sqrt{B_{kk}}$) reported in Table 6 suggest substantial heterogeneity in preference among both teens and parents. Across all attributes, parents exhibit higher preference heterogeneity than teens. The revision multiplier estimates (ϕ) indicate that preference revision does vary by attribute. This is particularly true for parents. With price as the comparison attribute (ϕ is set to 1), multiplier estimates for the parents suggest that the magnitude of preference revision for a loudspeaker (prob($\phi < 1$) > 0.95) is lower than the preference revision for price. Teens, on the other hand, exhibit higher preference revision for the MP3 player attribute than price (prob($\phi > 1$) > 0.95) and lower preference revision for the video recorder/player attribute (prob($\phi < 1$) > 0.95). Next, we report estimates for the preference revision parameters.

As noted in Equation (4), there are nine (3×3) elements of the preference revision parameter (γ). Estimates for teens with respect to the price attribute are reported in Table 7(a). The row corresponding to a teen must-have in Table 7(a) should be interpreted as follows. For the price attribute, if a given teen indicates that low price is a must-have feature, then there are three possible hypothetical scenarios with regard to how this stated preference matches up with his or her parent's stated preference. If the parent also views low price as a must-have then the revision (γ) estimate suggests an upward shift of 0.374 in the teen's preference. On the other hand, if the parent views low price as a nice-to-have feature, then the revision estimate suggests a downward shift of −0.272 in the teen's preference. A don't-need stated preference for the parent also translates into a downward shift of −0.525.

Table 7(a) Teen Preference Revision for Price

	Parent		
Teen	Must have	Nice to have	Don't need
Must have	0.374 (0.105)	−0.272 (0.068)	−0.525 (0.081)
Nice to have	0.445 (0.103)	−0.267 (0.063)	−0.626 (0.092)
Don't need	0.600 (0.180)	−0.249 (0.104)	−0.545 (0.137)

Table 7(b) Parent Preference Revision for Price

	Teen		
Parent	Must have	Nice to have	Don't need
Must have	0.438 (0.134)	−0.232* (0.118)	−0.510 (0.134)
Nice to have	1.027 (0.158)	−0.236 (0.097)	−0.544 (0.110)
Don't need	1.011 (0.191)	−0.157* (0.120)	−0.476 (0.137)

*Insignificant at the 95% significance level.

We find it useful to report the estimates in Table 7(a) in the three groups of along, above, and below the diagonal. Elements along the diagonal suggest that teens revise their preferences even when the stated preferences are congruent. This is consistent with the group polarization phenomenon. We also observe downward preference revision in the case of nice to have/nice to have. This may suggest that participants associate the "nice to have" category of stated preference as somewhat negative rather than neutral. All elements above the diagonal are negative, indicating that teens shift their preferences for low price downwards (i.e., want it less) when they perceive that their parents like the low price attribute less than they do. With one exception, elements below the diagonal are positive, indicating that teens shift their preferences for low price upward (i.e., want it more) when they perceive that their parents like the low price attribute more than they do. The one exception to this pattern is the case of the don't-need feature for teens and the nice-to-have feature for parents. The negative sign is not surprising if "nice to have" is perceived as a somewhat negative evaluation, as noted earlier.

Despite our focus on the price attribute in Table 7(a), the revision estimates (γ) do vary by attribute, and this variation is captured by estimates of the ϕ parameters reported in Table 6. The general patterns of preference revision reported in Table 7(a) also hold for parents (see Table 7(b)). Two out of the nine estimates in Table 7(b) are not significantly different from zero.

Predictive Performance Tests

To validate the proposed methodology, we obtained joint choice data from each parent-teen dyad (Table 2). We asked respondents to provide joint choices for fifteen choice sets, each involving three alternatives. Ten joint choices were used to estimate joint preferences (β_g) of each dyad. The remaining five choice sets were holdouts that were reserved to conduct predictive tests. The predictive performance of preference estimates based on the joint choice data provided the benchmark against which we compare our proposed method. To demonstrate out-of-sample predictive performance, we computed hit rate and mean absolute deviation (MAD) associated with predicting the five holdout choices. Hit rate was calculated based on the "maximum utility" rule that uses the deterministic component of utilities (Green and Krieger 1985; Neslin and Greenhalgh 1983, 1986). This is reasonable because for an extreme value distribution although $E(\varepsilon) \neq 0$, all alternatives are constrained to have the same independent and identically distributed error. When an extreme value error is added to conduct these predictive tests, then as expected, across all tests, predictive fit declines a little but the pattern of

Table 8 Predictive Performance Results

Model	Predictor of joint choice	Model description			Predictive fit statistics (mean)	
		Teen revision	Parent revision	Concession	Hit rate[a]	MAD[b]
1	Teen's initial preference	N	N	N	0.469	1.275
2	Parent's initial preference	N	N	N	0.537	0.978
3	Teen's revised preference	Y	N	N	0.519	1.075
4	Parent's revised preference	N	Y	N	0.568	0.884
5	Weighted additive utility (Harsanyi) equal weights	Y	Y	Y	0.587	0.843
6	Rawls model	Y	Y	Y	0.541	0.984
7	Best weighted additive utility (Harsanyi) teen's weight = 0.4	Y	Y	Y	0.587	0.837
8	Joint preference (benchmark)	Y	Y	Y	0.586	0.765

[a] $\textit{Hit rate}^{M_i} = (1/(G \times T)) \sum_{g=1}^{G} \sum_{t=1}^{T} [I_{gt} = 1$ when the chosen alternative also has the highest utility for model M_i, 0 otherwise].

[b] $\textit{MAD}^{M_i} = (1/(G \times T)) \sum_{g=1}^{G} \sum_{t=1}^{T} |V_{gt}^{M_8}(\text{chosen}) - V_{gt}^{M_8}(\text{Predicted to be chosen by model } M_i)|$. g = group $1, \ldots, G$; t = choice task $1, \ldots, 5$, k = alternative 1, 2, 3; M_i = model i, where $i = 8$ is the benchmark model. $V_{gt}^{M_i}(k)$: group g's deterministic utility for task t, alternative k, and model i.

results and resulting conclusions remain unchanged from what is reported. For a given choice set, an alternative that provided the highest utility was assumed to be selected. In addition to hit rate, we also computed MAD by averaging the difference between the utility of the chosen option and that of the option predicted by each model across the five holdouts. To ensure comparability of the MAD measure across different models, utility differences associated with each model were computed based on parameter estimates from the benchmark model. Both hit rate and MAD were calculated at each iteration of the stationary posterior distribution and then averaged across those iterations. Next, we report a series of predictive performance tests (Table 8) to demonstrate how well our proposed approach works.

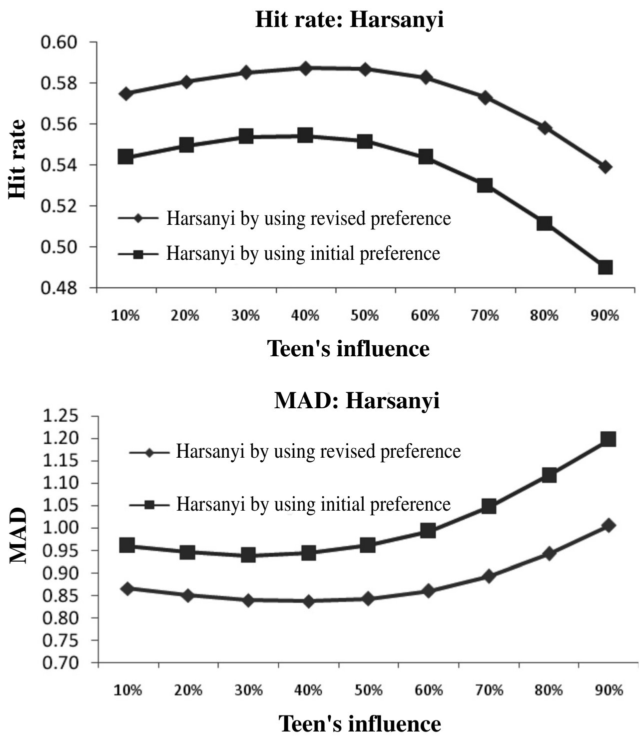
Predictive Gains as a Result of Accounting for Preference Revision. The spirit behind our study design and predictive testing is that joint choice data are rarely collected in practice because of practical difficulties. The predictive results based on the joint choice data and subsequent joint preference estimates are therefore the upper limit or benchmark against which our methodology can be compared.[3] As shown in model 8 (bottom of Table 8), based on joint preference estimates, the average hit rate and MAD for the five holdout choice sets are 0.586 and 0.765, respectively. In comparison, when the teen's initial preference is used to predict the five holdouts, the fit is poorer (hit rate = 0.469; MAD = 1.275; model 1) than the parent's initial preference (hit rate = 0.537; MAD = 0.978; model 2) is used (probabilities > 0.95). There is significant improvement in the fit if the teen's revised preference (hit rate = 0.519; MAD = 1.075; model 3) is used instead of the teen's initial preference (probabilities > 0.95). Similar improvement as a result of using revised preference (hit rate = 0.568; MAD = 0.884; model 4) instead of initial preference is also observed for parents (probabilities > 0.95). These results suggest that our proposed methodology of using a combination of stated and inferred preferences to estimate revised preferences does a nice job of predicting joint choice. Our findings demonstrate significant gains in the ability to predict joint choice when preference revision is properly accounted. Because neither the teen's nor the parent's revised preference estimates perform as well as our benchmark (the joint preference estimates), we next examine how much fit improvement we can gain by aggregating teen's and parent's revised preferences using the utility aggregation models. Such evidence of fit improvement would demonstrate the value of accounting for both preference revision and concession in predicting joint choice.

Predictive Gains as a Result of Accounting for Both Preference Revision and Concession. In Table 8, models 5 and 6 correspond to the utility aggregation models outlined earlier. We find that the Harsanyi utility aggregation model with equal weights leads to a better (probability > 0.94) predictive performance (hit rate = 0.587; MAD = 0.843) than "revision only" models. Rawls model (hit rate = 0.541; MAD = 0.984; model 6) does not perform as well. These results are consistent with those reported in Gupta and Kohli (1990).

We also use a grid search to find optimal weights for the weighted Harsanyi model that result in best predictive fits. Figure 5 demonstrates that our search for optimal weights does not have a corner solution. It is noteworthy that the best-fitting Harsanyi model (model 7) with a teen's influence of 0.4 (hit rate = 0.587; MAD = 0.837) performs as well as model 8—our benchmark model of joint preference estimates.

[3] We recognize that our benchmark is conditional on the assumption of a logit model; there may be other models of joint choice that perform better than the logit model.

Figure 5 **Utility Aggregation Models: Grid Search**



Although optimal weights may not always be known, our findings suggest that in the absence of any additional information, equal weights may be more reasonable to use than extreme weights (zero or one) that rely on the preference of only one member. These findings point to the significant disadvantage of using only one member's preference as a surrogate for the group's preference.

For sake of completeness we also include grid search results based on initial preference instead of revised preference in Figure 5. The predictive results, based on our proposed methodology that formally models preference revision, clearly dominate an approach that relies on members' initial preference and ignores the important phenomenon of preference revision inherent in any joint choice context. These results are also consistent with prior research that the Harsanyi model, using normalized utilities, works better when preferences of group members are more positively correlated (Dawes and Corrigan 1974).

In addition to predictive tests reported in Table 8, from a managerial standpoint another measure of model performance is the difference between actual market share and model based predicted market share. Similar in spirit to hit rate, mean absolute error (MAE) is one such commonly used (Huber et al. 1993) measure:

$$\mathrm{MAE} = \frac{1}{T \times K} \sum_{t=1}^{T} \sum_{k=1}^{K} \Big| \text{Actual market share}_{tk} - \text{Model based predicted market share}_{tk} \Big|,$$

where t represents the number of joint choice sets, k represents the number of options in a given choice set, and G is the total number of dyads (Actual market $\text{share}_{tk} = (1/G)\sum_{g=1}^{G} y_{gtk}^{\text{joint}}$). Consistent with our earlier predictive results, we find that incorporating preference revision and concession results in market share forecasts that are more accurate. Compared to the MAE of 0.038 based on joint preference (model 8 in Table 8), MAE based on teen and parent initial preferences is 0.086 and 0.060, respectively. This indicates that using initial prefrences to predict joint choice can lead to market share forecasts that are significantly worse (probabilities > 0.95). Consistent with previous results, using teen ($\mathrm{MAE} = 0.051$) and parent ($\mathrm{MAE} = 0.043$) revised preferences leads to much more accurate (probabilities > 0.90) predictive performance. The MAE associated with the best Harsanyi model results in marginal additional improvement (0.042) in accuracy.

Predictive Performance When Dyadic Data Are Not Matched. In our study, we collected data from each member within a dyad. Such matched data may not always be easy to collect in all joint choice contexts. For example, it may be infeasible to collect member-specific data from a physician and an anesthesiologist with regard to features of specialized hospital equipment. If we had obtained data from an unmatched sample of teens and parents, how well would our proposed approach work? To answer this question we need to first assume that for a given family, data from only the teen or the parent (not both) are available.

Equations (1)–(3) in our model do not require matched data. However, Equation (4) allows us to estimate member-specific revised preference conditional on dyad-specific incongruence and Equations (7) and (8) involving utility aggregation. To obtain revised preference for a given teen m in the case of unmatched data, we need to respecify Equation (4) as follows:

$$\hat{\beta}_{mk}^{R} = \beta_{mk}^{I} + \int \phi_{\bar{m}k} \sum_{l=1}^{9} \gamma_{\bar{m}l} c'_{n'kl}\, dc'. \tag{9a}$$

We obtain revised preference for each teen by using actual stated preferences of all other parents in the sample except his or her own parent (m'). Specifically, for a given teen m, we derive preference shift by averaging across preference incongruence ($c'_{n'kl}$) between teen m and other n' parents ($n' \neq m'$) instead of preference incongruence between teen m and their own parent m' ($c^{*}_{m'kl}$ in Equation (4); see also Gilula et al. 2006). Analogously, revised preference for a given parent m' can be derived as follows:

$$\hat{\beta}_{m'k}^{R} = \beta_{m'k}^{I} + \int \phi_{\bar{m}'k} \sum_{l=1}^{9} \gamma_{\bar{m}'l} c'_{nkl}\, dc'. \tag{9b}$$

Finally, deriving joint choice predictions in the case of unmatched dyadic data is a bit more complicated than in the case of matched data. Unlike the matched data case where we have a single joint choice prediction associated with each dyad, we have separate joint choice predictions for teens and for parents in the unmatched data case. Specifically, from teen m's perspective, the joint choice prediction $\delta_{mn'}$ is derived based on (1) his or her revised preferences $\hat{\beta}^R_{mk}$ from Equation (7), and (2) revised preferences of all unmatched parents $\hat{\beta}^R_{n'k}$ that exist in the sample. Prediction that alternative j is the joint choice from teen m's perspective is given by

$$\left\{\delta_{mn'}(\text{choice}=j)\colon \int u_{gj}(\hat{\beta}^R_m, \hat{\beta}^R_{n'})\, d\hat{\beta}^R_{n'} > \int u_{gk}(\hat{\beta}^R_m, \hat{\beta}^R_{n'})\, d\hat{\beta}^R_{n'} \text{ for } \forall k\right\}. \tag{10a}$$

Analogously, from the parent m''s perspective, the joint choice prediction $\delta_{m'n}$ is given by

$$\left\{\delta_{m'n}(\text{choice}=j)\colon \int u_{gj}(\hat{\beta}^R_{m'}, \hat{\beta}^R_{n})\, d\hat{\beta}^R_{n} > \int u_{gk}(\hat{\beta}^R_{m'}, \hat{\beta}^R_{n})\, d\hat{\beta}^R_{n} \text{ for } \forall k\right\}. \tag{10b}$$

Similar to the derivation of revised preference in Equations (9a) and (9b), we rely on draws of other parents' revised preferences ($\hat{\beta}^R_{n'}$; $n' \neq m'$) to obtain joint choices from teen m's perspective and draws of other teens' revised preferences ($\hat{\beta}^R_{n}$; $n \neq m$) to obtain joint choices from parent m''s perspective.

This raises the natural question whether one should rely on $\delta_{mn'}$ or $\delta_{m'n}$ to predict the dyad's joint choice. To formally examine this issue, we first specify a 0–1 loss function to capture the deviation of $\delta_{mn'}$ and $\delta_{m'n}$ from true $\delta_{mm'}$, which is the actual joint choice derived from matched dyad members. That is, $L(\delta_{mn'}, \delta_{mm'})$ and $L(\delta_{m'n}, \delta_{mm'})$ are equal to 1 when $\delta_{mn'} \neq \delta_{mm'}$ and $\delta_{m'n} \neq \delta_{mm'}$, respectively, and equal to 0 otherwise. With this specification, we can define Bayes posterior expected loss associated with $L(\delta_{mn'}, \delta_{mm'})$ and $L(\delta_{m'n}, \delta_{mm'})$ as

$$\begin{aligned} &E(L(\delta_{mn'}, \delta_{mm'})) \\ &\quad = \iint L(\delta_{mn'}, \delta_{mm'}) p(u_{gj}(\hat{\beta}^R_m, \hat{\beta}^R_{n'}) \mid c'_{n'}, \beta^I_{n'}) \\ &\qquad \cdot p(c'_{n'}) p(\beta^I_{n'} \mid \text{data})\, dc'_{n'}\, d\beta^I_{n'}, \\ &E(L(\delta_{m'n}, \delta_{mm'})) \\ &\quad = \iint L(\delta_{m'n}, \delta_{mm'}) p(u_{gj}(\hat{\beta}^R_{m'}, \hat{\beta}^R_{n}) \mid c'_{n}, \beta^I_{n}) \\ &\qquad \cdot p(c'_{n}) p(\beta^I_{n} \mid \text{data})\, dc'_{n}\, d\beta^I_{n}. \end{aligned} \tag{11}$$

From the decision theoretic perspective, a better decision is the one that is associated with a lower integrated risk. In the Bayesian framework, evaluating the posterior expected loss associated with each teen m (parent m') in our case is equivalent to evaluating the integrated risk associated with all teens (parents) in the sample (Robert 2001). Recall that to derive joint choice from unmatched data from the perspective of member m (m'), we first have to integrate over the preference congruence data of the other member from unmatched data $c'_{n'}$ and c'_n in Equations (9a) and (9b), and then also integrate over $\hat{\beta}^R_{n'}$ and $\hat{\beta}^R_{n}$, which are functions of $\beta^I_{n'}$ and β^I_n, as shown in Equations (10a) and (10b). As a result, we should expect the posterior expected loss associated with member m (m') to be larger when we have to integrate over more disperse distributions of both preference congruence $c'_{n'}$ (c'_n) and initial preferences $\beta^I_{n'}$ (β^I_n) of other unmatched members n' (n). Given that preference congruence is induced by stated initial preferences, and stated initial preferences and inferred initial preferences ($\beta^I_{n'}$ and β^I_n) are expected to correlated, we can focus only on the distributions of initial preferences. According to Table 6, parent's initial preferences are shown to be more heterogeneous (i.e., dispersed). As a result, we expect joint decisions from parent's perspectives to have better predictive performance.

Next we conducted predictive tests to investigate how well our proposed methodology works in contexts where matched dyadic data may be unavailable. Using revised preferences obtained from Equations (9a) and (9b) we computed hit rate and MAD for the five holdout joint choices as before. Again, all fit calculations were conducted using posterior distributions of the parameter estimates. Predictions based on the teens' unmatched revised preference (hit rate = 0.488; MAD = 1.170) outperform those based on their initial preference (model 1, Table 8; hit rate = 0.469; MAD = 1.275). Similarly, predictions based on the parents' unmatched revised preference (hit rate = 0.568; MAD = 0.882) also outperform those based on their initial preference (model 2, Table 8; hit rate = 0.537; MAD = 0.978). Although the predictions based on unmatched revised preference for teens (hit rate = 0.488; MAD = 1.170) are not as good as those based on the matched case (model 3 in Table 8; hit rate = 0.519; MAD = 1.075), both unmatched (hit rate = 0.568; MAD = 0.882) and matched (model 4 in Table 8, hit rate = 0.568; MAD = 0.884) predictions based on the parent's revised preferences work equally well. Finally, we also computed hit rate and MAD when concession is also taken into account by using the Harsanyi's model with equal weights. With the parent as the focal member, predictions based on a utility aggregation model (hit rate = 0.576, MAD = 0.861) were not found to be significantly better than predictions using parents' revised preference for the unmatched case (hit rate = 0.568; MAD = 0.882). Overall, predictions based on revised preferences of unmatched members are surprisingly good. Our proposed methodology therefore does not mandate that matched data be available for all dyads. In the extreme case when the data are completely unmatched, predictions based on revised preference are found to be quite good.

In summary, our empirical results convincingly demonstrate that initial preference of a member, even when that member is the primary user (e.g., teen in our context) can be a poor predictor of joint choice. Revised teen preference, based on our proposed methodology, does significantly better. A similar pattern of results holds for parents—although parent's initial preference and revised preference does better than the teen's initial preference and revised preference, respectively. Preference concession or the use of utility aggregation also improves a researcher's ability to predict joint choice. Empirical evidence in our study suggests that revised preference of both teens and parents, when combined with concession through the use of Harsanyi's utility aggregation model, leads to the best predictive performance. The results also suggest that our proposed methodology applies to contexts in which dyadic data are matched or unmatched. Despite the value of our approach in providing firms with more accurate joint choice prediction, one needs to weigh the potential costs and benefits of implementing our approach. An obvious additional cost incurred from our approach is that firms need to collect data from more than one class of customers (e.g., both teens and parents). However, by using our approach, managers no longer have to be constrained by the need to get customer dyads to make joint decisions, or even to get matched dyads of customers from different classes.

Model Extensions

We propose two extensions of the proposed model. Each requires new data and experimental design. The first could be viewed as relatively straightforward, whereas the data collection demands in the second extension are significant.

Nash Model (Multiplicative Aggregation). The well-known Nash utility aggregation model (1950, 1953) is shown to predict cooperative negotiation, or nonzero sum game outcomes, quite well (Curry et al. 1991, Eliashberg et al. 1986, Neslin and Greenhalgh 1983). The original Nash model, which arises from the Nash solution for cooperative games, aggregates utilities simply by multiplying utilities of members in a group (Davis 1970; Luce and Raiffa 1957; Nash 1950, 1953; Owen 1969). Roth (1979) extends the original Nash model to allow asymmetric influences across different members by incorporating different decision weights for different members (Peters and Van Damme 1991). The utility associated with group g alternative j derived from the weighted Nash model can be written as

$$u_{gi}(u_m^R, u_{m'}^R) = (u_{mj}^R - u_{mo}^R)^{w_m}(u_{m'j}^R - u_{m'o}^R)^{w_{m'}}, \qquad (12)$$

where u_{mj}^R and $u_{m'j}^R$ are revised utilities associated with members m and m', respectively, and u_{mo}^R and $u_{m'o}^R$ are utilities corresponding to the "no-settlement" situation for each member. The weights w_m and $w_{m'}$ reflect relative degree of concession between members m and m', respectively; $w_m > w_{m'}$ suggests relatively lower concession by member m.

The key difference between the Nash and Harsanyi models, from the standpoint of our paper, is that the Nash model requires the specification of status quo or nonsettlement utility. Translated into our context, this implies that an alternative has to exceed each member's baseline or status quo utility (u_{m0}^R and $u_{m'0}^R$) for it to be considered. In the event that all alternatives have utility below either member's status quo utility implies that the group chooses none of the available alternatives. The Nash aggregation model is thus not appropriate for the conditional on choice model used in our research. To assess the status quo or "no-settlement" utility central to the Nash model we will need (1) observations that allow respondents not to select any of the alternatives if they so choose and (2) an unconditional on choice model that formally captures the utility of the no-choice option (u_{mo}^R and $u_{m'o}^R$). The former requires data where respondents are given the "none" option so that they can choose not to select any of the options available. A threshold model (e.g., Gilbride and Allenby 2006) can then be used to obtain the no-settlement utility. In the presence of "no-choice data," the Nash utility aggregation is therefore a very straightforward extension of our proposed approach. Because groups may often decide not to select any of the available options, an extension of our approach to incorporate the no-choice option should be explored. Embedded implicitly in Nash models is the notion of fairness that is supposedly optimal for group members who expect to engage in a long-term negotiation relationship (Keeney and Kirkwood 1975). Also, although the Nash model relies on cardinal utilities, it does not require the interpersonal comparability assumption.

Larger Groups. Our proposed model can be extended to larger groups. For larger groups, member-specific preference shifts in Equation (3) could be incorporated as follows:

$$\beta_{mk}^R = \beta_{mk}^I + \sum_{m' \neq m} \sum_{l=1}^{9} \phi_{\bar{m}'k} \gamma_{\bar{m}'l} c_{m'kl}. \qquad (13)$$

Shift in preference of member m for attribute k is caused by his or her incongruence ($c_{m'kl}$) with *each* member m' in the group. The resulting shift captured by the product $\phi_{m'k}\gamma_{m'}$ is expected to vary by member m' because it is plausible that member m reacts more strongly to the views of one member than the others. Utility aggregation then takes the following general form for the M member Harsanyi case:

$$u_{gj}(u_1^R, \ldots, u_M^R) = \sum_m w_m u_{mj}^R. \tag{14}$$

For the Rawls model, the group utility is given by

$$u_{gj}(u_1^R, \ldots, u_M^R) = \min(u_{1j}^R, \ldots, u_{Mj}^R). \tag{15}$$

Although the model extension to larger groups is conceptually straightforward, it mandates significant design accommodations. Unlike the dyadic case where each member is exposed to the other member's preference, for larger groups incongruence needs to be manipulated for multiple members. For example, when the number of members equals three (e.g., teen, mom, and dad) stated preference manipulation (Figure 3) needs to also include a similar manipulation for dad. Referring back to our earlier observation that all nine cells of the incongruence matrix (Table 1) for each attribute need to be sufficiently populated to be able to estimate the revision parameters, this is particularly important as the number of members exceeds two. One area worth exploring is manipulating incongruence in an adaptive manner. Conditional on the stated preference of a given member, it is possible to generate the manipulated "stated preference" of another member in such a manner that across groups all nine incongruence cells are well balanced. Such on-the-fly designs are easy to implement and appear to be well suited for contexts that involve larger groups. Equation (13) can also be expanded to incorporate interaction terms in the revision process and may help understand the formation of coalitions in larger groups.

Discussion

Accurate assessment of joint preference is critical in a wide variety of business-to-business and business-to-consumer applications. Oftentimes collecting joint data from group members to estimate joint preference is infeasible or cost prohibitive. Our main goal in this research is to propose a novel methodology to estimate joint preference based only on data collected separately from each group member. We accomplish this goal by merging experimental design, statistical modeling, and utility aggregation theories to capture the joint decision process of preference revision and concession. Our approach augments inferred preference measures based on choice data with stated preference measures to estimate preference revision. Using data collected from over 200 parent-teen dyads, we demonstrate that the proposed methodology works well when data are collected from matched or unmatched members. The ability of our approach to recover joint preference using unmatched members is particularly valuable in certain business contexts where it may be impossible to contact all members in the same group (e.g., a purchase manager and a physician buying hospital equipment). Note also that although our modeling framework is developed on the assumption that preference aggregation occurs between members who belong to different classes of people with distinct preferences, it is also applicable to the situation where members cannot be easily classified (e.g., co-owners of a business) into distinct groups. In this situation, one needs to specify only one heterogeneity distribution (i.e., members are exchangeable) for initial preferences and estimate only one set of aggregate preference revision parameters.

In addition to our main objective of predicting joint choice, our proposed methodology to measure revised preference can also be used to study preference interdependence in the conjoint choice setup. For example, future research may consider expanding our design to measure preference revision as a result of social pressures, in addition to the preference of another group member. In recent years, research in the area of conjoint experimental design has focused on topics such as design efficiency (e.g., Huber and Zwerina 1996, Sándor and Wedel 2005), how to handle a large number of attributes and levels (e.g., Bradlow et al. 2004, Srinivasan and Park 1997, Toubia et al. 2003), and matching conjoint choice share with actual market share (e.g., Gilbride et al. 2008). In light of our research, we see opportunities for follow-up research that can capture an individual's intrinsic preference and influence of others in a unifying framework.

The utility aggregation concept is also of interest for goods that are consumed in multiple contexts. Individual preferences are likely to be context dependent for a wide array of products such as digital cameras, personal computers, and televisions. Individual preference for functions such as resolution, size, and zoom for a digital camera are likely to be quite different for a child's birthday versus a family vacation. This presents potential opportunities for follow-up research that carefully integrates utilities over an individual's multiple-consumption contexts.

Despite merits, our research has several limitations. First, we test our methodology in a static joint choice context; that is, each joint choice is made independently. Future research, for example, may examine whether the Harsanyi model still performs the best in a more dynamic choice context (Su et al. 2003), where members make a sequence of joint choices and may expect reciprocity. In this case, another form of utility aggregation (e.g., maximize maximum utility) may work better. Also, the very nature of product evaluation by a group may be noncompensatory—members may systematically rule out alternatives that are below a certain utility threshold. The dynamic and noncompensatory aspects of group decision making present significant conceptual and methodological challenges to study conflict which this paper does not quite address. Second, our tests for different utility aggregation models are conducted at the aggregate level (i.e., average across groups). Future research may investigate potential heterogeneity in utility aggregation methods across groups and examine factors that affect such heterogeneity. Third, we currently rely on the three simple categories of "must have," "nice to have," and "don't need" to capture preference congruence. Given the wealth of research in the area of self-explicated preference (Srinivasan and Park 1997), future research may develop a continuous scale that better measures extreme preference congruence to examine the polarization effect. Finally, as suggested earlier it may be fruitful to examine the effectiveness of our method as the number of members in a group increases. Larger groups also present opportunities to test novel and perhaps more efficient designs to estimate preference revision estimates.

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Appendix
The Metropolis-Hastings algorithm (Chib and Greenberg 1995) was used to generate the empirical draws for estimation. Subscripts m and m' correspond to the two groups of parents and teens. Draws for each parameter were obtained as follows:

(1) Generate $\{\beta_m^I,\ m=1,\ldots,N\}$:

$$f(\beta_m^I \mid \bar{\beta}_m, B_m, \gamma_{\bar{m}}, \phi_{\bar{m}}) \propto \exp\big[-(1/2)(\beta_m^I-\bar{\beta}_m)' B_m^{-1}(\beta_m^I-\bar{\beta}_m)\big]\prod_t \mathrm{Pr}_{mt}^I(j)\mathrm{Pr}_{mt}^R(j),$$

where

$$\mathrm{Pr}_{mt}^I(j)=\frac{\exp(\sum_k x_{mjk}^I\beta_{mk}^I)}{\sum_{n=1}^3\exp(\sum_k x_{mnk}^I\beta_{mk}^I)},$$

$$\mathrm{Pr}_{mt}^R(j)=\frac{\exp(\sum_k x_{mjk}^R[\beta_{mk}^I+\phi_{\bar{m}k}\sum_{l=1}^9\gamma_{\bar{m}l}c_{m'kl}])}{\sum_{n=1}^3\exp(\sum_k x_{mnk}^R[\beta_{mk}^I+\phi_{\bar{m}k}\sum_{l=1}^9\gamma_{\bar{m}l}c_{m'kl}])}.$$

(2) Generate $\bar{\beta}_m$:

$$f(\bar{\beta}_m|\{\beta_m^I\},B_m)=N\bigg(\sum_{m=1}^N\frac{\beta_m^I}{N},\frac{B_m}{N}\bigg).$$

(3) Generate B_m:

$$[B_m \mid \{\beta_m^I\},\bar{\beta}_m] \sim \text{Inverted Wishart}\bigg[b_0+N,\ B_0+\sum_{m=1}^N(\beta_m^I-\bar{\beta}_m)'(\beta_m^I-\bar{\beta}_m)\bigg],$$

where b_0 and B_0 are the prior degrees of freedom and precision, respectively. In our analysis, we set $b_0=10$ and $B_0=10\mathbf{I}+\mathbf{J}$, where $\mathbf{I}$ is a (7×7) identity matrix and $\mathbf{J}$ a (7×7) matrix of 1s.

(4) Generate $\gamma_{\bar{m}}$:

$$f(\gamma_{\bar{m}} \mid \{\beta_m^I\},\bar{\beta}_m,B_m,\phi_{\bar{m}}) \propto \exp\big[-(1/2)(\gamma_{\bar{m}}-\bar{\gamma}_{\bar{m}})'G_{\bar{m}}^{-1}(\gamma_{\bar{m}}-\bar{\gamma}_{\bar{m}})\big]\prod_{m=1}^N\prod_t \mathrm{Pr}_{mt}^R(j),$$

where $\bar{\gamma}_{\bar{m}}$ and $G_{\bar{m}}$ are priors. In our analysis, we set $\bar{\gamma}_{\bar{m}}$ as a (9×1) vector of 0s and $G_{\bar{m}}$ as a (9×9) identity matrix.

(5) Generate $\phi_{\bar{m}}$:

$$f(\phi_{\bar{m}} \mid \{\beta_m^I\},\bar{\beta}_m,B_m,\gamma_{\bar{m}}) \propto \exp\big[-(1/2)(\phi_{\bar{m}}-\bar{\phi}_{\bar{m}})'F_{\bar{m}}^{-1}(\phi_{\bar{m}}-\bar{\phi}_{\bar{m}})\big]\prod_{m=1}^N\prod_t \mathrm{Pr}_{mt}^R(j),$$

where $\bar{\phi}_{\bar{m}}$ and $F_{\bar{m}}$ are priors. In our analysis, we set $\bar{\gamma}_{\bar{m}}$ as a (6×1) vector of 0s and $F_{\bar{m}}$ as a (6×6) identity matrix.

(6) Repeat steps 1–5 for member m'.

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