A Polarization Model for Describing Group Preferences

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This article develops a model for describing the preferences of a group in terms of its individual members. The model incorporates the empirically observed group-polarization phenomenon. It is interesting that the resulting group preference evaluation is essentially a weighted linear model of individual preferences with the addition of an intercept term. The polarization model is empirically tested in two experimental contexts, faculty-candidate and restaurant selection. For both experimental situations, the polarization model performed better for the majority of groups tested in predicting a holdout sample than did either the more common weighted linear model without an intercept (with weights summing to one) or the multilinear model.

Group decision making has long been a major topic in a wide variety of social sciences: anthropology, sociology, political science, marketing, and psychology (see Hare 1976). The basic thrust of this research has been to determine those factors that affect the process by which groups make decisions (Swap 1983). In consumer research, the groups that have been studied include families (Davis 1976) and organizational buying centers (Webster and Wind 1972). Research has centered on identifying the individuals involved in the decision process (Davis and Rigaux 1974; Silk and Kalwani 1982), decision role structure (Davis 1976; McMillan 1973), and the determinants of relevant influence (Kriewall 1980; Thomas 1982).

In consumer research (or the social sciences in general), limited progress has been made with respect to developing and testing mathematical representations of group processes that can then be used to predict decision outcomes in consumer behavior. Three exceptions in marketing and consumer research are Choffray and Lilien (1980), Corfman and Lehmann (1987), and Eliashberg et al. (1986). Choffray and Lilien (1980) propose a set of four models that mathematically transforms a set of individual choice probabilities into a group choice probability. Each model corresponds to a different conceptualization of the interaction process within the group, that is, whether members vote, use the inputs of individuals in proportion to their importance, search for a consensus, or attempt to be least perturbing to other members. Unfortunately, Choffray and Lilien do not test these models empirically. Corfman and Lehmann (1987) develop and test a different set of algebraic models in which the group members' personal traits (i.e., resources and goals) are used to predict the outcomes of conflict resolutions. The forms of the models are basically linear or linear with interactions. Models are estimated using data collected on couples' decisions. The dependent variable is the probability of getting one's own way. The independent variables are the resources an individual brings to the group decision (e.g., expertise, social debt) relative to those of his or her partner(s). While this initial work is a step in the right direction, the particular algebraic forms seem ad hoc and not well-grounded in psychological theory. In contrast, Eliashberg et al. (1986) have tested models from the decision analysis literature, which follow from sets of axioms, to predict a group's preference judgment as a function of the judgments of its individual members. These weighted linear and multilinear models are similar in algebraic form to Corfman and Lehmann's (1987). The axioms from which these models are derived prescribe reasonable behavior. However, they ignore some fundamental behavioral aspects of group decision making that have been discovered through behavioral research (Hare 1976), such as informational influences and social comparisons, and therefore are limited in describing and understanding group processes.

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A basic premise of this article is that new models that incorporate behavioral phenomena could have an advantage in prediction (see Menasco and Curry 1989). This notion is implicit in Choffray and Lilien's (1980) reliance on specific interaction processes in their modeling efforts. The behavioral phenomena to be included in modeling usually depend on the domain of the decision processes studied (e.g., role structure may be important in situations in which individuals differ in terms of their expertise about separate aspects of the decision). Extensive evidence suggests that group discussion generally produces attitudes that are more extreme in the direction of the average of prediscussion attitudes in a variety of situations. This phenomenon is called the group-polarization hypothesis (Myers and Lamm 1976).

Group polarization can exist on a variety of dimensions. In a traditional decision-process paradigm an individual forms perceptions of choice alternatives on the basis of available information. These perceptions lead to preferences and, eventually, to choice. An individual may discuss any one of the above with peers. Such discussions may lead each individual to conform to some type of group norm to a greater degree and therefore tend to produce the observed polarization. For example, Asch (1952) has demonstrated that group pressure (if not discussion) can lead individual perceptions to conform to those advocated by the group.

In this article we focus on polarization of preferences. Groups composed of individuals favorably (unfavorably) disposed toward a given alternative will become even more (less) so after discussion. We develop a simple model that provides a paramorphic representation of the polarization effect that can be used to predict group preference judgments. The model has the advantage of being derived from observed empirical phenomena and ultimately takes the form of a linear regression model with an intercept and certain parameter constraints. Therefore, the model is simple to estimate from data and extremely practical. Eliashberg and Winkler (1981) have developed a model that allows for partial polarization of risk attitudes (i.e., the group is less risk averse than the average of its individuals). However, their model does not explicitly allow for polarization of preferences and requires considerable effort to calibrate it from data.

In this article, we develop a polarization model for describing group preferences and present two experiments designed to examine its predictive validity. Experiments have been the traditional vehicle in group-decision research (Swap 1983). Although naturalistic studies are more likely to capture the processes of real, functioning groups, their use would sacrifice experimental control. More important, many real-life groups are not accessible to direct observation. Notable exceptions include the industrial purchase described in Cyert, Simon, and Trow (1956) and Kalven and Zeisel's (1966) monumental study of American juries.

CONCEPTUAL BACKGROUND

Research on group polarization, initiated by Stoner (1968), involves a small number of participants responding to a series of story problems called choice dilemmas (see Kogan and Wallach [1964] for an elaboration of this concept). Each problem involves a decision faced by some individual. For example, consider Henry's dilemma and the corresponding instructions to each respondent in a group:

> Henry is a writer who is said to have considerable creative talent but who so far has earned a comfortable living by writing cheap westerns. Recently, he has come up with an idea for a potentially significant novel. If it could be written and accepted it might have considerable literary impact and be a big boost to his career. On the other hand, if he was not able to work out his idea or if the novel was a flop he would have expended considerable time and energy without remuneration.
>
> Imagine that you are advising Henry. What is the lowest probability that you would consider acceptable for Henry to attempt to write the novel? [Myers 1982, p. 126]

After recording their advice individually, participants get together and discuss the dilemma until they agree on a final judgment. Stoner discovered that group judgments are generally lower than the average of prediscussion individual responses, which implies that groups are more risk prone than is the average individual. This phenomenon was dubbed the "risky shift."

Note that the probability responses that Stoner requested were really von Neumann–Morgenstern (1947) utilities for the certain option, writing cheap Westerns (Currim and Sarin 1983; Hauser and Urban 1979). The above task implies that a respondent's utility for writing cheap Westerns, U(cheap Westerns), is equal to the expected utility of the lottery between the novel's being a success with a utility of one and its being a flop with a utility of zero. With this calibration, the utility of cheap Westerns to Henry is equal to p, where p corresponds to the required probability of success checked by the respondent. Preferences, as reflected by von Neumann–Morgenstern utilities, encompass both the intrinsic desirability of the alternative in question to a respondent and that respondent's attitudes toward risk (Currim and Sarin 1983). This being the case, risk attitude may not be what produced the observed phenomenon of lower group judgments (Mackenzie 1971). When a shift in probabilities was observed in prior experiments, it could have been due to risk attitudes, as the experimenters claim, or to the intrinsic desirability of the certain option. For example, an identical result would emerge if, during the discussion, much negative information about cheap Westerns was exchanged, which would make Henry's job less intrinsically desirable to the participants. It is impossible to make a distinction between the two possibilities. Rather, we simply

refer to the shift as one of preference, which encompasses both.

In any event, Stoner's finding was replicated by several researchers. However, Teger and Pruitt (1967) demonstrated that choice dilemmas that elicited relatively cautious responses (i.e., a high-probability response or high utility for the certain option) tended to produce even more cautious responses after discussion. This cautious shift, when coupled with the earlier risky-shift findings, suggests what has come to be called the group-polarization hypothesis (Myers and Lamm 1976). Postdiscussion responses tend to become more extreme in the direction of the prediscussion average responses.[1]

Myers and Arenson (1972) have shown that the magnitude of the polarization effect is approximately a linear function of the mean initial response (see Fig. 1). There is some value of mean judgment in Henry's problem (not necessarily .5) that produces no polarization. If the mean response is below (above) that value, which we shall call the "pivot point," denoted by K, the utilities are polarized downward (upward), which produces the apparent risky (cautious) shift. The size of the shift is directly proportional to the difference between the mean value and the no-polarization point.

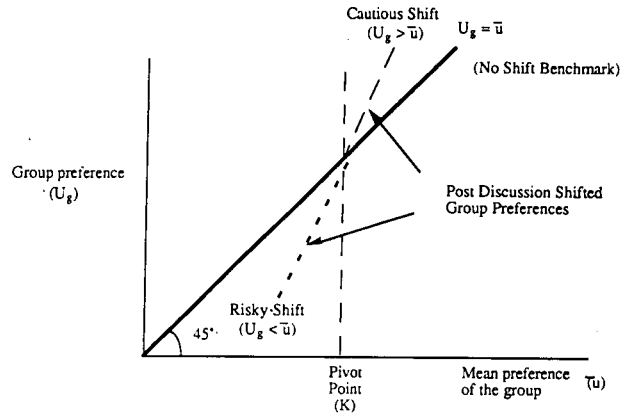
A variety of theoretical explanations for the polarization effect have been proposed. Although none is generally accepted, two views, the informational-influence explanation and the social-comparison explanation, appear to dominate (Myers 1982). These implicitly assume that there is a variability of opinion among the group members. According to the informational-influence explanation, more arguments are drawn out in support of the majority opinion than of the minority one. The minority is more likely to be swayed. Furthermore, it is unlikely that any given person in the majority will have considered all the relevant arguments. Therefore, the majority's leanings are likely to be reinforced.[2] Alternatively, the social-comparison view (Pruitt 1971a, 1971b) suggests that people, motivated by a concern for presenting oneself favorably, will tend to amplify their responses when others are found to share their beliefs. The basic model proposed in this article is consistent with both of these views. It is a paramorphic representation of the empirical polarization phenomenon that can be used for the prediction of group preferences.

[1]Similar results emerged when individual subjects were asked to make postdiscussion individual responses; i.e., individual responses became more extreme in the direction of the prediscussion average (Burnstein and Vinokur 1975). In fact, these shifts seem to occur if an individual simply reflects about the matter under consideration in the absence of discussion (Tesser 1978). However, given our focus on group preference, we emphasize the group-level finding.

[2]Bordley (1983) proposes a formal model, based on the informational influence viewpoint, that also leads to the observed polarization.

FIGURE 1

GRAPHICAL REPRESENTATION OF THE POLARIZATION HYPOTHESIS



THE MODEL

Let u_i be the idiosyncratic preference judgment of the benefits received by the ith individual from an alternative in a group of m individuals, and let U_g be the group preference of the alternative's benefits. For simplicity, we assume that u_i and U_g are all scaled to be between 0 and 1. To begin with, we consider a formulation in which the group as a whole does not exhibit the polarization phenomenon and the group's preference is a simple linear combination of those of its members. Then,

$$U_g = \sum_{i=1}^{m} \lambda_i u_i, \tag{1}$$

where λ_i is a relative weight assigned to the ith individual. We expect that $0 \leq \lambda_i \leq 1$ and $\sum_{i=1}^{m} \lambda_i = 1$. This is a simple weighted utility model (see, e.g., Curry and Menasco 1979).

Equation 1 provides a good starting point since the conditions of the problem correspond to those that lead to a linear model providing a good paramorphic representation of the process (Dawes and Corrigan 1974). First, the individual and group preference evaluations cannot be measured without error. Second, the independent variables (individual preferences) have conditionally monotonic relationships with the dependent variable (group preference). Either or both of these conditions could be violated in the current context for certain group dynamics. However, we expect that they would both hold in a majority of situations.

We must modify Equation 1 to account for the observed (empirical) polarization phenomenon described in the previous section. We express the group preference evaluation as:

$$U_g = \sum_{i=1}^{m} \lambda_i u_i + \phi(\bar{u} - K), \tag{2}$$

where $\bar{u}$ is the average of the preferences of the group members. Equation 2 states that the adjustment of the group preference is directly proportional to the difference between the group's mean utility and a base value, K, defined to be between 0 and 1 (Myers and Arenson 1972). The parameter ϕ is a shift parameter constrained to be nonnegative. Equation 2 represents the tendency for the group to shift upward for values of the group mean higher than K and downward for values lower than K.

The parameter K is specific to a particular group (i.e., size and composition of individuals) and the decision situation it faces. One may think of K as a group norm. For example, under the presumption that polarization is purely one of risk attitude, if the group has a culture that reflects a tendency to avoid risk, K will be relatively low and the shift will be upward. Extreme values of K (i.e., 0 and 1) will only move the group preference in one direction (i.e., upward or downward) relative to the group mean.[3]

The linear formulation in Equation 2 has the potential for logical inconsistencies. Suppose $\bar{u}$ is close to one of the extreme values. Unless K is at the same extreme value, the model implies a shift off the scale. To accommodate this, a sigmoid function (e.g., logistic) might be hypothesized. This function would have to be bounded by 0 and 1, and a special nonlinear procedure would need to be developed for estimating its parameters. Thus, we trade apparent consistency for ease in estimation when using the linear formulation. Recall that the linear formulation seems to hold over a wide range of $\bar{u}$ values (Myers and Arenson 1972).

Algebraic Formulation

If we rewrite the function in Equation 2 by setting $\bar{u} = {}^1/_m \sum_{j=1}^{m} u_j$, then Equation 2 becomes

$$U_g = \sum_{i=1}^{m} \left(\lambda_i + \frac{\phi}{m}\right) u_i - \phi K. \tag{3}$$

Therefore, the group preference function of Equation 2 is the same as a linear function of the individual preferences with an intercept term added to it and subject to certain constraints in the weights of the linear function. Written explicitly, the function is

$$u_g = w_0 + w_1 u_1 + w_2 u_2 + \cdots + w_m u_m, \tag{4}$$

where $w_0 = -\phi K$ and $w_i = \lambda_i + {}^{\phi}/_m$, $i = 1, 2, \ldots, m$. Given the linear formulation of Equation 3, the model is easy to estimate, although several constraints need to be imposed on the parameters. Once estimated, the model can be used for making predictions.

Because the λ's sum to 1, it follows that $K = w_0/(1 - \sum_{i=1}^{m} w_i)$. Thus, the parameters of the model satisfy the following constraints:

$$\begin{aligned} &w_0 \le 0; \\ &\sum_{i=1}^{m} w_i \ge 1; \\ &0 \le \frac{w_0}{1 - \sum w_i} \le 1. \end{aligned} \tag{5}$$

The second constraint owes itself to the fact that $\sum_{i=1}^{m} w_i = 1 + \phi$ and $\phi > 0$. When the polarization slope parameter ϕ is zero, the model reduces to the simple weighted linear model. The last constraint comes from the fact that K must be between zero and one. If the constant term, $-\phi K$, is zero then either ϕ or K is equal to zero. We could determine whether or not ϕ is zero by determining whether or not the constraint $\sum_{i=1}^{m} w_i \ge 1$ is binding. If it is not, then $\phi > 0$ and $K = 0$ will produce a cautious shift. If it is, then $\phi = 0$ and K is indeterminate.

We adopt a two-stage estimation procedure to obtain parameter estimates that satisfy these constraints.[4] First, we run an ordinary least squares (OLS) regression. We then examine which constraints are violated, set these constraints at the boundary of the inequality, and reestimate the model using OLS. If any of the constraints are still violated, this procedure is iterated until all the constraints are satisfied. The resulting parameters will obey all the above constraints.[5] Ordinary least squares regression is used here simply as a means of model fitting, and the assumptions required to perform statistical tests on the parameters cannot be expected to hold, in general. However, we can recover the estimates of λ's, ϕ, and K from the estimates of $w_0, w_1, \ldots, w_m$ by solving the relationships described above between Equations 4 and 5.

Process Origins

The social-comparison viewpoint discussed earlier (Pruitt 1971a, 1971b) can provide an interesting justification for the polarization phenomenon at the group

[3]When both $\bar{u}$ and K are close to the same extreme value, the shift will be toward the center rather than toward the extreme values. However, to be consistent, we will also label this situation as polarization.

[4]These parameters can be estimated by formulating a linear-programming problem with the objective of minimizing the sum of absolute deviations. But, generally, the solution may yield multiple optima.

[5]In the two experimental studies reported in this article, the second stage of estimation was needed for 15 out of 38 groups in the first study, and for 14 out of 37 groups in the second study, and for no group was the third stage needed. We must note that setting parameters at boundary values uses up degrees of freedom. Further, for five groups of Study 2, the rank order of w-estimates made from our procedure and linear programming was the same. The actual magnitudes were naturally somewhat different owing to the difference in the objective function.

level. Suppose in a discussion an individual hears that the predominant opinion is one that he shares (i.e., u_i is in the same direction from K as $\bar{u}$). In an attempt to present himself more favorably, the individual will amplify his position. Accordingly, we may write the revised preference, u_i' for the ith individual as $u_i' = u_i + \phi_i(\bar{u} - K)$. If, on the other hand, an individual finds that the predominant opinion is not his (i.e., u_i is in the opposite direction from K as $\bar{u}$), he may represent himself as being more in accord with the dominant view in order to present a favorable image (Festinger 1954). We may also write the individual's revised preference as above. Substituting the u_i' for the u_i in Equation 1, we obtain $U_g = \sum_{i=1}^{m} \lambda_i u_i + \sum_{i=1}^{m} \phi_i(\bar{u} - K)$, which is essentially Equation 2 with $\phi = \sum_{i=1}^{m} \phi_i$.

EXPERIMENTAL STUDIES

We conducted two small-scale experiments to empirically test the polarization model. Various details of these experiments are described below. The studies differ with respect to context, measurement procedures, and subject motivation. Testing a model under a variety of circumstances provides confidence in the generality of common results (Campbell and Stanley 1966).

The polarization model, Equations 2–4, consists of simple modifications of the weighted linear model, Equation 1. Therefore, it makes sense to compare the polarization model to its source as well as to another modification of Equation 1, the multilinear utility model (Keeney and Raiffa 1976):

$$U_g = \sum_{i=1}^{m} \lambda_i u_i + \sum_{i=1}^{m} \sum_{j=1}^{m} \lambda_{ij} u_i u_j + \sum_{\substack{i=1 \\ i \neq j}}^{m} \sum_{j=1}^{m} \sum_{\substack{k=1 \\ j \neq k}}^{m} \lambda_{ijk} u_i u_j u_k + \dots \quad (6)$$

These forms have been used to model both individual and group preference (Eliashberg 1980; Eliashberg et al. 1986). The most general developments on individual preference (Fishburn and Keeney 1974, 1975) place no restrictions on either the sign or the magnitude of the parameters. For a three-person group (i.e., $m = 3$), the number of parameters estimated is 4, 3, and 7, respectively, for the polarization, linear, and multilinear models.

Study 1

Context. The context for this experiment was the evaluation of a number of hypothetical faculty candidates in marketing. Subjects were asked to assume that they were responsible for hiring a new assistant professor for their marketing department.

Stimuli Design. Each hypothetical faculty candidate's résumé was described as a profile on seven characteristics that were chosen on the basis of the authors' judgment and experience with faculty recruiting over a period of time. The levels were selected to provide dispersion on each characteristic and to be representative of the variety of possibilities available in the marketplace. The seven characteristics and the description of alternative levels on each are (1) undergraduate education (three levels: business, engineering, and behavioral sciences), (2) school awarding doctorate (four levels: School A, School B, School C, and School D; actual names of the schools were used in the experiment), (3) length of time since doctorate (two levels: two years and five years), (4) number of "important" publications (two levels: two and four), (5) teaching ratings at previous school (four levels: top 10 percent, next 15 percent, second quartile, and bottom half), (6) personality (two levels: friendly and open, and shy and reserved), and (7) reputation for collegiality (two levels: works well with others and tends to work alone). Sixteen candidate profiles were developed using an orthogonal, fractional, factorial experimental design of the above seven characteristics (Hahn and Shapiro 1966). Four other profiles were included as validation stimuli for a total of 20 profiles.

Differences in individual evaluations are important for interesting group discussion. While all respondents would agree on the direction of preference for some of the attributes (e.g., publications), they are likely to differ with respect to preferences for other attributes (e.g., undergraduate education).

Subjects. The experiment was conducted among 38 groups of three subjects each. Fifteen of these groups were composed of selected marketing faculty members in a number of business schools; the rest were groups of M.B.A. students at a major eastern business school. The subjects participated in the study on a voluntary basis. All members of every group had worked together previously. Each of the faculty groups consisted of members of the same marketing department in a given business school, and the student groups were part of ongoing course project teams at their school.

Experimental Tasks. The data we analyze were collected in two phases. In Phase I, each subject in the group made idiosyncratic evaluations of the resumes of the 20 candidates. First, subjects were asked to pick their most- and least-preferred candidates. For each of the remaining 18 candidates, the evaluation was given by providing a probability so that the respondent would be indifferent between each candidate and a lottery between that respondent's most- and least-preferred candidate with the given probability. If the most- and least-preferred candidates are assigned utilities of 1 and 0, these indifference probabilities correspond to those in Henry's problem and translate into utilities. The exact procedure used for deriving these measures and detailed

TABLE 1

THE FOUR VALIDATION STIMULI USED IN THE MODEL COMPARISON

Undergraduate education	Doctoral school	Number of years since doctorate was received	Number of publications	Teaching ratings	Personality	Collegiality
Business	School D	5	4	Bottom half	Shy and reserved	Tends to work alone
Engineering	School C	5	2	Second quartile	Shy and reserved	Works well with others
Engineering	School B	2	4	Top 10 percent	Friendly and open	Tends to work alone
Behavioral sciences	School A	2	2	Next 15 percent	Friendly and open	Works well with others

instructions were adapted from Currim and Sarin (1983).

After each member of the group completed the task in Phase I, the group met to discuss and to provide a set of group preference evaluations or utilities. This task constituted Phase II. The procedure for eliciting the evaluations in Phase II was identical to that used in Phase I. The members met as a committee to evaluate the résumés and arrive at a consensus in their evaluations. The group sessions typically lasted between 30 minutes and an hour. In no case did a group fail to reach a consensus. Each member had their initial evaluations available to them. However, they were under no obligation to reveal them to each other.

Estimation and Analyses. The polarization model, $U_g = \lambda_1 u_1 + \lambda_2 u_2 + \lambda_3 u_3 + \phi(\bar{u} - K)$; the linear model, $U_g = \beta_1 u_1 + \beta_2 u_2 + \beta_3 u_3$; and the multilinear model, $U_g = \alpha_1 u_1 + \alpha_2 u_2 + \alpha_3 u_3 + \alpha_{12} u_1 u_2 + \alpha_{13} u_1 u_3 + \alpha_{23} u_2 u_3 + \alpha_{123} u_1 u_2 u_3$, were each estimated via OLS regression with the appropriate constraints over the first 16 observations (corresponding to the orthogonal array) for every group.

We compare the predictive validity of the group-polarization model with those of the linear and multilinear models. We use the three models and parameters for each group estimated on the first 16 observations to predict the judgments on the four validation stimuli. These stimuli are shown in Table 1. Using the root mean squared error (RMSE) of these predictions from each model, several comparisons among the models are made.

Results—Model Comparison. The summaries developed from the predictive validity RMSE comparisons for all the groups are shown in Tables 2 and 3. Taking all three models into account, the polarization model performed best for 18 groups. The weighted linear model performed best for seven, while the multilinear model performed best for six. Of the nine groups in which the polarization model reduced to the linear one ($\phi = 0$), the two models are tied for the best seven times.

A Friedman's two-way analysis of variance applied to the RMSEs demonstrated that the three models did indeed perform differently ($\chi^2 = 15.67$; $df = 2$; $p < .001$). With respect to pairwise comparisons, the polarization model outperformed the multilinear model by 31 to 7 (sign test $Z = 3.89$; $p < .001$). The polarization model also outperformed the linear model by a count of 20 to 9 with nine groups having identical predictions for both models ($Z = 1.78$; one-sided $p < .05$). However, if one were to enter this analysis with strong prior beliefs in the linear model, then one interpretation of ties is that the polarization model has not been shown to be superior and therefore a tie is a win for the linear model. If this is the case then the margin of victory is 20 to 18, much less and, of course, not statistically significant. Finally, the linear model outperformed the multilinear one by a count of 24 to 14 ($Z = 1.62$; $.10 >$ one-sided $p > .05$).

It appears that the polarization model performs at least as well as the other two, and, depending on one's standards for confidence, the multilinear model performs worst. The multilinear finding is in contrast to Eliashberg et al. (1986) who found that the multilinear model was superior to the linear one in a group decision-making context, albeit by a very slight margin. However, their study differed from ours in several ways, including context and parameter-estimation method.

Although this study shows preliminary support for the polarization formulation of Equation 5, three limiting aspects must be noted. First, the context is not of immediate relevance to consumer research. Second, there was no chance subjects would have to live with the consequences of their decisions, which could possibly skew their behavior. Finally, the measurement methodology still confounds risk attitude and intrin-

TABLE 2

MODEL COMPARISONS FOR THE FACULTY HIRING STUDY

Row model	Polarization model[a]	Weighted linear model[a]	Multilinear model[a]	Number of times model performed best
Polarization model		20[b] (11, 9)	31 (20, 11)	18[c]
Weighted linear model	9[b] (5, 4)		24 (16, 8)	7[c]
Multilinear model	7 (3, 4)	14 (7, 7)		6

[a]Numbers in this column indicate the number of groups for which the row model's RMSE is lower than that of the model listed here. Numbers in parentheses indicate the number of student groups and the number of faculty groups, respectively.
[b]There are nine other groups (seven student and two faculty) for which these two models are tied.
[c]In addition to the seven ties between the polarization and linear models.

sic desirability. These limitations are addressed in Study 2.

Study 2

The competing models, their estimation, and tests are the same as those in Study 1. Study 2 differs with respect to the experimental context, measurement procedures, and subject motivations.

Context. This study centered on the evaluation of a set of actual restaurants in a major northeastern metropolitan city, which we will call "New City." Subjects were asked to assume that they were to choose a restaurant to go to together. This context is of more direct relevance to typical consumer research.

Stimuli. Twenty restaurants were selected from a local guidebook. The particular restaurants were all in the same price range ($35–$50 for dinner for two, excluding tax, tip, and wine) but differed with respect to cuisine, neighborhood, and ambience. We incorporated such differences to ensure that the entire set would contain restaurants that individuals who were not perfectly indifferent would like and some that they would not like. The actual guidebook descriptions served as the stimuli. Fifteen stimuli were used for estimation purposes, and five were used for validation.

TABLE 3

DISTRIBUTION OF ROOT MEAN SQUARED ERRORS FOR THE FACULTY HIRING STUDY

Range	Polarization model	Weighted linear model	Multilinear model
0–5.00	9 (5, 4)	7 (4, 3)	6 (4, 2)
5.01–10.0	13 (7, 6)	17 (11, 6)	14 (7, 7)
10.01–15.00	11 (8, 3)	4 (3, 1)	12 (8, 4)
15.01–20.00	4 (2, 2)	7 (3, 4)	2 (1, 1)
20.01 and over	1 (1, 0)	3 (2, 1)	4 (3, 1)
Total	38 (23, 15)	38 (23, 15)	38 (23, 15)

NOTE.—Data indicate the number of groups for which the RMSE (×100) was within a given range for a particular model. Numbers in parentheses indicate the number of student groups and the number of faculty groups, respectively.

Subjects. This study was conducted among 37 groups of three subjects each. Each subject was an undergraduate enrolled in an introductory marketing class at a university located in "New City." Since they signed up together, most of the subjects knew each other before they began the experiment. The subjects in several of the groups had previously made similar restaurant choices with the other members of their group.

Experimental Tasks. The data were collected in three phases, all during a single one-hour experimental session. In Phase I, each subject evaluated the 20 restaurants. First, they were asked to pick their favorites and least favorites and assign to them the values of 100 and 0. For each of the remaining 18 restaurants, they were asked to provide an intermediate value that reflected the relative attractiveness of the restaurant in question. This procedure is much simpler than the Currim and Sarin (1983) procedure used in Study 1. Furthermore, the instructions (and the lack of a probability response) focused the judgment on intrinsic desirability without consideration of risk. The responses were divided by 100 to be between zero and one.

Upon the completion of Phase I, the group provided a single collective set of judgments in Phase II. Again, they had their initial evaluations available to them. This time we instructed the subjects not to reveal their individual numerical judgments. They could express preference in any other way, however. As an incentive, the subjects were told that upon completion of the experiment four groups would be chosen at random to receive a $75 gift certificate at one of the 20 restaurants. The particular restaurant chosen would depend on the group responses provided by each winning group. The mechanism was not revealed, but the subjects were told that they would not necessarily get their first choice so they should pay careful attention to all of their judgments.[6]

[6]In reality, we gave the winning groups $75 in cash. They did not know this at the time, though.

TABLE 4

MODEL COMPARISONS FOR THE RESTAURANT STUDY

Row model	Polarization model[a]	Weighted linear model[a]	Mutilinear model[a]	Number of times model performed best
Polarization model		19[b]	31	16[c]
Weighted linear model	13[b]		27	11[c]
Multilinear model	7	10		6

[a]Numbers in this column indicate the number of groups for which the row model's RMSE is lower than that of the model listed here.
[b]There are five other groups for which these two models are tied.
[c]In addition to the four ties between the polarization and linear models.

Analyses. We examine the RMSEs of the predictions made by the estimated polarization, linear, and multilinear models for the five validation restaurants in order to compare the predictive validities of the three models.

Results. Tables 4 and 5 show the details of the predictive validity RMSE comparisons in the same manner as Tables 2 and 3. Here, the polarization model performed best for 16 groups, with four ties with the weighted linear model. The weighted linear model performed best for 11 groups (in addition to four ties with the polarization model) and the multilinear for six. Of the five groups in which the polarization model reduced to the linear one ($\phi = 0$), it (the polarization model or the linear model) beat the multilinear model four times. A Friedman's two-way analysis of variance on the RMSEs demonstrated that the three models performed differently ($\chi^2 = 17.31$; $df = 2$; $p < .001$). With respect to pairwise comparisons, the polarization model outperformed the multilinear one by 31 to 7 (sign test $Z = 9.86$; $p < .001$) and the linear one by 19 to 13 with five ties ($Z = 0.99$; NS), or 19 to 18 in the Bayesian view with strong priors on the linear model. The linear model outperformed the multilinear one by 27 to 10 ($Z = 2.79$; $p < .01$).

TABLE 5

DISTRIBUTION OF ROOT MEAN SQUARED ERRORS FOR THE RESTAURANT STUDY

Range	Polarization model	Weighted linear model	Multilinear model
0–5.00	0	10	0
5.01–10.00	11	11	3
10.01–15.00	9	8	11
15.01–20.00	10	6	10
20.01–25.00	4	2	4
25.01 and over	3	0	9
Total	37	37	37

NOTE.—Data indicate the number of groups for which the RMSE (×100) was within a given range for a particular model.

In this study, it appears that the multilinear model performs worse than the other two. However, the difference between the polarization and linear models is not statistically significant. We believe, though, that the directional superiority (albeit not significant) of the polarization model, when coupled with the more significant support from Study 1, lends further credence to the paramorphic form in Equation 4.

DISCUSSION AND FUTURE RESEARCH

This article presents a group-polarization model for predicting group preference judgments. The model draws from the group-polarization literature (Myers and Lamm 1976). Our basic premise is that postdiscussion group utilities are more extreme in the direction of the average of prediscussion individual utilities. The resulting model is a variation of the simple weighted linear model, with the presence of a constant term and constraints on the coefficients. Eliashberg et al. (1986) showed that the multilinear model, another variation of the basic linear model, could outperform the linear model in a predictive sense, although our results were to the contrary. The question then arises as to which modification of the weighted linear model performs better. In our experiments, the modification according to the polarization model seems to be appropriate. It performed better for a majority of the groups tested. The results across both studies are consistent if not compelling. The degree of superiority is greater in the faculty hiring study than in the restaurant study. One factor that may have a bearing on the difference between these two studies is that all the faculty groups had worked together previously as faculty colleagues and some of the student groups in Study 2 were ad hoc ones with limited or no prior interactions. But even there, when the polarization model performs better than the linear model, it does not do so by much. In contrast, when the multilinear model performs poorly, it loses badly to the other two models. Nevertheless, the relative performance of the polarization model is consistent, and consistency is evidence in and of itself.

TABLE 6

RANGES OF ERRORS FOR THE FACULTY HIRING STUDY

Model	Range of RMSE (×100)	Percentage of errors (predicted − actual)		
		Positive	Negative	Zero[a]
Polarization model	2.81–34.27	42	45	13
Weighted linear model	2.23–34.27	46	43	11
Multilinear model	2.94–39.20	39	46	15

[a]When predicted is rounded to nearest hundredth.

TABLE 7

RANGES OF ERRORS FOR THE RESTAURANT STUDY

Model	Range of RMSE (×100)	Percentage of errors (predicted − actual)		
		Positive	Negative	Zero[a]
Polarization model	6.65–28.06	50	48	2
Weighted linear model	5.18–28.06	52	47	1
Multilinear model	8.10–52.56	54	44	2

[a]When predicted is rounded to nearest hundredth.

Combining Forecasts. Our results relate to a recent stream of research on combination of expert forecasts. Bordley (1986), Clemen (1986), and Granger and Ramanathan (1984) seem to suggest that weighted linear combinations of forecasts in which the weights sum to one may be dominated by a regression-type equation with an intercept and either unconstrained coefficients or constraints other than those in which the weights sum to one. This essentially coincides with the superiority of the simple parametric form in Equation 5 in our experiments, which thereby recommends this form as a practical tool. That it corresponds to an empirically established phenomenon is a bonus in this regard.

Axiomatic Models of Decision Making. The models of decision making tested in various empirical studies do correspond to sets of axioms that can be taken to prescribe behavior. This is true not only of group decision making (Dyer and Sarin 1979; Eliashberg et al. 1986; Keeney and Kirkwood 1975), but also of bargaining (Bartos 1974; Nash 1950) and of individual decision making as well (Eliashberg 1980; Kahnemann and Tversky 1979; Krantz et al. 1971; von Neumann and Morgenstern 1947; Wright 1984, chap. 3). Thus, often there is not a clear distinction between normative and descriptive models of decision making. It is frequently a matter of interpretation as to whether the relevant axioms describe what decision-making units should do or what they do indeed do.

The axiomatic tradition in groups can be traced back to Fleming (1952) and Harsanyi (1955) who focused on simple weighted linear models. In their formulations, like ours, the weights were not required to sum to one. This idea seems to have gotten lost in recent applications (see Eliashberg et al. 1986). Thus, our model provides a connection to the early seminal work in the field.

Owing to its linear form and linear transformation of utilities, our model has the underlying axiomatic structure of the simple weighted linear model (Keeney and Raiffa 1976). Recall that choices resulting from von Neumann–Morgenstern utilities are invariant under linear transformations. If we transform the u_is to u_i^*s using the $u_i^* = [1/(w_1 + w_2 + w_3)]\ (u_i - w_0)$; $i = 1, 2, \ldots, m$, and substitute the u_i^*s into Equation 4, we get a form for the group utility identical to the weighted linear model (i.e., Eq. 1). However, the corresponding axioms bear no conceptual similarity to the polarization effect (see Keeney 1976; Keeney and Kirkwood 1975). Therefore, it remains to be seen whether an axiomatic structure could be developed for the polarization model that has the appropriate behavioral interpretation. Thus, our contribution lies in the use of the intercept to paramorphically describe the polarization phenomenon rather than to capture an inherent behavioral process of a group.

Group Heterogeneity. While our research has focused on the predictive power of the models using a group as the unit of analysis, an interesting avenue for future research is to investigate the reasons for the heterogeneity in the parameters (e.g., K and ϕ) across groups. For example, descriptors such as the degree of experience of the group with the decision problem may partially explain the heterogeneity. Additionally, such descriptors may also explain why one model may work better for some groups and another one for others. For example, homogeneous expertise could lead to increased concerns for equity and greater performance for the multilinear model (Keeney and Raiffa 1976, chap. 10).

Future Research. One can often learn about conditions for use and potential model refinements by examining residuals. We in fact attempted this. When we separated out those groups for which the polarization model had (or tied with) the lowest RMSE, we found an increased proportion of overprediction (predicted − actual > 0) with the polarization model. The percentage of over-, under-, and correct predictions changes from those in the first lines of Tables 6 and 7 to 45 39 16 for Study 1, and 54 43 3 for Study 2. This shift did not occur with either of the other two models. The shift is surprising in light of the $w_0 \leq 0$ constraint. Apparently, the $\sum w_i > 1$ constraint is very powerful. Exactly why this is true is not clear. Perhaps future researchers can use this as a point of departure in future modeling efforts.

Future research should also study models of group decision making that involve other comparisons of as-

pects of decisions besides earlier preferences. Polarization of preferences is just one example. The classical model of decision making alluded to at the outset of this article could provide a framework. In reality, group members share opinions and modify them as a result of the exchange, perhaps before forming preferences (see, e.g., DeGroot 1974). Furthermore, there is a need to explore the range of substantive problems for which the polarization model would be useful; some of these issues could include joint decision making in families and decisions by management committees such as purchasing groups, boards of directors, and the like.

Finally, progress in the area of group decision making would be well-served with studies, such as those of Cyert et al. (1956) and Kalven and Zeisel (1966), involving direct observation of actual groups at work. Participant or direct observation would enable the researcher to identify the appropriate social motives and comparison processes. Protocol methods could also help in understanding the workings of group processes. Such research will help in further discriminating between the informational-influence and social-comparison explanations for the polarization effect. Indeed, since we never observed the processes of our participating groups, we have no direct evidence that the polarization effect actually occurred. Experimental manipulations in which one or more subjects are coached to act in a particular way may lead to further understanding of the group processes. Such experimentation and mathematical model building could then complement each other much in the same way that protocol statements and regression models have worked together to further the study of individual decision making (Einhorn, Kleinmutz, and Kleinmutz 1979).

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