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Quantitative models in marketing typically focus on the household as the unit of analysis while ignoring the individual family members' behavior and the behavioral interactions among household members. However, knowledge of such intrahousehold behavioral interaction enables marketers to target their communications more effectively. In this article, the authors propose a modeling framework to capture the intrahousehold behavioral interaction based on family members' actual consumption behavior over time. The authors develop a model to capture multiple agents' (more than two individuals') simultaneous choice decisions over more than two choice alternatives. This is extremely difficult with other previously developed modeling approaches. The authors apply the proposed model to a context of family members' television viewing and simultaneously model whether the television is on, which type of program is playing, and which family members are watching. The proposed model makes it possible to estimate the individual's intrinsic preference and the extrinsic preference from a joint consumption with other members. In turn, these estimates enable the authors to test several alternative group decision-making heuristics that may operate in those joint consumption occasions and to conduct managerially useful counterfactual simulations.

Keywords: autologistic choice model, joint consumption, behavioral interaction, family-member decision making, hierarchical Bayesian analysis

Modeling the Intrahousehold Behavioral Interaction

Consumption choices of individuals can be interdependent. Such interdependencies can be especially common in household consumption choices. For example, individual household members determine whether they spend time alone or together with other family members on various activities and may affect other members' choices. Such intrahousehold behavioral interactions are likely to be significant because of the strong emotional ties among household members. In this article, we study a specific consumption context—namely, television viewing. In the context of watching television, some family members may be more likely to watch television with other members because they are likely to receive utility from spending time together with their spouses, children, or parents. It is this behavioral interaction among family members that we study in this research.

Intrahousehold behavioral interaction has drawn an increasing amount of attention from marketers. For example, McCann-Erickson, one of the largest advertising agencies in the United States, routinely collects information on consumer communication media usage, including whether a consumer uses a specific medium together with other family members. PepsiCo keeps a rolling database of a consumer diary panel to understand consumer beverage consumption habits, including whether a beverage is consumed with other family members present. This knowledge of

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intrahousehold behavioral interaction enables marketers to target their communications more accurately and potentially influence the family purchase and consumption behavior.

However, despite the importance of this topic, there is little understanding of intrahousehold behavioral interactions. In the previous literature, researchers have studied the influence of other family members' preferences on an individual family member's preference (Yang, Narayan, and Assael 2006) and the influence of family members on the process of a group decision making (Aribarg, Arora, and Bodur 2002; Park 1982). Nevertheless, no study to date has examined family members' simultaneous decisions on whether to participate in an activity that potentially leads to a joint consumption.

To study the television-viewing decisions of each household member (mother, father, and child) and the behavioral interactions in these decisions, we propose a model that essentially captures a system of discrete endogenous variables in which one family member's decision is dependent on other family members' decisions. Estimating such a simultaneous equations model with multiple discrete endogenous variables is challenging. As Maddala and Lee (1976) and Heckman (1978) show, the reduced form of the simultaneous system of equations is not well defined, and there are multiple equilibria. Additional assumptions, such as Pareto optimality, are needed to solve the system, and even in that case, the solution is difficult to implement in a system with more than two players (Hartmann 2008).

We develop a statistical model to solve the simultaneous equations system. The essence of this model is that a joint probability distribution of the occurrence of multiple events can be derived when there is proper specification of the conditional probability of the event occurrence, conditional on the occurrence of other events. In essence, the proposed model is a reduced-form model, but it complies with good properties of a structural model based on the theory of simultaneous-move games developed in the economics literature (Bresnahan and Reiss 1991). In our econometric specification, the utility function of an individual family member can be viewed as the person's payoff function depending on the actions taken by other family members.

This study makes several important methodological and substantive contributions. First, we develop a model to capture multiple agents' (more than two individuals') simultaneous choice decisions over more than two choice alternatives with behavioral interactions based on each family member's actual consumption behavior over time. As we show subsequently, this is extremely difficult with other modeling approaches, such as modeling preference interaction (Yang, Narayan, and Assael 2006) and modeling simultaneous decision making by multiple agents (Hartmann 2008). To the best of our knowledge, this work is the first to address the challenges that arise from modeling such a complicated simultaneous-move discrete game.

Second, the proposed model enables us to obtain estimates on individual family members' own consumption utility, the joint consumption utility with other members, and the strength of behavioral interactions across three dyads (father–mother, father–child, and mother–child). As our policy experiments show, we are able to simulate a measure of power for each family member on each type of television program. This analysis offers marketers many insights into developing targeting and communication strategies.

Third, we test several group decision-making heuristics that are likely to operate in the joint consumption occasions we observe in the data, using estimates of an individual family member's own intrinsic preference and his or her extrinsic preference for a joint consumption with other members. We believe that this constitutes yet another original aspect of the study. Most previous work in joint decision making has adopted a specific decision rule but has never tested its validity. We are particularly interested in three types of family decision-making strategies developed in the welfare economics literature (Atkinson 1970): the Harsanyi (1955) decision heuristic, the minimum decision heuristic (MIN), and the maximum decision heuristic (MAX). The findings suggest that there is substantial heterogeneity across families on which decision heuristic to use, though overall the Harsanyi decision heuristic dominates the other two.

We organize the remainder of this article as follows: We first review the relevant literature and position this study in relation to previous studies. We then develop the econometric model that captures the intrahousehold behavioral interactions. In the following section, we apply the model to the consumer television-viewing context and discuss the empirical results and their implications. We offer some conclusions and discuss the limitations of this study and potential areas for further research.

LITERATURE REVIEW

This study is related to three streams of literature: modeling of consumer preference interaction/interdependence, modeling of simultaneous decision making by multiple agents, and modeling of joint family decision making. We review each of the three lines of research and discuss how our study differs from and extends them.

Modeling of Preference Interaction/Interdependence

Economic models of choice often assume that a consumer's latent utility is a function of brand and attribute preferences, not the preferences of others. However, a growing body of literature recognizes and models consumer preference interaction (Case 1991; Smith and LeSage 2000; Yang and Allenby 2003; Yang, Narayan, and Assael 2006). This study differs from and extends this line of research. That is, we study the intrahousehold behavioral interactions. Despite the similarity between the behavioral interactions we study and the preference interactions studied in prior literature, many differences exist between the two.

Preference interaction is modeled as the dependence of one person's utility on another person's utility, whereas behavioral interaction is modeled as the dependence of one person's utility on another person's choice, which may determine joint consumption. The sources of preference interaction can be similar preferences or joint consumption effects, whereas the only source of behavioral interaction is joint consumption effects. For example, in the context of television viewing, if the data reveal that both the husband and the wife spend a lot of time watching television, we are most likely to find a positive preference interaction between the husband and the wife. However, this positive preference interaction does not necessarily imply a positive behavioral interaction—for example, if the husband and the wife enjoy watching a great deal of television alone. However, if the husband and wife rarely watch television alone but watch television a lot together, there is likely to be a positive behavioral interaction. In other words, a positive behavioral interaction suggests a strong preference for a joint consumption and joint consumption effects, whereas a positive preference interaction may not necessarily suggest a positive behavioral interaction.

Modeling of Simultaneous Decision Making by Multiple Agents

There is a large body of literature on modeling simultaneous decision making by multiple players. These models were developed on the basis of the theory of simultaneous-move games. In a seminal study, Bresnahan and Reiss (1991) discuss several important issues related to empirical models of discrete games. A special case of the simultaneous-move game models has also been studied in the "peer effect" literature (Brock and Durlauf 2001; Manski 1993). In these multiple-person choice models, one player's payoff (utility) is a function of another player's actions plus an error term. There are two modeling approaches developed in the literature, and we offer a brief review of each. For ease of comparison, we fix the context to be two players, each choosing one option from two alternatives. To write it as an econometric model, we have the following:

(1a) $$Z_1 = I(U_1 > 0);\ U_1 = \pi_1 + \theta Z_2 + \varepsilon_1, \text{ and}$$

(1b) $$Z_2 = I(U_2 > 0);\ U_2 = \pi_2 + \theta Z_1 + \varepsilon_2,$$

where I is the indicator function, Z_1 and Z_2 are two binary discrete variables for Person 1 and Person 2, and U_1 and U_2 are the correspondent utilities.

Unconditional approach. This approach has been widely used in the economics literature. In this approach, the error term in the utility function is specified to be unconditional on the other player's action. For ease of demonstration, we assume that it is distributed independently as logistic. The probabilities of the four decision outcomes can then be written as follows:

(2a) $$p(Z_1 = 1, Z_2 = 1) = \frac{\exp(\pi_1 + \theta)}{1 + \exp(\pi_1 + \theta)} \frac{\exp(\pi_2 + \theta)}{1 + \exp(\pi_2 + \theta)},$$

(2b) $$p(Z_1 = 1, Z_2 = 0) = \frac{\exp(\pi_1)}{1 + \exp(\pi_1)} \frac{1}{1 + \exp(\pi_2 + \theta)},$$

(2c) $$p(Z_1 = 0, Z_2 = 1) = \frac{1}{1 + \exp(\pi_1 + \theta)} \frac{\exp(\pi_2)}{1 + \exp(\pi_2)}, \text{ and}$$

(2d) $$p(Z_1 = 0, Z_2 = 0) = \frac{1}{1 + \exp(\pi_1)} \frac{1}{1 + \exp(\pi_2)}.$$

The four probabilities do not add up to one unless the interaction effect θ is equal to zero. In other words, some pairs of $(\varepsilon_1, \varepsilon_2)$ correspond to multiple outcomes, leading to existence of multiple equilibria. Bresnahan and Reiss (1991) propose the standard solution to solve the multiple equilibrium problem; we refer to this as the BR approach. Hartmann (2008) adopts the same approach in studying behavioral interactions. In this solution, realizations of the error terms in this overlapping region correspondent to multiple equilibria are forced to be associated with one decision outcome using the Pareto-optimal assumption.

The BR approach is difficult to apply to our context of household-member television viewing for the following reasons: First, the BR approach requires that a researcher know the sign of θ a priori. However, in our context, these behavioral interactions among family members can be either positive or negative, and we do not have a strong prior for their signs. Furthermore, there is household heterogeneity, which means that θ could be positive for some families and negative for other families. Second, the Pareto-optimality assumption can be difficult to justify in a context with more than two choice alternatives. Third, it is difficult to extend the BR approach to a context with more than two decision makers because it becomes infeasible to keep track of the multiple equilibrium regions.

Conditional approach. This approach has been widely used in the statistics literature. In this approach, the error term in the utility function is specified to be conditional on the other player's action. The conditional distributions of the error terms are assumed to be logistic; that is,

(3a) $$p(Z_1 = 1|Z_2) = \frac{\exp(\pi_1 + \theta Z_2)}{1 + \exp(\pi_1 + \theta Z_2)},\quad p(Z_1 = 0|Z_2) = \frac{1}{1 + \exp(\pi_1 + \theta Z_2)}; \text{ and}$$

(3b) $$p(Z_2 = 1|Z_1) = \frac{\exp(\pi_2 + \theta Z_1)}{1 + \exp(\pi_2 + \theta Z_1)},\quad p(Z_2 = 0|Z_1) = \frac{1}{1 + \exp(\pi_2 + \theta Z_1)}.$$

Then, by directly applying Besag's (1974) theorem, we can derive the joint probability distribution as follows:

(4a) $$p(Z_1 = 1, Z_2 = 1) = \frac{\exp(\pi_1 + \pi_2 + \theta)}{1 + \exp(\pi_1) + \exp(\pi_2) + \exp(\pi_1 + \pi_2 + \theta)},$$

(4b) $$p(Z_1 = 1, Z_2 = 0) = \frac{\exp(\pi_1)}{1 + \exp(\pi_1) + \exp(\pi_2) + \exp(\pi_1 + \pi_2 + \theta)},$$

(4c) $$p(Z_1 = 0, Z_2 = 1) = \frac{\exp(\pi_2)}{1 + \exp(\pi_1) + \exp(\pi_2) + \exp(\pi_1 + \pi_2 + \theta)}, \text{ and}$$

(4d) $$p(Z_1 = 0, Z_2 = 0) = \frac{1}{1 + \exp(\pi_1) + \exp(\pi_2) + \exp(\pi_1 + \pi_2 + \theta)}.$$

This is called the autologistic model. The probabilities associated with the combinations of the four actions arising from the choices of two people are all uniquely determined and form a valid probability system (summing up to one). By adopting the conditional approach, we bypass the multiple equilibrium problem.

In this study, we adopt the conditional approach but extend the standard autologistic model to a more complex scenario. The proposed model offers a solution to a complicated discrete game in which there are more than two people and each chooses from a choice set with more than two choice alternatives.

Modeling of Joint Family Decision Making

Note that we are interested in modeling simultaneous decisions while accounting for the potential intrahousehold behavioral interaction rather than modeling group decision making. However, the proposed model makes it possible to separately estimate an individual's own preference and his or her preference for a joint consumption with other members, which enables us to test several group decision-making heuristics that are likely to be applied in a joint consumption occasion.

We briefly review three group decision-making heuristics developed in the welfare economics literature that involve more than two group members. These heuristics differ in how group utility (preference) is formed according to individual group members' utility (preference). As we mentioned, the first decision strategy is called the Harsanyi solution. In the Harsanyi group decision heuristic, the group utility is a weighted average of individual group members' utility, and the weights reflect members' relative influence in the joint decision making. The other two decision strategies are referred to as the MAX and the MIN. In MAX, the group utility is formed according to the utility of the member who has the strongest preference among the family members. In MIN, the group utility is formed according to the utility of the member who has the weakest preference among the family members.

Little work has been done to test the alternative group decision-making heuristics, possibly because of the difficulty of incorporating the behavioral interactions among group members. However, such an empirical test can prove useful. First, most previous studies on relative influence of individual members in a group decision context have assumed that the group adopts the Harsanyi decision rule (e.g., Aribarg, Arora, and Bodur 2002; Arora and Allenby 1999; Krishnamurthi 1988). However, this assumption needs to be validated. Second, we want to test whether different families use different joint decision heuristics. If there is a difference, it suggests that such heterogeneity should be accounted for when modeling a joint decision.

THE PROPOSED MODEL

We assume that a household h consists of J (J = 3) types of family members: father, mother, and child. For convenience of model presentation, we fix the context as watching television. Furthermore, because the focus of this article is to explore behavioral interactions, we focus on family members' television-viewing behavior in the single television context. We assume that the jth type of family member from household h at time t makes a decision about whether he or she watches the kth type of television program. At any time point, each household member also has the option of not watching any television.

Let Z_{htjk} denote the member j's decision, where $Z_{htjk} = 1$ when member j from family h watches type k program at time t and $Z_{htjk} = 0$ otherwise. Because there is one television set, it is impossible that two types of programs play at the same time, implying the following constraint on the decision vector Z:

$$P(Z_{htjk} = Z_{htj'k'} = 1;\ j \neq j',\ k \neq k') = 0. \quad (5)$$

To derive the joint probability of the observed decision outcomes (denoted with a "b" superscript) $Z^b_{ht} = [Z^b_{ht1}, \ldots, Z^b_{htK}]$, where $Z^b_{htk} = [Z_{ht1k}, Z_{ht2k}, Z_{ht3k}]$ are the three members' observed decisions on program type k (k = 1, …, K), where 1 stands for father, 2 stands for mother, and 3 stands for child, we first need to derive the probability of member j to watch program type k conditional on other members' decisions. To do so, we define the utility of watching program type k for member j conditional on choices of other members as follows: The conditional approach was first proposed by Besag (1974) and is fairly new in marketing (Moon and Russell 2008; Russell and Peterson 2000). In the first case, when at least one other family member is watching type k program (i.e., $\Sigma_{j' \neq j} Z_{htj'k} > 0$), we specify the utility of watching each program type for member j, conditional on decisions of other members, as follows:

$$U_{htjk} | (Z_{htj'k'};\ j' \neq j) = \pi_{htjk} + \sum_{j' \neq j} \theta^{j,j'}_{hk} Z_{htj'k} + \varepsilon_{htjk} | (Z_{htj'k'};\ j' \neq j), \quad (6a)$$

$$U_{htjk''} | (Z_{htj'k'};\ j' \neq j) = -\infty + \varepsilon_{htjk''} | (Z_{htj'k'};\ j' \neq j) \text{ if } k'' \neq k, \text{ and} \quad (6b)$$

$$U_{htj0} | (Z_{htj'k'};\ j' \neq j) = \varepsilon_{htj0} | (Z_{htj'k'};\ j' \neq j), \quad (6c)$$

where k′ = 1, …, K. Specifically, Equation 6a defines the conditional utility of member j watching program type k. Equation 6b defines the conditional utility of member j for any other program type k″. Equation 6c defines the conditional utility of member j for not watching any television.

In Equation 6a, we model that the deterministic part of the utility is influenced by the member's own preference π_{htjk} and other members' decisions. Here, $\theta^{j,j'}_{hk}$ measures the degree of behavioral interaction between the two family members, j and j′. A positive $\theta^{j,j'}_{hk}$ suggests a complementary (or positive externality) effect between the two members; that is, the presence of member j (j′) tends to increase the utility of member j′ (j). Similarly, a negative $\theta^{j,j'}_{hk}$ suggests a substitution (or negative externality) effect between the two members; that is, the presence of member j (j′) tends to decrease the utility of member j′ (j). Finally, a zero effect of $\theta^{j,j'}_{hk}$ suggests the behavioral independence between the two members. In Equation 6b, we set the deterministic part of the utility to negative infinity because we have a one-television-set constraint, which suggests that given that type k program is playing, the probabilities for any member watching type k″ (≠ k) are equal to zero, and accordingly, the utilities in these cases are set as negative infinity.

In the second case, when none of the other members watch any television (i.e., $\Sigma_{j' \neq j} \Sigma_{k'} Z_{htj'k'} = 0$), the utility of watching type k program and not watching any television for member j conditional on choices of other members is defined as follows:

$$U_{htjk} | (Z_{htj'k'};\ j' \neq j) = \pi_{htjk} + \varepsilon_{htjk} | (Z_{htj'k'};\ j' \neq j), \text{ and} \quad (7a)$$

$$U_{htj0} | (Z_{htj'k'};\ j' \neq j) = \varepsilon_{htj0} | (Z_{htj'k'};\ j' \neq j). \quad (7b)$$

We now define matrix W_{hk}:

$$(8)\qquad W_{hk} = \left[W_{h1k}, W_{h2k}, W_{h3k}\right]' = \begin{bmatrix} 0 & \theta_{hk}^{1,2} & \theta_{hk}^{1,3} \\ \theta_{hk}^{2,1} & 0 & \theta_{hk}^{2,3} \\ \theta_{hk}^{3,1} & \theta_{hk}^{3,2} & 0 \end{bmatrix}.$$

We further assume that the error terms in Equations 6a–6c and 7a–7b follow the Gumbel distribution. If at least one other family member is watching type k program, the conditional probability of family member j to watch type k program at time t, conditional on the other member's decision, is as follows:

$$(9a)\quad P\left(Z_{htjk} = 1 | Z_{htj'k}, \sum_{k' \neq k}\sum_{j'' \neq j} Z_{htj''k'} = 0, \sum_{j'' \neq j} Z_{htj''k} > 0; j' \neq j\right) = \frac{\exp\left(\pi_{htjk} + W_{hjk}{}'Z_{htk}^{b}\right)}{1 + \exp\left(\pi_{htjk} + W_{hjk}{}'Z_{htk}^{b}\right)}.$$

If any other family member is watching a non–type k program, the conditional probability of family member j to watch type k program at time t, conditional on other members' decision, is as follows:

$$(9b)\qquad P\left(Z_{htjk} = 1 | Z_{htj'k}, \sum_{k' \neq k}\sum_{j'' \neq j} Z_{htj''k'} > 0; j' \neq j\right) = 0.$$

If other family members are not watching any television, the conditional probability of family member j to watch type k program at time t, conditional on other members' decision, is as follows:

$$(9c)\qquad P\left(Z_{htjk} = 1 | Z_{htj'k}, \sum_{k'}\sum_{j'' \neq j} Z_{htj''k'} = 0; j' \neq j\right) = \frac{\exp\left(\pi_{htjk}\right)}{1 + \sum_{k'} \exp\left(\pi_{htjk'}\right)}.$$

Next, from the conditional probability derived in Equations 9a–9c and under the constraint that $\theta_{hk}^{j,j'}$ is equal to $\theta_{hk}^{j',j}$, we can derive the joint probability of observing the decisions from the three family members for all types of programs $Z_{ht}^{b} = [Z_{ht1}^{b}, ..., Z_{htK}^{b}]$. The symmetric constraint directly follows from the autologistic modeling literature (Besag 1974). Only under the symmetric constraint can we derive a proper joint distribution based on the assumed conditional distributions. Furthermore, such constraint is a theoretical constraint rather than an empirical identification constraint because a violation of such a condition will not allow us to derive the joint probability among the members and across program types based on the conditional probability specification.

If program type k is watched by at least one member, we have a total of seven possibilities for the decision vector Z_{htk}^{b}. These seven possibilities are as follows: Program type k is watched (1) by the father alone (Z_{htk}^{b} = [1, 0, 0]), (2) by the mother alone (Z_{htk}^{b} = [0, 1, 0]), (3) by the child/children alone (Z_{htk}^{b} = [0, 0, 1]), (4) by the father and mother together (Z_{htk}^{b} = [1, 1, 0]), (5) by the father and child/children together (Z_{htk}^{b} = [1, 0, 1]), (6) by the mother and child/children together (Z_{htk}^{b} = [0, 1, 1]), and (7) by the father, mother, and child/children together (Z_{htk}^{b} = [1, 1, 1]). This suggests that when the television is turned on (i.e., at least one member is watching any of the K types of programs), there are K × 7 possible outcomes. So in total, we observe K × 7 + 1 outcomes, the last one indicating no television watching by any of the three members.

Under this model setup, we can derive the joint probability of watching each type of program or not watching any television by the three family members as follows:

$$(10)\qquad P\left(Z_{htk} = Z_{htk}^{b}, \sum_{k' \neq k}\sum_{j} Z_{htjk'} = 0\right) = \frac{\exp\left(\pi_{htk}{}'Z_{htk}^{b} + \frac{1}{2}Z_{htk}^{b}{}'W_{hk}Z_{htk}^{b}\right)}{1 + \sum_{k'}\sum_{b^*} \exp\left(\pi_{htk'}{}' + \frac{1}{2}Z_{htk'}^{b^*}{}'W_{hk'}Z_{htk'}^{b^*}\right)}.$$

Details on the derivation of Equation 10 appear in Appendix A. Note that in Equation 10, $\Sigma_{k' \neq k}\Sigma_{j}Z_{htjk'} = 0$ simply reflects the one-television-set constraint. This concludes the basic structure of modeling family members' simultaneous decision on whether to participate in an activity while capturing the intrahousehold behavioral interaction. We describe how we model the individual family members' intrinsic preference π_{htjk} and the intrahousehold behavioral interaction $\theta_{hk}^{j,j'}$ in the next section, after we present the data.

To verify that the joint choice probability is properly derived from the conditional choice probability, we conducted a simulation study. The simulation results suggest that that the true parameter values are recovered accurately and that the predicted choice shares are almost identical to the actual choice shares (for details, refer to the Web Appendix at http://www.marketingpower.com/jmrjune10).

EMPIRICAL APPLICATION

Data Description and Model Implementation

We apply the model to household television-viewing data in which each family member's viewing behaviors for both broadcast programs and cable programs are observed. The data were collected from September 30 to October 27 in 2002. We focus the analysis on 187 single-parent or two-parent families that have at least one child between the ages of 2 and 18 and own one television set.[1] There are 56 single-parent families, 11 of which have a father and at least one child and 45 of which have a mother and at least one child. The remaining 131 families have two parents and at least one child. The reason for including single-parent families as well is to investigate the impact of family structure on individual family-member consumption patterns and the intrahousehold behavioral interaction.

We focus on the consumer television-viewing behavior for five types of television programs: "news" (news/documentary), "movie" (drama/movie), "kids" (children's programs), "sports" (sports programs), and "talk" (talk show/comedy/entertainment programs). These are the five major types of the most-watched television programs,

[1]For households with multiple television sets, we observe only whether each family member at time t watches a program, but we do not observe whether family members watched the program together at time t. Although Nielsen Media Research collects this information, we do not have access to these additional data.

accounting for 99.22% of total television-viewing occasions in this sample. Table 1, Panel A, reports the number of shows included in each of the five types of television programs.

Table 1, Panel B, reports the variable definition and summary statistics of all the demographic information we know about the family and individual family members. The family-specific demographic variables include household income, number of children, race, education of the household head, geographic location, and Internet access. The individual-specific demographic variables include age.

We have each family member's viewing data for every 15th minute of an hour. We specifically focused on the time window between 6:30 P.M. and 10:15 P.M. on weekdays during the four consecutive weeks. During these periods, all three family members are the least likely to be at work, at school, or outside. At each quarter hour, we have information about whether at least one member is watching television, which type of program is watched, and who is watching it. There are 18,940 viewing occasions in which there is at least one member watching television. The remaining 59,600 occasions are associated with no television watching.

Panels A–C in Figure 1 plot the distribution of viewing occasions across the five types of television programs at the household level, for an individual household member, and for each viewing pattern, based on the 18,940 observations for which there is at least one family member watching television. Some noteworthy patterns emerge. First, we find some difference between family viewing patterns and individual members' viewing patterns. For example, if the unit of analysis is the family, the total number of viewing occasions for each of the five types of programs watched by at least one family member reflects the family's overall preference. The frequency distribution is 41.38%, 14.88%, 9.68%, 17.04%, and 17.01% for the five types of programs, respectively, as Figure 1, Panel A, shows. If the unit of analysis is a family member, we can calculate the frequency distributions on the five types of programs for father, mother, and child separately. We provide this information in Figure 1, Panel B, which shows that the distribution is 40.41%, 15.34%, 4.38%, 25.03%, and 14.84% for the father; 46.05%, 16.27%, 5.48%, 13.17%, and 19.03% the for mother; and 41.70%, 11.25%, 16.62%, 14.25%, and 16.17% for the child. These differences between the family viewing patterns and individual members' viewing patterns suggest that the household-level analysis does not capture each household member's viewing behavior well. Second, we find different viewing patterns across the seven types of family viewing combinations on the five types of television programs, as Figure 1, Panel C, shows. We find that consumer preferences vary significantly across the seven types of family viewing patterns. This difference emphasizes the importance of modeling the intrahousehold behavioral interactions.

Next, we discuss the implementation of the proposed model with the data. We model individual family members' intrinsic preferences as follows:

$$\pi_{htjk} = \alpha_{hjk} + \beta_{hjk}\text{Last}_{htjk}. \quad (11)$$

According to Equation 11, family member j's intrinsic preference for type k television program is determined by the baseline effect α_{hjk} and the state dependence effect—that is, the impact of an individual family member's viewing behavior in the last period on his or her current-period utility for type k program. We create a variable called Last, where $\text{Last}_{htjk} = 1$ if household member j in family h watched the type k program in his or her most recent viewing occasion from time t and $\text{Last}_{htjk} = 0$ if otherwise.

To complete the model specification, we allow the random coefficients to vary across different types of families and follow multivariate normal (MVN) distributions:

$$\alpha_{hj} \sim \text{MVN}(\Gamma_j^{\alpha}D_{hj}, \Omega_j^{\alpha}), \quad (12a)$$

$$\beta_{hj} \sim \text{MVN}(\bar{\beta}_j, \Omega_j^{\beta}), \text{ and} \quad (12b)$$

$$\theta_h^{jj'} \sim \text{MVN}\left(\Gamma_{jj'}^{\theta}D_h, \Omega_{jj'}^{\theta}\right) \text{ for } 1 < j < j' < 3, \quad (12c)$$

where D is a vector of demographic characteristics about of the family and the individual family members, Γ are

Table 1

SUMMARY STATISTICS OF THE DATA

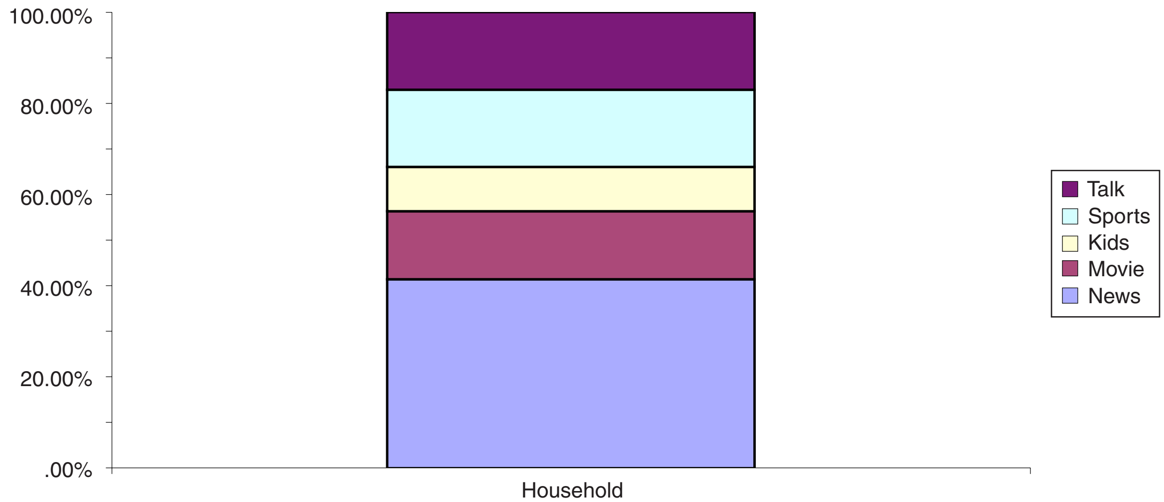
A: Types of Television Programs		
Program Type	*Description*	*Number of Programs*
News	Documentary and news	611
Movie	Drama and movie	598
Kids	Children's program	253
Sports	Sports program	295
Talk	Talk show, comedy, and entertainment	399

B: Household Demographics Information		
Variable	*Description*	*Percentage*
INCOME (household income)	1 < $10,000	7.28
	2 = $10,000–$14,000	5.50
	3 = $15,000–$19,000	5.65
	4 = $20,000–$29,000	12.04
	5 = $30,000–$39,000	17.24
	6 = $40,000–$49,000	13.37
	7 = $50,000–$59,000	6.39
	8 = $60,000–$74,000	11.44
	9 = $75,000 or more	21.10
NCHREN (number of children)	1	38.78
	2	41.01
	3	10.55
	4	9.66
RACE	0 = White	79.64
	1 = Nonwhite	20.36
EDUCATION (education of the household head)	1 = Grade school (0–8 years)	4.31
	2 = Some high school (9–11 years)	8.47
	3 = High school graduate (12 years)	24.52
	4 = Some college (1–3 years of college)	23.77
	5 = College graduate (4 or more years of college)	38.93
CITY	1 = from the largest 25 metropolitan areas	37.74
	0 = Otherwise	62.26
INTERNET	0 = No Internet	42.79
	1 = With Internet	57.21
AGE_FATHER	Age of father	37.73 (17.99)[a]
AGE_MOTHER	Age of mother	35.19 (10.32)[a]
AGE_CHILD	Age of child	7.75 (4.61)[a]

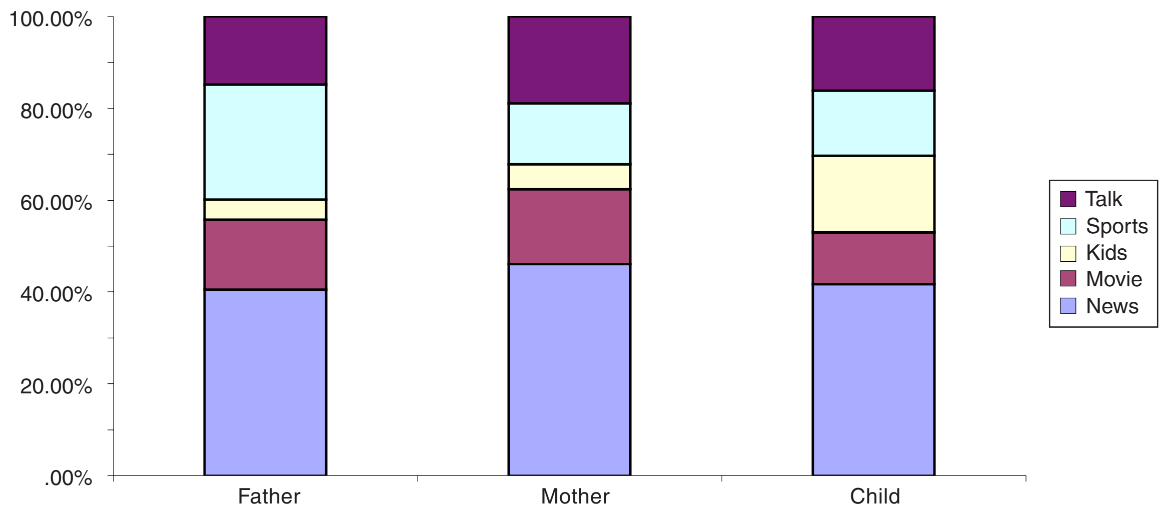
[a]Sample mean (sample standard deviation).

Figure 1
SHARE OF TELEVISION PROGRAMS

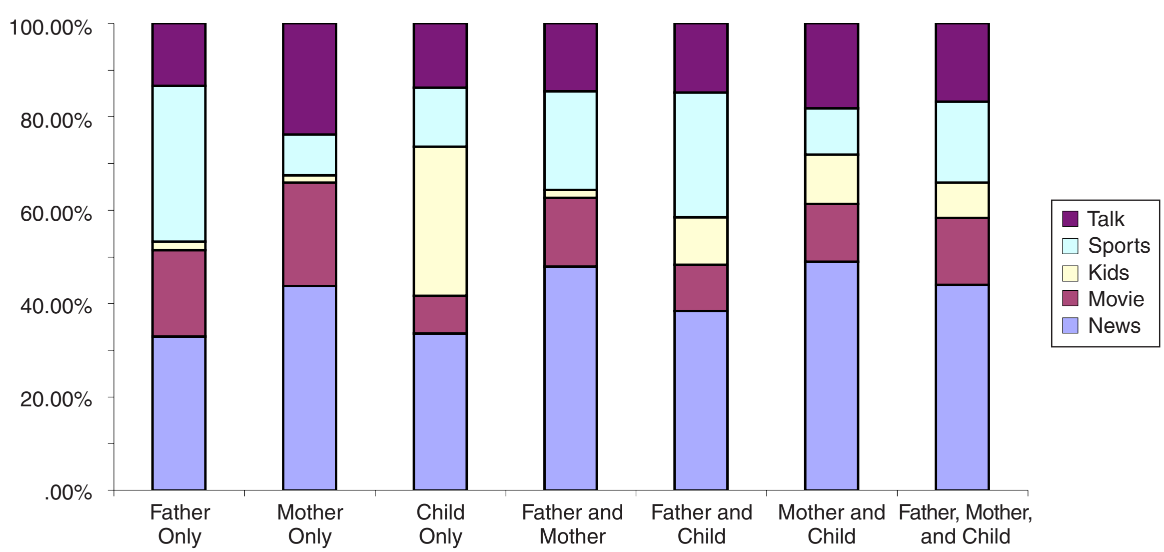
A: Shares of Five Types of Programs by Household



B: Shares of Five Types of Programs for Household Member



C: Shares of Five Types of Programs by Each Interaction Pattern



the regression coefficients, and Ω are the unobserved heterogeneity or variances on the random coefficients across families.

Note that there are families with multiple children. In such case, we model the composite utility of watching television by any child without specifically modeling the child–child behavioral interaction. In other words, we treat an occasion in which one child is watching television together with another child as an occasion in which children are watching television alone without any parent. Although the model can be readily applied to account for the child–child behavioral interaction, we choose to focus on the father–mother, father–child, and mother–child pairs of behavioral interactions in this study.[2]

We use the Bayesian estimation approach to estimate the model. The advantage of this approach is that the large parameter space is partitioned into smaller spaces. Consequently, parameters can be iteratively drawn from their proper posterior conditional distributions. We carried out the model estimation using Markov chain Monte Carlo (MCMC) methods implemented in the Gibbs sampler and the Metropolis–Hastings algorithm. The chain ran for 40,000 iterations. We used the first 20,000 iterations as a "burn-in" period and the last 20,000 iterations to estimate the conditional posterior means and standard deviations. We assessed convergence by inspecting the time series of model parameters. Details of the MCMC algorithm appear in Appendix B.

To validate the proposed model, we compare it with several benchmark models on their in-sample and out-of-sample performance. The first benchmark model is a nested version of the proposed model because it does not allow any intrahousehold behavioral interaction ($\theta = 0$). The other three benchmark models are not nested with our proposed model. The first one is a model based on the observed frequency of joint and separate consumption. The second one is a multinomial logit model that treats the 36 outcomes (in combinations of who are watching what types of television programs) as the possible choice outcomes. The third one is a multivariate probit model on who are watching. The proposed model outperforms the four benchmark models in terms of both in-sample fit and out-of-sample fit.[3]

Parameter Estimates

We first discuss the behavioral interaction estimates that reflect the influence of others' decisions on an individual family member's decision to watch television. Panels A–C in Table 2 report the behavioral interaction estimates for each pair of the three family members. Because we mean-center all the demographic variables in our analysis, the intercept can be viewed as the average strength of the behavioral interaction. We find that the behavioral interactions are significantly positive for all three dyads across all five types of shows. The mother–child behavioral interactions are significantly higher than the father–child behavioral interactions at the mean level, except for sports programs. This is consistent with the traditional wisdom that mothers are spending more time with children, leading to a stronger behavioral interaction than the father–child dyad. As we expected, the father–mother behavioral interactions are stronger than the other two dyads on most of the programs, except for kids shows.

Panels A–C in Table 2 also show that many family and individual-specific characteristics explain these behavioral interaction effects. For the father–child dyad, we find a higher interaction on kids programs for families with higher income. As the number of children increases, the father–child behavioral interaction tends to increase for all types of shows, except for news. The father–child behavioral interaction in the case of kids shows is smaller in nonwhite families, in families with Internet access, and for older fathers. As children grow older, the father–child interaction becomes stronger for sports programs. Finally, the family structure also has an impact. We find that the behavioral interaction is stronger in a single-parent (father) family than in a dual-parent family for all five types of programs, the strongest being the sports shows.

For the mother–child behavioral interaction, we find some similarities and differences in the impact of demographics compared with the father–child interaction. For example, the Internet access tends to reduce the behavioral interaction between mother and child for watching movies, kids shows, and talk programs. As mothers (child) grow older, their behavioral interaction for watching kids programs increases (decreases). Similarly, we find that a single-mother family tends to have a stronger behavioral interaction between mother and child in the case of news, sports, and talk shows. There are also some different patterns. For example, the mother–child behavioral interaction is higher for nonwhite families for news programs, higher for families with higher education for movies, and higher for families who live in large cities for sports programs.

Finally, Table 2, Panel C, reveals some noteworthy findings regarding the father–mother behavioral interactions. We find a consistent effect of income on the degree of father–mother interaction. High-income families tend to have smaller parent–parent interactions, except for sports programs, than low-income families. As the number of children increases, the father–mother interaction tends to increase in the case of news programs. Finally, the father and mother watch kids programs together more in nonwhite families and watch talk programs together more if they live in big cities.

Next, we discuss what determines an individual family member's own preference. Table 3 reports the baseline preference estimates for the three family members on the five types of television programs. Note that because the baseline preference for each type of television program is estimated relative to the preference for the activity of not watching any television, these baseline preference estimates are comparable across television types. Furthermore, because we mean-center all the demographic variables, we can interpret the intercept as the average baseline preference for a program type for a given household member. As we expected, the intercept estimates suggest that the father likes sports programs more than the mother and child, the mother likes talk programs more than the father and child, and the child likes

[2]Ideally, if there were more data available, we could estimate the model to separately account for child–child interactions for different types of families, such as families with parents and two children, families with parents and three children, and so on. However, if we did so, we would significantly lose the statistical power because of the limited number of families we would have for each type of family.

[3]Details are available on request.

Table 2
BEHAVIORAL INTERACTION PARAMETER ESTIMATES

	News	Movie	Kids	Sports	Talk
A: The Father–Child Behavioral Interaction Estimate (Γ^θ)					
INTERCEPT	**1.447** (.246)	**2.397** (.279)	**3.015** (.304)	**3.151** (.366)	**2.257** (.250)
INCOME	.183 (.138)	–.002 (.192)	**.615** (.229)	–.089 (.175)	–.188 (.135)
NCHREN	.218 (.275)	**.806** (.317)	**1.120** (.352)	**1.120** (.413)	**.613** (.309)
RACE	–.331 (.611)	–.522 (.696)	**–3.369** (.708)	1.474 (.854)	.545 (.673)
EDUCATION	.009 (.295)	.096 (.335)	.156 (.371)	.600 (.383)	.373 (.258)
CITY	–.394 (.517)	.609 (.642)	1.052 (.772)	–.269 (.691)	–.902 (.541)
INTERNET	–.098 (.629)	–.337 (.755)	**–3.465** (.811)	.116 (.875)	.866 (.637)
AGE_FATHER	–.090 (.064)	–.117 (.079)	**–.157** (.069)	.029 (.080)	–.029 (.070)
AGE_MOTHER	N.A.	N.A.	N.A.	N.A.	N.A.
AGE_CHILD	1.127 (.970)	–.950 (1.380)	–1.597 (1.460)	5.145 (1.676)	–.762 (1.188)
FATHER ONLY	**4.282** (.764)	**3.968** (.975)	**2.170** (.596)	**6.792** (1.387)	**3.556** (.998)
B: The Mother–Child Behavioral Interaction Estimate (Γ^θ)					
	News	Movie	Kids	Sports	Talk
INTERCEPT	**2.697** (.307)	**3.868** (.349)	**5.889** (.463)	**2.249** (.449)	**3.597** (.290)
INCOME	–.134 (.137)	–.246 (.165)	–.089 (.133)	–.254 (.219)	.096 (.143)
NCHREN	–.428 (.332)	–.475 (.342)	–.323 (.318)	–.752 (.467)	–.277 (.288)
RACE	**1.093** (.544)	–.274 (.659)	–.319 (.635)	–.766 (.902)	.670 (.591)
EDUCATION	–.200 (.295)	**.612** (.313)	–.265 (.284)	–.580 (.427)	–.029 (.251)
CITY	.270 (.528)	.771 (.572)	–.209 (.685)	**1.402** (.727)	–.367 (.515)
INTERNET	–.728 (.630)	**–1.652** (.667)	**–1.297** (.626)	–.175 (.904)	**–1.416** (.610)
AGE_FATHER	N.A.	N.A.	N.A.	N.A.	N.A.
AGE_MOTHER	–.016 (.042)	.028 (.043)	**.143** (.031)	.019 (.052)	–.011 (.035)
AGE_CHILD	–.017 (.070)	.007 (.078)	**–.181** (.075)	–.082 (.095)	–.082 (.062)
MOTHER ONLY	**1.579** (.654)	.338 (.718)	–.454 (.672)	**2.215** (.960)	**1.358** (.576)
C: The Father–Mother Behavioral Interaction Estimate (Γ^θ)					
	News	Movie	Kids	Sports	Talk
INTERCEPT	**3.951** (.226)	**3.542** (.263)	**2.904** (.392)	**4.997** (.308)	**3.886** (.252)
INCOME	**–.339** (.127)	**–.475** (.167)	**–.871** (.212)	–.257 (.134)	**–.270** (.132)
NCHREN	**.650** (.242)	–.039 (.319)	.144 (.469)	.606 (.363)	.205 (.284)
RACE	–.496 (.610)	.135 (.729)	**2.360** (.889)	1.217 (.776)	–.625 (.717)
EDUCATION	.170 (.244)	–.175 (.303)	–.200 (.444)	–.034 (.314)	–.213 (.263)
CITY	.573 (.468)	–.062 (.634)	–.819 (.808)	–.077 (.628)	**1.060** (.508)
INTERNET	–1.046 (.623)	.718 (.758)	**2.680** (1.021)	–.417 (.679)	–.487 (.621)
AGE_FATHER	–.025 (.037)	.005 (.044)	.053 (.065)	.028 (.048)	.054 (.038)
AGE_MOTHER	.089 (.051)	.054 (.053)	.093 (.078)	.005 (.055)	.012 (.048)

Notes: Posterior means and posterior standard deviations are reported. Significant estimates at 95% level are in bold. N.A. = not applicable.

kids programs more than the father and mother. These results reveal a great deal of face validity.

Table 3 also reveals many findings on how individual preferences for the five types of television programs vary across families and individuals. We highlight some important ones here. First, both parents tend to have a higher own preference for watching a sports program in high-income families than in low-income families, and a child from a higher-income family tends to have a stronger preference in general for watching television, which holds for most programs. Second, as the number of children increases, we find a decreased preference for watching most of the five types of programs for the father and mother but an increased preference for watching television for the child. This is likely because a parent with more children tends to spend more time on housekeeping and children and therefore has less time available for watching television. Third, as a person grows older, the mother has less preference for watching most of the television programs, whereas the child has more preference for watching television. Fourth, regarding the impact of family structure, we find a stronger preference for watching most of the television programs for the father or mother from a single-parent family.

Next, we discuss the dynamics in the individual family member's own preference. Table 4 reports the state dependence estimates for the father, the mother, and the child. As we expected, the intercept estimates indicate that there is significant inertia on all five types of television programs for the father, the mother, and the child; that is, each family member's own preference for one type of television pro-

Table 3

BASELINE PREFERENCE ESTIMATES FOR FATHER, MOTHER, AND CHILD (Γ^{α})

	Father					*Mother*					*Child*				
	News	*Movie*	*Kids*	*Sports*	*Talk*	*News*	*Movie*	*Kids*	*Sports*	*Talk*	*News*	*Movie*	*Kids*	*Sports*	*Talk*
INTERCEPT	**–5.231**	**–5.952**	**–7.942**	**–6.041**	**–6.054**	**–5.168**	**–5.909**	**–8.242**	**–7.311**	**–5.647**	**–5.746**	**–7.150**	**–6.415**	**–7.491**	**–6.193**
	(.166)	(.185)	(.206)	(.184)	(.169)	(.140)	(.168)	(.292)	(.238)	(.152)	(.149)	(.177)	(.222)	(.210)	(.131)
INCOME	.165	.156	.072	**.292**	.148	.036	**.171**	.131	**.202**	.026	**.200**	**.297**	**.251**	**.235**	.087
	(.093)	(.099)	(.107)	(.111)	(.090)	(.076)	(.084)	(.098)	(.105)	(.078)	(.081)	(.097)	(.118)	(.089)	(.072)
NCHREN	–.232	**–.509**	**–1.120**	–.334	**–.338**	**–.326**	**–.590**	–.160	**–.724**	**–.491**	**.400**	.166	**.619**	.017	**.351**
	(.196)	(.185)	(.261)	(.205)	(.171)	(.166)	(.193)	(.204)	(.245)	(.185)	(.167)	(.209)	(.225)	(.195)	(.146)
RACE	–.223	.192	**1.280**	–.295	–.183	–.462	–.507	.247	**–1.459**	–.531	.543	**.808**	.696	.633	**.742**
	(.451)	(.440)	(.442)	(.503)	(.450)	(.323)	(.399)	(.470)	(.537)	(.353)	(.327)	(.399)	(.452)	(.396)	(.316)
EDUCATION	–.155	–.192	**–.617**	–.075	–.204	**.409**	.304	–.046	.248	**.345**	**–.306**	**–.586**	.009	–.235	–.132
	(.172)	(.169)	(.183)	(.197)	(.180)	(.160)	(.185)	(.223)	(.235)	(.166)	(.156)	(.181)	(.220)	(.173)	(.137)
CITY	–.109	–.610	–.168	–.102	–.401	.210	–.327	–.160	.248	.102	–.087	**–.989**	.039	–.410	–.219
	(.364)	(.375)	(.398)	(.417)	(.349)	(.296)	(.331)	(.474)	(.432)	(.313)	(.297)	(.376)	(.433)	(.350)	(.277)
INTERNET	–.066	.415	**.930**	.185	.456	–.465	.076	.575	–.638	–.052	–.190	.414	.080	–.663	.057
	(.438)	(.425)	(.460)	(.487)	(.436)	(.322)	(.383)	(.434)	(.467)	(.349)	(.349)	(.426)	(.486)	(.386)	(.323)
AGE	–.007	–.012	–.011	–.010	–.010	**–.042**	–.038	**–.135**	–.006	**–.032**	**.149**	.015	.010	**.144**	**.143**
	(.017)	(.017)	(.016)	(.018)	(.018)	(.019)	(.024)	(.026)	(.022)	(.016)	(.032)	(.037)	(.043)	(.034)	(.029)
FATHER ONLY	.861	**1.339**	.916	**1.455**	**1.701**						.339	–.821	–.953	**6.234**	–.250
	(.628)	(.595)	(.656)	(.669)	(.553)						(.639)	(.691)	(.803)	(1.322)	(.525)
MOTHER ONLY						**1.067**	**1.115**	**.929**	**1.069**	**.846**	.250	–.495	**–1.024**	.048	.219
						(.340)	(.397)	(.500)	(.487)	(.344)	(.373)	(.454)	(.487)	(.407)	(.330)

Notes: Significant estimates at 95% level are in bold.

Table 4
STATE DEPENDENCE ESTIMATES FOR FATHER, MOTHER, AND CHILD (Γ^β)

	News	*Movie*	*Kids*	*Sports*	*Talk*
Father	**.980**	**1.277**	**1.205**	**1.644**	**1.369**
	(.132)	(.149)	(.232)	(.152)	(.134)
Mother	**1.202**	**1.366**	**1.195**	**1.876**	**1.296**
	(.096)	(.140)	(.222)	(.200)	(.102)
Children	**1.259**	**1.659**	**1.254**	**1.911**	**1.158**
	(.105)	(.171)	(.129)	(.180)	(.117)

Notes: Significant estimates at 95% level are in bold.

gram in the current period increases if he or she watched the same type of television program in the last period. Given the formulation of the period (15-minute slots), this implies that consumers tend to watch a show from the beginning to end.

In summary, we find that the model estimates are reasonable and insightful. They can help companies better understand the influence of intrinsic preferences and extrinsic preferences on individual overall viewing preferences and, more important, the influence of characteristics of television programs and individual/family type on these intrinsic and extrinsic preferences.

MANAGERIAL AND THEORETICAL IMPLICATIONS

Opportunity for Targeting

An important goal of a television station is to increase its viewership. To increase viewership of a particular type of program, a viable strategy for a television station is to target its advertising to members who have relatively low preference for this type of program but have high power in affecting others' viewing behavior.[4] We conducted counterfactual simulations to illustrate how the proposed model and empirical findings can help achieve such targeting strategy.

An important feature of the model is that it enables us to make separate inferences regarding a family member's intrinsic preference and extrinsic preference for watching specific types of television programs. Using the model estimates of an individual's intrinsic preferences, we can simulate the individual j's probability of watching type k program alone, given that he or she is watching television. We denote this probability as P_k^j. Similarly, we can simulate the probability of member j and j′ jointly watching type k program, given that they are watching television together, which we denote as $P_k^{jj'}$. Then, consistent with the literature on joint decision making, we can define a measure of power of member j over member j′ on program type k as follows:

$$\text{Power}_k^{jj'} = P_k^{jj'} - P_k^{j'}. \tag{13a}$$

In the context of a three-member family, we can construct the overall power of member j as the average of his or her power over other two family members:

$$\text{Power}_k^{j} = \frac{\sum_{j' \neq j} \text{Power}_k^{jj'}}{2}. \tag{13b}$$

[4]We thank a reviewer for pointing this out as a targeting opportunity.

We simulated the measure of power for each of three members from 131 families (non-single-parent families) on each of the five types of television programs (3 × 131 × 5). As a demonstration, in Figure 2, Panels A–C, we plot the father's power against his own preference for news programs, the mother's power against her own preference for movie programs, and the child's power against his or her own preference for children's programs, respectively. The lower-right quadrant is associated with the case of high power and low preference. This represents a potential group of customers to target. First, this group has low preference, suggesting additional room for improvement. Second, this group has high power in affecting others.

We also conducted regression analyses on individual family members' power and found a substantial heterogeneity across families. For example, we find that a father from a nonwhite family has a higher power in the case of sports programs than a father from a white family. A mother from a nonwhite family has a higher power in the case of news programs than a mother from a white family.

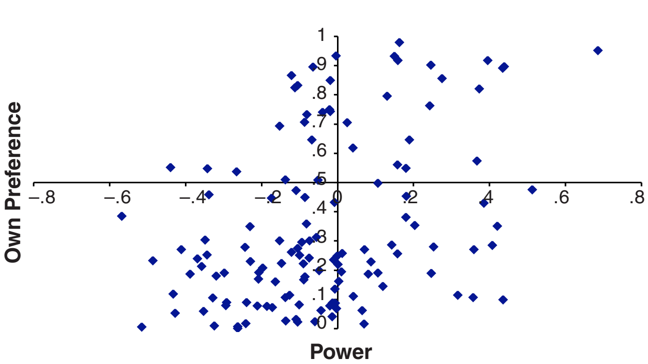
Testing Alternative Joint Decision Heuristics

The preceding modeling exercise enables us to test several alternative family decision-making heuristics developed in the welfare economics literature. As we claimed previously, we are not modeling joint decision making per se in this study, because the assumption of joint decision making requires the household members either to participate jointly in an activity or to decide not to participate in the activity. Rather, we are interested in behavioral interactions. However, we observe some joint consumption occasions by all three family members—that is, they are watching a particular type of television program together on some occasions. On these occasions, group decision making is likely to occur; that is, the family members will jointly determine which of the five types of television programs to watch. Because the model enables us to obtain estimates of an individual's own preference and estimates of an individual's utility from joint consumption for each of the five types of television programs relative to not watching any television, we can test alternative group decision-making heuristics.

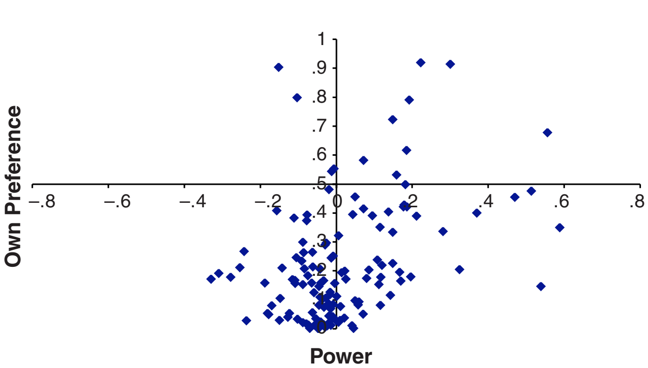
The first group decision heuristic is the Harsanyi solution. Under Harsanyi's additive model assumption, family members will first obtain the group utility constructed by a weighted average across the three individual members' utility for each type of television program. For type k programs, the group utility is as follows:

Figure 2
AN INDIVIDUAL'S POWER AGAINST OWN PREFERENCES

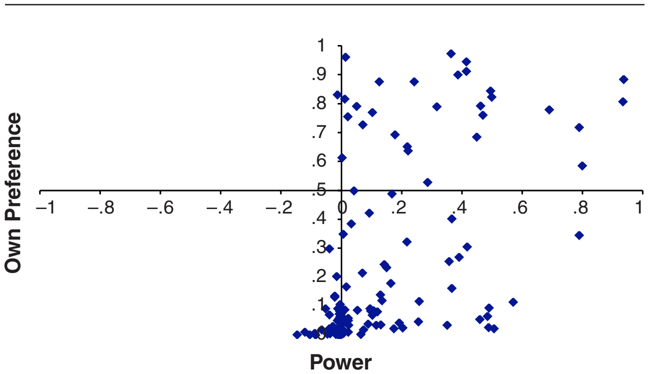
A: Father's Power Against Own Preference for News Programs



B: Mother's Power Against Own Preference for Movie Programs



C: Child's Power Against Own Preference for Children's Programs



(14a) $$U^*_{htk} = \sum_{j=1}^{3} w_j U_{htjk}, \text{ where } w_1 + w_2 + w_3 = 1.$$

Then, the family will choose the program type that provides the highest group utility among the alternatives.

In the second decision heuristic, the MAX, the family will regard the utility of the member who has the lowest preference for the kth type of programs among all the family members as the group utility:

(14b) $$U^*_{htk} = \text{Min}\left\{U_{htjk}, j = 1, 2, 3\right\}.$$

Then, the family will choose the program type that provides the highest group utility among the alternatives (Atkinson 1970).

In the third decision heuristic, the MIN, the family will regard the utility of the member who has the highest preference for the kth type of programs among all the family members as the group utility:

(14c) $$U^*_{htk} = \text{Max}\left\{U_{htjk}, j = 1, 2, 3\right\}.$$

Then, the family will choose the program type that provides the highest group utility among the alternatives (Atkinson 1970).

Using the parameter estimates, we explore which of these decision heuristics best approximates the data. The test is based on 2383 joint consumption occasions in which all three family members were watching a television program together, from 80 families. We exclude families in which the joint consumption occasions are too few to estimate the individual-member weight parameters for each family through optimization.

First, we find that the Harsanyi decision heuristic correctly predicts the type of television programs for 72% of the 2383 joint consumption occasions, which is higher than correct predictions by the MIN (52%) or the MAX (28%) heuristic. This finding validates the assumption of the Harsanyi decision heuristic adopted in the previous group decision literature. Notably, we find a substantial amount of heterogeneity across families on which decision heuristic to use. The Harsanyi decision heuristic does not dominate the other two in 32.5% of families. This finding suggests that it is important to consider such heterogeneity when modeling joint decision making, which the literature has typically ignored.

Second, the estimated average weight is .31, .16, and .53 for the father, the mother, and the child, respectively, under the Harsanyi decision heuristic. This suggests that, on average, the child has the most influence, and the mother has the least influence, in choosing which type of television program to watch in a three-member joint consumption occasion. We also find that these decision weights vary significantly across families.

CONCLUSION

Quantitative models in the marketing literature typically focus on the household as the unit of analysis while ignoring the individual family members' behavior and behavioral interactions among household members. However, there is considerable evidence to suggest that (1) significant heterogeneity among individual family members' intrinsic preferences exists, and the analysis at the family level may not capture this intrahousehold heterogeneity, and (2) an intrahousehold behavioral interaction is present, that is, an individual's behavior is affected by other family members' behavior.

In this article, we propose a modeling framework to capture intrahousehold behavioral interaction based on family members' actual consumption behavior over time. We develop a model to capture multiple agents' (more than two individuals') simultaneous choice decisions over more than two choice alternatives. This is extremely difficult with other previously developed modeling approaches. To the best of our knowledge, this work is the first to address the challenges that arise in modeling a complicated simultaneous-move discrete game.

We apply the proposed model to a context of family members' television viewing and simultaneously model whether the television is on, which type of program is playing, and which family members are watching. The proposed model enables us to decompose the individual's preference into two components: the intrinsic preference and the preference from joint consumption with other members. The empirical analysis leads to several noteworthy findings: First, there is substantial heterogeneity in individual intrinsic preference for different television programs among the three family members. Second, intrahousehold behavioral interactions are significantly positive in many cases. More specifically, mother–child interactions are stronger than father–child interactions and father–mother interactions are stronger than parent–child interactions for most of the television programs. Third, the strength of the intrahousehold behavioral interactions tends to vary across types of family-member dyads, across families, and across types of television programs. Fourth, the Harsanyi group decision heuristic is more likely to operate than the MAX and the MIN decision heuristics on joint consumption occasions involving all three family members. However, there is substantial heterogeneity across families on which decision heuristic to use.

Finally, this study is subject to limitations, which suggest opportunities for further research. First, the model does not allow for asymmetric behavioral interactions for each dyad. Although the approach is an important first step to modeling a complicated multiple-person simultaneous-move discrete game, it would be useful to consider the case of asymmetric behavioral interactions in future work. Second, there are opportunities for developing structural models to incorporate bargaining strategies among group members to analyze household-member television-viewing behavior. Third, the data are constrained to families with one television set, which may lead to a nonrepresentative sample analyzed in this study.

Overall, the impact of intrahousehold behavioral interactions on individual consumer behavior is important but has been understudied in the empirical modeling literature in marketing. We hope that this article provides a modeling approach to study the intrahousehold behavioral interactions based on individual family members' consumption behavior and stimulates further research in this direction.

APPENDIX A: MODEL DERIVATION

We first define the probability of the case in which none of the three members watch any television as follows:

$$\text{(A1)}\quad P(Z^b_{ht} = 0) = P(Z_{ht1k} = 0, Z_{ht2k} = 0, Z_{ht3k} = 0; k = 1, ..., K) = P(Z^0_{ht1}, Z^0_{ht2}, Z^0_{ht3}).$$

For simplifying the notation, we use Z^0_{htjk} to indicate $Z_{htjk} = 0$. Then, applying the distribution theory, we obtain the following expressions:

$$\text{(A2)}\quad P\left(Z_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) = P\left(Z_{ht1k} | Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) \times P\left(Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right), \text{ and}$$

$$\text{(A3)}\quad P\left(Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) = \frac{P\left(Z^0_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}{P\left(Z^0_{ht1k} | Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}.$$

After substituting Equation A3 into Equation A2, we obtain the following:

$$\text{(A4)}\quad P\left(Z_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) = P\left(Z_{ht1k} | Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) \times \frac{P\left(Z^0_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}{P\left(Z^0_{ht1k} | Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}.$$

Following the same logic, we can obtain the other two counterparts as follows:

$$\text{(A5)}\quad P\left(Z^0_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) = P\left(Z_{ht2k} | Z^0_{ht1k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) \times \frac{P\left(Z^0_{ht1k}, Z^0_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}{P\left(Z^0_{ht2k} | Z^0_{ht1k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}, \text{ and}$$

$$\text{(A6)}\quad P\left(Z^0_{ht1k}, Z^0_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) = P\left(Z_{ht3k} | Z^0_{ht1k}, Z^0_{ht2k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right) \times \frac{P\left(Z^0_{ht1k}, Z^0_{ht2k}, Z^0_{ht3k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}{P\left(Z^0_{ht3k} | Z^0_{ht1k}, Z^0_{ht2k}, \sum_{k'\neq k}\sum_j Z_{htjk'} = 0\right)}.$$

After combining Equations A4–A6, we obtain the following:

$$\text{(A7)}\quad \frac{P\left(Z_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)}{P\left(Z^0_{ht1k}, Z^0_{ht2k}, Z^0_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)} = \frac{P\left(Z_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)}{P\left(Z_{ht10}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)} \times \frac{P\left(Z_{ht2k}|Z^0_{ht1k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)}{P\left(Z^0_{ht2k}|Z^0_{ht1k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)} \times \frac{P\left(Z_{ht3k}|Z^0_{ht1k}, Z^0_{ht2k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)}{P\left(Z^0_{ht3k}|Z^0_{ht1k}, Z^0_{ht2k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right)}.$$

Substituting Equations 5a–5c in the text into Equation A7, we can write the joint probability of the three family members' decisions as follows:

$$\text{(A8)}\quad P\left(Z_{ht1k}, Z_{ht2k}, Z_{ht3k}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right) = P\left(Z^0_{ht1}, Z^0_{ht2}, Z^0_{ht3}\right)\exp\left[Z_{ht1k}\left(\pi_{ht1k} + W_{h1k}'Z^b_{htk}\right)\right] \exp\left[Z_{ht2k}\left(\pi_{ht2k} + W_{h2k}'Z^{(023)}_{htk}\right)\right] \exp\left[Z_{ht3k}\left(\pi_{ht3k} + W_{h3k}'Z^{(003)}_{htk}\right)\right] = P\left(Z^0_{ht1}, Z^0_{ht2}, Z^0_{ht3}\right)\exp\left[\pi_{htk}'Z^b_{htk} + \sum_{i<j}\theta^{i,j}_{hk}Z_{htik}'Z_{htjk}\right],$$

where $Z^{(023)}_{htk} = (0, Z_{ht2k}, Z_{ht3k})'$ and $Z^{(003)}_{htk} = (0, 0, Z_{ht3k})'$. Because $\theta^{i,j'}_{hk} = \theta^{j',j}_{hk}$, we have the following:

$$\text{(A9)}\quad Z^b_{htk}{}'W_{hk}Z^b_{htk} = 2\sum_{i<j}\theta^{i,j}_{hk}Z_{htik}Z_{htjk}.$$

Finally, we can write the joint probability as

$$\text{(A10)}\quad P\left(Z_{htk} = Z^b_{htk}, \sum_{k'\neq k}\sum_{j} Z_{htjk'} = 0\right) = \exp\left(\pi_{htk}'Z^b_{htk} + \tfrac{1}{2}Z^b_{htk}{}'W_{hk}Z^b_{htk}\right)P\left(Z^0_{ht1}, Z^0_{ht2}, Z^0_{ht3}\right)$$

because the probability of each outcome sums to 1, and this leads to Equation 10.

APPENDIX B: THE MCMC ALGORITHM

We estimate the model parameters using a hierarchical Bayesian approach. We executed 40,000 iterations of the Markov chain. We discarded the first 20,000 draws as the initial "burn-in" and kept the last 20,000 draws for inference.

1. Draw $\theta^{jj'}_h$.

We use Metropolis–Hastings algorithm with a random walk chain to generate draws (see Chib and Greenberg 1995). Let $\theta^{jj'(p)}_h$ denote the previous draw, and then the next draw $\theta^{jj'(n)}_h$ is given by the following:

$$\theta^{jj'(n)}_h = \theta^{jj'(p)}_h + \Delta,$$

with the accepting probability as follows:

$$\min\left\{\frac{\exp\left[-\frac{1}{2}\left(\theta^{jj'(n)}_h - \Gamma^{\theta}_{jj'}{}'D_h\right)'\Omega^{\theta^{-1}}_{jj'}\left(\theta^{jj'(n)}_h - \Gamma^{\theta}_{jj'}{}'D_h\right)\right]l_h\left(\theta^{jj'(n)}_h\right)}{\exp\left[-\frac{1}{2}\left(\theta^{jj'(p)}_h - \Gamma^{\theta}_{jj'}{}'D_h\right)'\Omega^{\theta^{-1}}_{jj'}\left(\theta^{jj'(p)}_h - \Gamma^{\theta}_{jj'}{}'D_h\right)\right]l_h\left(\theta^{jj'(p)}_h\right)}, 1\right\},$$

where $l_h(\cdot)$ is the likelihood function of viewing behaviors for household h,

$$l_h = \prod_{t=1}^{T_h}\frac{\left[\exp\left(\pi_{htk}'Z^b_{htk} + \frac{1}{2}Z^b_{htk}{}'W_{hk}Z^b_{htk}\right)\right]^{WATCH_{ht}}}{1 + \sum_{k'}\sum_{b^*}\exp\left(\pi_{htk'}'Z^{b^*}_{htk'} + \frac{1}{2}Z^{b^*}_{htk'}{}'W_{hk'}Z^{b^*}_{htk'}\right)}$$

and Δ is a draw from the density Normal(0, .01I), where I is the identity matrix, and $WATCH_{ht}$ is a dummy variable that equals 1 when household h watched television at time t and 0 otherwise.

2. Draw $\Gamma^{\theta}_{jj'}$.

For convenience of the estimation, we assume the heterogeneity matrix is diagonal; that is,

$$\Omega^{\theta}_{jj'} = \text{diag}\left(\Omega^{\theta}_{jj'(1)}, \Omega^{\theta}_{jj'(2)}, \Omega^{\theta}_{jj'(3)}, \Omega^{\theta}_{jj'(4)}, \Omega^{\theta}_{jj'(5)}\right).$$

We define

$$\Gamma^{\theta}_{jj'} = \left(\Gamma^{\theta}_{jj'(1)}, \Gamma^{\theta}_{jj'(2)}, \Gamma^{\theta}_{jj'(3)}, \Gamma^{\theta}_{jj'(4)}, \Gamma^{\theta}_{jj'(5)}\right)',$$
$$\theta^{jj'}_{(k)} = \left(\theta^{jj'}_{(1k)}, \ldots, \theta^{jj'}_{Hk}\right)', D = \left(D_1', \ldots, D_H'\right)'.$$

On the basis of this assumption, we can draw $\Gamma^{\theta}_{jj'(k)}$ for each program type k separately and assume $\Gamma^{\theta}_{jj'(k)}$ follows the prior distribution:

$$\Gamma^{\theta}_{jj'(k)} \sim MVN\left(\Gamma_0, A_0^{-1}\right).$$

Then the posterior can be given by the following:

$$\Gamma^{\theta}_{jj'(k)}\left|D, \theta^{jj'}, \Omega^{\theta}_{jj'(k)} \sim MVN\left[\tilde{\Gamma}^{\theta}_{jj'(k)}, \left(D'D\Omega^{\theta}_{jj'(k)}{}^{-1} + A_0\right)^{-1}\right]\right.,$$

where H is the total number of households,

$$\tilde{\Gamma}^{\theta}_{jj'(k)} = \left(D'D\Omega^{\theta}_{jj'(k)}{}^{-1} + A_0\right)^{-1}\left(D'\theta^{jj'}_{(k)}\Omega^{\theta}_{jj'(k)}{}^{-1} + A_0\Gamma_0\right),$$
$$A_0 = .01I, \Gamma_0 = 0.$$

3. Draw $\Omega^{\theta}_{jj'}$.

We assume the prior of $\Omega^{\theta}_{jj'(k)}$, k = 1, ..., 5, follows an inverted-gamma distribution:

$$\Omega^{\theta}_{jj'(k)} \sim \text{IG}(v_0, V_0).$$

Then, the posterior can be given by the following:

$$\text{(A7)} \quad \Omega^{\theta}_{jj'(k)} \Big| \Gamma^{\theta}_{jj'(k)}, \theta^{jj'}_{(k)}, D \sim \text{IG}\left[v_0 + \frac{H}{2}, V_0 + \frac{1}{2}\sum_{h=1}^{H}\left(\theta^{jj'}_{hk} - \Gamma'^{\theta}_{jj'(k)} D_h\right)\right],$$

where $v_0 = 10$ and $V_0 = 10$.

4. Draw α_{hj} similar to Step 1.

5. Draw Γ^{α}_{j} similar to Step 2.

6. Draw Ω^{α}_{j} similar to Step 3.

7. Draw β_{hj} similar to Step 1.

8. Draw $\bar{\beta}_{j}$ similar to Step 2.

9. Draw Ω^{β}_{j} similar to Step 3.

REFERENCES

Aribarg, Anocha, Neeraj Arora, and H. Onur Bodur (2002), "Understanding the Role of Preference Revision and Concession in Group Decisions," *Journal of Marketing Research*, 39 (August), 336–49.

Arora, Neeraj and Greg M. Allenby (1999), "Measuring the Influence of Individual Preference Structures in Group Decision Making," *Journal of Marketing Research*, 36 (November), 476–87.

Atkinson, Anthony B. (1970), "On the Measure of Inequality," *Journal of Economic Theory*, 2 (3), 244–63.

Besag, Julian E. (1974), "Spatial Interaction and the Statistical Analysis of Lattice Systems," *Journal of the Royal Statistical Society: Series B*, 36 (2), 192–236.

Bresnahan, Timothy F. and Peter C. Reiss (1991), "Empirical Models of Discrete Games," *Journal of Econometrics*, 48 (1), 57–81.

Brock, William A. and Steven N. Durlauf (2001), "Discrete Choice with Social Interaction," *Review of Economic Studies*, 68 (2), 235–60.

Case, Anne C. (1991), "Spatial Patterns in Household Demand," *Econometrica*, 59 (4), 953–65.

Chib, S. and E. Greenberg (1995), "Understanding the Metropolis-Hastings Algorithm," *The American Statistician*, 49 (4), 327–35.

Harsanyi, John C. (1955), "Cardinal Welfare, Individualistic Ethics, and Interpersonal Comparisons of Utility," *Journal of Political Economy*, 63 (August), 309–321.

Hartmann, Wesley R. (2008), "Demand Estimation with Social Interactions and the Implications for Targeted Marketing," working paper, Graduate School of Business, Stanford University.

Heckman, J.J. (1978), "Dummy Endogenous Variables in a Simultaneous Equation System," *Econometrica*, 46 (4), 931–59.

Krishnamurthi, Lakshman (1988), "Conjoint Models of Family Decision Making," *International Journal of Research in Marketing*, 5 (3), 185–98.

Maddala, G.S. and Lun-Fei Lee (1976), "Recursive Models with Qualitative Endogenous Variables," *Annals of Economic and Social Measurement*, 5 (4), 525–45.

Manski, Charles F. (1993), "Identification of Endogeneous Social Effects: The Reflection Problem," *Review of Economic Studies*, 60 (3), 531–42.

Moon, Sangkil and Gary J. Russell (2008), "Predicting Product Purchase from Inferred Customer Similarity: An Autologistic Model Approach," *Management Science*, 54 (January), 56–70.

Park, C. Whan (1982), "Joint Decisions in Home Purchasing: A Muddling-Through Process," *Journal of Consumer Research*, 9 (2), 151–62.

Russell, Gary J. and Ann Petersen (2000), "Analysis of Cross Category Dependence in Market Basket Selection," *Journal of Retailing*, 76 (Fall), 367–92.

Smith, Tony E. and James P. LeSage (2004), "A Bayesian Probit Model with Spatial Dependencies," in *Advances in Econometrics: Volume 18: Spatial and Spatiotemporal Econometrics*, James P. LeSage and R. Kelley Pace, eds. Amsterdam: Elsevier Science, 127–60.

Yang, Sha and Greg M. Allenby (2003), "Modeling Interdependent Consumer Preferences," *Journal of Marketing Research*, 40 (August), 282–94.

———, Vishal Narayan, and Henry Assael (2006), "Estimating the Interdependence of Television Program Viewership Between Spouses: A Bayesian Simultaneous Equation Model," *Marketing Science*, 25 (3), 336–49.