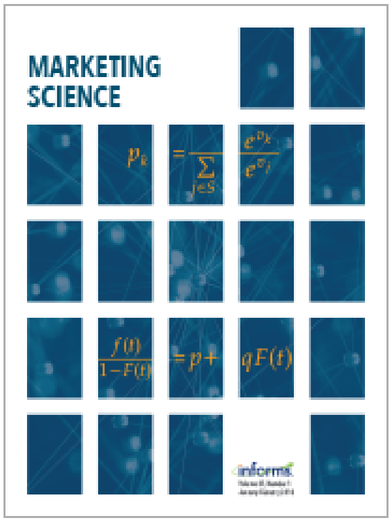

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Estimating the Interdependence of Television Program Viewership Between Spouses: A Bayesian Simultaneous Equation Model

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When making product choices, consumers are influenced by the preferences of other consumers, such as family members, friends, neighbors, and colleagues. Preference interdependence among family members is likely to be significant because of cohabitation and strong emotional ties. To estimate the preference interdependence, we specify a simultaneous equation model and propose a Bayesian estimation approach. Unlike existing models that use a spatial autoregressive structure to capture the interdependence of consumer preferences, we are able to estimate the potential asymmetry in the preference interdependence among family members in a more flexible way. In a simulation study, we show that models that ignore interdependence of preferences yield biased estimates of consumers' sensitivity to observed attribute preferences. In an empirical application, we estimate the interdependence of the viewership of television programs between husbands and wives in 481 households. We find that wives' viewing behavior depends more strongly on their husbands' viewing behavior than husbands' viewing behavior depends on their wives' viewing behavior. There exist significant differences in parameter estimates of dependence across categories of television programs. Differences in levels of spousal interdependence across households are partially explained by the age and the education level of the spouses.

Key words: hierarchical Bayesian analysis; interdependent preferences; simultaneous equation models; television programs
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1. Introduction

When making product choices, consumers are influenced not only by the attributes of the products they consider buying but also by a host of other factors, such as their experience with the product category, their own needs and wants, the context of purchase, and the preferences of other consumers such as family members, friends, neighbors, and colleagues. Consumers could be influenced by other individuals when they identify with certain social groups, when they aspire to be like others, or when they learn something new about products from others' experiences and preferences.

Preference interdependence among family members is likely to be significant because of cohabitation and strong emotional ties. In this research we propose a model for estimating how preferences among family members are interdependent. In an empirical application of the model, we estimate how husbands' viewership of television programs is affected by their wives' viewing intentions and how wives' viewership is affected by their husbands' viewing intentions.

Although there can be little doubt that spouses affect each other's preferences, the nature of this interdependence poses several interesting research questions. For example, in the context of consumer products, are husbands' preferences more strongly dependent on wives' preferences, or vice versa? How does the magnitude of spousal preference interdependence vary across the products? For a given product category, what is the level of heterogeneity in the interdependence across families? Can this heterogeneity be explained on the basis of the demographic characteristics of the family members? Does ignoring the interdependence of preferences between spouses produce biased estimates of their sensitivities to observed covariates such as product attributes and state dependence? We answer these research questions in the context of television programs aired on network television.

In this article we develop a hierarchical Bayesian model of interdependent preferences between husbands and wives in a television-viewing context. We specify a parsimonious autoregressive structure that captures the endogenous relationship between a consumer's viewing behavior and the viewing behavior of his/her spouse. We demonstrate our approach using two applications. The first application illustrates our method on simulated data. The second application is based on data of viewership of television programs of husbands and wives in 481 households. The results from the simulated data application show that our Bayesian estimation approach performs well in recovering the true parameters. More importantly, we find that models that ignore interdependence can yield biased estimates of consumers' sensitivity to observed attributes. The results from the second application show that in the context of television programs, husbands' viewing intentions are less dependent on wives' viewing intentions than vice versa. We also find significant differences in the estimates of interdependence across categories of television programs. Differences in levels of interdependence across households are partially explained by the age and the education level of the spouses.

Models to determine the preference interdependence among family members aid in the allocation of resources for marketing programs. Knowledge of asymmetry in interdependence can be used to effectively direct marketing and media strategies. For example, if a marketer knows that husbands' viewership of TV is higher than that of wives, then she would perhaps target marketing communication and promotions more at husbands than at wives. However, the additional knowledge that wives affect their husbands' viewing behavior more strongly than husbands affect their wives' viewing behavior would suggest a reallocation of marketing resources such that wives are allocated a larger share of resources than what was being allocated to them based on viewership alone. Furthermore, determining relative spousal preference dependence affects not only the allocation of marketing resources but also the content of marketing communication such as advertising themes.

The remainder of this article is organized as follows. In §2, we review the relevant literature and explain how we extend it. In §3, we introduce the model and propose a Bayesian estimation approach. We also demonstrate the validity of the proposed model in a simulation exercise. In §4, we discuss the empirical application and its results. Section 5 concludes with implications for future research.

2. Literature Review

Our study draws upon two streams of literature: modeling interdependent consumer preferences and modeling the choice of television programs.

Models of Interdependent Consumer Preferences. Although the idea that consumer preferences are interdependent is not new (see Duesenberry 1949 and Leibenstein 1950), empirical models of consumer decision making typically ignore the fact that preferences are interdependent. 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. Preferences are assumed to vary across consumers in a manner described either by exogenous covariates such as demographics or by independent draws in a mixing distribution (Kamakura and Russell 1989, Allenby and Rossi 1998). However, there is a small but growing body of literature in quantitative marketing and economics that recognizes and models the interdependence of consumer preferences.

Case (1991) studies the interdependent preferences of rice consumption in Indonesia by modeling the spatial patterns in household demand for rice. Smith and LeSage (2004) estimate a spatial autoregressive model that captures spatial dependencies in voting behavior in the 1996 American presidential election. Using cross-sectional survey data on the household consumption of several product categories, Kapteyn et al. (1997) model the expenditure of a household in a category as a function of the mean expenditure of households of various reference groups in the same time period. Households are grouped together based on the education levels, ages, and occupations levels of household members. Yang and Allenby (2003) model how consumer preferences of cars are impacted by the preferences of multiple networks of consumers. They estimate the degree of overall association among consumers based on their geographical proximity and on similarities in their demographic characteristics.

Our objective is to propose a model for estimating the interdependence between the preferences of two types of consumers (husbands and wives). Interdependence, in our context, is defined as the direct impact of the husband's (wife's) viewing intention on the wife's (husband's) viewing intention. In our model, the covariation between the husband's and the wife's viewing intentions has been decomposed into observed covariation and unobserved covariation. The observed covariation is due to the observed spousal characteristics. The unobserved covariation is further attributed to two components: the unobserved spousal characteristics, and the direct impact of husband's viewing intention on wife's viewing intention and vice versa. It is this direct impact of the spouses' viewing intentions on each other that we define as interdependence.

For such a scenario, where we estimate the dependence of one type of consumer's (husband's or wife's) preferences on another type of consumer's (his/her spouse's) preferences, existing models of interdependent consumer preferences assume that preference interdependence is symmetric. In other words, the level of dependence of husbands on wives is constrained to be the same as the level of dependence of wives on husbands. We are able to relax the assumption of symmetric interdependence in this study and estimate separate parameters for the dependence of husbands on wives and for the dependence of wives on husbands.

The consumer behavior of husbands and wives typically has been studied in the context of group decision making. This literature differs from the literature on interdependent consumer preferences in the following way. Models of group decision making often study how an individual consumer's preference influences the joint group preference. Models of interdependent consumer preferences, however, do not focus on the joint decision making, but rather focus on studying how one individual's behavior and his/her latent preferences (or behavioral intentions) are dependent on those of other individuals. Unlike studies of group decision making, an implicit assumption in these studies of preference interdependence is that an individual's preference can depend on that of others even if that individual's decision is made without others being physically present in that decision-making context. For example, a consumer's choice of automobiles might be dependent on the choices of her colleagues or her neighbors, even when her colleagues and neighbors are absent from the place where she actually makes her choice. We now briefly review the literature on the joint decision making.

In the context of group decision making, inferences about group members' influences on the joint decision have been based on either stated or outcome-based data. The stated approaches use measures such as a constant sum scale to assess influence (Corfman 1989, 1991). On the other hand, the outcome-based approaches infer influence from data about the individual preferences of each consumer and from the outcome of a joint decision. Using conjoint analysis data, Krishnamurthi (1988) proposes three models that combine individual preferences of MBA students and their spouses to approximate joint preferences and predict joint decisions. Arora and Allenby (1999) develop a hierarchical Bayesian model of group decision making that uses conjoint analysis data and yields individual-level estimates of influence at the product attribute level. Su et al. (2003) study temporal effects in husband-wife decision making using conjoint analysis data. Aribarg et al. (2002) use stated preference data to decompose member influence in a group's (parents and teenage children) decision into two distinct elements of "preference revision" and "preference concession."

We specify a parsimonious simultaneous equation model and estimate the spousal interdependence on viewership of television programs. Similar to the extant research on modeling interdependence preferences, we observe the actual viewing behavior of individuals, based on which we infer the asymmetric preference dependence structure.[1] Furthermore, unlike existing studies of group decision making, we are able to explicitly control for state dependence because we have data across two years.

Models of Choice of TV Programs. The allocation of billions of dollars of TV advertising expenditure every year is done largely on the basis of predicted viewership of TV programs. However, the literature on modeling choice or viewership of TV programs is relatively scarce, presumably due to the difficulty of obtaining disaggregate data on viewers' choices of TV programs. The following is a brief review of the empirical modeling literature on the choice of TV programs.

Aggregate models that predict viewership of programs have been proposed by Gensch and Shaman (1980), Horen (1980), and Henry and Rinne (1984). Pioneering work in the area of modeling TV program choice was done by Rust and Alpert (1984). The authors specify the utility of viewing a program as a function of her demographics, the categories of TV programs, and an "audience flow state" variable that represents TV-related characteristics. Rust, Kamakura and Alpert (1992) build a multidimensional scaling map for programs, based on the similarity of viewers' choices. They then use this space to develop a program choice model. Shachar and Emerson (2000) extend Rust and Alpert (1984) by introducing a new program characteristic—the demographic characteristics of a program cast—and by incorporating a more flexible measure of state dependence.

More recently, Danaher and Mawhinney (2001) use experimental data to develop a method for the rescheduling of TV programs to maximize the total viewership for one television network across one week. Goettler and Shachar (2001) specify a structural model of TV program choices that explicitly considers competition among shows and state dependence in choices. This model is used to estimate latent program attributes and to compute Nash equilibria of

[1] Because we do not observe whether the viewership of programs in our data is the result of joint or individual decision making, we refrain from claiming that we are estimating spousal "influence." We thank the review team for pointing this out.

a program location game. They find that networks' scheduling strategies are generally optimal. Moshkin and Shachar (2002) find that viewers' utilities of viewing TV programs depend not only on their previous program choices, but also on the dependence of their information sets on their previous choices. Godes and Mayzlin (2004) find that word of mouth has explanatory power in a model of TV ratings. Liu et al. (2004) theoretically model the competition between commercial TV broadcasters, and find that having more channels does not necessarily maximize viewer welfare.[2]

All these studies ignore the potential interdependence between the viewership of different household members. This article proposes a structural model that captures the interdependence of husbands' and wives' program viewership. Through a simulation study and an empirical application, we demonstrate that models that ignore the viewership interdependence between spouses yield biased estimates of spouses' sensitivities to observed attributes.

3. A Model for Estimating the Interdependence of Preferences of Husbands and Wives

In this section, we first present a model aimed at estimating the preference interdependence between husbands and wives. We then introduce a Bayesian method to estimate such a model via data augmentation. Finally, through a simulation exercise we demonstrate the validity of the proposed estimation method, demonstrate that the model is empirically identified even with sparse data, and illustrate the biases due to ignoring the preference interdependence.

Consider a model where we observe the husband's consumption (y_{ij}^h) and the wife's consumption (y_{ij}^w) of product j in household i. We further assume that both the husband's and the wife's consumptions are driven by the latent utilities, y_{ij}^{h*} and y_{ij}^{w*}, which have the following relationships with the observed consumptions:

$$y_{ij}^k = y_{ij}^{k*} \quad \text{if } y_{ij}^{k*} > 0, \tag{1a}$$

$$y_{ij}^k = 0 \quad \text{if } y_{ij}^{k*} \leq 0, \tag{1b}$$

where k stands for either husband (h) or wife (w). This will be a standard Type 1 Tobit model (Tobin 1958, Amemiya 1985) if we assume the latent utility is normally distributed.

[2] A related stream of literature is the modeling of consumer choices of movies. Recent work in this area includes Ainslie et al. (2005) and Krider et al. (2005). The reader is referred to Eliashberg et al. (2005) for a comprehensive review of the movie industry literature.

We incorporate interdependence in the husband's and the wife's latent utilities in the following structural manner, where the latent utility of an individual directly affects the latent utility of his/her spouse,

$$y_{ij}^{h*} = X_{ij}^{h\prime}\beta_i^h + y_{ij}^{w*}\omega^{hw} + \varepsilon_{ij}^h, \tag{2a}$$

$$y_{ij}^{w*} = X_{ij}^{w\prime}\beta_i^w + y_{ij}^{h*}\omega^{wh} + \varepsilon_{ij}^w, \tag{2b}$$

where

$$\varepsilon_{ij} = [\varepsilon_{ij}^h, \varepsilon_{ij}^w]' \sim MVN(0, \Sigma), \tag{3}$$

$$\beta_i = [\beta_i^{h\prime}, \beta_i^{w\prime}]' \sim MVN(\bar{\beta}, \Psi). \tag{4}$$

X_{ij}^h (X_{ij}^w) is a vector of explanatory variables that are specific to the husband (wife) and variables that are common to both husband and wife. The usual identification condition, that there is at least one variable in each of X_{ij}^h and X_{ij}^w that is not included in the other vector, holds. The observed similarity in preferences between spouses is captured by $X_{ij}^h\beta_i^h$ and $X_{ij}^w\beta_i^w$. ω^{hw} measures the direct effect of wife's utility on husband's utility, and ω^{wh} measures the direct effect of husband's utility on wife's utility. Σ captures potentially the unobserved covariation between the husband's and the wife's latent utilities.

Note that Equations (1a), (1b), (2a), (2b), and (3) form a full-blown simultaneous equation model with the limited dependent variables y_{ijc}^h and y_{ijc}^w both being endogenous. This is because ω^{hw} and ω^{wh} are not constrained to be zero, and there is nonzero covariance between ε_{ij}^h and ε_{ij}^w. This leads to correlation between y_{ijc}^{w*} (y_{ijc}^w) and ε_{ij}^h and correlation between y_{ij}^{h*} (y_{ij}^h) and ε_{ij}^w. There are two challenges in estimating such a structural model. First, the endogenous variables are truncated, which renders a likelihood function of a complicated form because it involves multiple integrals when either y_{ij}^h or y_{ijc}^w equals zero. The likelihood is further complicated by the random coefficients specification of the coefficients of the exogenous covariates, β_i. Second, the proposed model is more generalized than a fully recursive model that can be obtained by restricting either ω_{ic}^{hw} or ω_{ic}^{wh} to 0. The fully recursive model can be simplified to a seemingly unrelated regression (SUR) model (Zellner 1971, Li 1998) and is therefore simpler to estimate than the proposed model.

In this paper, we propose a Bayesian approach to estimating the proposed simultaneous equation Tobit model. Our estimation approach is based on the framework introduced by Chib (1992) for the estimation of a Tobit censored regression model, but extends that model to a simultaneous equation setting. We use data augmentation (Gelfand and Smith 1990, Tanner and Wong 1987) to generate the latent utilities. Thus, we are able to respecify the proposed simultaneous equation model with limited dependent variables as a set of linear simultaneous equations. This leads to a Markov chain Monte Carlo (MCMC) solution. Rather than directly estimating the structural parameters, we choose to work with the reduced form of Equations (2a) and (2b):

$$y_{ij}^{h*} = \Pi_{11}[X_{ij}^{h\prime}\beta_i^h] + \Pi_{12}[X_{ij}^{w\prime}\beta_i^w] + v_{ij}^h, \tag{5a}$$

$$y_{ij}^{w*} = \Pi_{21}[X_{ij}^{h\prime}\beta_i^h] + \Pi_{22}[X_{ij}^{w\prime}\beta_i^w] + v_{ij}^w, \tag{5b}$$

where

$$\Pi_{11} = \frac{1}{1-\omega^{hw}\omega^{wh}}, \tag{6a}$$

$$\Pi_{12} = \frac{\omega^{hw}}{1-\omega^{hw}\omega^{wh}}, \tag{6b}$$

$$\Pi_{21} = \frac{\omega^{wh}}{1-\omega^{hw}\omega^{wh}}, \tag{6c}$$

$$\Pi_{22} = \frac{1}{1-\omega^{hw}\omega^{wh}}, \tag{6d}$$

and

$$v_{ij} = [v_{ij}^h, v_{ij}^w]' \sim MVN(0, \Omega), \tag{7}$$

where

$$\Omega = (I-W)^{-1}\Sigma(I-W)^{-1\prime}, \tag{8}$$

$$W = \begin{bmatrix} 0 & \omega^{hw} \\ \omega^{wh} & 0 \end{bmatrix}. \tag{9}$$

The basic Gibbs sampling routine starts with drawing the latent utilities y_{ij}^{h*} and y_{ij}^{w*}, conditional on all the other parameters. This involves generating y_{ij}^{h*} (y_{ij}^{w*}) from a truncated normal distribution conditional on y_{ij}^{w*} (y_{ij}^{h*}) if $y_{ij}^h = 0$ ($y_{ij}^w = 0$). The second step involves drawing Πs and Ω. This becomes a standard routine, because y_{ij}^{h*} and y_{ij}^{w*} are available from the first step. Note that the following relationships between the reduced-form parameters (Πs and Ω) and the structural parameters (ω^{hw}, ω^{wh}, and Σ) enable us to identify the structural parameters:

$$\omega^{hw} = \Pi_{12}/\Pi_{22}, \tag{10a}$$

$$\omega^{wh} = \Pi_{21}/\Pi_{11}, \tag{10b}$$

$$\Sigma = (I-W)\Omega(I-W)'. \tag{11}$$

Finally, conditional on y_{ij}^{h*}, y_{ij}^{w*}, ω^{hw}, ω^{wh}, and Σ, we can generate β_i, $\bar{\beta}$, and Ψ, as is done in a standard Bayesian random coefficients regression based on Equations (2a), (2b), and (4).

This method of estimation requires specification of prior distributions of the model parameters, and the derivation of the posterior conditional distributions of the model parameters. We set the prior distributions of the model parameters to be diffuse and conjugate. The Markov chain proceeds by generating draws iteratively from the set of conditional posterior distributions of the parameters. A detailed description of the full conditional distributions is provided in the appendix.

We now present a simulation study that intends to achieve the following three objectives. The first objective is to demonstrate the validity of the MCMC estimation procedure for estimating the proposed model. The second objective is to demonstrate that the proposed model is empirically identified even with sparse data. The third objective is to ascertain the level of bias in the parameter estimates of exogenous covariates if spousal interdependence is ignored, and to explore whether the level of bias depends on the level of interdependence.

Validity of the Estimation Procedure. The simulated data set comprises 500 households, with 50 observations per household. We assume 10 exogenous covariates generated from standard normal distributions. All covariates vary both within and across individuals, enabling us to estimate random effects for all covariates. We compute latent utilities for all observations based on certain values of the parameters and then compute the observed consumptions of both spouses based on the censoring procedure described in Equations (1a) and (1b). We specify the following true values:

$$\omega^{hw} = 0.5, \qquad \omega^{wh} = 0.8,$$

$$\Sigma = \begin{bmatrix} \sigma_h^2 & \sigma_{hw} \\ \sigma_{wh} & \sigma_w^2 \end{bmatrix} = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.0 \end{bmatrix}, \qquad \bar{\beta} = [1, \ldots, 1],$$

and Ψ is a matrix with all diagonal elements $= 0.1$ and all other elements $= 0.05$. We run the Markov chain for 2,000 iterations and use the last 1,000 iterations for calculating the posterior means and standard deviations of the parameters. We find that all true parameter values lie within the 95% highest posterior density intervals of their respective posterior distributions. We also ran the simulation study for different true values of the interdependence parameters ω^{hw} and ω^{wh} to investigate whether this method can be used to estimate asymmetric interdependence across a wide range of parameter values. The true parameter values were again recovered. Thus, we conclude that the proposed model is statistically identified and that our estimation method is valid.

Empirical Identification with Sparse Data. To ensure that the model is fully identified even with sparse data (data in which a large proportion of consumption observations are zero), we conduct a simulation where the independent variables are the same as what we use for the empirical application. Based on these independent variables, and the parameter estimates that we obtain from our empirical analysis, we compute the latent utilities of all consumers and products. In this way, the data we use in this simulation very closely mimic the actual TV-viewing behavior we observe in our data set. We are again able to recover the parameter values, which shows that the proposed model is empirically identified with the real data.

Biases Due to Ignoring Spousal Interdependence. The third objective of the simulation study is to ascertain the level of bias in the parameter estimates of exogenous covariates if spousal interdependence is ignored. We use simulated data but assume away the interdependence in the estimation, i.e., $\omega^{hw} = 0$, $\omega^{wh} = 0$. Indeed, we find that the posterior means of the random effects of the exogenous covariates are biased. Also, the covariance matrix of the error terms is biased. Furthermore, the larger the true absolute values of ω^{hw} and ω^{wh}, the larger the bias in the estimates of the other parameters.

We conclude that the proposed estimation procedure is valid, even with sparse data. Furthermore, models that do not take into account the interdependence of consumer preferences produce biased estimates of the effect of other covariates. Detailed results of the simulation studies are available from the authors upon request.

4. Empirical Application

The data used in this application were collected by AC Nielsen from a national sample of respondents utilizing People Meters during November 1996 and November 1997. The People Meter requires respondents to press a button on the Nielsen monitor when viewing TV. The data on viewers' program viewership were made available by CBS, one of the four major television network companies.

The viewership of a program by a viewer is defined as the ratio of the total time that the viewer viewed the program for the entire month to the total time the program was aired in that month. We focus on 51 programs that were aired in November 1996 and also in November 1997, between 6:30 P.M. and 11 P.M. on the four network channels (CBS, ABC, NBC, and FOX). In our empirical application, we estimate the model on data for 1997, and use program viewership for 1996 to account for state dependence. Based on the categorization of programs by AC Nielsen, each program in our data belongs to one of the following three categories: drama, comedy, or news/documentary. This categorization is commonly used by television programmers, media planners, and market researchers.

The data set contains data pertaining to both the husband and the wife in each household across 500 households. Nineteen of these households did not watch any of the 51 programs and were excluded from the data set used for model estimation. Table 1 reports the program-level summary viewership of husbands and wives and their correlations. The program with the highest viewership among both husbands and wives was "E.R." The program with lowest viewership among both spouses was "ABC WORLD NEWS TONIGHT SP(S)" aired on November 28. Comedy was the most-viewed category and news was the least-viewed category for both spouses. The average correlation between husbands' and wives' viewership across the 51 programs was 0.506, with viewership of the news programs being least correlated, followed by comedy and then by drama. It might be argued that for any program, the correlation between husbands' and wives' viewership is a measure of spousal interdependence. However, it is impossible to infer the direction of interdependence from this measure. The proposed model decomposes the covariation of spousal preferences into the direct interdependence (captured by ω^{hw} and ω^{wh}), observed similar preferences (captured by $X'\beta$), and unobserved preference covariation (captured by Σ).

Our data also include household-specific demographics like household size and the number of children in the household. At an individual level, we have data on gender, age, and level of education. Table 2 reports the summary statistics of demographic characteristics of all 962 viewers.

We assume that the viewership y_{ij}^k is related to the latent variable y_{ij}^{k*} of viewer k ($k = h, w$) in household i for program j. We interpret the latent variable y_{ij}^{k*} for viewer k ($k = h, w$) in household i as this viewer's intention to view program j.[3] We observe that 77.8% of the program viewership in our data is zero. In other words, out of the 51 programs in our data set, on an average, a viewer views only 11 programs in that month. When a viewer views a program, she has a positive viewership and her latent viewing intention is equal to her viewership as defined in Equation (1a). Therefore, a viewer's latent viewing intention cannot exceed one. As such, assuming y_{ij}^{k*} to be normally distributed could be a misspecification. We circumvent this problem by applying the following transformation for both h and w:[4]

$$\log\left(\frac{1+y_{ij}^k}{1-y_{ij}^k}\right) = y_{ijc}^{k*} \quad \text{if } y_{ij}^{k*} > 0, \tag{12a}$$

$$y_{ij}^k = 0 \quad \text{if } y_{ij}^{k*} \le 0. \tag{12b}$$

[3] We refrain from interpreting y_{ij}^{k*} as the latent utility of viewing a program. In the TV-viewing context, it is possible that the program an individual views is not the program that maximizes his utility but really a compromise between his utility-maximizing choice and his spouse's utility-maximizing choice. In that sense, viewership does not necessarily indicate preference or utility. We thank the AE for pointing this out.

[4] Two hundred forty out of a total of 49,062 observations of viewership in our data are equal to 1. Because this transformation is not defined for $y_{ij}^k = 1$, we replace $y_{ij}^k = 1$ with $y_{ij}^k = 0.99999$ for these observations.

Table 1 Program-Level Viewership of Husbands and Wives

S. no.	Program name	Category	Channel	Average viewership—husband	Average viewership—wife	Correlation between husbands' and wives' viewership
1	3RD ROCK FROM THE SUN	Comedy	NBC	0.0453	0.0642	0.6071
2	BOY MEETS WORLD	Comedy	ABC	0.0324	0.0529	0.5058
3	CAROLINE IN THE CITY	Comedy	NBC	0.0376	0.0676	0.4614
4	COSBY	Comedy	CBS	0.0361	0.0528	0.6392
5	CYBILL	Comedy	CBS	0.0358	0.0543	0.6369
6	DREW CAREY SHOW	Comedy	ABC	0.0834	0.1094	0.5703
7	ELLEN	Comedy	ABC	0.0547	0.0797	0.5633
8	EVERYBODY LOVES RAYMOND	Comedy	CBS	0.0390	0.0565	0.6857
9	FRASIER	Comedy	NBC	0.0570	0.0863	0.6379
10	HOME IMPROVEMENT	Comedy	ABC	0.0925	0.1338	0.5047
11	MAD ABOUT YOU	Comedy	NBC	0.0330	0.0784	0.4027
12	MEN BEHAVING BADLY	Comedy	NBC	0.0395	0.0362	0.6397
13	MURPHY BROWN	Comedy	CBS	0.0181	0.0381	0.3673
14	NANNY	Comedy	CBS	0.0222	0.0526	0.4261
15	NEWSRADIO	Comedy	NBC	0.0332	0.0655	0.4681
16	SABRINA-TEENAGE WITCH	Comedy	ABC	0.0322	0.0601	0.5171
17	SEINFELD	Comedy	NBC	0.1349	0.1667	0.5090
18	SPIN CITY	Comedy	ABC	0.0471	0.0551	0.4676
19	SUDDENLY SUSAN	Comedy	NBC	0.0329	0.0552	0.5204
20	BEVERLY HILLS 90210	Drama	FOX	0.0310	0.0493	0.7097
21	CHICAGO HOPE	Drama	CBS	0.0428	0.0694	0.5449
22	DIAGNOSIS MURDER	Drama	CBS	0.0216	0.0409	0.4315
23	DR. QUINN MEDICINE WOMAN	Drama	CBS	0.0268	0.0496	0.6569
24	E.R.	Drama	NBC	0.1458	0.2160	0.5034
25	EARLY EDITION	Drama	CBS	0.0392	0.0622	0.6886
26	LATE SHOW/DAVID LETTERMAN	Drama	CBS	0.0168	0.0218	0.5356
27	LAW AND ORDER	Drama	NBC	0.0526	0.0613	0.5697
28	MELROSE PLACE	Drama	FOX	0.0265	0.0494	0.3989
29	MILLENNIUM	Drama	FOX	0.0320	0.0382	0.4629
30	NASH BRIDGES	Drama	CBS	0.0390	0.0494	0.5799
31	PARTY OF FIVE	Drama	FOX	0.0300	0.0565	0.5770
32	PRETENDER	Drama	NBC	0.0384	0.0333	0.6917
33	PROFILER	Drama	NBC	0.0363	0.0513	0.6705
34	PROMISED LAND	Drama	CBS	0.0284	0.0456	0.5526
35	TONIGHT SHOW	Drama	NBC	0.0287	0.0377	0.6458
36	TOUCHED BY AN ANGEL	Drama	CBS	0.0475	0.0720	0.5686
37	X-FILES	Drama	FOX	0.1014	0.0954	0.7179
38	20/20	News	ABC	0.0510	0.0979	0.4144
39	48 HOURS	News	CBS	0.0285	0.0416	0.3615
40	60 MINUTES	News	CBS	0.0442	0.0364	0.4601
41	ABC NEWS:NIGHTLINE	News	ABC	0.0171	0.0213	0.3814
42	ABC NEWS:NIGHTLINE	News	ABC	0.0232	0.0139	0.1886
43	ABC WORLD NEWS TONIGHT	News	ABC	0.0272	0.0335	0.4603
44	ABC WORLD NEWS TONIGHT SP(S)-11/28/1996	News	ABC	0.0079	0.0037	0.0879
45	CBS EVENING NEWS-RATHER	News	CBS	0.0260	0.0317	0.4182
46	CBS EVENING NEWS-THU(S)-11/28/1996	News	CBS	0.0123	0.0119	0.4503
47	DATELINE NBC-FRI SPECIAL(S)-11/29/1996	News	NBC	0.0139	0.0253	0.0832
48	DATELINE NBC-SUN	News	NBC	0.0301	0.0277	0.4941
49	DATELINE NBC-TUE	News	NBC	0.0428	0.0847	0.4774
50	NBC NIGHTLY NEWS	News	NBC	0.0239	0.0293	0.4721
51	PRIMETIME LIVE	News	ABC	0.0493	0.0733	0.4295

We incorporate spousal interdependence in the husband's and the wife's latent viewing intentions in the following structural manner.[5] The latent viewing intention of an individual directly affects the latent viewing intention of his/her spouse.

$$y_{ij}^{h^*} = X_j\theta_i^h + R_{ij}^h\gamma_{ic}^h + Z_i^h\delta^h + y_{ij}^{w^*}\omega^{hw} + \varepsilon_{ij}^h, \tag{13a}$$

$$y_{ij}^{w^*} = X_j\theta_i^w + R_{ij}^w\gamma_{ic}^w + Z_i^h\delta^w + y_{ij}^{h^*}\omega^{wh} + \varepsilon_{ij}^w. \tag{13b}$$

[5] We adopt a linear specification for the latent viewing intention, which has been used in most empirical models of TV-viewing choices.

Table 2 Demographic Characteristics of All Viewers

Demographic variable	Variable value	Meaning	No. of viewers	% of all viewers (%)
Household income (annual)	1	<$20,000	48	5.0
	2	$20,000–$29,999	60	6.2
	3	$30,000–$39,999	146	15.2
	4	$40,000–$49,999	144	15.0
	5	$50,000–$59,999	168	17.5
	6	$60,000 or higher	396	41.2
Number of children	2	Zero or one child under 18	338	35.1
	3	More than one child under 18	624	64.9
Household size	3	Three or fewer people	234	24.3
	4	Four or more people	728	75.7
Age	1	<25	16	1.7
	2	25–34	253	26.3
	3	35–44	480	49.9
	4	45–54	192	20.0
	5	55–64	14	1.5
	6	65+	7	0.7
Education	1	Less than 8 years grade school	332	34.5
	2	1–3 years high school	185	19.2
	3	4 years high school	280	29.1
	4	1 or more years of college	165	17.2

In this model, ω^{hw} measures the effect of the wife's viewing intention on her husband's viewing intention for all 51 programs. ω^{wh} measures the effect of the husband's viewing intention on his wife's viewing intention for these programs. $\mathbf{X}_j$ is a vector that includes the intercept term and the program characteristics of program j. Specifically, other than the intercept, X_j comprises dummy variables that indicate which category the program belongs to and which channel it was aired on. R_{ij}^h and R_{ij}^w are the vectors of the viewership of program j in the month of November 1996 of husband and wife, respectively, and capture the effect of state dependence on the viewer's utility. θ_i^h and θ_i^w are the individual-level parameter vectors of husbands and wives that capture the effect of observed product characteristics. γ_{ic}^h and γ_{ic}^w capture the effect of state dependence across each category c ($c = 1, 2, 3$) of programs. Z_i^h and Z_i^w are vectors of the demographic characteristics of the husband and wife, respectively, comprising age, education, number of children in the household, household size, and household income. An important element of these vectors is the total viewing time of the viewer, which is the total number of minutes a viewer views all 51 programs in our data for November 1997. This variable serves as a proxy for the overall propensity of a viewer to watch TV. By including this variable, we intend to control for the effect of a viewer's TV viewing propensity on his/her intention to view a specific program. δ^h and δ^w measure the fixed effects of demographics and total viewing time across households. The vector of individual-level coefficients, $\beta_i = [\theta_i^h \ \gamma_{ic}^h \ \theta_i^w \ \gamma_{ic}^w]$ is normally distributed as in Equation (4).

To understand how spousal interdependence varies with the demographic characteristics of the spouses and across different categories of programs, we adopt the following estimation strategy.[6] We divide our sample of 481 households into four (2×2) groups based on the sum of ages of the spouses (two levels) and the sum of their education levels (two levels). Age and education are two demographic variables that we believe may drive the difference in the level of spousal interdependence across families. For example, the interdependence may be stronger in older families than in younger families, and more-educated families may have a different interdependence pattern compared with less-educated families. It is this expectation that leads us to formulate this segmentation scheme. We further allocate each observation in each of these four demographic groups into three mutually exclusive subgroups based on the category of the program in that observation. As such, all our observations are divided into $4 \times 3 = 12$ segments ($s = 1, \ldots, 12$). We then estimate fixed effects for the parameters of spousal interdependence (ω_s^{hw} and ω_s^{wh}) for each of these 12 segments. This enables us to estimate differences in interdependence across program categories and important household demographics such as age and education. To reflect this procedure, we rewrite Equations (13a) and (13b) as follows:

$$y_{ij}^{h^*} = X_j\theta_i^h + R_{ij}^h\gamma_{ic}^h + Z_i^h\delta^h + y_{ij}^{w^*}\omega_s^{hw} + \varepsilon_{ij}^h; \qquad (14a)$$

$$y_{ij}^{w^*} = X_j\theta_i^w + R_{ij}^w\gamma_{ic}^w + Z_i^h\delta^w + y_{ij}^{h^*}\omega_s^{wh} + \varepsilon_{ij}^w. \qquad (14b)$$

ω_s^{hw} and ω_s^{wh} are estimated at a segment-specific level, so they vary across the 12 segments but do not vary across the households within a segment.

Model Comparison. We compare the proposed model with some benchmark models. The model fit is measured based on the logmarginal density calculated using Newton and Raftery's (1994, p. 21) importance-sampling method.

Model 1 is a simultaneous equation Tobit model that assumes away the direct interdependence of spousal viewing intentions. In this model, the effects of all covariates are fixed across households. However, we allow the error terms of the viewing intentions of both spouses to be correlated. In this way, we do capture the unobserved covariance of the viewing

[6] Because for most viewers (husbands or wives) the viewership of a majority of programs is zero, we are not able to estimate individual and program-category specific interdependence parameters.

intentions. In Model 2, we estimate the fixed effects of all exogenous covariates as well as the parameters of interdependence, ω^{hw} and ω^{wh}. However, we constrain ω^{hw} and ω^{wh} to be the same—i.e., we assume that interdependence is symmetric. Model 3 is different from Model 2 in that it allows for asymmetry, i.e., ω^{hw} and ω^{wh} are not the same. However, here we constrain the sum of the parameters of interdependence to equal 1. In Model 4, we do not constrain the parameters of interdependence in any manner. All of Models 1 to 4 assume fixed effects of all covariates. In Model 5, which is our proposed model, we account for consumer heterogeneity in both attribute sensitivity and dependence parameters across households, as specified in Equations (14a) and (14b).

The following are the logmarginal densities of the five models. Model 1: −32,029.1, Model 2: −32,207.0, Model 3: −32,706.6, Model 4: −31,987.6, and Model 5: −30,588.1. The higher in-sample fit of Model 1 as compared to Models 2 and 3 indicates that estimating the interdependence parameters under constraints of equality or of constant sum leads to worse in-sample fit. Also, it is better to model the direct interdependence, as we do in Model 4, than to only capture it as a covariance parameter, as we do in Model 1. Finally, there exists considerable heterogeneity in the response parameters across households and across categories of programs, which explains why Model 5 fits the data better than Model 4.

We now report the estimation results from Model 5 based on the data of viewership of television programs. In this application, we estimate the dependence of husbands' latent viewing intentions on their wives and the dependence of the wives' latent viewing intentions on their husbands. Furthermore, we explore differences in spousal interdependence across program categories and across the demographic characteristics of household members. Finally, we also report how spouses' latent intentions of viewing television programs depend on program attributes, state dependence, and their demographic characteristics.

Asymmetric Interdependence. To assess the level of asymmetry in interdependence across all households and across all program categories, we estimate a model where we specify ω^{hw} and ω^{wh} to be the same across all households and TV programs. Our estimate of ω^{hw} is 0.2976 (standard deviation = 0.0265) and that of ω^{wh} is 0.5022 (standard deviation = 0.0496). In other words, the dependence of wives on their husbands' intentions of viewing TV programs is greater than the dependence of husbands on their wives' intentions of viewing TV programs. This provides evidence of the existence of asymmetric interdependence of spouses' intentions of viewing television programs.

Differences in Interdependence Across Program Categories and Household Demographic Groups. Coefficient estimates of interdependence for each of the three program categories (drama, comedy, and news) and the four demographic groups are reported in Tables 3, 4, and 5.

We find that for news programs, wives' viewing intentions are affected by their husbands' viewing intentions to a greater extent than husbands' viewing intentions are affected by their wives' viewing intentions. This result holds irrespective of the age and education level of spouses. However, for the comedy and drama categories, patterns of interdependence show considerable variations across the demographic groups.

For comedy programs, the dependence of husbands' viewing intentions on wives' viewing intentions is higher for more educated couples. Also, this dependence is higher among older couples than among younger couples. On the other hand, depending on the age and education levels of spouses, the effect of husbands on their wives' viewing intentions is either statistically insignificant or negative.

For drama programs, the result that wives' viewing intentions are affected by their husbands to a greater extent than husbands' viewing intentions are affected by their wives holds for all spouses the sum of whose

Table 3 **Interdependence of Spouses' Viewing Intentions for the "Drama" Category of TV Programs Across Demographic Groups—Posterior Means and Standard Deviations**

	Dependence of husbands' viewing intentions on wives' viewing intentions		Dependence of wives' viewing intentions on husbands' viewing intentions	
	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90
Sum of education level of spouses < 8*	**0.3760** **(0.0428)**	**0.2865** **(0.0540)**	**0.5389** **(0.0945)**	0.2646 (0.1616)
Sum of education level of spouses ≥ 8*	**0.3186** **(0.0464)**	**0.3596** **(0.0514)**	**0.5510** **(0.0827)**	**0.5383** **(0.1171)**

*The education level of viewers is measured on the following 5-point scale. 1—Less than eight years grade school; 2—One to three years grade school; 3—Four years high school; 4—One to three years college; 5—Over three years college. Coefficient estimates whose posterior 95% confidence interval does not contain 0 are in bold.

Table 4 Interdependence of Spouses' Viewing Intentions for the "Comedy" Category of TV Programs Across Demographic Groups—Posterior Means and Standard Deviations

	Dependence of husbands' viewing intentions on wives' viewing intentions		Dependence of wives' viewing intentions on husbands' viewing intentions	
	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90
Sum of education level of spouses < 8*	**0.2257**	**0.2970**	0.1531	**−0.8080**
	(0.0416)	**(0.0474)**	(0.1195)	**(0.3287)**
Sum of education level of spouses ≥ 8*	**0.3573**	**0.3839**	0.1998	0.2197
	(0.0413)	**(0.0563)**	(0.1201)	(0.1686)

*The education level of viewers is measured on the following 5-point scale. 1—Less than eight years grade school; 2—One to three years grade school; 3—Four years high school; 4—One to three years college; 5—Over three years college. Coefficient estimates whose posterior 95% confidence interval does not contain 0 are in bold.

ages is less than 90. For older couples, the asymmetry in interdependence also depends on the education levels of the spouses.

Effect of Other Covariates on Individual's Viewing Intentions. The effects of other covariates on spouses' viewing intentions for Model 5 are presented in the last column of Table 6. Consistent with the literature on modeling of TV program choice (Shachar and Emerson 2000, Goettler and Shachar 2001), we find that viewers' intention to view a program is affected by their own past experiences. Table 6 (Model 5) shows that state dependence has a strong effect on both spouses across program categories. For husbands, the effect of lagged viewership is larger for the news category and drama category than for the comedy category. For wives, the effect of lagged viewership is the largest for the drama category and the least for the news category. Overall, the state dependence is larger for wives than for husbands. As the wife's age increases, her viewing intention lowers. On the other hand, demographics do not significantly predict the variation of husbands' viewing intentions.

Table 6 also compares the estimates of the coefficients of the exogenous variables of Model 1, Model 4, and Model 5. We find that the magnitudes of many of the parameter estimates are different in Model 4 from those in Model 1, reflecting the bias that might creep in if the direct spousal interdependence of viewing intentions is ignored. We also find that the magnitudes of many of the parameter estimates are different in Model 5 from those in Model 4, indicating the importance of accounting for consumer heterogeneity. It is worth noting that the state-dependence parameters across all three categories of TV programs are significant but smaller in size in Model 5 than in Model 4, indicating the importance of accounting for both state dependence and consumer heterogeneity (Keane 1997).

5. Conclusion

Quantitative models in the marketing literature typically focus on the household or the individual as the unit of decision making. There is considerable evidence to suggest that individual preferences are strongly affected by the preferences of others, such as friends and family members. In this article, we present an autoregressive random-effects Tobit model to study the interdependence of the viewing behavior of husbands and wives on television programs.

Table 5 Interdependence of Spouses' Viewing Intentions for the "News" Category of TV Programs Across Demographic Groups—Posterior Means and Standard Deviations

	Dependence of husbands' viewing intentions on wives' viewing intentions		Dependence of wives' viewing intentions on husbands' viewing intentions	
	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90	Sum of ages of spouses < 90	Sum of ages of spouses ≥ 90
Sum of education level of spouses < 8*	**0.2580**	**0.5141**	**0.7971**	**0.7474**
	(0.0645)	**(0.1050)**	**(0.1237)**	**(0.1708)**
Sum of education level of spouses ≥ 8*	**0.3384**	**0.2358**	**0.7489**	**0.8374**
	(0.0592)	**(0.0661)**	**(0.1159)**	**(0.1482)**

*The education level of viewers is measured on the following 5-point scale. 1—Less than eight years grade school; 2—One to three years grade school; 3—Four years high school; 4—One to three years college; 5—Over three years college. Coefficient estimates whose posterior 95% confidence interval does not contain 0 are in bold.

Table 6 Effect of State Dependence, Demographics, and Program Attributes on Husbands' and Wives' Viewing Intentions—Posterior Means and Standard Deviations of Coefficient Estimates

	Model 1 (no spousal interdependence of latent viewing intentions; fixed effects of exogenous covariates)		Model 4 (with spousal interdependence of latent viewing intentions; fixed effects of exogenous covariates)		Model 5 (with spousal interdependence of latent viewing intentions; random effects of exogenous covariates)	
	Posterior mean	Posterior S.D.	Posterior mean	Posterior S.D.	Posterior mean	Posterior S.D.
Coefficient estimates of husband's viewing intentions						
Intercept	**−3.2808**	**0.1986**	**−3.0977**	**0.2050**	**−2.5958**	**0.2371**
Total viewing time in minutes	**0.0017**	**0.0001**	**0.0015**	**0.0001**	**0.0011**	**0.0001**
Own lagged viewership (News)	**2.7257**	**0.2440**	**2.8820**	**0.2295**	**2.4921**	**0.2767**
Own lagged viewership (Drama)	**3.5783**	**0.1389**	**3.2390**	**0.1632**	**2.4351**	**0.2340**
Own lagged viewership (Comedy)	**2.7612**	**0.1319**	**2.5514**	**0.1322**	**1.4383**	**0.2598**
Household income	**−0.1915**	**0.0596**	**0.0332**	**0.0138**	0.0124	0.0232
No. of children	**0.1878**	**0.0703**	**−0.1232**	**0.0603**	0.0828	0.0964
Household size	**−0.1018**	**0.0223**	**0.2041**	**0.0662**	0.0649	0.0938
Age	**−0.0131**	**0.0208**	**−0.0765**	**0.0231**	0.0541	0.0442
Education	−0.1915	0.0596	0.0091	0.0208	0.0089	0.0358
Category—News	**0.1490**	**0.0478**	**0.1937**	**0.0507**	−0.0117	0.0888
Category—Drama	**0.3352**	**0.0486**	**0.3249**	**0.0544**	0.1537	0.0968
Channel—ABC	**0.3582**	**0.0636**	**0.2629**	**0.0549**	**0.1463**	**0.0721**
Channel—FOX	−0.0551	0.0794	−0.0609	0.0720	−0.1365	0.0806
Channel—NBC	**0.3348**	**0.0449**	**0.2536**	**0.0450**	**0.2008**	**0.0576**
Variance of error term	**4.2817**	**0.0870**	**3.4669**	**0.0910**	**2.3473**	**0.0647**
Coefficient estimates of wife's viewing intentions						
Intercept	**−3.1612**	**0.2381**	**−2.8629**	**0.2847**	**−2.8573**	**0.3466**
Total viewing time in minutes	**0.0018**	**0.00004**	**0.0016**	**0.0001**	**0.0014**	**0.0001**
Own lagged viewership (News)	**3.4008**	**0.2813**	**3.8398**	**0.2863**	**2.7447**	**0.3952**
Own lagged viewership (Drama)	**4.6625**	**0.1545**	**4.9304**	**0.1825**	**3.8798**	**0.2434**
Own lagged viewership (Comedy)	**3.7114**	**0.1460**	**3.8825**	**0.1524**	**3.2763**	**0.3028**
Household income	**0.0564**	**0.0218**	**0.0543**	**0.0197**	0.0425	0.0338
No. of children	**−0.2587**	**0.0777**	**−0.2531**	**0.0800**	−0.2702	0.1400
Household size	**0.0886**	**0.0803**	0.1371	0.0883	0.1129	0.1314
Age	**−0.0893**	**0.0335**	**−0.0764**	**0.0308**	**−0.1827**	**0.0637**
Education	**−0.1398**	**0.0303**	**−0.1449**	**0.0313**	−0.0716	0.0550
Category—News	−0.0449	0.0637	−0.0514	0.0648	**0.9026**	**0.1472**
Category—Drama	**0.2186**	**0.0738**	**0.1619**	**0.0681**	**0.8844**	**0.1684**
Channel—ABC	**0.4892**	**0.0754**	**0.4094**	**0.0692**	**0.4530**	**0.1109**
Channel—FOX	−0.0109	0.0950	−0.0378	0.0891	−0.1215	0.1313
Channel—NBC	**0.3761**	**0.0589**	**0.2908**	**0.0605**	**0.2646**	**0.0993**
Variance of error term	**7.3522**	**0.1238**	**6.4369**	**0.1863**	**5.0123**	**0.2477**
Covariance of error terms in husband's and wife's viewing intentions	**3.0841**	**0.0832**	**1.1092**	**0.1656**	**−0.5356**	**0.1786**

Note. Coefficient estimates whose posterior 95% confidence interval does not contain 0 are in bold. The baseline category is "comedy." The baseline channel is CBS.

We find that wives' dependence on their husbands' viewing behavior is higher than the dependence of husbands on their wives' viewing behavior. Moreover, interdependence varies across program categories. Differences in interdependence are partially explained based on the ages and education levels of family members.

We contribute to the marketing literature in significant ways. First, models that capture interdependence of preferences typically assume symmetric interdependence, that is, the dependence of Person A on Person B is the same as that of Person B on Person A. In this study, we propose a model that relaxes this constraint and captures the potential asymmetry in the preference interdependence between spouses. Second, we demonstrate that models that ignore interdependence and/or constrain the interdependence structure yield biased estimates of coefficients of observed attribute preferences. Finally, this research also extends our understanding of how viewers of television programs make choices. We find that incorporating the interdependence of viewership results in better model fit, as compared to models that ignore interdependence. As such, when modeling viewer preferences of television programs, it is important to consider incorporating interdependence of viewing behavior of spouses.

The results of this study have strategic ramifications for the network television industry. First, because our findings suggest that husbands affect their wives' viewing behavior more strongly than vice versa, marketing resources for television programs should perhaps be reallocated such that husbands' share of marketing reflects not just their lower viewership relative to their wives, but also their higher relative importance in affecting spouses' viewing behavior. Second, identifying a program as male or female oriented based on viewership alone without accounting for the impact of other viewers could lead to biased conclusions about true viewer preferences. Consider a program with high viewership from female viewers. It might be the case that female viewers do not have a strong inherent viewing intention for that program, but are heavily impacted by the male members of their households. A systematic effort to account for spousal dependence in estimating TV program effectiveness would help ascertain true viewer preferences.

Finally, our empirical application is subject to limitations, which also suggest opportunities for further research. Because we have data for only two months of consecutive years, we are not able to examine the dynamic aspects of spousal dependence. It would be interesting to explore how viewers learn from their spouses' viewing experiences across long periods of time. Spouses' experiences could influence a viewer's viewing intention. Also, spouses' experiences could lead to a reduction in a viewer's uncertainty about a program. Estimating the true nature of learning could further our understanding of how spouses' preferences are dependent on each other.

Our research can be extended in several ways. The proposed model can be used to further explore intrahousehold interdependence of utilities. Interdependence could be estimated between parents and children, between different age groups, between male and female viewers, and so on. Also, the model can be extended to simultaneously estimate interdependence across three or more kinds of viewers. For example, extending this model to include children as a third group might provide a more complete picture of how household members' preferences are interdependent.[7]

[7] The possibility of the existence of interdependence between husbands and children and between wives and children could affect our empirical results. However, we do capture the effect of such omitted variables on the covariation in spouses' viewership intentions by building a covariance between the error terms of the latent viewerships as per Equation (3).

The proposed model therefore provides a useful foundation for studying the nature of consumer preference interdependence.

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Appendix. Markov Chain Monte Carlo Estimation Algorithm

Estimation of the model specified in Equations (1a) to (11) is carried out by sequentially generating draws from the following distributions:

1. *Generating latent utility*, y_{ij}^{k*} $(i=1,\ldots,N;\ j=1,2,\ldots,J;\ k=h,w)$. If the consumption $y_{ij}^k>0$, then $y_{ij}^{k*}=y_{ij}^k$. If the consumption $y_{ij}^k=0$, $y_{ij}^{k*}\sim N(\bar{y}_{ij}^{k*},\eta_k^2)$ and $y_{ij}^{k*}\le 0$.

$$\begin{aligned}\bar{y}_{ij}^{h*}&=\Pi_{11}[X_{ij}^{h\prime}\beta_i^h]+\Pi_{12}[X_{ij}^{w\prime}\beta_i^w]\\&\quad+\Omega_{12}\{y_{ij}^{w*}-\Pi_{21}[X_{ij}^{h\prime}\beta_i^h]-\Pi_{22}[X_{ij}^{w\prime}\beta_i^w]\}/\Omega_{22},\\ \bar{y}_{ij}^{w*}&=\Pi_{21}[X_{ij}^{h\prime}\beta_i^h]+\Pi_{22}[X_{ij}^{w\prime}\beta_i^w]\\&\quad+\Omega_{21}\{y_{ij}^{h*}-\Pi_{11}[X_{ij}^{h\prime}\beta_i^h]-\Pi_{12}[X_{ij}^{w\prime}\beta_i^w]\}/\Omega_{11},\\ \eta_h^2&=\Omega_{11}-(\Omega_{12}*\Omega_{21}/\Omega_{22}),\\ \eta_w^2&=\Omega_{22}-(\Omega_{21}*\Omega_{12}/\Omega_{11}),\quad\text{and}\\ \Omega&=\begin{bmatrix}\Omega_{11}&\Omega_{12}\\ [3pt]\Omega_{21}&\Omega_{22}\end{bmatrix}=(I-W)^{-1}\Sigma(I-W)^{-1\prime}.\end{aligned}$$

2. *Generating ω^{hw} and ω^{wh}*. We first generate

$$\Pi=[\Pi_{11}\quad\Pi_{12}\quad\Pi_{21}\quad\Pi_{22}]\sim MVN(U,S),$$

where

$$U=S\left(\sum_{i=1}^N\sum_{j=1}^J D_{ij}'\Omega^{-1}y_{ij}^*+0.01I*U_0\right);$$

$$S=\left(\sum_{i=1}^N\sum_{j=1}^J D_{ij}'\Omega^{-1}D_{ij}+0.01I\right)^{-1};\quad U_0=0.$$

$$D_{ij}=\begin{bmatrix}X_{ij}^{h\prime}\beta_i^h & X_{ij}^{w\prime}\beta_i^w & 0 & 0\\ 0 & 0 & X_{ij}^{h\prime}\beta_i^h & X_{ij}^{w\prime}\beta_i^w\end{bmatrix}.$$

We recover ω^{hw} and ω^{wh} from Π as follows: $\omega^{hw}=\Pi_{12}/\Pi_{22}$ and $\omega^{wh}=\Pi_{21}/\Pi_{11}$.

3. *Generating Σ*. We first generate

$$\Omega\sim\text{Inverted Wishart}\left(\sum_{i=1}^N\sum_{j=1}^J[y_{ij}^*-\hat{y}_{ij}^*]'[y_{ij}^*-\hat{y}_{ij}^*]+Q_0,NJ+q_0\right),$$

where

$$\hat{y}_{ij}^{*} = \begin{bmatrix} \hat{y}_{ij}^{h*} \\ \hat{y}_{ij}^{w*} \end{bmatrix} = \begin{bmatrix} \Pi_{11}[X_{ij}^{h\prime}\beta_i^h] + \Pi_{12}[X_{ij}^{w\prime}\beta_i^w] \\ \Pi_{21}[X_{ij}^{h\prime}\beta_i^h] + \Pi_{22}[X_{ij}^{w\prime}\beta_i^w] \end{bmatrix},$$

$$Q_0 = 10I \quad \text{and} \quad q_0 = 10.$$

We recover Σ from Ω as follows: $\Sigma = (I - W)\Omega(I - W)'$.

4. *Generating random coefficients of exogenous covariates.* $\beta_i = [\beta_i^{h\prime}, \beta_i^{w\prime}]'$ $(i = 1, \ldots, N)$. $\beta_i \sim MVN(M_i, S_i)$, where

$$S_i = \left[\sum_{j=1}^{J}(X_{ij}'\Sigma^{-1}X_{ij}) + \Psi^{-1}\right]^{-1};$$

$$M_i = S_i\left[\sum_{j=1}^{J}[X_{ij}'\Sigma^{-1}(I - W)y_{ij}^{*}] + \Psi^{-1}\bar{\beta}\right];$$

$$X_{ij} = \begin{bmatrix} X_{ij}^h & 0 \\ 0 & X_{ij}^w \end{bmatrix}; \qquad y_{ij}^{*} = \begin{bmatrix} y_{ij}^{h*} & y_{ij}^{w*} \end{bmatrix}'.$$

5. *Generating* $\bar{\beta}$. $\bar{\beta} \sim MVN(U, S)$, where

$$U = S\left(\Psi^{-1}\sum_{i=1}^{N}\beta_i/N + 0.01I * U_0\right);$$

$$S = ((\Psi^{-1}/N)^{-1} + 0.01I)^{-1}; \quad U_0 = 0.$$

6. *Generating* Ψ.

$$\Psi \sim \text{Inverted Wishart}\left(\sum_{i=1}^{N}(\beta_i - \bar{\beta})'(\beta_i - \bar{\beta}) + Q_0, N + q_0\right);$$

$$Q_0 = 10I \quad \text{and} \quad q_0 = 10.$$

References

Ainslie, Andrew, Xavier Drèze, Fred Zufryden. 2005. Modeling movie life cycles and market share. *Marketing Sci.* **24**(3) 508–517.

Allenby, Greg M., Peter E. Rossi. 1998. Marketing models of consumer heterogeneity. *J. Econometrics* **89**(1/2) 57–78.

Amemiya, Takeshi. 1985. *Advanced Econometrics*. Harvard University Press, Cambridge, MA, 360–364.

Aribarg, Anocha, Neeraj Arora, H. Onur Bodur. 2002. Understanding the role of preference revision and concession in group decisions. *J. Marketing Res.* **39**(3) 336–349.

Arora, Neeraj, Greg M. Allenby. 1999. Measuring the influence of individual preference structures in group decision making. *J. Marketing Res.* **36**(4) 476–487.

Case, Anne C. 1991. Spatial patterns in household demand. *Econometrica* **59**(4) 953–965.

Chib, Siddhartha. 1992. Bayesian inference in the Tobit censored regression model. *J. Econometrics* **51** 79–90.

Corfman, Kim P. 1989. Measures of relative influence in couples: A typology and predictions for accuracy. *Adv. Consumer Res.* **16**(1) 659–664.

Corfman, Kim P. 1991. Perceptions of relative influence: Formation and measurement. *J. Marketing Res.* **28**(2) 125–136.

Danaher, Peter J., Donald F. Mawhinney. 2001. Optimizing television program schedules using choice modeling. *J. Marketing Res.* **38**(3) 298–312.

Duesenberry, James S. 1949. *Income, Saving, and the Theory of Consumer Behavior*. Harvard University Press, Cambridge, MA.

Eliashberg, Jehoshua, Anita Elberse, Mark Leenders. 2005. The motion picture industry: Critical issues in practice, current research and new research directions. *Marketing Sci.* **25**(6). Forthcoming.

Gelfand, Alan E., Adrian F. M. Smith. 1990. Sampling based approaches to calculating marginal densities. *J. Amer. Statist. Assoc.* **85**(410) 398–409.

Gensch, Dennis, Paul Shaman. 1980. Predicting TV viewership. *J. Advertising Res.* **20**(4) 85–92.

Godes, David, Dina Mayzlin. 2004. Using online conversations to study word-of-mouth communication. *Marketing Sci.* **23**(4) 545–560.

Goettler, Ronald L., Ron Shachar. 2001. Spatial competition in the network television industry. *RAND J. Econom.* **32**(4) 624–656.

Henry, Michael D., Heikki J. Rinne. 1984. Predicting program shares in new time slots. *J. Advertising Res.* **24**(2) 9–17.

Horen, Jeffrey H. 1980. Scheduling of network television programs. *Management Sci.* **26**(4) 354–370.

Kamakura, Wagner A., Gary J. Russell. 1989. A probabilistic choice model for marketing segmentation and elasticity structure. *J. Marketing Res.* **26**(4) 370–390.

Kapteyn, Arie, Sara van de Geer, Huib van de Stadt, Tom Wansbeek. 1997. Interdependent preferences: An econometric analysis. *J. Appl. Econometrics* **12**(6) 665–686.

Keane, Michael P. 1997. Modeling heterogeneity and state dependence in consumer choice behavior. *J. Bus. Econom. Statist.* **15**(3) 310–327.

Krider, Robert E., Tieshan Li, Yong Liu, Charles B. Weinberg. 2005. The lead-lag puzzle of demand and distribution: A graphical method applied to movies. *Marketing Sci.* **24**(4) 635–645.

Krishnamurthi, Lakshman. 1988. Conjoint models of family decision making. *Internat. J. Res. Marketing* **5**(3) 185–198.

Leibenstein, Harvey. 1950. Bandwagon, snob, and veblen effects in the theory of consumer's demand. *Quart. J. Econom.* **64**(2) 183–207.

Li, Kai. 1998. Bayesian inference in a simultaneous equation model with limited dependent variables. *J. Econometrics* **85** 387–400.

Liu, Yong, Daniel S. Putler, Charles B. Weinberg. 2004. Is having more channels really better? A model of competition among commercial television broadcasters. *Marketing Sci.* **23**(1) 120–133.

Moshkin, Nickolay V., Ron Shachar. 2002. The asymmetric information model of state dependence. *Marketing Sci.* **21**(4) 435–454.

Newton, Michael A., Adrian E. Raftery. 1994. Approximating Bayesian inference with the weighted likelihood bootstrap. *J. Roy. Statist. Soc.* (*B*) **56**(1) 3–48.

Rust, Roland T., Mark I. Alpert. 1984. An audience flow model of television viewing choice. *Marketing Sci.* **3**(2) 113–124.

Rust, Roland T., Wagner A. Kamakura, Mark I. Alpert. 1992. Viewer preference segmentation and viewing choice models for network television. *J. Advertising* **21**(1) 1–18.

Shachar, Ron, John W. Emerson. 2000. Cast demographics, unobserved segments and heterogeneous switching costs in a television viewing choice model. *J. Marketing Res.* **37**(2) 173–186.

Smith, Tony E., James P. LeSage. 2004. A Bayesian probit model with spatial dependencies. James P. LeSage, R. Kelley Pace, eds. *Spatial and Spatiotemporal Econometrics. Advances in Econometrics*, Vol. 18. Elsevier Science, Oxford, UK, 127–160.

Su, Chenting, Edward F. Fern, Keying Ye. 2003. A temporal dynamic model of spousal family purchase-decision behavior. *J. Marketing Res.* **40**(3) 268–281.

Tanner, Martin A., Wing H. Wong. 1987. The calculation of posterior distribution by data augmentation. *J. Amer. Statist. Assoc.* **82** 528–550.

Tobin, James. 1958. Estimation of relationships for limited dependent variables. *Econometrica* **26**(1) 24–36.

Yang, Sha, Greg M. Allenby. 2003. Modeling interdependent consumer preferences. *J. Marketing Res.* **40**(3) 282–294.

Zellner, Arnold. 1971. *An Introduction to Bayesian Inference in Econometrics*. Wiley-Interscience, New York.