MODELING UNOBSERVED CONSIDERATION SETS FOR HOUSEHOLD PANEL DATA

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Modeling Unobserved Consideration Sets for Household Panel Data

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Modeling Unobserved Consideration Sets for Household Panel Data

Abstract

We propose a new method to model consumers' consideration and choice processes. We develop a parsimonious probit type model for consideration and a multinomial probit model for choice, given consideration. Unlike earlier models of consideration ours is not prone to the curse of dimensionality, while we allow for very general structures of unobserved dependence in consideration among brands. In addition, our model allows for state dependence and marketing mix effects on consideration.

Unique to this study is that we attempt to establish the validity of existing practice to infer consideration sets from observed choices in panel data. To this end, we use data collected in an on-line choice experiment involving interactive supermarket shelves and post-choice questionnaires to measure the choice protocol and stated consideration levels. We show with these experimental data that underlying consideration sets can be successfully retrieved from choice data alone and that there is substantial convergent validity of the stated and inferred consideration sets. We further find that consideration is a function of point-of-purchase marketing actions such as display and shelf space, and of consumer memory for recent choices.

Next, we estimate the model on IRI panel data. We have three main results. First, compared with the single-stage probit model, promotion effects are larger and are inferred with smaller variances when they are included in the consideration stage of the two-stage model. Promotion effects are significant only in the two-stage model that includes consideration, whereas they are not in a single-stage choice model. Second, the price response curves of the two models are markedly different. The two-stage model offers a nice intuition for why promotional price response is different from regular price response. In addition and consistent with intuition, the two-stage model also implies that merchandizing has more effect on choice among those who did not buy the brand before than among those who already did. It is explained why a single-stage model does not harbor this feature. In fact, the single-stage model implies the opposite for smaller or more expensive brands. Third, we find that the consideration of brands does not covary greatly across brands once we take account of observed effects. Managerial implications and future research are also discussed.

Keywords: Consideration, choice, probit models.

1 Introduction

The theory of consideration sets, developed in the seventies from the work by Bettman (1979), Howard and Sheth (1969) and Newell and Simon (1972), has led to much empirical work in marketing science (for overviews see, for example, Malhotra, 1999; Manrai and Andrews, 1998; Roberts and Lattin, 1997) and has had important implications for marketing practice. Its basic postulate is that consumers follow a two-stage decision process of brand choice. In the first stage, they are thought to narrow down the global set of alternatives to a smaller set, the consideration set, from which a choice is made in the second stage. Researchers in marketing have provided ample empirical evidence corroborating this two-stage process of consumer choice (Lussier and Olshavsky, 1979; Payne, 1976; Wright and Barbour, 1977).

Consideration sets are interesting from a marketing perspective because they vary across households (Alba and Chattaopadhyay, 1985; Belonax and Mittelstaedt, 1978; Chiang *et al.*, 1999; Roberts and Lattin, 1991) and are sensitive to marketing instruments such as promotions (Siddarth *et al.*, 1995) and advertizing (Mitra, 1995). Ignoring consideration sets in models of choice may lead one to underestimating the impact of marketing control variables (Bronnenberg and Vanhonacker, 1996; Chiang *et al.*, 1999). So, with the rapid proliferation of the number of brands in the market place and the increase in cognitive demands placed on consumers choosing among them, understanding consideration set formation and how marketing affects it, has become of great relevance to marketing managers. Entering the consideration set has become an important strategic goal (see, for example, Corstjens and Corstjens, 1999)

Therefore, it is not surprising that econometric representations of choice and consideration for fast moving consumer goods have received great interest from marketing researchers. These models are traditionally formulated in a random utility theory framework (see for example, McFadden, 1973 or Guadagni and Little, 1983) and have built upon the postulate of utility maximizing consumers. Including the consideration stage into such a random utility framework is not trivial because these sets are not observed nor can they

be identified with certainty (Ben-Akiva and Boccara, 1995). Essentially, two approaches have been suggested to identify the sets of brands considered by consumers. One stream of research approaches this problem by assessing consideration set membership of individual brands. Hence, these studies model the marginal distribution of consideration for each brand (for example, Roberts and Lattin, 1991) and then transform the consideration-set inclusion probabilities into consideration sets. The usual conduit for doing this is an assumption of independence (for example, Ben-Akiva and Boccara, 1995) that remains untested in empirical research. Therefore, whereas this approach –which we will call the *stated consideration set* approach– works even for larger global choice sets, it has limitations in handling unobserved set-membership dependencies across brands.

Another stream of research identifies the distribution of consideration sets directly from the choice data (for example, Chiang *et al.*, 1999; Manski, 1977) by conditioning choice on unobserved consideration. To account for the unobserved nature of consideration, and to obtain marginal choice probabilities, it next integrates over all possible consideration sets of which there are $2^J - 1$, where J is the number of choice options. This method is suited for modeling unobserved dependencies across brands, because the realization of a consideration set is modeled directly, rather than the set-membership of individual brands. This approach, which we will call the *revealed consideration set approach*, is therefore not burdened with the assumption of independence of consideration set membership across brands. However, a number of problems exist with its empirical application. First, the number of possible consideration sets is exponential in the number of brands contained in the global choice set (see Chiang *et al.*, 1999). With more than four brands, the method becomes rapidly unfeasible because of combinatorial complexity. Second, the method provides the likelihood that a given consideration set occurs, but it does not directly provide a marginal probability of consideration set membership of a given brand. Therefore, it offers neither a natural way to study marginal brand set-membership probabilities nor their responsiveness to marketing action. Third, to achieve model identification, it is often necessary to assume static consideration sets for a given household. This appears to be contrary to what consumer learning theory predicts. Finally, there is no existing empirical

evidence as to whether the "consideration probabilities", that these models estimate from choice data, actually reflect consideration sets. This obviously is an important empirical problem that bears directly on the validity of the interpretations of modeling actions and the resulting recommendations for marketing practice.

In this paper, we propose a model for consideration set formation and brand choice that may be considered to provide a unifying framework of the stated and revealed approaches to consideration set identification. It combines their strengths and can either be estimated on revealed choice data alone or on stated consideration and choice data combined. At the core of our approach is a multivariate probit model (MVP) for consideration, compounded with a multinomial probit (MNP) model for brand choice, given consideration. In the MVP model, we directly specify the *joint* distribution of the probabilities of brands' consideration set-membership, by modeling consideration set membership of brands as binary probits that can covary across brands.

This approach offers a good alternative to the revealed approach, when estimated on actual choice data alone, for the following reasons. First, through the covariance structure of the MVP model, the consideration of one brand is allowed to depend on the consideration of the other brands. So, our approach retains the advantage of the context-dependence that is inherent in the revealed approach to consideration sets. Second, our approach does not suffer from the curse of dimensionality. In the worst case, that is, when we use a completely structure-free covariance matrix across brands, the number of parameters to be estimated is quadratic in the number of brands rather than exponential. More realistically, there are many cases in which theoretical guidelines exist for a parsimonious structure on the cross-brand consideration process. When such a structure is independent of the number of brands in the global choice set, our approach provides a fully tractable and general model of consideration set formation, the complexity of which is only *linear* in the global number of choice options. Our approach offers the advantages of the stated approaches to consideration set identification that describe the marginal consideration set membership probabilities, but rather than assuming independence of the memberships across brands, we can investigate whether independence actually holds. Third, we can include marketing

control variables and "the hand of the past" in the MVP model of the consideration stage.

Our approach can be calibrated on both stated consideration and choice indicators, or on the choice indicators alone. This allows us to investigate the validity of the consideration set probabilities assessed in the latter case. Indeed, a unique aspect of this study is that we intend to validate the inference of consideration from choice data using actually measured consideration sets. To our knowledge this has not yet been done in the consideration set literature.

We next lay out the model and its (MCMC) estimation procedure. We demonstrate the performance of the model on synthetic data. Then we investigate the convergent validity of the approach to identify consideration sets from choice behavior, using data from an experimental study that was conducted specifically for this purpose. Subsequently we apply our model to a scanner panel data set on saltine crackers and discuss our findings both in a numerical and a graphical way. We finish by discussing the limitations and prospects on future research.

2 The model

2.1 Preliminaries

In this section we propose a model to describe the brand choice decision of household i $(i = 1, \ldots, I)$ choosing brand j $(j = 1, \ldots, J)$ at purchase occasion t $(t = 1, \ldots, T_i)$. If household i chooses brand j at time t we denote this by $d_{it} = j$. Without loss of generality we consider here the -more complex- situation where only such choice data are available and the consideration sets themselves are unobserved. Households typically do not consider all brands in their choice decision, but choose a brand from their consideration or choice set. This choice set may contain one, two or even all brands that are available to the household. For each household, there are $Q = 2^J - 1$ potential consideration sets. We denote the consideration set of household i at time t by C_{it}. As we assume that households choose a brand from their unobserved consideration set, after observing the actual brand choice, the number of potential consideration sets for a household equals 2^{J-1}. We denote

the collection of potential consideration sets for household i at purchase occasion t by $\mathcal{C}_{it}$. For explaining brand choice, managers are interested in the effects of marketing control variables, such as price, feature and displays. We use a subset of these variables, denoted by X_{ijt} in the consideration stage, and another, possibly partly overlapping subset, denoted by W_{ijt}, in the brand choice stage.

The model that we propose consists of the two well-established stages. In the first stage, it describes the consideration set of the households and in the second stage, it describes the actual choice of the household from the brands in its consideration set.

2.2 Stage 1: Consideration set

The consideration set of household i at time t, C_{it}, is described by a J-dimensional vector with binary elements

$$C_{it} = \begin{pmatrix} C_{i1t} \\ \vdots \\ C_{ijt} \end{pmatrix}, \tag{1}$$

where C_{ijt} equals 1 if brand j occurs in the consideration set of household i at time t, and 0 otherwise. In the case where household i considers buying only the first two brands the consideration set thus equals $C_{it} = (1, 1, 0, \ldots, 0)$. To describe if a brand is in the consideration set of household i, we consider a multivariate probit formulation that involves

$$C^*_{ijt} = X'_{ijt}\alpha + \varepsilon_{ijt}, \qquad j = 1, \ldots, J, \tag{2}$$

where X_{ijt} is a vector containing brand and purchase-related explanatory variables including brand-specific intercepts, where α is a parameter vector, and where ε_{ijt} is an unknown disturbance term. Note that X_{ijt} may also contain lagged purchase dummies, enabling us to model memory effects.

Brand j enters the consideration set of household i at time t, that is, $C_{ijt} = 1$, if $C^*_{ijt} > 0$. For the household considering buying only the first two brands, the first two elements of the vector C^*_{it} are positive, while the remaining elements are all negative. To

illustrate, the probability that the consideration set of household i contains only the first two brands equals

$$\begin{aligned}\Pr[C_{it} = (1,1,0,\ldots,0)'] &= \Pr[C^*_{i1t} > 0, C^*_{i2t} > 0, C^*_{i3t} \leq 0, \ldots, C^*_{iJt} \leq 0] \\ &= \Pr[\varepsilon_{i1t} > -X'_{i1t}\alpha, \varepsilon_{i2t} > -X'_{i2t}\alpha, \\ &\qquad \varepsilon_{i3t} \leq -X'_{i3t}\alpha, \ldots, \varepsilon_{iJt} \leq -X'_{iJt}\alpha]. \end{aligned} \tag{3}$$

This probability depends on the distribution of the disturbance terms. We assume that the vector of disturbances $\varepsilon_{it} = (\varepsilon_{i1t}, \ldots, \varepsilon_{iJt})'$ is normally distributed, that is,

$$\varepsilon_{it} \sim \mathrm{N}(\mathbf{0}, \Sigma), \tag{4}$$

where the off-diagonal elements in the covariance matrix Σ describe the dependencies among the probabilities that the brands are contained in the consideration set. In this formulation, multiplying all utilities C^*_{ijt} by a positive constant would result in the same consideration set. Therefore, for identification purposes we need to set the diagonal elements of Σ all equal to 1.

The multivariate probit model allows for the possibility of an empty consideration set, that is $C_{it} = (0, \ldots, 0)'$. This occurs if at the particular purchase occasion the household does not buy from the category altogether. Here we are interested primarily in characterizing consideration and not in purchase incidence. The probability that the consideration set of a household i includes only the first two brands is then equal to probability (3) divided by 1 minus the probability of the occurrence of an empty set.

2.3 Stage 2: Brand choice

Given the consideration sets of households, we describe their brand choice by a multinomial probit model. We assume that household i perceives utility U_{ijt} from buying brand j at purchase occasion t, that is,

$$U_{ijt} = W'_{ijt}\beta + \eta_{ijt}, \qquad j = 1, \ldots, J \tag{5}$$

where W_{ijt} is a vector containing explanatory variables including brand-specific intercepts, where β is a parameter vector, and where η_{ijt} is a disturbance term. The vector of the

probit disturbances $\eta_{it} = (\eta_{i1t}, \ldots, \eta_{iJt})'$ is assumed to be normally distributed, that is,

$$\eta_{it} \sim \mathrm{N}(\mathbf{0}, \Omega). \tag{6}$$

Household i buys brand j at purchase occasion t if the perceived utility of buying brand j is the maximum over all perceived utilities for buying the other brands in the consideration set, that is, if

$$U_{ijt} = \max(U_{ikt} \text{ for all } k | C_{ikt} = 1). \tag{7}$$

Hence, the probability that household i chooses brand j at purchase occasion t given the consideration set C_{it} equals

$$\begin{aligned} \Pr[D_{it} = j | C_{it}] &= \Pr[U_{ijt} > U_{ikt} \text{ for all } k \neq j | C_{ijt} = C_{ikt} = 1] \\ &= \Pr[U_{ijt} - U_{ikt} > 0 \text{ for all } k \neq j | C_{ijt} = C_{ikt} = 1] \\ &= \Pr[\eta_{ikt} - \eta_{ijt} < W'_{ijt}\beta - W'_{ikt}\beta \text{ for all } k \neq j | C_{ijt} = C_{ikt} = 1]. \end{aligned} \tag{8}$$

This expression shows that utility differences and not the levels of the utilities determine brand choice. Therefore, not all elements of the covariance matrix Ω are identified, see Bunch (1991) for a discussion. Additionally, Keane (1992) shows that the off-diagonal elements are often empirically non-identified, which was corroborated in a few unreported test runs of our model and hence we opt for a diagonal covariance matrix. As multiplying the utilities U_{ijt} by a positive constant does not change actual brand choice, we restrict one of the diagonal elements of Ω to be 1 such that $\Omega = \mathrm{diag}(\omega_1^2, \ldots, \omega_{J-1}^2, 1)$.

Our modeling approach is related to Chiang *et al.* (1999). There are however some important differences. In their approach they assign to each possible consideration set q, $q = 1, \ldots, Q$, a household-specific probability mass, which is not related to any covariates. The drawback of this approach is that the number of probabilities and hence parameters to be estimated increases exponentially in J. In contrast, in our approach we model the probability that a brand j is included in the consideration set, which means that we only deal with J instead of Q alternatives. The covariance structure in the multivariate probit model models the dependencies between the inclusion of the brands. The number of

parameters in this approach therefore increases at most quadratically in J. Another important difference with the approach of Chiang *et al.* (1999) is that we include explanatory variables in the consideration stage of the model.

3 Estimation

3.1 Likelihood function

We consider the case of revealed consideration data, where only choices of households have been observed. To estimate the model parameters, we consider the likelihood as a function of the brand choices of the households $d = \{d_{it}, i = 1, \ldots, I, t = 1, \ldots, T_i\}$, that is,

$$\mathcal{L}(d|\theta) = \prod_{i=1}^{I} \prod_{t=1}^{T_i} \sum_{\forall c_{it} \in \mathcal{C}_{it}} \frac{\Pr[C_{it} = c_{it}|\alpha, \Sigma]}{1 - \Pr[C_{it} = \mathbf{0}|\alpha, \Sigma]} \cdot \Pr[D_{it} = d_{it}|c_{it}, \beta, \Omega], \tag{9}$$

where $\theta = (\alpha, \beta, \Sigma, \Omega)$ and $\mathcal{C}_{it}$ is the set of potential consideration sets for household i at time t. The likelihood function contains the product of the probability that the consideration set of household i is c_{it}, see (3), and the probability that the brand choice is d_{it} given c_{it}, see (8), over all households. As we do not observe the consideration sets c_{it} of the households, we have to sum over all potential consideration sets for each household.

If we apply our model to *stated* consideration data, the situation simplifies and we observe, next to the choice indicators d_{it}, also the choice set membership indicators, c_{it}. The expression for the likelihood is similar to that shown above, but the summation across all possible consideration sets vanishes and the approach reduces to the separate estimation of the MVP and MNP components. Since that situation is more straightforward, we focus on the case of revealed consideration sets in the further description of the estimation methodology.

3.2 MCMC Approach

The likelihood function (9) is too complicated to optimize numerically over the parameter space as the evaluation already requires the computation of many multivariate integrals. To estimate the model parameters θ we opt for a Bayesian approach, where Bayesian

posterior means and posterior standard deviations are used as parameter estimates and standard errors. We assume flat priors for the model parameters such that the posterior distribution is proportional to the likelihood function (9). To obtain posterior results, we use the Gibbs sampling technique of Geman and Geman (1984) with data augmentation, see Tanner and Wong (1987). The idea of Gibbs sampling is to sample iteratively from the full conditional posterior distributions of the model parameters contained in θ. This creates a Markov chain that converges under mild conditions, such that the draws can be used as draws from the joint distribution (see for example Tierney, 1994, or Casella and George, 1992 for a lucid introduction). The unobserved utilities U_{ijt} and C^*_{ijt} and the unobserved consideration sets C_{ijt} are sampled alongside with the other model parameters. The posterior means and standard deviations of the parameters of interest can be obtained by computing the sample means and variances of the draws.

The Gibbs sampling simulation algorithm to sample from the joint distribution of (θ, U, C^*, C) proceeds as follows:

Step 1 Specify starting values $(\theta^{(0)}, U^{(0)}, C^{*(0)}, C^0)$ and set $g = 0$. We initialize the parameter vectors in θ as vectors of ones, the covariance matrices in θ as identity matrices, the unobserved utilities U and C^* at zeroes for all i, j, t and the unobserved consideration sets C as universal sets (that is containing all brands)[1].

Step 2 Simulate

- $\alpha^{(g+1)}|\beta^{(g)}, \Sigma^{(g)}, \Omega^{(g)}, U^{(g)}_{it}, C^{*(g)}_{it}, C^{(g)}_{it}$
- $\beta^{(g+1)}|\alpha^{(g+1)}, \Sigma^{(g)}, \Omega^{(g)}, U^{(g)}_{it}, C^{*(g)}_{it}, C^{(g)}_{it}$
- $\Sigma^{(g+1)}|\alpha^{(g+1)}, \beta^{(g+1)}, \Omega^{(g)}, U^{(g)}_{it}, C^{*(g)}_{it}, C^{(g)}_{it}$
- $\Omega^{(g+1)}|\alpha^{(g+1)}, \beta^{(g+1)}, \Sigma^{(g+1)}, U^{(g)}_{it}, C^{*(g)}_{it}, C^{(g)}_{it}$
- $U^{(g+1)}_{it}|\alpha^{(g+1)}, \beta^{(g+1)}, \Sigma^{(g+1)}, \Omega^{(g+1)}, C^{*(g)}_{it}, C^{(g)}_{it}$
- $C^{*(g+1)}_{it}|\alpha^{(g+1)}, \beta^{(g+1)}, \Sigma^{(g+1)}, \Omega^{(g+1)}, U^{(g+1)}_{it}, C^{(g)}_{it}$

[1] We have also used other starting values and found no difference in the resulting posterior means and standard deviations.

- $C_{it}^{(g+1)} | \alpha^{(g+1)}, \beta^{(g+1)}, \Sigma^{(g+1)}, \Omega^{(g+1)}, U_{it}^{(g+1)}, C_{it}^{*(g+1)}$.

Step 3 Set $g = g + 1$ and go to step 2.

The described iterative scheme generates a Markov Chain. After the chain has converged, say, at G iterations (which is called the number of burn in iterations), the simulated values for $g > G$ can be used as a sample from the joint distribution of (θ, U, C^*, C) to compute posterior means, variances and marginal densities.

The derivation of the full posterior distributions of α, β, Ω, C^* and U proceeds in a similar way as in Albert and Chib (1993), McCulloch and Rossi (1994), Geweke *et al.* (1997), Chib and Greenberg (1998) and Paap and Franses (2000). To determine the sampling distributions of the mean (α and β) and covariance parameters Ω, we rewrite the MVP and MNP model in such a way that they represent standard univariate or multivariate regression models with the parameter to be sampled acting as a regression parameter or (co-)variance parameter of the error term. For a standard regression model we know that the full conditional posterior distribution of the regression parameter is normal with mean and variance resulting from the ordinary least squares (OLS) estimators. The full conditional posterior distribution of the variance (covariance matrix) of the error term is an inverted χ^2 (or inverted Wishart) distribution.

Full conditional posterior distribution of α

To obtain the full conditional posterior distribution of α we rewrite (2) as

$$\Sigma^{-\frac{1}{2}} C_{it}^* = \Sigma^{-\frac{1}{2}} X_{it} \alpha + \Sigma^{-\frac{1}{2}} \varepsilon_{it}, \tag{10}$$

where $X_{it} = (X_{i1t} \; X_{i2t} \; \ldots \; X_{iJt})'$, for $i = 1, \ldots, I$, $t = 1, \ldots, T_i$. This represents J regression equations with regression coefficient α and uncorrelated normally distributed error terms with unit variance. Hence, the full conditional posterior distribution of α given Σ and C^* is normal. The mean and variance result from the OLS estimators of α in (10)

Full conditional posterior distribution of β

In the brand choice model, β is sampled in a similar way as α. We rewrite the equations (5) for which $C_{ijt} = 1$ as

$$\omega_j^{-1} U_{ijt} = \omega_j^{-1} W'_{ijt}\beta + \omega_j^{-1}\eta_{ijt}, \tag{11}$$

for $j = 1, \ldots, J$, $i = 1, \ldots, I$ and $t = 1, \ldots, T_i$. This represents $\sum_{i=1}^{I}\sum_{t=1}^{T_i}\sum_{j=1}^{J} C_{ijt}$ regression equations with regression coefficient β and uncorrelated normally distributed error terms with unit variance. Hence, the full conditional posterior distribution of β given Ω, C and U is normal. The mean and variance result from the OLS estimators of β in (11).

Full conditional posterior distribution of Σ

To sample Σ we note that

$$p(\Sigma|\alpha, C^*) \propto \pi(\Sigma|\alpha) = |\Sigma|^{-\frac{1}{2}\sum_{i=1}^{I} T_i} \exp(-\frac{1}{2}\sum_{i=1}^{I}\sum_{t=1}^{T_i}(C^*_{it} - X_{it}\alpha)'\Sigma^{-1}(C^*_{it} - X_{it}\alpha)). \tag{12}$$

As Σ is not a free covariance matrix (the diagonal elements are 1), the full conditional distribution is not inverted Wishart. In fact the full conditional posterior distribution of Σ is not standard. To sample Σ we propose a sampler based on Basag and Green (1993) and Damien *et al.* (1999). Loosely speaking, this sampler interchanges the two steps in the Metropolis-Hasting sampler of Metropolis *et al.* (1953). The Metropolis-Hastings sampler amounts to sampling a candidate Σ^{new} draw from a target distribution in a first step and accept or reject this candidate in a second step based on a draw from a uniform distribution. If the draw is rejected one continues with the previous draw Σ^{old}, see Chib and Greenberg (1995) for a lucid discussion. A possible Metropolis-Hasting sampler for Σ is:

Step 1 Draw the elements of the matrix Σ from a uniform distribution on the interval $[-1, 1]$ under the restriction of positive definiteness resulting in Σ^{new}.

Step 2 Draw u from a uniform distribution on the interval $[0, 1]$ and accept Σ^{new} if $\pi(\Sigma^{\text{new}})/\pi(\Sigma^{\text{old}}) > u$ otherwise take $\Sigma^{\text{new}} = \Sigma^{\text{old}}$.

For the sampler used in this paper we switch around these two steps. We first draw u from a uniform distribution on the interval $[0, 1]$. In the second step we keep sampling candidate draws of the elements of Σ from a uniform distribution on the interval $[-1, 1]$ until Σ^{new} is positive definite and $\pi(\Sigma^{\text{new}})/\pi(\Sigma^{\text{old}}) > u$. The advantage of the latter approach is that it always results in a new draw, which is not the case for the Metropolis-Hasting sampler, see Damien *et al.* (1999) for details. The disadvantage is that the sampler is slower as one has to draw new candidates until acceptance. Another possibility to generate Σ based on the Metropolis-Hasting sampler is given in Chib and Greenberg (1998) or the hit-and-run algorithm in Manchanda *et al.* (1999).

Full conditional posterior distribution of Ω

To sample the elements of the covariance matrix Ω we use that

$$p(\omega_j|\beta, U, C) \propto \frac{1}{\omega_j^{\nu}} \exp(-\frac{1}{2\omega_j^2} \sum_{i=1}^{I} \sum_{t=1}^{T_i} I[C_{ijt} = 1](U_{ijt} - W'_{ijt}\beta)^2), \tag{13}$$

and hence

$$\frac{\sum_{i=1}^{I} \sum_{t=1}^{T_i} I[C_{ijt} = 1](U_{ijt} - W'_{ijt}\beta)^2}{\omega_j^2} \sim \chi^2(\nu) \tag{14}$$

with $\nu = \sum_{i=1}^{I} \sum_{t=1}^{T_i} I[C_{ijt} = 1]$ for $j = 1, \ldots, J-1$.

Full conditional posterior distribution of U

To sample U_{it}, $i = 1, \ldots, I$, $t = 1, \ldots, T_i$, we consider

$$U_{it} = W_{it}\beta + \eta_{it}, \tag{15}$$

and hence U_{it} is normally distributed with mean $W_{it}\beta$ and variance Ω. The full conditional posterior distributions of the elements of U_{it} are of course also normal. Hence, U_{ijt} for $C_{ijt} = 1$ can be sampled from truncated normal distributions in the following way

$$U_{ijt}|U_{i,-j,t} \sim \begin{cases} \text{normal on } (-\infty, U_{i,d_{it},t}) & \text{if } d_{it} \neq j \\ \text{normal on } (\max(U_{ikt} \text{ for all } k \neq j | C_{ikt} = 1), \infty) & \text{if } d_{it} = j \end{cases} \tag{16}$$

where $U_{i,-j,t} = (U_{ikt} \text{ for all } k \neq j | C_{ikt} = 1)$, see Geweke (1991) for details.

Full conditional posterior distribution of C^*

To sample C^*_{it}, $i = 1, \ldots, I$, $t = 1, \ldots, T_i$ we consider

$$C^*_{it} = X_{it}\alpha + \varepsilon_{it},$$

and hence C^*_{it} is normally distributed with mean $X_{it}\alpha$ and covariance matrix Σ. The full conditional distribution of the elements of are of course also normal and hence C^*_{ijt} can be sampled from truncated normal distributions as follows

$$C^*_{ijt}|C^*_{i,-j,t} \sim \begin{cases} \text{normal on } (0,\infty) & \text{if } C_{ijt} = 1 \\ \text{normal on } (-\infty,0] & \text{if } C_{ijt} = 0 \end{cases} \tag{17}$$

for $j = 1, \ldots, J$ and where $C^*_{i,-j,t} = (C^*_{i1t}, \ldots, C^*_{i,j-1,t}, C^*_{i,j+1,t}, \ldots, C^*_{iJt})'$, see also Chib and Greenberg (1998).

Full conditional posterior distribution of C

The full posterior distribution of C_{it} is less standard. To obtain the posterior distribution of C_{it}, we note that

$$p(C_{it}|\theta) \propto \Pr[C_{it}|\alpha, \Sigma] \Pr[D_{it}|C_{it}, \beta, \Omega] \tag{18}$$

for $C_{it} \in \mathcal{C}_{it}$. As the random variable C_{it} can only take 2^{J-1} discrete values, we can easily construct sampling probabilities that sum up to 1. Hence, we can use a uniform number to sample the consideration set for household i at purchase occasion t. Evaluation of the probabilities in (18) may however be computational intensive as it involves many integrals. To avoid evaluating these integrals, we condition on the sampled utilities U and C^*, that is,

$$p(C_{it}|\theta, U, C^*) \propto \phi(C^*_{it}|X_{it}\alpha, \Sigma) \prod_{j|C_{ijt}=1} \phi(U_{ijt}|W_{ijt}\beta, \omega_j), \tag{19}$$

where $\phi(\cdot|m, V)$ is the density function of a (multivariate) normal distribution with mean m and variance V. If we define the density function of the utilities in potential consideration set S_{it} at purchase occasion t of household i as

$$h(U_{it}|S_{it}) = \prod_{j|S_{ijt}=1} \phi(U_{ijt}|W_{ijt}\beta, \omega_j), \tag{20}$$

the full conditional probability of the consideration sets is given by

$$\Pr[C_{it}|\theta, U, C^*] = \frac{\phi(C^*_{it}|X_{it}\alpha, \Sigma))h(U_{it}|C_{it})}{\sum_{S_{it}\in\mathcal{C}_{it}} \phi(S^*_{it}|X_{it}\alpha, \Sigma)h(U_{it}|S_{it})}, \tag{21}$$

where S^*_{it} is the latent value associated with potential consideration set S_{it}. As the probabilities (21) sum up to 1, we can sample the consideration set for household i at purchase occasion t in each iteration using a uniform number generator.

For the estimation of the parameters of each model considered in this paper, we generate 2000 iterations of the Gibbs sampler for burn in and 10000 iterations for analysis, where we retain every fifth draw. The (unreported) iteration plots are inspected to see whether the sampler converges to stationary draws from the posterior distributions of the model parameters.

In order to illustrate the performance of our model on revealed choice data, we generate choices, based on the full model of consideration and choice, assuming a specific set of parameter values. We submit the generated data to our Gibbs sampling estimation procedure. Appendix A provides the true and estimated values. The analysis supports our model and estimation procedure. In all cases we find that the true parameter values are contained in the 95% posterior credible interval obtained from the Gibbs sampler. Thus, our procedure accurately identifies the true underlying parameters from a synthetic data set.

3.3 Interpretation and inference

Running the Gibbs sampling scheme a large number of times results in a sample from the posterior distribution of the model parameters. All posterior inferences are based on the sample furnished by the Markov chain procedure. The analysis yields results such as posterior probabilities for each brand whether it is present or not in the consideration set of a household, influence of marketing variables on consideration and purchase probabilities, influence of marketing variables on conditional purchase probabilities, that is purchase given consideration. We use graphical methods to display these results.

4 Empirical Analysis

4.1 Data

We apply our model to two data sets. The first consists of stated choice and consideration protocol data collected in an on-line experiment. We use that experiment to investigate the convergent validity of stated consideration sets and the sets identified from choice data only. The second data set consists of revealed choice data, collected in a scanner panel. In this data set we compare the results from the proposed model to those of a single-stage MNP model and compare price and merchandizing effects. We demonstrate that the benefits of our model accrue in both the stated and revealed approaches to consideration set identification. A description of these data sets is provided next.

4.1.1 Data from the on-line experiment

We use data from a choice experiment designed to validate the model. In the on-line shopping experiment, subjects chose among 8 brands of laundry detergent over 10 choice occasions. In the experiment, consumers interfaced with a digital image of a supermarket shelf, containing the universal set of choice options. The choice environment was constant across individuals but varied across choice occasions. We manipulated promotion, price, brand position on the shelf and shelf facings.

Figure 1 shows a screen-shot from the sixth choice occasion. If subjects clicked on any of the brands on the shelf they received product information, that is, the brand slogan put on the front of the package by the manufacturer (for example Cheer has as its slogan "With Colorguard"). It may be noted that these slogans could not be seen by the subject by just looking at the shelf (see Figure 1). They had to make the effort to click the box. If they clicked on the corresponding bar-codes on the shelves they received price information. We simulated a promotion environment by putting "end-of-aisle" displays into the simulation. These were created by showing the brand on promotion in isolation with a price message prior to showing the entire shelf. Subjects had the option to choose the promoted brand (and entirely bypass the shelf) or skip the "end-of-aisle" promotion and visit the regular

shelf.

——— insert Figure 1 about here ———

The experiment served to measure the full choice protocol. This is to say, we measured (revealed) choice, information acquisition, and stated consideration set membership. The latter was measured through two questions using 100 point sliders: (1) did you consider brand j seriously, (2) is brand j acceptable to you? This operationalization of consideration is taken from Lehmann and Pan (1994) and Nedungadi (1990).

The experiment was administered to 65 undergraduate subjects in a large U.S. university who received a diskette with the experiment on it. Subjects were reminded once a week by e-mail to make a choice. Diskettes were collected after 10 weeks. In total, 55 subjects completed the experiment. Because 2 of the 8 brands were rarely chosen, these were dropped from the analysis. This left us with $N = 528$ observations. Table 1 shows the description of the data set.

——— insert Table 1 about here ———

The stated levels of consideration in this table are computed as the average of the two questions (divided by 100) averaged across purchase occasions and individuals. For estimation purposes, we need discrete consideration set memberships. These were constructed by dichotomizing the average of the two questions (divided by 100) around 0.5 for each choice occasion and each individual. The variable shelf space represents the surface of the facings of the 6 brands. Display frequency is the fraction of purchase occasions that the brand was positioned at "end-of-aisle." The price variable is measured in US dollars.

Table 1 shows that there is considerable variation in choice shares and consideration across brands. An interesting aspect to note from Table 1 is that the ratio between choice

share and consideration is very different across brands (for a similar observation see Siddarth *et al.*, 1995). It can be inferred that, with similar unconditional shares, Arm & Hammer has a very high choice share when it is considered for choice (0.56) and that Bold, for instance, does not (0.20). Hence, whereas a single-stage choice model would treat these brands as equally large, a two-stage model would suggest that these are two very different types of brands. Arm & Hammer is more of a niche brand with high choice share but low consideration. On the other hand, Bold is a small brand with low choice share and average consideration.

4.1.2 Scanner Panel Data

For the illustration of the model, we also consider an optical scanner panel data set on purchases of four brands of saltine cracker in the Rome (Georgia) market, collected by Information Resources Incorporated. The data set contains information on all 3292 purchases of crackers made by 136 households during about 2 years. Of these data, we randomly sampled about half of the households for estimation ($N = 1805$ purchases by 73 households). Four brands were used: Sunshine, Keebler, Nabisco and Private Label. Table 2 contains the description of the data

——— insert Table 2 about here ———

The variation in choice shares of the brands is somewhat higher than for the experimental data in Table 1. The relative choice share of Nabisco is by far the highest. Display and feature frequency are defined as the fraction of occasions that a brand is on display or feature. Prices are expressed in US dollars. But, it may be observed that price variation in this data set is much larger than in the experimental data. The variation in display frequency across brands is somewhat higher as well. The data reflect substantially different strategies in terms of promotions and pricing.

4.2 Operationalizations

To estimate the full model it is necessary to define the covariates affecting consideration and those affecting choice, respectively. In the past, some studies have simply included all variables in both stages of the model (for example, Andrews and Srinivasan, 1995). In this paper, we follow a different strategy. We are explicit about which marketing actions we believe to affect consideration and choice separately and we validate our choices using the measured consideration sets from the experiment.

We assume that consideration is driven by memory for the brand chosen last, and by in-store merchandizing activity to make a brand more salient at point-of-purchase. Consumer memory is operationalized in this study as the effect of the previous choice. Thus our formulation is one of choice event feedback, where it is assumed that the outcome of a previous choice directly affects current consideration. Other operationalizations are of course possible if so desired, but the present one is both parsimonious and intuitively appealing. The influence of point-of-purchase merchandizing is operationalized in this study as the effect of display, feature and shelf-space measures.

With respect to brand choice, given consideration, we assume that it is determined by the value of the brand to a consumer given the information that the consumer has at the time. This means that we assume that the effect of price takes hold in the choice stage. In both stages we allow for brand intercepts that serve to capture the effects of factors not depending on the marketing or choice environment as well. We currently restrict ourselves to homogeneous effects models. Those choices can be relaxed if so desired, depending on the amount of information in the data set at hand.

4.3 Estimation results from the on-line experiment

We estimated three models on the data from the choice experiment. First, we estimated the full multivariate probit/multinomial probit (MVP+MNP) model of choice and consideration. This model is estimated on *choice data alone*. Second, for benchmarking, we estimated the MVP model by itself using the reported consideration sets. Third, we estimated a multinomial probit (MNP) model. We needed to drop the price variable from

these analyses because of lack of temporal variation. When estimating the parameters, the price parameter was difficult to separate from the brand intercepts. This is due to the fact that there is little price variation beyond the differences among brands.

——— insert Table 3 about here ———

First, it is of some interest to inspect the estimates of the brand intercepts. In the MNP, the brand intercept is considered as an overall measure of brand equity. There is a clear ordering of the brands, with Bold lowest and Arm & Hammer highest. However, in the MNP-component of the full model this effect is reversed: Bold's intercept is higher than that of Arm&Hammer. This finding is consistent with Table 1. In the MVP-component, the intercept of Bold is much lower than that of Arm&Hammer. Thus, the full model partitions the overall equity effect into a brand memory effect that reflects the probability of consideration, and an effect that reflects brand utility (given consideration).

Table 3 shows that both the proposed (MVP+MNP) model (estimated on choice data) and the MVP model (estimated on consideration data) reveal that consideration is strongly determined by point-of-purchase merchandizing, that is, by display and shelf space. Both of these parameters have posterior means that are several times the posterior standard deviation away from zero. Choice feedback, measured by the impact of last purchase (*prev*), also has strong effects on consideration. Comparing the MVP+MNP estimates with the single-stage MNP choice model estimates, we see that there is less uncertainty about the effects of point-of-purchase merchandizing and shelf-space derived from the two-stage model. But, the magnitude of these effects is smaller in the full model.

Using the full model, we can infer the consideration sets from which the subjects made their final choices. We call these sets the "inferred consideration sets." The self-reported measures of consideration are called "reported consideration sets." Note that both reported and inferred consideration sets comprise of numbers in-between 0 and 1, that vary across brands and subjects. In order to establish the legitimacy of inferring consideration sets from choice data, we compute for each brand, individual and choice occasion, the inferred

set-membership and its correlation with reported set membership. We find that inferred and reported set membership correlate very highly for each brand. Specifically, for the six brands these correlations are in the range of 0.554 to 0.826 with an average of 0.664. We take this as quite strong evidence for the validity of inferring consideration sets from choice data with our model. From these results we also conclude that the combination of in-store display, shelf-space, and last-purchase captures a large part of the variation in consideration sets across individuals and purchase occasions. Note that the estimates from the MVP+MNP and MVP models estimated on choice, respectively consideration data, are also relatively close (correlation of 0.967), while the same holds for the estimated posterior standard deviations (Table 3). Thus, our results support the contention that this operationalization of consideration, identified from choices only, is capable of tracking the differences in choice sets both across time as well as across individuals.

Comparing the estimated brand choice intercepts between the full and the MNP models, note that given consideration, the choice probabilities of All, Arm&Hammer, and Surf decrease substantially, while that of Cheer increases. The –unreported– covariance terms in the MVP model are close to 0 and all posterior intervals cover the zero value. Therefore, it seems that after taking into account in-store variables and last purchase, little covariation among consideration of brands is left[2]. Hence, it appears that in order for a brand to enter the consideration set –at least for these data– it does not matter greatly which brands are already in it. This finding provides some empirical support for the assumption of independence of consideration set membership across brands, which has been rather extensively used in the stated consideration set approach. What seems to matter is whether a brand was chosen last time and whether there is in-store merchandizing at the time of choice.

4.4 Estimation results from the empirical data

We estimated the following models on the cracker data. The full two-stage model is estimated with marketing effect parameters α in the consideration stage, and marketing effect

[2]This conclusion remains true even if we use informative priors away from zero for the covariance terms.

parameters β in the choice stage. The estimates of the proposed model and a single-stage MNP choice model are displayed in Table 4.

——— insert Table 4 about here ———

From the results of the proposed (MVP+MNP) model we see that all marketing parameters are estimated to be far away from zero (when compared to the posterior deviation) and that they are all of the expected sign. Consistent with the controlled choice experiment, the covariation in consideration is close to zero. The brand intercepts for the MNP-component of the full model in this case display the same ordering as those from the MNP model, with highest brand utility being derived from Nabisco. However, the MVP brand intercepts reveal that Nabisco also has a high base probability of being considered, irrespective of marketing activity. This may point to a strong memory effect for this brand.

The MNP model also shows marketing effects with the expected sign. However, the display effects are insignificant in the single-stage MNP model. Thus, due to the misspecification of this model, the posterior standard deviations of the parameters tend to increase, which is a phenomenon also observed for the experimental data, thereby leading to insignificance of the promotional effects. In our view, this supports the face-validity of our approach. The posterior deviation in the promotion variables is less but the effect sizes are bigger for the MVP+MNP model than for the MNP model. Thus, the appropriate model structure in combination with appropriate specification of the effects of marketing mix variables leads to more precise estimation. We would like to point to the very large difference in the price coefficient between the proposed model and the MNP model. The price effect, given consideration, is over three times as large (the posterior standard deviations are comparable). This finding, that has been previously documented in the literature, is a very important one from a strategic perspective. It shows that, once a brand has entered the consideration set, the price instrument is very effective in increasing market share and decreasing that of competitors in the consideration set.

However, both the full and MNP models do equally well in predictive validity. Out-of-sample predictions shows that the hit rate of the two models is 77% (MVP+MNP) and 78% (MNP). The posterior distributions of the hit rate for the two models overlap almost completely, showing that there is no difference in prediction between the two models. Of course one would have liked to see the added complexity of our model to result in improved predictive performance, but as has been found previously, a more simple and theoretical mis-specified model such as the MNP predicts equally well. We think that the major advantage of our model accrues from its diagnostic value. Due to limited information in the data, the simple MNP model may show good predictive validity. We conjecture that the main reason why estimation of consideration set formation is important to a marketing manager may not be prediction, but lies in the insights in competitive and positioning issues it provides ("Who are we competing against in the mind of the consumer?", "What is my vulnerability to competitive attacks?") and in control issues ("What will be the effect of my marketing mix variables in various stages, and how do they interact?"). It is with these important issues that the insights derived from single-stage and two-stage models of choice really differ. To bring out the different implications for marketing mix effects of the two-stage MVP/MNP and the single-stage MNP model, we conduct a series of price experiments. In the next section we explore these added insights derived from our model in detail.

5 Implications

We illustrate the differences in own and cross price effects derived from the two models. For each brand, we compute the effect of its price changes on the share of all brands. We change the price of, for instance, Nabisco across a relevant price interval, and compute the share of all four brands (Nabisco, Sunshine, Keebler, and Private Label) using both the single-stage MNP model and the proposed model. By varying price over a wide-enough interval, we obtain price own- and cross- effects curves that are specific to the type of model. We compute the price curves conditional on the past-purchase variable and the merchandizing variables. This gives us, for both models, for each brand four separate price

response curves for all combinations of past-purchase status (yes/no) and merchandizing status (yes/no). For the sake of illustration, we focus on Nabisco's (the market leader) own price effects and its cross-price effects on the Private Label brand. Figure 2 gives the own and cross price effects for Nabisco according to the single-stage MNP model, whereas Figure 3 give the same effects according to the proposed model. In both figures the vertical axis expresses the aggregate *marginal* choice probability.

——— insert Figures 2 and 3 about here ———

The left panel in Figure 2 contains four curves representing the own price effects of Nabisco from the MNP model. The bottom curve entails the scenario that Nabisco was not bought on the previous occasion and that there is no current merchandizing. We see the usual S-shaped price response curve, specific to the probit model. The dashed curve above it represents the response to price in the presence of display and feature but for consumers who have not bought the brand on the previous occasion. The dotted curve, which is uniformly higher than the previous two, represents the price response for consumers who have bought the brand on the previous occasion but when there is no point-of-purchase merchandizing. Finally, the short-dashed curve -the highest one- represents price response for Nabisco given that the brand was bought previously, and that it is now displayed and featured. First, one observes that all price response curves are nonintersecting, due to the fact that the utilities implied by the various conditions are parallel. Thus, there is nothing inherently different in consumer price responses across the four scenarios. The effects are additive on the latent utility scale. The shape of the MNP price response is the same whether a brand is featured or not or whether the brand has been bought before or not. The relative heights of the marginal probabilities under the four scenarios are intuitively clear. But, keeping price fixed, we observe that comparisons of steepness of the price curve across the scenarios can be counter intuitive. For instance, for low regular Nabisco price, the own price curve is steepest when there is no feature and for customers who have not bought the brand previously. This implies that price changes are most effective when the

product is not displayed and for consumers who did not buy the product before. This implication of the MNP estimates does not appear to be sensible, but it is enforced by the functional form of the MNP. Equally unlikely, the price curve is flattest when the brand is featured and when the brand was purchased last time. In addition, the figure shows that for high regular price, this order is completely reversed, which is yet another result that is difficult to explain.

A similar result is obtained for the price response in relation to brand share (results are not shown). For large share brands, the price curve is steeper, if there is no merchandizing or previous purchase, and for small share brands the opposite holds. Again, the form of the price response follows directly from the mathematics of the MNP that involve additive effects of price and the other variables on the utility scale. We would like to note that such limitations apply despite the fact that the MNP model specification that we use (with a diagonal covariance matrix) mitigates the restrictive IIA assumption.

Figure 3 is decidedly different since in the proposed model consideration structurally mediates price response. First, as opposed to the price response curves under the four conditions being close to parallel, we now see a fanning pattern of the curves associated with display and previous purchase. In agreement with intuition and the literature on promotions (for example, Blattberg *et al.*, 1995), the implied price curve of the MVP+MNP model is steepest with both merchandizing and for consumers who bought the brand on the last purchase occasion. Almost no reaction to price is implied by the model when there is no merchandizing activity and for consumers who did not buy the brand last time, which is evidenced by the solid curve in the left panel. This finding is consistent with the notion that when there is no merchandizing activity, consumers who did not buy the brand last time will hardly notice the current price of the brand (see Dickson and Sawyer, 1990; Hoyer, 1984). Note the substantial increase in the purchase probability across the entire price range when merchandizing to those customers. Second, Figure 3 shows that at any given price, the effect of merchandizing is larger for consumers who have not bought the brand in the previous period than for users of the brand. Indeed, merchandizing is a means to raise in-store brand awareness among those who need to be reminded of it. For those

who bought the brand previously such an effect must logically be weaker than for those who did not buy the brand recently. From Figure 2 it can be seen that the single-stage MNP model implies the exact opposite. Third, from our model follows the intuitive implication that price response during promotions is larger than price response during off-promotion periods. Again, the single-stage MNP model does not have such an intuitively appealing implication.

The right panel in Figure 3 shows the cross-price effects for Nabisco's largest competitor: the Private Label brand. For instance, the solid curve represents the predicted aggregate marginal choice probability of the Private Label brand in response to Nabisco price changes, when Nabisco is not merchandizing and for consumers who did not buy Nabisco previously. We see that there is almost no effect on the Private label brand in response to price changes of Nabisco. However, the Figure shows that if Nabisco is featured and displayed (and thus considered more), then the share of the Private label brand is very sensitive to the price of Nabisco. Compare this to the implications derived for the MNP model in the right panel of Figure 2, where these effects are almost completely reversed and counter intuitive. The strongest cross price effect is obtained when Nabisco is not merchandizing and for consumers that did not buy Nabisco before.

In order to further investigate these effects, we compute the effects of price changes on choice – *conditional on consideration*. Figure 4 shows the results for the proposed model. Now the vertical axis represents the aggregate *conditional* choice probability. We show the effect of actions of Nabisco for all 4 brands in the data set.

——— insert Figure 4 about here ———

As can be seen from the two upper graphs in Figure 4, the choice probability of the two small brands Sunshine and Keebler, given that they are considered, lies between 0.5 and 0.6 if Nabisco undertakes no marketing action. (Note that effects discussed here are qualitatively similar for the Private label brands, be it that the effects are somewhat more pronounced). So, given that, for example, Sunshine is in the consideration set, it will be

bought with a substantial probability. If Nabisco price is low, marketing actions of Nabisco may reduce this probability, but for high prices, the conditional probabilities stay high. From this, we conclude that the smaller brands will be bought with a substantial probability, once they have entered the consideration set of a household. Only a combination of low price and intensive merchandizing by the market leader may reduce the probability of being bought, once considered. Thus, if the manufacturers of the smaller brands focus on entering the consideration sets of households through merchandizing, it becomes a very costly operation for the market leaders to reduce their (conditional) market share.

The left bottom part of Figure 4 reveals that for Nabisco the conditional probability of purchasing it, decreases at higher prices. The differences are close to negligible across the entire price range. The explanation for this is that if Nabisco undertakes marketing activity, the brand enters consideration sets more often, but is not always bought. Our model specification predicts that merchandizing will not affect the conditional price response, given that the brand is considered (merchandizing only enters the consideration -MVP- component of the model, not the choice given consideration -MNP- component).

This illustrates that the implications for price and promotion effects of the two models may be very different. In this application, the two-stage model has price and promotion patterns that accord much more with intuition. The single-stage model does frequently harbor unintuitive implications that are associated with the effects of those marketing control variables, caused by the fact that they are included in the model in a way that is not supported by marketing theory.

6 Conclusion

Entering consumers' consideration set is one of the top priorities in marketing strategy, and the implementation of those strategies is contingent upon knowledge of the consideration sets of individual consumers. Such knowledge has been obtained by either asking a sample of respondents to state their considered set of brands, or by inferring those sets from their revealed choices. Taking the latter approach, we have proposed, operationalized and estimated a new model to capture unobserved consideration from discrete choice data. It

offers important advantages of parsimony over models proposed previously and moreover bridges the stated and revealed approaches, enabling the analysis of either one, or both sources of data to infer sets of brands considered for purchase.

The issue of whether consideration sets can be validly inferred from revealed choice data is one with a long history (cf. Roberts and Lattin, 1997). This study has begun to address this very question by studying the convergent validity of stated and revealed consideration sets in our on-line choice experiment. While more research in this area is needed, our first findings are promising indeed and we tentatively conclude that we do infer consideration from revealed choice behavior using our model.

The consideration set literature postulates two major classes of factors shaping the consideration set: individual and situational factors. The individual factors relate to retrieval of alternatives from memory, the situational factors involve their recognition at the point of purchase (Alba and Chattaopadhyay, 1985). Consistent with this distinction, we included in-store merchandizing (display and feature) as an operationalization of situational factors and brand intercepts and last choice as an operationalization of individual memory-based factors. In our model, based on prior theory arguments, we allow different marketing control variables to affect the choice process in a different manner: while price is assumed to affect choice directly, merchandizing is specified to affect choice through its effect on consideration. Although we found our model to reproduce consideration levels for individual brands well, our operationalization of individual and situational factors is necessarily partial and therefore has its limitations. Other situational factors may affect consideration, and memory of alternatives beyond the one last bought may also have an effect. However, we think these to be empirical questions that can be addressed if sufficient data are available. We believe that our operationalization in the two studies provides a reasonable representation of the choice processes for the products in question. This holds in particular for the choice experiment, where situational factors were almost completely under experimental control. In the analysis of the scanner panel choice data, the operationalization of individual and situational factors and the identification of their effects is limited by both the variables and the amount of information in the data set. Nevertheless,

we do believe our model specification captures the main features of the choice process in that case. The fact that effects of in-store merchandizing on consideration are very strong and are more tightly distributed in the two-stage model than in the single-stage model provides support for our model specification.

Several studies on consideration have focused on the dependencies of alternatives in the consideration set. In particular, the attractiveness of an alternative for consideration has been reported to increase if an inferior alternative is added to the set (cf. Huber and Puto, 1982). Our approach can account for such phenomena through the covariance structure of the consideration stage model component. However, our empirical analyses, both on experimental and scanner data, reveal that, after accounting for in-store merchandizing and past purchase, consideration is essentially independent across brands, as evidenced by zero covariance. Context effects may be absent since we study mature markets where unattractive alternatives have been eliminated from the marketplace or since they are already accounted for by the inclusion of individual and situational factors. We suspect that there are product categories for which consideration may be dependent across brands. This would be especially true for categories with clear clusters of choice options, such as beverages, and for emerging markets where unattractive alternatives may still be available. The empirical verification of the attraction effect from revealed choice data remains an important topic for future research.

From our policy experiments, we find that the two-stage model offers a more appealing interpretation for the role of in-store merchandizing on consumer choice than a single-stage model. In the two-stage model, in-store merchandizing has information effects. In contrast, the implication of a single-stage model is that display and feature are components of brand *utility*. This attribution is questionable on logical grounds. The goal of the consumer is to buy a (utility maximizing) brand and not to acquire brand information. Therefore, contextual information such as feature ads and display seem to be out-of-place in the utility function that consumers maximize. At a minimum, these variables do not generate the same utility as when paying low price or receiving high quality of a brand. Rather, the role of these variables is to facilitate, that is, lower the cost of, consideration of brands.

In-store merchandizing programs are therefore more suitably seen as fulfilling the goal of lowering the mental cost of information acquisition. Economic theory suggests that consumers will be more price-oriented, the easier it is to obtain price information (for example, Stigler, 1961). This is exactly what is implied by our model. As we have shown, single-stage choice models do not have this property. Thus, we like to see our model as a useful tool in analyzing both stated and revealed consideration data and studying the role of consideration set formation in choice behavior.

A Synthetic data analysis

To check that the estimation procedure retrieves the data generating parameters, we conduct a numerical experiment where data are generated under conditions closely and intentionally matching those of the empirical study. In the MCMC estimation method, the number of burn-in draws for the Gibbs sampler is 2000, the number of valid draws 10000. One out of 5 draws is stored for posterior analysis. The model consists of equation (2) and equation (5). We take the covariance matrix Ω in equation (6) an identity matrix I_J, although alternative specifications are also possible. An unreported graph, displaying posterior values over the iterations performed, indicates that the pattern is stable for both parameter vectors.

Some of the results of this experiment are included in Table A.1. Taken together, these results suggest that the actual data generating parameters are satisfactorily retrieved by the estimation process.

Table A.1: Posterior results for synthetic data ($N = 950$)

		actual value	estimated mean	std. dev
consideration	α_{01}	-1.3	-1.301	0.075
stage	α_{02}	-1.5	-1.868	0.146
	α_{03}	-0.6	-0.729	0.072
	α_{04}	-0.8	-0.800	0.067
	α_{display}	0.5	0.312	0.077
	α_{prev}	1.5	1.592	0.073
choice	β_{01}	-0.3	-1.004	0.828
stage	β_{02}	-0.5	-0.941	1.083
	β_{03}	2.0	2.150	0.520
	β_{price}	-7.0	-6.434	0.802

Table 1: Descriptive statistics for the experimental data set ($N = 528$)

Brand	share	considered	display frequency	average shelf	average price
All	0.106	0.276	0.10	0.35	3.04
Arm&Hammer	0.114	0.203	0.10	0.39	2.69
Bold	0.047	0.233	0.10	0.37	3.54
Cheer	0.273	0.588	0.20	0.79	3.67
Surf	0.049	0.171	0.00	0.43	3.59
Tide	0.411	0.668	0.20	0.73	3.66

Table 2: Descriptive statistics for the cracker data ($N = 1805$)

Brand	share	display frequency	feature frequency	average price
Sunshine	0.070	0.120	0.033	0.958
Keebler	0.080	0.104	0.037	1.127
Nabisco	0.542	0.330	0.087	1.078
Private Label	0.308	0.108	0.045	0.684

Table 3: Posteriors for the experimental data set[a]

		MVP+MNP		MVP		MNP	
		mean	std dev	mean	std dev	mean	std dev
Consideration stage	α_{All}	-1.57	0.16	-1.56	0.13	–	
	$\alpha_{\text{A\&H}}$	-1.52	0.16	-1.91	0.14	–	
	α_{Bold}	-2.01	0.21	-1.68	0.12	–	
	α_{Cheer}	-1.82	0.24	-1.40	0.21	–	
	α_{Surf}	-1.53	0.17	-1.94	0.15	–	
	α_{Tide}	-1.51	0.23	-1.05	0.21	–	
	α_{displ}	1.04	0.12	0.78	0.11	–	
	α_{shelf}	1.00	0.29	1.41	0.27	–	
	α_{prev}	1.09	0.09	1.23	0.08	–	
Choice stage	β_{All}	-1.66	0.51	–		-0.23	0.30
	$\beta_{\text{A\&H}}$	-1.63	0.50	–		-0.19	0.23
	β_{Bold}	-0.96	1.05	–		-0.73	0.28
	β_{Cheer}	-0.18	0.58	–		-0.47	0.12
	β_{Surf}	-2.91	0.71	–		-0.29	0.25
	β_{displ}	–		–		1.42	0.17
	β_{shelf}	–		–		1.49	0.59
	β_{prev}	–		–		1.41	0.10

[a] The covariances in the MVP model are close to 0 and are not shown here

Table 4: Posteriors for the cracker data set[a]

		MVP+MNP		MNP	
		mean	std dev	mean	std dev
Consideration stage	α_{Sunshine}	-1.36	0.058	–	
	α_{Keebler}	-1.33	0.059	–	
	α_{Nabisco}	-0.82	0.053	–	
	α_{Private}	-1.03	0.052	–	
	α_{displ}	0.16	0.056	–	
	α_{feat}	0.51	0.094	–	
	α_{prev}	1.75	0.053	–	
Choice stage	β_{Sunshine}	-0.02	0.611	0.06	0.114
	β_{Keebler}	1.52	0.758	0.61	0.189
	β_{Nabisco}	3.30	0.495	1.29	0.184
	β_{price}	-9.16	0.458	-2.73	0.446
	β_{displ}	–		0.12	0.077
	β_{feat}	–		0.63	0.124
	β_{prev}	–		1.63	0.052

[a] The covariances in the MVP model are close to 0 and are not shown here

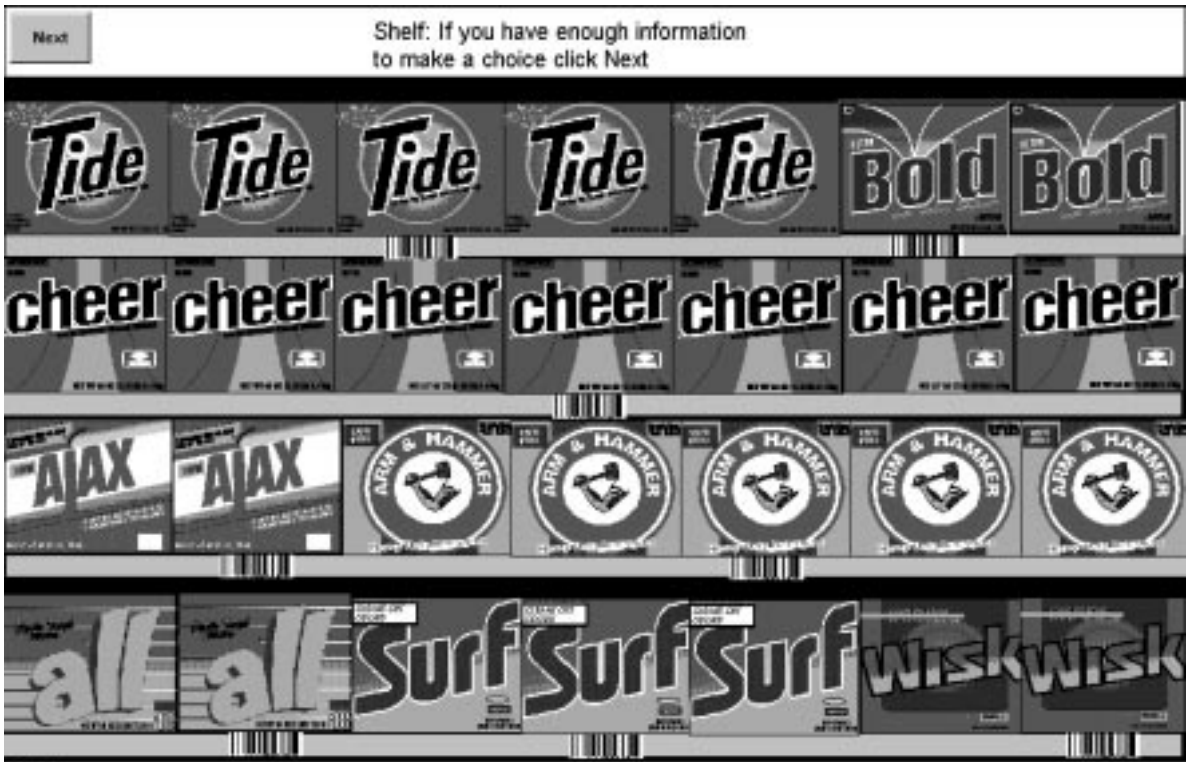

Figure 1: Screen-shot from sixth choice occasion.

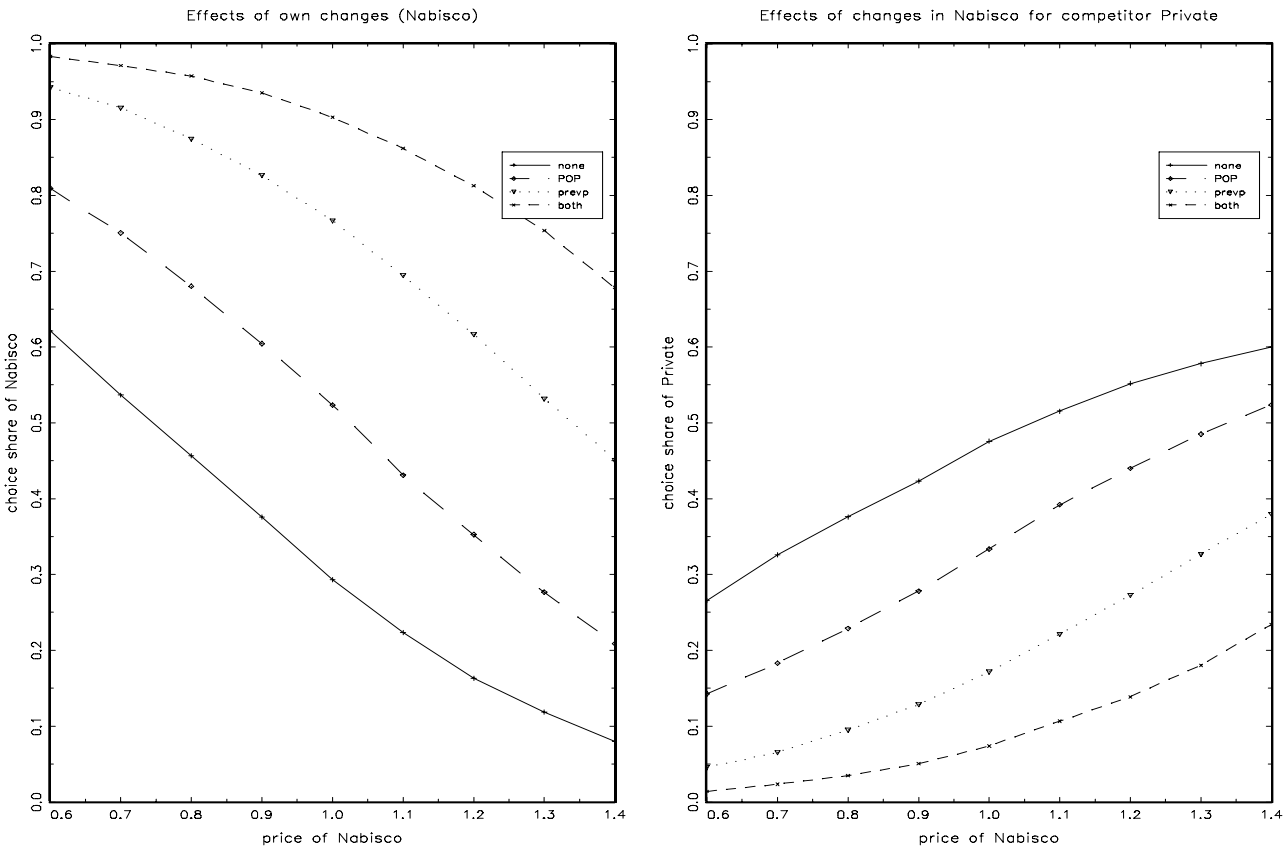

Figure 2: Price response curves for MNP model.

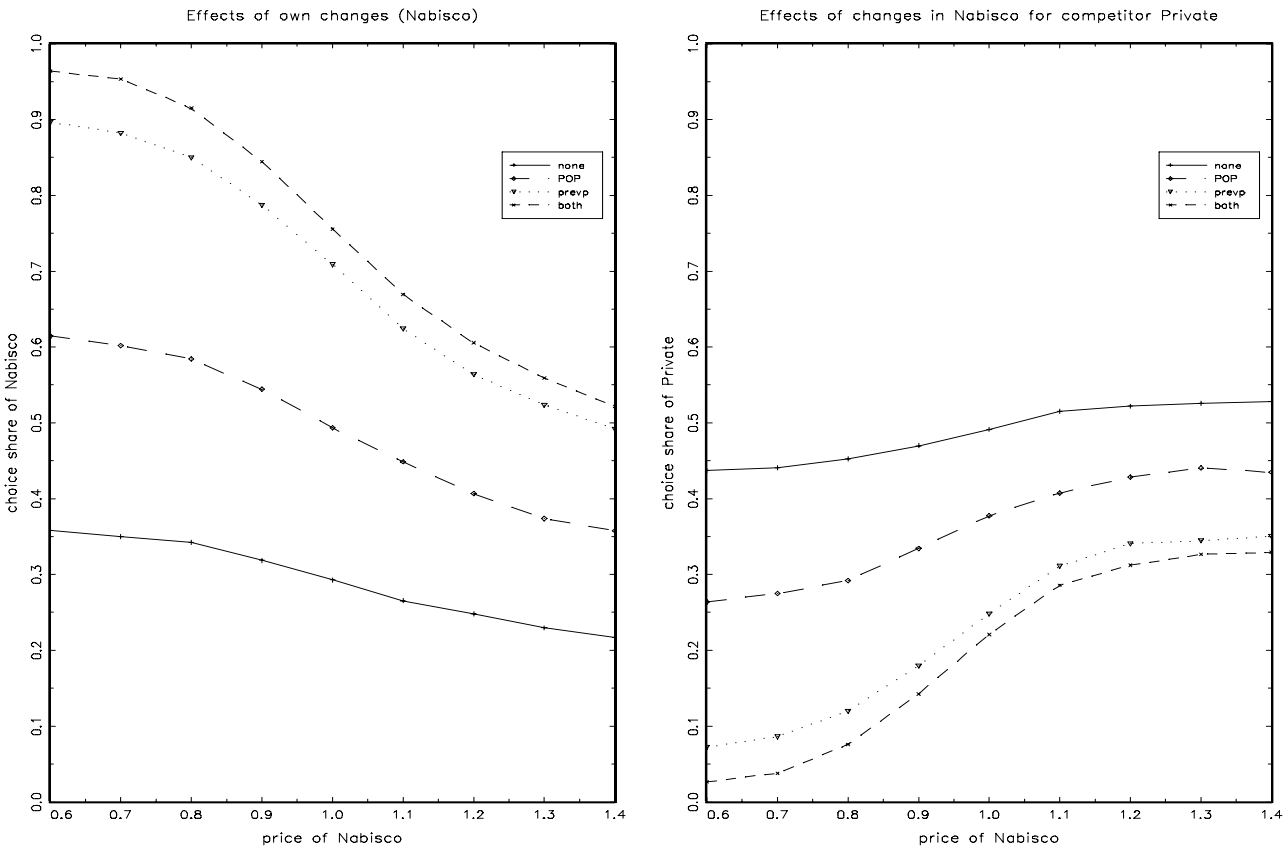

Figure 3: Price response curves for MVP+MNP model.

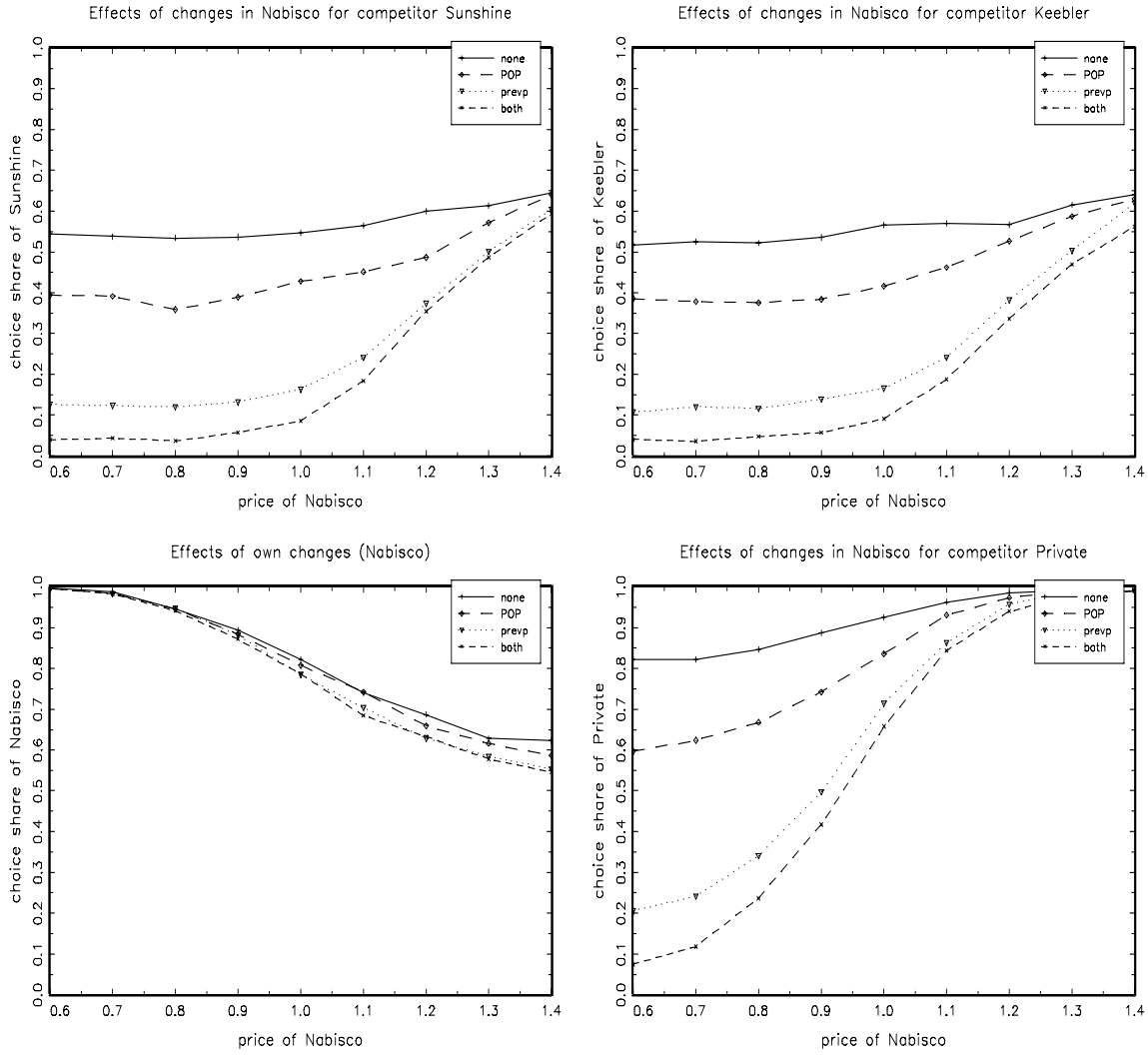

Figure 4: Price response curves for MVP+MNP model, conditional on consideration.

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