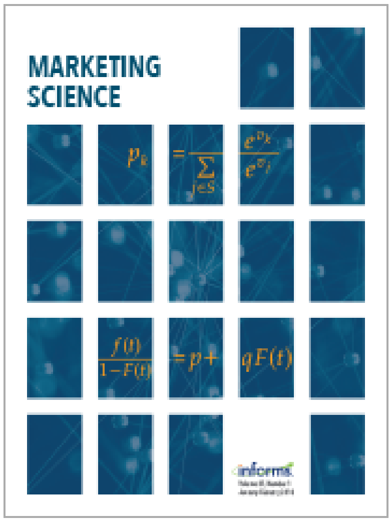

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Modeling Multiple Sources of State Dependence in Random Utility Models: A Distributed Lag Approach

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We propose a utility-theoretic brand-choice model that accounts for four different sources of state dependence: 1. effects of lagged choices (*structural state dependence*), 2. effects of serially correlated error terms in the random utility function (*habit persistence type 1*), 3. effects of serial correlations between utility-maximizing alternatives on successive purchase occasions of a household (*habit persistence type 2*), and 4. effects of lagged marketing variables (*carryover effects*). Our proposed model also allows habit persistence to be a function of lagged marketing variables, while accommodating the effects of unobserved heterogeneity in household choice parameters. This model is more flexible than existing state-dependence models in marketing and labor econometrics. Using scanner panel data, we find structural state dependence to be the most important source of state dependence. Marketing-mix elasticities are systematically understated if state-dependence effects are incompletely accounted for. The Seetharaman and Chintagunta (1998) model is shown to recover spurious variety-seeking effects while overstating habit-persistence effects. Ignoring habit persistence type 1 leads to an underestimation, while ignoring habit persistence type 2 leads to an overestimation of structural state-dependence effects. We find lagged promotions to have carryover effects on habit persistence. Ignoring one or more sources of state dependence underestimates the total incremental impact of a sales promotion. We draw implications for manufacturer pricing.

Key words: brand choice; state dependence; habit persistence; lagged choices; lagged utilities; serial correlation; distributed lags; marketing carryover; random utility
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1. Introduction

A household's prior purchase experiences with specific brands typically influence the household's purchase propensities for the same brands in the future. In such cases, there is said to be *structural state dependence* in the household's brand choices over time. Structural state dependence can be positive or negative, in which cases they are called *inertia* (Jeuland 1979) and *variety seeking* (McAlister 1982), respectively. The existence of inertia motivates marketers' employment of promotional schemes such as free sampling in the hope that the current-period costs of distributing free samples will be more than offset by the benefits of "hooking" households to the brand for the long term. The existence of variety seeking motivates the lengthening of product lines by manufacturers, in the hope that households' variety-driven brand switching benefits their franchise. There has been a lot of empirical work in marketing over the past 20 years on the estimation of structural state-dependence effects using scanner panel data. The consensus that has emerged in this literature is that there is substantial evidence of structural state dependence in households' brand choices even after adequately controlling for unobserved heterogeneity across households (Keane 1997, Abramson et al. 2000, Moshkin and Shachar 2002). In this literature, structural state dependence is modeled using an exponentially smoothed loyalty variable constructed on the basis of all previous choices of the household as a covariate in the household's random utility for a brand (Guadagni and Little 1983).

In addition to the abovementioned structural state-dependence effects (i.e., the effects of *lagged choices*), there is a second source of state dependence in a household's brand choices over time, namely, the effects of the household's *lagged utilities* for brands. This source of state dependence is called *habit persistence* (Heckman 1981b). For example, if a household's relative evaluation of brand j is high during a shopping trip at time t, the household's favorable evaluation of brand j is likely to persist during the household's next shopping trip at time $t+1$ even if the household does not actually purchase brand j at time t. Such lagged utility effects imply that even if a brand's current promotions do not stimulate households to purchase the brand in the current period, they may induce them to purchase the brand in the future (through the persistence in favorable brand evaluations). In this study, we propose a distributed lag model of brand choices that accounts for not only structural state dependence, using a loyalty variable, but also three distinct sources of habit persistence. The first, called *carryover effects*, arises on account of marketing-mix effects on households' brand choices "spilling over" into future periods, for example, due to decaying effects of advertising and reference price effects. The second, called *habit persistence type 1*, arises on account of temporal persistence in households' utilities for brands for reasons unknown to the researcher, for example, due to the effects of guests staying over at home, which necessitates purchases of similar brands to suit their needs over time. The third, called *habit persistence type 2*, measures temporal dependencies between a household's successive brand choices that arise on account of multiple (unobserved) information signals that households keep receiving over time between purchases (from such sources as billboard signs, television advertisements, etc., that are not recorded in the data). In other words, our proposed model accounts for state dependence[1] in as complete a manner as possible, and generalizes previously proposed state-dependence models such as Allenby and Lenk (1994), Roy et al. (1996), Keane (1997), etc. that have accounted for only a subset of the effects captured in our model. We derive implications for marketing strategy.

2. Model Formulation

Heckman's (1981b) model allows an individual's current utility for an alternative U_{jt} to be related both to the individual's lagged choice outcome for the alternative and the individual's lagged utility for the same alternative U_{jt-1}. One specific parametric form of Heckman's (1981b) model is given below.

$$U_{jt} = \alpha_j + \mathbf{X}_{jt} * \beta + \gamma * I_{jt-1} + \lambda * U_{jt-1} + \varepsilon_{jt}, \qquad (1)$$

where U_{jt} and U_{jt-1} stand for the household's random utility for brand j at time t and $t-1$, respectively; $\mathbf{X}_{jt}$ is a vector of explanatory variables (marketing variables such as price, display, and feature in the context of brand choices) characterizing alternative j at time t; I_{jt-1} is an indicator variable that takes the value 1 if alternative j was purchased at time $t-1$ and 0 otherwise; and ε_{jt} is a random error term that captures the effects of unobserved variables. In this model, α_j and β are the alternative-specific intercept and the vector of marketing-mix response parameters, respectively, while parameter γ estimates the effect of *structural state dependence*, while parameter λ estimates the effect of *habit persistence*.

Consider the following distributed lag model.

$$\begin{aligned} U_{jt} = \alpha_j &+ (\mathbf{X}_{jt} + \mathbf{X}_{jt-1} * \lambda + \mathbf{X}_{jt-2} * \lambda^2 \\ &+ \mathbf{X}_{jt-3} * \lambda^3 + \cdots) * \beta + \gamma \\ &* (I_{jt-1} + I_{jt-2} * \lambda + I_{jt-3} * \lambda^2 + I_{jt-4} * \lambda^3 + \cdots) \\ &+ (\varepsilon_{jt} + \varepsilon_{jt-1} * \lambda + \varepsilon_{jt-2} * \lambda^2 + \varepsilon_{jt-3} * \lambda^3 + \cdots), \end{aligned} \qquad (2)$$

where the variables and parameters are as explained in Equation (1), except that λ here stands for a geometric decay parameter (which lies between 0 and 1). It is easy to show that Heckman's (1981b) model of structural state dependence and habit persistence, in the form laid out in Equation (1), is a reduced-form representation of this distributed lag model as long as the parameter of the lagged utility variable, λ, is constrained to lie within $[0, 1]$.[2] There are three distinct sources of state dependence modeled in the random utility formulation (2): one, carryover effects of marketing variables; two, geometrically decaying effects of lagged choices; three, geometrically decaying effects of lagged random errors. Despite this flexibility, this model is based on the restrictive assumption of identical decay parameter (λ) for all three sources of state dependence. We relax this assumption by allowing for separate λs for each of the three sources of state dependence to obtain a more flexible distributed lag model.

$$\begin{aligned} U_{jt} = \alpha_j &+ (\mathbf{X}_{jt} + \mathbf{X}_{jt-1} * \lambda_1 + \\ &\mathbf{X}_{jt-2} * \lambda_1^2 + \mathbf{X}_{jt-3} * \lambda_1^3 + \cdots) * \beta \\ &+ \gamma * (I_{jt-1} + I_{jt-2} * \lambda_2 + I_{jt-3} * \lambda_2^2 + I_{jt-4} * \lambda_2^3 + \cdots) \\ &+ (\varepsilon_{jt} + \varepsilon_{jt-1} * \lambda_3 + \varepsilon_{jt-2} * \lambda_3^2 + \varepsilon_{jt-3} * \lambda_3^3 + \cdots), \end{aligned} \qquad (3)$$

where $\lambda_1, \lambda_2, \lambda_3 \in [0, 1]$ capture geometric decay effects in marketing variables, lagged choices, and random error terms, respectively. This model is more flexible than (2) and allows us to endogenously test whether $\lambda_1 = \lambda_2 = \lambda_3$. A suitable parametric assumption on the random errors, ε_{jt}, yields an estimable model of discrete choices. We assume the contemporaneous error term $\eta_{jt} = (\varepsilon_{jt} + \varepsilon_{jt-1} * \lambda_3 + \varepsilon_{jt-2} * \lambda_3^2 + \varepsilon_{jt-3} * \lambda_3^3 + \cdots)$ to be distributed *Type-I extreme value*, which yields the familiar Multinomial Logit (MNL) model, except that the error terms are now serially correlated. We call this model Multinomial Logit with Serial Correlation (MNLSC, for short). The intuition for the three separate state-dependence effects

[1] In this paper, we will refer to structural state dependence, habit persistence, and carryover effects under the rubric "state dependence" although other papers in the literature use different nomenclatures. For a recent marketing paper that uses terminology identical to that used in this paper, see Seetharaman (2003).

[2] This can be seen by taking the first difference between U_{jt} and λU_{jt-1} in the distributed-lag formulation (2).

captured under this specification is as follows: λ_1, capturing *carryover effects*, arises on account of marketing-mix effects "spilling over" into future periods, for example, due to decaying effects of advertising over time, reference price effects etc.; λ_2, capturing *lagged choice effects*, arises on account of structural state-dependence phenomena such as households' brand loyalties, variety-seeking tendencies etc.; λ_3, capturing *habit persistence type 1*, arises on account of persistence in households' utilities for reasons unknown to the researcher, such as due to the effects of guests staying over at home, which necessitates purchases of similar brands to suit their needs over time.

A recent study by Roy et al. (1996) employed the mover-stayer formulation (Goodman 1961), a type of Markov chain, to estimate the effects of habit persistence. The estimable version of their model is shown below.

$$\begin{aligned} P_{jjt} &= \rho + (1-\rho) * \mathrm{MNL}_{jt}, \\ P_{ijt} &= (1-\rho) * \mathrm{MNL}_{jt}, \end{aligned} \tag{4}$$

where P_{jjt} stands for the household's conditional probability of buying brand j at time t given that the household bought brand j at time $t-1$ (i.e., repeat-purchase probability), P_{ijt} stands for the household's conditional probability of buying brand j at time t given that the household bought brand i at time $t-1$ (i.e., switching probability), $\rho \in [0, 1]$ is the habit-persistence parameter (with $\rho = 1$ yielding a pure habit-persistence model), and MNL_{jt} stands for the household's Multinomial Logit Probability for brand j, given by

$$\mathrm{MNL}_{jt} = \frac{e^{\alpha_j + \mathbf{X}_{jt} * \beta + \gamma * I_{jt-1}}}{\sum_{k=1}^{J} e^{\alpha_k + \mathbf{X}_{kt} * \beta + \gamma * I_{kt-1}}}, \tag{5}$$

where γ, the coefficient of the lagged choice variable, captures structural state dependence. Resnick and Roy (1990) show that the mover-stayer model of Equation (4) can be derived from utility maximization. Specifically, they show that ρ is a measure of serial correlation between the household's utility-maximizing alternatives on successive purchase occasions, using a utility framework called the "Lightning Bolt" framework. The serial correlation is motivated to arise on account of multiple (unobserved) brand-specific information signals that households keep receiving over time between purchases (from such sources as billboard signs, television advertisements, etc., that are not recorded in scanner panel data). We embed our MNLSC model, given in Equation (3), within the Lightning Bolt utility framework to obtain the following estimable model of state dependence.[3]

$$\begin{aligned} P_{jjt} &= \rho + (1-\rho) * \mathrm{MNLSC}_{jt}, \\ P_{ijt} &= (1-\rho) * \mathrm{MNLSC}_{jt}, \end{aligned} \tag{6}$$

where MNLSC_{jt} is the household's choice probability for brand j at time t, obtained using the random utility function in (3). Equations (3) and (6) collectively represent our proposed model. Four sources of state dependence are represented in this model: λ_1 captures the geometrically decaying effects of lagged marketing variables (*carryover effects*), λ_2 captures the geometric decay in the effects of lagged choices over time (*structural state dependence*), λ_3 is the serial correlation parameter for the random errors (*habit persistence type 1*), and ρ captures serial correlation in the household's utility-maximizing alternatives on successive purchase occasions (*habit persistence type 2*).

We restrict the state-dependence parameters λ_1, λ_2, λ_3, and ρ to lie within the closed interval $[-1, 1]$, where positive values represent inertia and negative values represent variety seeking. Suppose the most recent lagged choice has a negative effect on the current choice (i.e., $\gamma < 0$). A negative estimated value for λ_2 would then imply that the second-most recent lagged choice has a positive effect on the current choice, which is consistent with the variety-seeking explanation that encourages alternating between brands rather than repeat-purchasing them. Allowing the parameter ρ to lie within the closed interval $[-1, 1]$, as in Seetharaman and Chintagunta (1998), yields the following final version of our proposed model.

$$\begin{aligned} P_{jjt} &= \frac{\rho + |\rho|}{2} + (1-|\rho|) * \mathrm{MNLSC}_{jt}, \\ P_{ijt} &= \frac{\rho - |\rho|}{2 * (J-1)} + (1-|\rho|) * \mathrm{MNLSC}_{jt}, \end{aligned} \tag{7}$$

where $\rho > 0$ corresponds to positive state dependence (and reduces the model to the form given in Equation (6)), while $\rho < 0$ corresponds to negative state dependence.[4] In Table 1, we present a detailed comparison of our model with previously proposed random utility models of state dependence in marketing.

It is easy to show that our measure of carryover effects is similar to that of Erdem and Sun (2001), our measure of structural state dependence is mathematically equivalent to the exponentially

[3] An explicit derivation of this model using utility-maximization primitives, which is based on extending the derivation provided in Resnick and Roy (1990), is available from the authors.

[4] When $\rho < 0$, the mover-stayer structure is no longer utility consistent as in Resnick and Roy (1990). Because our results, however, recover only positive estimates for ρ, this issue becomes moot.

Table 1 A Comparison of This Study with Other Random Utility Models of State Dependence in the Marketing Literature

Study	Structural state dependence	Habit persistence 1	Habit persistence 2	Carryover effects
Guadagni and Little (1983)	**Yes**	No	No	No
Jones and Landwehr (1988)	**Yes** (1 lag only)	No	No	No
Allenby and Lenk (1994)	No	**Yes** (+only)	No	No
Erdem (1996)	**Yes**	**Yes**	No	No
Roy et al. (1996)	**Yes** (1 lag only)	No	**Yes** (+only)	No
Gupta et al. (1997)	**Yes**	No	No	No
Keane (1997)	**Yes** (+only)	**Yes** (+only)	No	No
Seetharaman and Chintagunta (1998)	No	No	**Yes**	No
Seetharaman et al. (1999)	**Yes** (1 lag only)	No	No	No
Abramson et al. (2000)	**Yes**	No	No	No
Erdem and Sun (2001)	**Yes**	No	No	**Yes**
Seetharaman (2003)	**Yes**	No	**Yes**	No
This study (2003)	**Yes**	**Yes**	**Yes**	**Yes**

smoothed brand loyalty measure of Guadagni and Little (1983), our measure of *habit persistence type 1* is mathematically equivalent to the AR(1) measure of Allenby and Lenk (1994), and our specification of *habit persistence type 2* is identical to that in Seetharaman and Chintagunta (1998). We integrate all of these effects within a random utility formulation for the first time in the literature.

We model the effects of unobserved heterogeneity (a.k.a. "spurious" state dependence, Heckman 1981a) by assuming that all parameters follow a joint, multivariate discrete distribution across households, whose supports' locations and probability masses are estimated from the data. Such a semiparametric specification of heterogeneity has been extensively used in brand-choice models to estimate household segments, and has been shown to have favorable statistical properties compared to parametric specifications of heterogeneity (see, for example, Chintagunta et al. 1991). We assume the existence of K segments, hence K support points for the heterogeneity distribution, and estimate separate parameter vectors for each support point (as will be explained in the estimation section). To test the robustness of our empirical findings to alternative heterogeneity specifications, we also allow all parameters to follow a joint, multivariate normal distribution across households (as in, for example, Seetharaman et al. 1999).

Managerial Implications

Here we discuss the managerial implications of separately modeling the four sources of state dependence as well as unobserved heterogeneity in our proposed model: Because *structural state dependence* and *habit persistence type 2* measure the effects of lagged brand choices, a marketing implication of such effects, when they are positive, is that distributing free samples of a brand can "hook" households into consuming the same brand in the future at regular prices. The marketing implication of such effects, when they are negative, is that increasing the length of the firm's product line in the product category will retain variety-seeking households who switch between the firm's brands within the firm's "franchise." The estimated *carryover effects*, on the other hand, have implications for dynamic marketing policies of firms. For example, even if a price reduction on a brand benefits current sales of the brand, it may adversely impact future sales of the brand to the extent that households' reference price for the promoted brand is lowered subsequent to the price reduction (Kopalle et al. 1999). The estimated effects of *habit persistence type 1* have no obvious direct consequences for planning marketing strategy because they measure temporal persistence due to variables that are not observed by the marketing researcher. However, to the extent that the marketing manager is in a better position than the academic researcher to speculate on what may drive such unobserved temporal persistence in brand choices—because they observe more variables of interest in the product market under study than does the marketing researcher—the manager may be able to strategically respond to such estimated effects in practice. At the very least, accommodating the effects of *habit persistence type 1* in the brand-choice model aids model specification, and therefore enables the correct recovery of the effects of marketing variables and the other state-dependence effects in the model. Last, but not least, the estimated extent of *unobserved heterogeneity* in model parameters across households spells possible opportunities for the brand manager to develop differentiated marketing offerings to appeal to different segments of the marketplace. It also allows the manager to develop targeted couponing activities based on households' differential sensitivities to marketing variables and their state-dependence proclivities.

Effects of Lagged Promotions on State Dependence Modeling the effects of prior promotional purchases on current choices has precedence in the brand-choice literature (see, for example, Shoemaker and Shoaf 1977, Dodson et al. 1979, Guadagni and Little 1983, Neslin and Shoemaker 1989). In line with this research stream, and following up on an experimental study by Kahn and Louie (1990), we investigate whether a household's propensity to be state dependent is a function of lagged marketing variables. We accommodate the effects of lagged promotions by allowing the parameter ρ to be a function of the marketing variables of the brand during the previous purchase occasion.

$$\rho = \frac{1 - e^{\rho_0 + \rho_P * P_{t-1} + \rho_D * D_{t-1} + \rho_F * F_{t-1}}}{1 + e^{\rho_0 + \rho_P * P_{t-1} + \rho_D * D_{t-1} + \rho_F * F_{t-1}}}, \tag{8}$$

where P_{t-1}, D_{t-1}, and F_{t-1} stand for the price, display, and feature values associated with the brand during the previous purchase occasion.

3. Estimation

Each household's conditional (on its location in the unobserved heterogeneity distribution) likelihood function ($L_{h|s}$) is computed by applying the proposed model's probability formulas (Equation (7)) over the household's observed string of purchases.

$$L_{h|s} = \left(\prod_{j=1}^{J} P_{hsj1}^{\delta_{hj1}}\right) * \prod_{t=2}^{N_h} \left(\prod_{j=1}^{J} P_{hsjt}^{\delta_{hjt}}\right), \tag{9}$$

where P_{hsjt} stands for household h's probability of buying brand j on purchase occasion t conditional on its observed choice of brand on its previous purchase occasion (computed using the appropriate choice of formula from Equation (7)), given that it belongs to support s of the heterogeneity distribution, N_h stands for the number of purchase occasions corresponding to household h, J stands for the total number of brands, and δ_{hjt} is an indicator variable that takes the value 1 if brand j is purchased by household h at time t and 0 otherwise.

Each household's unconditional likelihood function is then computed by integrating the conditional likelihood function over a multivariate, discrete distribution of unobserved heterogeneity across households (Chintagunta et al. 1991).

$$L_h = \sum_{s=1}^{S} \{\pi_s * L_{h|s}\}, \tag{10}$$

which is multiplied across households to obtain the sample likelihood function:

$$L = \prod_{h=1}^{H} L_h. \tag{11}$$

The sample likelihood function is then maximized using gradient-based methods to obtain maximum-likelihood estimates of model parameters. We also test a continuous distribution for unobserved heterogeneity, specifically a multivariate normal distribution with unknown means and variances. In this case, the household's unconditional likelihood function is computed as follows:

$$L_h = \int_{f(s)} L_{h|s}\, ds, \tag{12}$$

where $f(s)$ stands for the multivariate normal density characterizing the unobserved heterogeneity distribution. Because this multivariate integral does not have an analytical closed form, the likelihood function in this case is computed using Monte Carlo simulation, i.e., by making a large number (say S^*) of draws from the multivariate normal distribution and using the following approximation for the likelihood function:

$$L_h = \frac{1}{S^*} \sum_{s^*=1}^{S^*} L_{h|s^*}. \tag{13}$$

One issue that deserves discussion is the specification of the *initial conditions*, i.e., the value of the choice probability for the first purchase occasion of each household (P_{hsj1}). Investigating this presents a problem of significant computational and economic complexity (as discussed in Keane 1997). We assume the initial conditions to be exogenously prespecified. Specifically, we use only those lags for which data is available and ignore earlier lags. To the extent that lags are geometrically decaying and each panelist gives a reasonably long time-series of purchases, this assumption may not be restrictive in our application. This is also consistent with the procedure adopted in Roy et al. (1996) and Seetharaman et al. (1999).

A last issue that deserves mention pertains to the accounting of the serial correlation in the Type-I extreme value errors of the random utility function. Because we assume an AR(1) scheme, the errors are simulated using the following scheme (Landwehr et al. 1979):

$$\begin{aligned} \varepsilon_i &= -\ln\{-\ln \Phi(z_i)\}, \\ z_i &= \lambda_3 * z_{i-1} + \sqrt{1-\lambda_3^2} * u_i, \end{aligned} \tag{14}$$

where Φ is the standard normal cdf, λ_3 is the first-order autocorrelation parameter, and u_i is a standard normal variate. We tested a parsimonious approximation procedure for this serial correlation structure that yielded nice closed-form expressions for the likelihood function (details of this procedure are available from the authors).

4. Empirical Results and Discussion

We employ A. C. Nielsen's scanner panel data on household purchases in the ketchup category from January 1985 to January 1987.[5] Choosing households that bought only among the top eight brands (that account for 87% of all product sales) in the product category yields 3,032 households. From these households, we use only those that made at least seven purchases over the study period. This yields a sample of 529 households, making a total of 5,954 purchases in the category. The largest item—Heinz 32 oz.—has a conditional market share of 37.8% and enjoys the maximum display activity.

We estimate the proposed model of state dependence as well as six nested versions of the model in order to investigate the consequences of incompletely specifying state dependence in households' brand choices. Given in Table 2 are the fit results for the seven models.[6] The full model fits observed brand-choice outcomes better than the other seven models. In order to ascertain that we are not overfitting the data by using models with more parameters, we perform a validation task using a holdout sample. Specifically, we re-estimate the seven models using the first 80 weeks of the data and compute the validation log-likelihoods based on the estimated parameters for the last 25 weeks of the data. Given in the last row of Table 2 are the results of this exercise. The proposed model outperforms the other models in the holdout sample. *This underscores the importance of accounting for state-dependence effects in as complete a manner as possible*.

For the full model, the discrete heterogeneity specification fits the data better than the continuous heterogeneity specification. The structural state-dependence measure turns out to be much more predictive of observed brand choice outcomes than either source of habit persistence. For example, including the Guadagni and Little (1983) loyalty variable in the MNL model improves fit by 11.4% (Models 5 versus 7), while adding both types of habit persistence improves fit only by an additional 0.4% (Models 1 versus 5). It is remarkable that despite the number of papers and alternative model specifications that it has spawned, Guadagni and Little's (1983) measure of structural state dependence still remains the most important source of state dependence characterizing brand-choice data. Even a flexible model such as that of Seetharaman and Chintagunta (1998)—i.e., Model 3—while fitting better than the MNL model with a lagged choice variable—i.e., Model 6 (Jones and Landwehr 1988, Seetharaman et al. 1999)—fits worse than the other four state-dependence models tested in this study. Our findings that structural state dependence and unobserved heterogeneity capture most of the observed temporal dynamics in households' brand choices are consistent with the findings in Keane (1997).

We present the parameter estimates for the seven estimated models in Table 3. The estimates of the effectiveness of marketing variables are *understated* in models that incompletely account for state-dependence effects. For example, the magnitude of the estimated price/display/feature parameter in Model 7 is lower than that in Model 6, which in turn is lower than that in Model 5, etc. To the extent that the estimated price elasticities are systematically understated if the effects of state dependence are ignored or incompletely accounted for, optimal pricing policies derived therefrom will be systematically distorted as well.

The inertia and variety-seeking model of Seetharaman and Chintagunta (1998), i.e., Model 3, recovers one segment of consumers (i.e., support 3, with a probability mass of 0.20) that shows negative structural state dependence (lagged choice coefficient of −5.95). Model 2, however, which uses all lagged choices (using the distributed lag structure) instead of the most recent lagged choice only, shows positive structural state dependence for all three supports. This shows that underspecifying structural state dependence, using only the most recent lagged choice variable (as in Seetharaman and Chintagunta 1998, Roy et al. 1996, etc.), may lead one to spuriously estimate variety-seeking effects when in fact they do not exist. If the marketing manager used the results of Model 3, she may be tempted to extend the product line of her franchise to exploit the benefits of variety seeking when, in fact, the results of Model 3 do not justify such a line-extension strategy.

Under the inertia and variety-seeking model of Seetharaman and Chintagunta (1998), i.e., Model 3, the magnitude of habit persistence type 2 is overestimated. For example, the estimated habit persistence for one segment of consumers (support 3, with a probability mass of 0.20) is 0.78 according to Model 3, and only 0.05 according to Model 1. Distortions in estimated state dependencies such as these may lead product managers to advertise more than necessary in the hope that favorable household evaluations of their products will persist over time and increase their long-term profits, when in fact the reality may dictate more cautious optimism.

Ignoring habit persistence type 1 (going from Models 1 and 4 to Models 2 and 5, respectively)

[5] We also estimated our proposed model on three other product categories: toilet tissue, detergents, and yogurt. Because the results were remarkably consistent across the four categories, we have reported results for ketchup only. The detailed results from all product categories are available upon request.

[6] The effects of marketing carryover were found to be insignificant under all specifications.

Table 2 **Fit and Validation Results**

Fit criterion	1. Full model	2. HP2 & SD	3. HP2 & Lag	4. HP1 & SD	5. SD only	6. Lag choice	7. MNL
In-Sample BIC	14,140	14,254	14,754	14,256	14,280	14,884	16,118
Validation LL	−2,251	−2,265	−2,396	−2,266	−2,277	−2,422	−2,573

Notes. HP1 = Habit persistence 1; HP2 = Habit persistence 2; SD = Structural state dependence; BIC, *B*ayesian *I*nformation *C*riterion.

understates the estimated structural state-dependence effect. This indicates that even though the estimated serial correlation in the errors of the random utility function may not be directly useful for managerial action, because it captures state dependencies in households' brand choices for reasons unobserved to the researcher, modeling its effects is useful to obtain correct estimates of managerially useful lagged choice effects. Ignoring the effects of habit persistence type 1 may lead marketing managers to undervalue the long-term effects of promotional incentives such as free sampling.

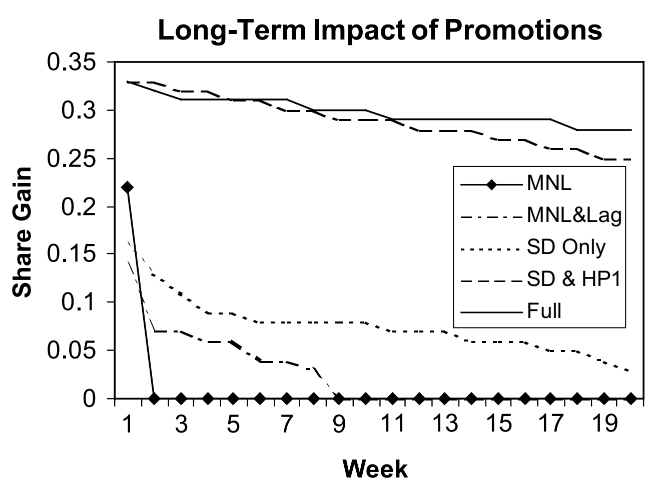
Ignoring habit persistence type 2 (going from Models 1, 2, and 3 to Models 4, 5, and 6, respectively) overstates the estimated structural state-dependence effect. This means that the structural state-dependence parameter would proxy for the effects of unmodeled habit persistence, say, if one used Keane's (1997) model instead of our proposed model. In order to understand whether the total documented extent of state dependence is recovered correctly (even if the source to which it is attributed is wrong), we compute the incremental share gain, by numerical simulation, for the leading brand of ketchup (Heinz 32 oz.) from running an integrated promotional campaign of 20% price off, coupled with a store display and a newspaper feature advertisement during a single week. In Figure 1 we plot the incremental gain in share points as a function of time since promotion. The predicted impact of a sales promotion is observed to increase and last a longer time as one includes additional sources of state dependence in the brand choice model. This means that underspecified models suffer from an inability to accurately assess the total incremental impact of a sales promotion.[7] This finding, coupled with the predictive validation findings of Table 2, suggests that even if decomposing state dependence into its four sources is not useful in and of itself, it is still necessary from the standpoint of accurately estimating market demand.

Ignoring habit persistence type 1 (going from Models 1 and 4 to Models 2 and 5, respectively) or habit persistence type 2 decreases the magnitude of the intercept associated with the largest-share brand, i.e., Heinz 32 oz. This means that measures of brand equity for large brands may be systematically understated if one ignored habit-persistence effects. Because brand equity stands for the intrinsic strength of a brand, i.e., the share of market it will attain in the absence of marketing activities and state-dependence effects, it is important for firms to be able to quantify it correctly to signal brand strength to the marketplace.

The estimated values of the choice decay parameter, i.e., λ_2, are close to 0.8 and consistent with values typically used for the exponential smoothing parameter in previous operationalizations of the Guadagni and Little (1983) loyalty variable. The estimated values of the error decay parameter, i.e., λ_3, are close to 0.9 and consistent with those estimated by Allenby and Lenk (1994) and Keane (1997). Because these estimates are close to one in magnitude for two of the three supports of the heterogeneity distribution, we explicitly test for the possible presence of (undesirable) unit roots. Using a one-sided t-test, we are able to reject the null hypothesis of the error decay being equal to 1 at the 0.01 level of significance (for example, under Model 1, the estimates of 0.93, 0.08, and 0.94 are associated with standard errors of 0.02, 0.0003, and 0.02, respectively). In other words, we conclude that the estimated serial correlations are less than one in all cases.

To investigate whether habit persistence is a function of lagged marketing variables, we allow the parameter ρ to be a logistic function of lagged

Figure 1 **Incremental Share Gain Over Time**



[7] This stylized example ignores such obvious things as category expansion effects, competitive reactions, etc., and is meant only to illustrate the managerial pitfalls of using simpler models.

Table 3 Parameter Estimates

Parameter	1. Full model (New)	2. HP2 & SD (New)	3. HP2 & Lag (Seetharaman and Chintagunta 1998)
α_1 (Heinz 32)	1.82, 2.17, 6.20	1.06, 2.13, 3.05	2.37, 2.97, 1.81
α_2 (Control 32)	−2.53, −0.62, 5.54	−2.01, −1.11, 2.62	−0.85, 1.94, −1.02
α_3 (Hunts 32)	0.36, 1.38, 5.53	0.12, 1.35, 2.57	0.37, 2.53, 0.76
α_4 (Heinz 28)	1.83, 2.50, 4.88	1.09, 2.63, 2.36	1.48, 2.41, 2.03
α_5 (D.Mont 28)	−2.59, 1.08, 4.24	−1.68, 1.12, 1.94	−0.79, 1.99, −2.29
α_6 (Heinz 14)	1.12, 1.02, 3.53	0.62, 1.17, 1.35	0.30, 1.59, 1.01
α_7 (Heinz 44)	1.15, 0.72, 1.74	0.64, 0.66, 1.09	1.19, 0.53, −1.02
α_8 (Heinz 64)	0	0	0
Price	−0.72, −4.27, −3.90	−0.42, −5.01, −1.80	−1.12, −3.02, −0.64
Display	0.90, 0.57, 0.52	0.67, 0.59, 0.36	0.56, 0.41, 0.38
Feature	0.30, 0.24, 1.18	0.19, 0.27, 0.55	0.20, 0.42, 0.57
Lagged choice	1.41, 0.26, 0.83	0.79, 0.21, 0.51	0.38, 0.56, −5.95
λ_2 (Choice decay)	0.86, 0.92, 0.93	0.78, 0.96, 0.84	NA
λ_3 (Error decay)	0.93, 0.08, 0.94	NA	NA
ρ	0.14, 0.12, 0.05	0.16, 0.11, 0.05	0.10, 0.07, 0.78
Support prob.	0.36, 0.36, 0.28	0.35, 0.28, 0.37	0.30, 0.50, 0.20
LL	−6,905	−6,939	−7,212

Parameter	4. HP1 & SD (Keane 1997)	5. SD only (Guadagni and Little 1983)	6. MNL w/lag (Seetharaman et al. 1999)	7. MNL (Gensch and Recker 1978)
α_1 (Heinz 32)	1.42, 2.79, 3.47	0.83, 2.79, 2.88	0.47, 3.03, 2.35	3.05, 3.38, 0.86
α_2 (Control 32)	−3.27, 0.10, 2.86	−2.37, 0.01, 2.42	−2.48, 2.33, −0.68	Insig., 3.31, −3.38
α_3 (Hunts 32)	0.15, 2.02, 2.88	−0.17, 2.02, 2.50	0.36, 2.66, 0.60	1.83, 3.07, −0.76
α_4 (Heinz 28)	1.63, 2.89, 2.62	0.91, 2.80, 2.47	0.72, 2.37, 1.73	2.05, 2.41, 1.11
α_5 (D.Mont 28)	−2.69, 1.79, 1.86	−1.81, 1.83, 1.81	−2.80, 2.17, −0.47	0.76, 2.63, −4.00
α_6 (Heinz 14)	1.03, 1.64, 1.04	0.52, 1.84, 1.13	0.69, 1.70, 0.43	0.73, 1.87, 0.88
α_7 (Heinz 44)	0.90, 1.04, 0.83	0.47, 1.02, 1.17	0.18, 0.54, 1.17	1.04, insig., 0.86
α_8 (Heinz 64)	0	0	0	0
Price	−1.01, −4.22, −2.65	−0.53, −4.35, −1.66	−0.13, −2.78, −1.25	−2.08, −2.44, 0.82
Display	0.94, 0.56, 0.39	0.69, 0.55, 0.34	0.49, 0.36, 0.52	0.47, 0.34, 0.62
Feature	0.30, 0.32, 0.83	0.15, 0.36, 0.51	0.17, 0.42, 0.24	0.28, 0.38, insig.
Lagged choice	1.66, 0.85, 0.99	1.14, 0.79, 0.66	2.64, 0.93, 0.82	NA
λ_2 (Choice decay)	0.76, 0.35, 0.84	0.66, 0.29, 0.81	NA	NA
λ_3 (Error decay)	0.85, 0.22, 0.84	NA	NA	NA
Support prob.	0.36, 0.31, 0.33	0.34, 0.26, 0.40	0.15, 0.50, 0.35	0.58, 0.27, 0.15
LL	−6,950	−6,975	−7,290	−7,920

ρ_0	ρ_{Price}	ρ_{Disp}	ρ_{Feat}	ρ_{Baseline}
1.04, 0.52, 2.17	−0.26, −0.48, −0.18	1.05, 1.02, 0.67	0.67, 1.72, 0.22	0.26, 0.37, 0.10

Notes. 3 supports for heterogeneity distribution. All estimates significant at the 0.05 level; std. errors suppressed for readability.

marketing variables. The results of this hierarchical regression are given below in Table 3. We find that lagged price has a negative effect (i.e., $\rho_{\text{Price}} < 0$), while lagged display and feature have positive effects (i.e., $\rho_{\text{Disp}} > 0$ and $\rho_{\text{Feature}} > 0$) on the habit-persistence parameter. That is, households are more habit persistent with brands that were on promotion during the previous purchase occasion. This is a new empirical finding in the state-dependence literature, and can be used by brand managers to investigate the relative benefits of free sampling versus competitive pricing in terms of boosting long-term profits for their brands.

5. Conclusions

We propose and estimate a random utility model of brand choices that accommodates four distinct sources of state dependence in addition to unobserved heterogeneity across households. The proposed model generalizes and is more flexible than previously proposed state-dependence models in the marketing and labor econometrics literatures. We demonstrate the empirical consequences of ignoring one or more of these sources, and run promotional simulations to illustrate the managerial consequences of using underspecified state-dependence models. Consistent with Keane (1997), we find that structural state dependence and unobserved heterogeneity capture most of the observed temporal dynamics in households' brand choices. All the results obtained are remarkably similar across four different categories of packaged goods, which highlights the cross-category generalizability of our findings.

It would be of interest to investigate the drivers of unobserved persistence in households' brand choices over time, such as due to habit persistence type 1. One driver of such persistence could be national advertising efforts of brands, which are typically unaccounted for in scanner panel datasets. Supplementing available datasets with information on national advertising expenditures of brands will allow one to explicitly understand both their effects on households' brand choices and whether they mitigate the estimated serial correlations in the unobservables.

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