Investigating Household State Dependence Effects Across Categories

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Overview

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Introduction

State Dependence

- **Positive state dependence**: Currently chosen brand has a **higher** probability of being chosen in the future than other brands.
- **Negative state dependence**: Currently chosen brand has a **lower** probability of being chosen in the future than other brands.

Add literature review, write down what other researches have done about similar topic.

Introduction

Exploratory Behavior

- A form of **appetitive** behavior that may be goal-orientated (e.g. the search for food or nesting material) or concerned with the examination of areas or articles with which an animal is unfamiliar, in which case the **behavior often exhibits signs of conflict**.
- State dependence is a household-specific trait.

Levels of Stimulation

- State dependence behavior of a given household will vary across categories if the categories differ in actual levels of stimulation for the household.
- State dependence is a category-specific trait.

Introduction

Marketing Variables and State Dependence Across Categories

- For example, is brand loyalty usually associated with lower price sensitivity, or does the relationship critically depend on the category under consideration?

Wear-out Effect

- Whatever form of state dependence exists at the household level, its effect could diminish over time.
- Whether such wear-out effects characterize state dependence and, if so, whether these effects are consistent across categories?

Introduction

Research Questions:

1. Are households that are relatively more inertial than average in one product category also relatively more inertial in other categories?
2. What is the relationship between a household's sensitivity to marketing variables (price, display, feature) and its level of state dependence?
3. Does a household's state dependence in a category decrease as the time until its next purchase in the category increases?
4. What is the influence of household variables on state dependence?
5. What is the influence of category variables on state dependence?

Single-Category Model of Dynamic Brand Choice

State dependence

A household's brand choice on the previous purchase occasion influences the household's latent utility for each brand at the current purchase occasion, as follows:

$$U_{jt} = \sum_{j=1}^{J} \alpha_j I_j + \beta_{sd} I_{jt-1} + \varepsilon_{jt} (j = 1, ..., J), \quad (1)$$

where

- U_{jt} is the household's latent utility for brand j at time t;
- I_j is an indicator variable that takes the value of 1 for brand j and 0 otherwise;
- α_j is a brand-specific constant (usually referred to as the intrinsic brand preference of the household);
- I_{jt-1} is an indicator variable that takes the value of 1 if brand j was purchased on the previous purchase occasion, t - 1, and 0 otherwise (the state dependence variable);
- β_{sd} is the corresponding parameter (the state dependence parameter);
- ε_{jt} is a stochastic component to the utility function.

Single-Category Model of Dynamic Brand Choice

Incorporating wear-out effects

Next, the paper allows the effects of state dependence to vary over time, as follows:

$$U_{jt} = \sum_{j=1}^{J} \alpha_j I_j + [\beta_{sd} + \beta_{wo} f(T)] I_{jt-1} + \varepsilon_{jt} (j = 1, ..., J), \tag{2}$$

where

- T is the time since the last purchase in the category under consideration (in days),
- f(.) is a suitably specified function. In the empirical analysis, we use $f(.) = ln(.)$.
- β_{wo} is a parameter that captures the time effect. (wear-out effect)

Single-Category Model of Dynamic Brand Choice

Incorporating the effects of marketing variables

The paper also includes:

1. a dummy variable denoting whether the brand was on display in week t ($DISP_{jt}$),
2. a dummy variable denoting whether the brand was featured in week t ($FEAT_{jt}$),
3. the natural logarithm of the brand's price in week t (lnP_{jt}).

In matrix notation, the paper includes this full set of variables in the design of matrix **X**. The household's latent utility for a brand j at purchase occasion t becomes

$$U_{jt} = \mathbf{X}_{jt}'\boldsymbol{\beta} + \varepsilon_{jt}, \tag{3}$$

where the vector β is given by $(\alpha_1, ..., \alpha_j, \beta_{sd}, \beta_{wo}, \beta_{disp}, \beta_{feat}, \beta_{price})'$.

Multipie-Category Model of Brand Choice

Distributional assumptions on the error term in the single-category model

To facilitate exposition, we introduce a category subscript and a household subscript in the latent utility formulation. Then, Equation 3 becomes

$$U_{hcjt} = \boldsymbol{X}'_{hcjt}\boldsymbol{\beta}_{hc} + \varepsilon_{hcjt}, \tag{4}$$

(h=1,...,H; c=1,...,C; j=1,...,J)

where

- h refers to the household,
- c refers to the category.

Assume the error term ε_{hcjt} to be distributed **multivariate normal** across brands, a **multinomial probit model** of brand choice is obtained.

Multipie-Category Model of Brand Choice

Hierarchical error components formulation

Equation 4 in vector form is

$$\boldsymbol{U}_{hct} = \boldsymbol{X}_{hct}\boldsymbol{\beta}_{hc} + \boldsymbol{\varepsilon}_{hct}, \tag{5}$$

where

- $\boldsymbol{U}_{hct} = (U_{hcit} \ldots U_{hcJt})'$ denotes the utility vector of household h for brands within category c at time t,
- $\boldsymbol{X}_{hct} = (\boldsymbol{X}_{hc1t} \ldots \boldsymbol{X}_{hcJt})'$, and $\boldsymbol{\varepsilon}_{hct} = (\varepsilon_{hc1t} \ldots \varepsilon_{hcJt})$,
- assume that $\boldsymbol{\varepsilon}_{hct} \sim N(\mathbf{0}, \Lambda_c)$, wherein Λ_c is the covariance matrix of the random component $\boldsymbol{\varepsilon}_{hct}$ across the J_c brands in category c.

We **decompose** $\boldsymbol{\beta}_{hc}$ to one component that is household-specific (and invariant across categories) and one component that depends on the category. That is,

$$\boldsymbol{\beta}_{hc} = \boldsymbol{\theta}_h + \boldsymbol{\eta}_{hc}, \tag{6}$$

where

- $\boldsymbol{\theta}_h$ is specific to household h (and common across categories),
- $\boldsymbol{\eta}_{hc}$ depends on both household h and category c.

Multipie-Category Model of Brand Choice

Then, the model becomes

$$\boldsymbol{U}_{hct} = \boldsymbol{X}_{hct}(\boldsymbol{\theta}_h + \boldsymbol{\eta}_{hc}) + \boldsymbol{\varepsilon}_{hct}, \tag{7}$$

We can decompose the components further (for an exposition about hierarchical models of this kind, in which response parameters are allowed to depend on explanatory variables, see Draper 1998). as follows:

$$\boldsymbol{\theta}_h = \boldsymbol{\Delta}^{\theta}\boldsymbol{Z}_h + \boldsymbol{v}_h,$$

and

$$\boldsymbol{\eta}_{hc} = \boldsymbol{\Delta}^{\eta}\boldsymbol{Z}_{hc} + \boldsymbol{w}_{hc}, \tag{8}$$

where

- $v_h \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\theta})$, and $w_{hc} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\eta})$;
- $\boldsymbol{Z}_h$ is a vector of household-specific characteristics, such as family size, income, and shopping frequency;
- $\boldsymbol{Z}_{hc}$ is a vector that contains category dummies and a category-dependent household variable (category purchase intensity);
- $\boldsymbol{\Delta}^{\theta}$ and $\boldsymbol{\Delta}^{\eta}$ are the corresponding matrices of parameters;
- $\boldsymbol{\Sigma}_{\theta}$ and $\boldsymbol{\Sigma}_{\eta}$ are the covariance matrices of the random vectors $\boldsymbol{v}_h$ and $\boldsymbol{w}_{hc}$.

Multipie-Category Model of Brand Choice

The correlation of a given response parameter β_i across categories is given by

$$corr(\beta_{ic}, \beta_{ic'}) = \frac{\sigma^2_{\theta,ii}}{\sigma^2_{\theta,ii} + \sigma^2_{\eta,ii}}, \tag{9}$$

where

- $\sigma^2_{\theta,ii}$ stands for the ith element along the diagonal of the matrix Σ_θ; that is, it stands for the variance of the random component in the random vector $\boldsymbol{v}_h$ that corresponds to parameter β_i.
- $\sigma^2_{\eta,ii}$ stands for the ith element along the diagonal of the matrix Σ_η.

The higher the value of this correlation, the higher is the similarity in household response behavior across categories along that dimension.

For example, if $corr(\beta_{sd,c}, \beta_{sd,c'})$ is high, households exhibit similar state dependence across categories. State dependence then can be interpreted as a household trait.

Data

The paper uses ACNielsen scanner panel data on household purchases of brands in **five product categories**: ketchup, peanut butter, stick margarine, toilet tissue, and canned tuna. Households that made **at least two purchases in each of the five categories** are selected from the panel of households.

This results in a set of 785 households. We track the households over a period of **three years** (1985 to 1988).

The total number of purchases made by the households in the five categories are as follows: 5556 for ketchup, 6153 for peanut butter, 13,380 for stick margarine, 8795 for toilet tissue, and 8289 for canned tuna. (Descriptive statistics for the five categories are given in Table 1.)

Hierarchical Variables

The paper uses the following demographic and shopping variables in the household-specific vector $\boldsymbol{Z}_h$:

1. RETIRE is the retirement status of the head of the household, equal to 1 if the head is retired and 0 otherwise;
2. UNEMP is the unemployment status of the head of the household, equal to 1 if the head is unemployed and 0 otherwise;
3. SMOM is the presence of a single mother, equal to 1 if head of the household is a single mother and 0 otherwise;
4. INCOME is the household income (in dollars);
5. SIZE is the size of the family;
6. FREQ is the average number of store visits made by the household in a week;
7. EXPEND is the average grocery expenditure incurred by the household on a store visit (in dollars).

Variables 1-5 are exogenously prespecified household demographic variables, variables 6 and 7 are based on the observed shopping behavior of the household.

Hierarchical Variables

The paper uses the following variables in the category-specific vector $\boldsymbol{Z}_{hc}$:

1. INTENSITY is the ratio of category expenditure to total shopping expenditure over the study period,
2. $DUMMY_c$ (c = 2,..., 5) is the four dummies included to capture category intercepts.

Table 2
DEMOGRAPHIC AND SHOPPING BEHAVIOR VARIABLES

Variable	*Mean*	*Standard Deviation*	*Minimum*	*Maximum*
RETIRE	.095	*	*	*
UNEMP	.084	*	*	*
SMOM	.095	*	*	*
INCOME ($)	30219 (10.1)	14091 (.62)	2500 (7.8)	87500 (11.7)
SIZE	3.53 (1.07)	1.31 (.47)	1 (0)	8 (2.08)
FREQ	2.7	1.3	.3	8.64
EXPEND ($)	152.72 (4.71)	107.41 (.78)	5.32 (.18)	805.8 (6.69)
INTENSITY	.001 (–7.61)	.001 (1.18)	.00002 (–13.1)	.03 (–3.51)

*These variables are dichotomous; therefore, all information about them is contained in the mean.
Notes: Mean values of the logarithmic transformations are provided in parentheses, when applicable.

Research Questions

QI: Are households that are relatively more inertial than average in one product category also relatively more inertial in other product categories?

- Measures: $corr(\beta_{sd,c}, \beta_{sd,c'}) = \frac{\sigma^2_{\theta,sd}}{\sigma^2_{\theta,sd}+\sigma^2_{\eta,sd}}$, where $\sigma^2_{\theta,sd}$ is the element along the diagonal of the matrix Σ_θ corresponding to the parameter β_{sd}.
- The state dependence parameter is highly correlated across categories (average correlation mean of .46 with a standard deviation of .04).

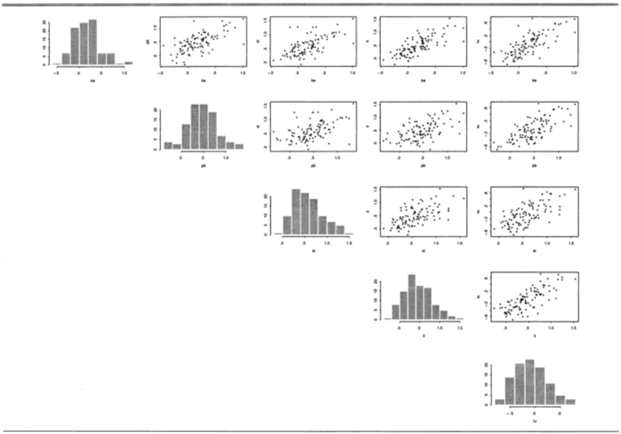
Q2: What is the relationship between the household's sensitivity to marketing variables (price, display, feature) and its state dependence?

- Measures: $corr(\beta_{h,sd}, \beta_{h,price})$, $corr(\beta_{h,sd}, \beta_{h,disp})$, $corr(\beta_{h,sd}, \beta_{h,feat})$.
- Average of $corr(\beta_{h,sd}, \beta_{h,price})$ is .13 with a posterior probability of .96, average of $corr(\beta_{h,sd}, \beta_{h,feat})$ -.13 with a posterior probability of .97, and average of $corr(\beta_{h,sd}, \beta_{h,disp})$ is -.01 with a posterior probability of .58.
- Lower sensitivity to price or feature is associated with greater inertia.

Research Questions

In these plots, the mean of the posterior distribution of each household's state dependence baseline in a category is plotted against the same household's mean in another category.

Figure 1
HISTOGRAMS AND SCATTERPLOTS OF STATE DEPENDENCE BASELINES



Research Questions

Q3: Does a household's state dependence in a category decrease as the time until its next purchase in the category increases?

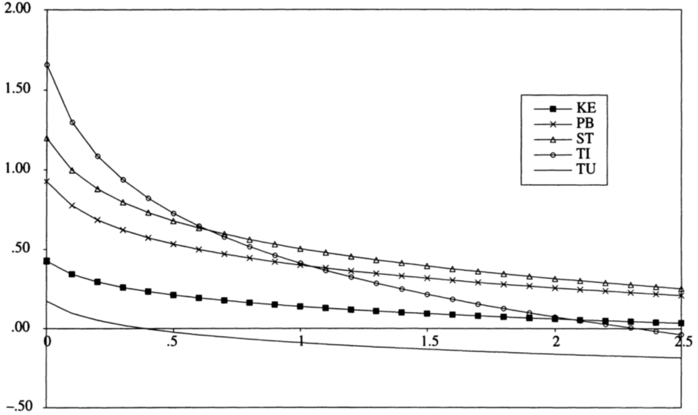
- In Table 3, we provide the aggregate state dependence baseline ($\hat{\beta}_{sd,c}$) and the aggregate wear-out effect ($\hat{\beta}_{wo,c}$) for each category separately.
- We show that $\hat{\beta}_{wo,c}$ signed oppositely to $\hat{\beta}_{sd,c}$ for four of the five categories, in line with our expectations.

Table 3
HIERARCHICAL PROBIT RESULTS

Parameter	*Estimate (Posterior Probability that Parameters Are Positive)*
$\bar{\beta}_{sd,ke}$	.15 (.97)
$\bar{\beta}_{wo,ke}$	–.12 (.06)
$\bar{\beta}_{sd,pb}$	.42 (1.00)
$\bar{\beta}_{wo,pb}$	–.22 (.00)
$\bar{\beta}_{sd,st}$	.53 (1.00)
$\bar{\beta}_{wo,st}$	–.29 (.00)
$\bar{\beta}_{sd,ti}$	.46 (1.00)
$\bar{\beta}_{wo,ti}$	–.52 (.00)
$\bar{\beta}_{sd,tu}$	–.08 (.13)
$\bar{\beta}_{wo,tu}$	–.11 (.01)
Coefficients of $\mathbf{Z}_h$	
RETIRE	.01 (.52)
UNEMP	.03 (.59)
SMOM	–.01 (.46)
ln(INCOME)	–.01 (.45)
ln(SIZE)	.01 (.53)
FREQ	–.04 (.18)
EXPEND	.25 (1.00)
Coefficients of $\mathbf{Z}_{hc}$	
INTENSITY	.12 (1.00)

Research Questions

Figure 2
STATE DEPENDENCE AS A FUNCTION OF TIME



Research Questions

Q4: What is the influence of household variables on state dependence?

- Measures: $\Delta^{\theta sd}$, that is, the row corresponding to the state dependence parameter in the matrix Δ^{θ}.
- Households undertaking planned shopping trips are more likely to buy predetermined brands.

Q5: What is the influence of category variables on state dependence?

- Measures: $\Delta^{\eta sd}$, that is, the row corresponding to the state dependence parameter in the matrix Δ^{η}.
- The category shopping intensity variable has a positive effect on state dependence.

Coefficients of $\mathbf{Z}_h$	
RETIRE	.01 (.52)
UNEMP	.03 (.59)
SMOM	–.01 (.46)
ln(INCOME)	–.01 (.45)
ln(SIZE)	.01 (.53)
FREQ	–.04 (.18)
EXPEND	.25 (1.00)
Coefficients of $\mathbf{Z}_{hc}$	
INTENSITY	.12 (1.00)

Related Questions

Q1: How much of the observed state dependence in brand choices is explained using household and category variables?

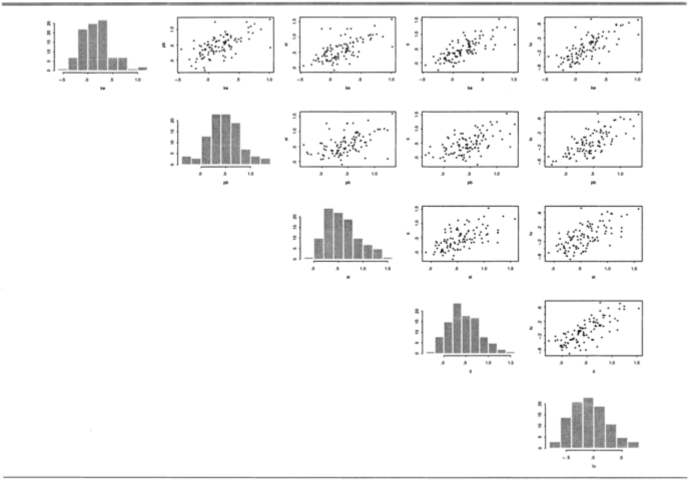
- This research finds that 10% of the variability in $\theta_{h,sd}$ can be explained using the variables in $\boldsymbol{Z}_h$, 20% of the variability in the $\eta_{hc,sd}$ can be explained using the variables in $\boldsymbol{Z}_{hc}$ and 16% of the total variability in $\beta_{hc,sd}$ explained using the variables in $\boldsymbol{Z}_h$ and $\boldsymbol{Z}_{hc}$.
- This means that, though observed variables have some explanatory power, state dependence is a fundamental household trait that can be gauged accurately only using actual brand choice data.

Q2: Second, what is the extent of unobserved heterogeneity across households in state dependence?

- The distributions of posterior means of state dependence baselines are given in Figure 1 for each category.
- For all categories except canned tuna, a majority of household means are to the right of 0, that is, exhibit positive state dependence, and there is substantial variation in these posterior means.

Related Questions

Figure 1
HISTOGRAMS AND SCATTERPLOTS OF STATE DEPENDENCE BASELINES



Related Questions

Q3: Do some categories exhibit higher levels of state dependence than others?

- Canned tuna exhibits lower state dependence than ketchup (posterior probability = .98). However, state dependence levels in peanut butter, stick margarine, and toilet tissue are not significantly different from one another.

Q4: what are the consequences of ignoring the marketing mix on the estimated state dependence parameter?

- The paper reeslimates the proposed model after omitting marketing variables and then compare the estimates of this model (SD only) with the estimates of the proposed mode! (full). The stale dependence baselines and the wear-out effect are overstated in the SD-only model.

Table 5
CONSEQUENCES OF IGNORING MARKETING VARIABLES ON ESTIMATED STATE DEPENDENCE

	Full Model	*State Dependence Only*
Baseline		
$\hat{\beta}_{sd,ke}$	.15 (.97)	.99 (1.00)
$\hat{\beta}_{sd,pb}$	.42 (1.00)	.52 (1.00)
$\hat{\beta}_{sd,st}$	.53 (1.00)	.66 (1.00)
$\hat{\beta}_{sd,ti}$	.46 (1.00)	.60 (1.00)
$\hat{\beta}_{sd,tu}$	−.08 (.13)	.58 (1.00)
Wear-Out		
$\hat{\beta}_{wo,ke}$	−.12 (.06)	−.55 (.00)
$\hat{\beta}_{wo,pb}$	−.22 (.00)	−.39 (.00)
$\hat{\beta}_{wo,st}$	−.29 (.00)	−.31 (.00)
$\hat{\beta}_{wo,ti}$	−.52 (.00)	−.80 (.00)
$\hat{\beta}_{wo,tu}$	−.11 (.01)	−.30 (.00)

Related Questions

Q5: What are the consequences of ignoring state dependence on the estimated marketing mix effects?

- In the case of display and feature, the coefficients for each category are larger in the full model.

Table 6
CONSEQUENCES OF IGNORING STATE DEPENDENCE ON ESTIMATED MARKETING MIX COEFFICIENTS

	Full Model	*Mix Only*
Price		
$\hat{\beta}_{pr,kc}$	−11.77 (.00)	−8.73 (.00)
$\hat{\beta}_{pr,pb}$	−14.97 (.00)	−10.33 (.00)
$\hat{\beta}_{pr,st}$	−13.24 (.00)	−9.70 (.00)
$\hat{\beta}_{pr,ti}$	−20.18 (.00)	−15.83 (.00)
$\hat{\beta}_{pr,tu}$	−5.14 (.00)	−13.35 (.00)
Display		
$\hat{\beta}_{di,kc}$	5.15 (1.00)	3.90 (1.00)
$\hat{\beta}_{di,pb}$	2.08 (1.00)	1.47 (1.00)
$\hat{\beta}_{di,st}$	2.46 (1.00)	1.86 (1.00)
$\hat{\beta}_{di,ti}$	3.28 (1.00)	2.45 (1.00)
$\hat{\beta}_{di,tu}$	3.10 (1.00)	2.03 (1.00)
Feature		
$\hat{\beta}_{feat,kc}$	3.17 (1.00)	2.08 (1.00)
$\hat{\beta}_{feat,pb}$	1.76 (1.00)	1.16 (1.00)
$\hat{\beta}_{feat,st}$	1.28 (1.00)	.87 (1.00)
$\hat{\beta}_{feat,ti}$	1.94 (1.00)	1.40 (1.00)
$\hat{\beta}_{feat,tu}$	4.27 (1.00)	1.37 (1.00)

Summary of Findings and Managerial Implications

1. Households display similar state dependence across categories.
   - A retailer could induce highly inertia! households to buy its store brands in various categories by providing sampling programs on "bundles" of store brands, so that these households continue to buy store brands in the future.
2. Lower sensitivity to the marketing mix is associated with greater inertia in brand choices.
   - Sampling programs might be employed periodically to induce house- hold trial o(the brand so that the inertia effect ensures their loyalty to the brand in the long run.
3. The longer the household waits to make its next category purchase, the less inertia! is its behavior.
   - Place coupons in the package that can be redeemed by mail.
4. Household demographics such as income and family size have little influence on state dependence. The shopping expenditure variable, however, exerts a significant positive effect on state dependence.
   - Identify planned shoppers from their shopping databases so that "image-building" promotions (e.g., television advertisements) can be targeted at them.
5. Four categories show positive state dependence, whereas the fifth (canned tuna) shows no state dependence.
   - Manufacturers may want not only to induce brand-switching, but also to stimulate product consumption.

Conclusions and Further Research

Conclusions

- This paper proposes a multicategory stochastic brand choice model that captures the effects of state dependence on household brand choices, estimates the effects of marketing variables, and allows for wear-out effects in the state dependence parameter.
- Bayesian technique proposed by Ainslie and Rossi (1998) is used to estimate model parameters.
- Five research questions about dynamic choice behavior are answered using the proposed model.

Further research

1. Investigating possible causal relationships between all possible variables not only between marketing mix sensitivities and state dependence.
2. Investigating differences in underlying mechanisms across categories.
3. Employing richer models of variety seeking substantially may increase the computational effort.
4. Testing the explanation offered by Menon and Kahn (1995) that households balance their need for variety across categories.

Strengths and weakness

Strengths:

- Incorporate wear-out effects in model.
- Study state dependence as well as wear-out effects across categories.
- Interesting and attractive in the form of paper. Use the way of coming up research questions and building model to answer questions.
- Use figure to help understand the state dependence between categories.

Weakness:

- Lack of some mathematical derivations.
- Estimate lots of parameters and coefficients but only present some of them in tables. This makes the empirical results part seems a little complicated and confused.
- Robustness check.

Possible future research

- Use other datasets to test the conclusions in this paper.
- Construct structural model to represent state dependence.
- Better simulation methods.