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EMPIRICAL ANALYSIS OF CONSUMER PURCHASE BEHAVIOR: INTERACTION BETWEEN STATE DEPENDENCE AND SENSITIVITY TO MARKETING-MIX VARIABLES[3]

People are intent to make similar choices especially in consumer goods markets. To address both explanations of this persistence, i.e. state dependence and heterogeneity in preferences, we use random coefficient logit model based on scanner panel data on juice purchases. The product differentiation of the chosen category allows us to model three dimensions of state dependence on brand, size and flavor characteristics. We provide evidence that the persistence in brand choices is positively correlated with persistence in size and flavor choices, thus the consumer pattern is prone to be inertial or variety seeking in every product characteristics. Simultaneously we show that the more sensitive to price and promotional activities consumers are, the less inertial is their behavior.

JEL Classification: M31, D12

Key words: State dependence, random coefficient logit, product differentiation

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1. Introduction

The analysis of consumer purchase behavior has been of interest to researchers in marketing and economics for many years. The availability of individual-level data prompted various empirical studies devoted to diverse range of questions that both academia and industries are interested in. This paper deals with the following contexts of consumer behavioral pattern in differentiated products choice: the influence of past choices (i.e. state dependence) and the effect of different preferences and sensitivities to marketing-mix variables (i.e. heterogeneity).

The past research has provided evidence that consumer choice especially in FMCG markets exhibits a form of persistence whereby households have a higher probability of choosing products that they have purchased previously. This causality between past and current choices is known as state dependence (Keane, 1997). However, despite the great product differentiation that we observe in the marketplace, the plurality of models in the framework still study only brand choices, eliminating the effects of other products attributes. We address this deficiency by modelling multi-dimensional state dependence, that is state dependence for several product attributes, such as brand, size and flavor. We are interested if consumer pattern is inertial in brand choices, is it inertial in other product characteristics? Furthermore, we investigate the relation between marketing mix sensitivities and multi-dimensional state dependence, because previously this correlation was studied only in relation to state dependence in brand choices (Dube, Hitsch, Rossi, 2010; Seetharaman, 2004).

As far as we focus our analysis on the investigation of product differentiation, the chosen unit of analysis is SKU (stock-keeping unit) in packaged juice category. Despite the fact that both retailers and manufacturers make decisions at SKU level, modelling SKU choice rather than brand choice is regarded as exception rather than a norm (Zanutto, Bradlow, 2006). We have chosen the packaged fruit juice category for the analysis.

To answer the questions we implement a random coefficient logit model based on scanner panel data. Random coefficients are used to incorporate different sensitivities to marketing instruments (i.e. price and promotion) and different dependence on past choices. Our model is calibrated on a unique dataset provided by one of the leading retail chain in Perm region, Russia. To form a dataset we match two types of retail scanner data: the observations of choices of loyalty cards owners and the information about product availability, assortment, in-store promotions and pricing strategies.

The paper will proceed as follows. We first review previous research and discuss the rationale for the current study. Further, we describe the discrete choice model applied to the collected data. Then we provide our findings and conclude with outlining limitations and directions for further research.

2. Theoretical Background and Research Questions

Going shopping people face various assortments of products offered in the marketplace. The majority of surrounding goods are differentiated, and manufacturers offer products that vary in a wide range of attributes. Firms differentiate their products vertically to capture consumers' different willingness to pay for quality (Draganska, Jain, 2006). At the same time, producers diversify their product lines offering products with distinguishing packages, sizes, flavors and product forms that relate to horizontal differentiation.

When the demand for whole product category is of interest, the justified unit of analysis is SKU (stock-keeping unit). SKU is an identification of a unique product that characterizes all attributes associated with it and that distinguishes it from other items. Demand for all SKUs offered by brands is essential for effective inventory planning and promotional strategies for retailers, as well as efficient product line management for manufacturers (Ho, Chong, 2003). Modelling demand for all SKUs allows addressing the product differentiation issue. Moreover, it was found that this unit of analysis is preferable to brand alternatives, brand-size or other aggregated variants, because it leads to lower estimation biases (Andrews, Currim, 2005).

As far as tastes differ, they demonstrate the effect of different preferences. People are known to be heterogeneous in their preferences for brands and other product characteristics, as well as in their price sensitivities, which results in different strengths of their demand. Retailers may conduct a policy of price discrimination between consumer segments, using promotional strategies (Allender, Richards, 2012). Different sensitivities to promotional activities represent another source of consumer's heterogeneity.

Substantial body of academic research investigates purchasing behavior within the frame of discrete choice models. Random utility models are perfectly suited for analyzing consumer behavior because of their ability to model demand for differentiated products by heterogeneous households. Discrete choice modelling approach incorporates product differentiation considering the goods as the bundles of their characteristics (McFadden, 1973). This attribute-based approach allows diminishing the number of parameters as compared to the inclusion of intercepts for all alternatives. Moreover, the advantage of this approach is potential estimation of completely new variants, which is precluded by the presence of product-specific intercepts (Nevo, 2001; Berry Levinsohn, Pakes, 1995, Inman et al., 2008).

Discrete choice models also enable researchers to incorporate the effects of unobserved heterogeneous preferences across households. Heterogeneity can be accounted for by allowing certain parameters of the utility function vary randomly across consumers. Extensive research has advanced the methodology of modeling demand for differentiated products by customers with heterogeneous tastes. These models have been estimated using both market-level data (Nevo, 2001; Berry Levinsohn, Pakes, 1995) and individual-level data (Shum, 2004; Osborne, 2011). The ability to examine disaggregated choices permits to form longitudinal customer history that eventually enables researchers to investigate the influences of past purchases.

It has been scientifically proven that people are prone to make similar choices especially in frequently purchased consumer goods markets (Keane, 1977). The behavioral pattern when an individual is likely to buy the alternative, because he bought it previously, is usually termed state dependence. A sustainable stream of research was dedicated to investigation whether the existence of state dependence in a model is caused by misspecification of heterogeneity effect. At present there is consensus on this question in academic literature: evidence of simultaneous existence of both state dependence and heterogeneity effects in consumer behavioral pattern is confirmed. This result is consistent to various specifications and functional forms used to model these effects (Gonul and Srinivasan (1993), Keane (1997), Dube, Hitsch, Rossi (2010), Seetharaman et al., 1999, Seetharaman (2004).

The repeated purchases can be mainly explained by two key drivers: *structural state dependence* and *habit persistence*. The methodological difference is that the former represents the lagged choice effect, while the latter reflects the lagged utilities effect. Looking in depth at the nature of two explanations, we note that structural state dependence is often connected with loyalty, which reflects positive perception (Liu-Thompkins, Tam, 2013). Arguing that people are estimated to make more than two hundred food choice decisions per day (Adamowicz, Swait, 2012) it is reasonable to assume that purchases are not always driven by positive reaction towards product characteristics. Thus, many purchase decisions may be habitual, not requiring cognitive efforts and representing routine choice patterns.

Although we acknowledge the rationale for distinguishing these two explanations of repetitive purchases in consumer pattern, there is no need to focus on this problem in the current research. As far as structural state dependence together with unobserved heterogeneity is found to capture most of the observed temporal dynamics in households' brand choices (Seetharaman et al. 2004), we will imply only this source of choice persistence referring later to state dependence.

It is common practice to use Guadagni, Little (1983) (further G&L) loyalty variable to measure the effect of lagged choices (Keane, 1997; Seetharaman, 2004). Estimated exponentially weighted average of past purchases of the brand is incorporated as a component of household's utility for the brand to capture the influence of prior choices. This method has become widespread because of its relative computational ease and good performance in fitting the scanner data. Moreover, Abramson et al. (2000) have provided evidence that G&L loyalty specification is relatively robust in relation to parameters' bias, despite the frequent criticism of this specification in the literature.

It should be noted that the state dependence itself might represent a source of consumer heterogeneity. It is revealed that some consumers may exhibit positive state dependence – when people go on choosing the same alternative – known as inertia and negative state dependence – when people tend to choose different variants – known as variety seeking. Furthermore, consumers are estimated to have different levels of persistence in choices that is they can be more or less persistent in their choices than average (Seetharaman et al., 1999; Alender, Richards, 2012; Empen et al., 2015).

As discussed previously there has been a lot of empirical work on the estimation of state dependence and heterogeneity effects of such characteristic of product as brand on choices. However, relatively little attention is given to the persistence of choices based on other product characteristics, i.e. sizes and flavors, which is extremely important when we analyze demand for multi-dimensional differentiated products (Inman et al., 2008; Singh et al., 2008). Consumers may have preference for particular package size, concrete flavors and are unlikely to switch to a brand that does not offer the preferable set of product attributes. Furthermore, the question how different types of state dependence are inter-related seems to be not enough investigated. For example, if consumer pattern is inertial in brand choices, is it inertial in other product characteristics too? Thus, the aim of the current research is to analyze the structure of multi-dimensional state dependence. We will refer to multi-dimensional state dependence meaning state dependence on choices of more than one characteristic. Particularly, we determine state dependence for three product attributes: brand, size and flavor.

Further, we are interested what is connection between sensitivity to marketing variables and multi-dimensional state dependence. Seetharaman et al. (1999) found that the less sensitive to price and promotion a consumer is, the more inertial his behavior is. However, these conclusions were drawn from investigation of state dependence on brand choices. We are investigating whether the same holds true if the state dependence for other product attributes is defined.

Overall, the substantial body of research was devoted to the investigation of consumer purchase behavior of heterogeneous households with state dependent utility. The aim of this paper is to analyze consumer behavioral pattern, taking into account the multidimensional product differentiation. Answering research questions we contribute to the literature by receiving more detailed understanding of state dependence effect and its relation to marketing-mix sensitivities.

3. Methodology (model)

To answer our research questions the discrete choice model based on scanner panel data is implemented. We model behavior of utility-maximizing households with indexes *i* that choose product *j*. Under a random-utility approach, consumer i's utility is

$$U_{ij} = V_{ij} + \varepsilon_{ij}, \tag{1}$$

where U_{ij} is a deterministic part of utility of individual *i* derived from purchase of alternative *j (j* $\in$ *J)*, ε_{ij} is a stochastic, random component of individual utility. We believe that consumers choose the alternative that derives the highest utility

$$p_{ik} = P[U_{ij} > U_{ir};\ j, r \epsilon J] \tag{2}$$

We assume that ε_{ij} is distributed independently and identically (iid) with the type I extreme-value distribution, called the Gumbel distribution, the probability of choosing the alternative *j* is following

$$p_{ij} = \frac{\exp(V_{ij})}{1 + \sum_{r=1}^{J} \exp(V_{ir})} for\ j = 1\ to\ J \tag{3}$$

We estimate random coefficient or mixed logit model and allow households to have different levels of state dependence and different sensitivities to price and promotion. We assume that on each purchase occasion *t* households gain the following utility buying the chosen alternative, which is more detailed specification of V_{ij} in (1):

$$V_{ijt} = \alpha X_j - \beta_i Price_{jt} + \gamma_i Discount_{jt} + \delta_i BrandStateDep_{ibt} + \eta_i SizeStateDep_{ist} + \\ + \theta_i FlavorStateDep_{ift}, \tag{4}$$

where $\alpha, \gamma_i, \beta_i, \delta_i, \eta_i, \theta_i$ are the parameters to be estimated.

The vector X_j represents the product characteristics. It consists of package size and dummy variables for every brand and flavor. The variable $Price_{jt}$ denotes the regular (depromoted) price for 1 litre of alternative *j* during purchase occasion *t*. The percent of discount at the time of promotion of alternative *j* on purchase occasion *t* is captured by the regressor $Discount_{jt}$.

Three variables $BrandStateDep_{ib}$, $SizeStateDep_{is}, FlavorStateDep_{ift}$ reflect state dependence on brands, sizes and flavors choices respectively. State dependence is estimated as G&L loyalty measure and is operationalized as the exponentially weighted average of past ten purchases. Thus,

$$BrandStateDep_{ibt} = \lambda_b \; BrandStateDep_{ibt-1} + (1-\lambda_b) y_{ibt-1}$$
$$y_{ibt-1} = \begin{cases} 1 \; if \; customer \; i \; purchased \; brand \; b \; at \; purchase \; occasion \; (t-1) \\ 0 \; otherwise \end{cases} \tag{5}$$

The variables for state dependence on size and flavors choices are estimated similarly. The smoothing parameters take the following values: $\lambda_b = 0{,}75$ for state dependence on brand choices, $\lambda_s = 0{,}82$ on package size choices and $\lambda_f = 0{,}75$ on flavor choices.

To consider consumer heterogeneity the parameters on the price, promotion and state dependence variables are allowed to vary randomly over households. Letting the parameters δ_i, η_i, θ_i vary randomly across customers acknowledges that people may differ in their willingness to purchase the alternative with the same characteristic repeatedly. We assume these parameters to be following a normal distribution.

Random parameter on the price β_i enables to take into account that some consumers may be more or less sensitive to price than others. This parameter is assumed to be log normally distributed, because the price effect is censored to be always negative (Baltas, Doyle, 2001). In the same manner, the random parameter assumption on the promotion effect implies that household may have different attitude towards temporary price cuts. The corresponding parameter γ_i that shows the discount effect, is supposed to have normal distribution to capture the possible negative in-store promotion effect.

We let all random parameters be correlated. Particularly this allows for interaction between different types of state dependence and sensitivities to marketing instruments. The likelihood function is obtained by integrating over the joint distribution of Ω for all the observations pertaining to household *i*. The joint distribution Ω depends on the estimated parameters, which take the values that allows maximizing the likelihood function.

$$L = \sum_{i=1}^{N} \left\{ \int \left[\prod_t^T \prod_{j=1}^{J} p_{ijt} d_{ijt} \right] dF(\Omega) \right\}, \tag{6}$$

where d_{ijt} – an indicator variable that takes value one if individual *i* chooses sku *j* at purchase occasion *t* and zero otherwise; p_{ijt} – the probability that individual *i* will choose the sku *j* at purchase occasion *t*, defined in (2). Because there is no analytical closed form and multidimensional integration is hardly managed we use simulated maximum likelihood to estimate the model (Train, 2003).

4. **Data**

Our research is based on the unique data set received from matching detailed consumer and store scanner data of a large retail chain located in Perm region, Russia. The retailer provides us with data on sales, promotion activities and product assortments, thus we observe peoples' choices, marketing-mix information, such as prices and in-store promotions and daily product availability at each store.

We match different sources of information to present the data in the necessary form. Data on every purchase are used to get the chosen stock keeping unit (SKU) and the price paid. Using data on stock availability, we reconstruct the choice set for every purchase occasion basing on information about non-chosen SKUs. Retail data on promotion activities add the information about the available percent of discount in times of promotion and regular prices for all alternatives.

The database consists of individual purchases observations during 2012 year. We restrict our observations to purchases made only by loyalty cards owners. This enables us to observe longitudinal customers history. We have randomly chosen 99 households that made 2367 purchases of juice in 2012. As far as discrete choice models requires choices to be mutually exclusive, multiple purchases of juice were eliminated from the analysis (Train, 2003).

The total juice product category is presented by 460 SKUs and characterized by a large number of brands. Eight brands constitute 93,8% of sales in our sample. The other brands with small market shares were aggregated in «no brand» group. All brands are either worldwide or nationally known, the retail chain does not offer private label in juice. Unfortunately, we are not able to disclose the brand names. Furthermore, the juice is characterized by different flavors and package sizes.

The descriptive statistics of juice characteristics and marketing-mix variables (price and discount) are presented in table 1. On average when a customer comes up to the shelf in store, he sees 253 alternatives of juice. The differences in choice sets are explained by the fact that retail chain has twenty-four stores of different size ranging from corner shops to hypermarkets. The total number of observations is 505 819.

Tab. 1. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
SKU Number in choice sets	253	53	97	357
price for 1 litre	81.594	76.282	27.323	888
package size (in litre)	1.070	0.539	0.2	3
percent of discount [1]	29.596	6.405	17.928	53.958
flavor_mix	0.224	0.417	0	1
flavor_orange	0.118	0.323	0	1
flavor_apple	0.171	0.377	0	1
flavor_cherry	0.032	0.175	0	1
flavor_peachapricot	0.051	0.220	0	1
flavor_pineapple	0.040	0.195	0	1
flavor_citrus	0.020	0.142	0	1
flavor_multifruit	0.114	0.317	0	1
flavor_tomato	0.085	0.279	0	1
flavor_grapefruit	0.041	0.198	0	1
flavor_berry	0.026	0.158	0	1
flavor_other	0.079	0.270	0	1
brand1	0.063	0.242	0	1
brand2	0.102	0.303	0	1
brand3	0.033	0.178	0	1
brand4	0.090	0.286	0	1
brand5	0.034	0.182	0	1
brand6	0.112	0.315	0	1
brand7	0.072	0.258	0	1
brand8	0.106	0.308	0	1
brand9	0.043	0.202	0	1
brand10	0.067	0.250	0	1
brand11	0.064	0.245	0	1
brand12	0.043	0.202	0	1
brand13	0.039	0.193	0	1
"no_brand" group	0.132	0.339	0	1

1 - in times of promotion

5. Results

The estimation results are presented in the table below. There are three specifications. They are standard logit, standard logit with three types of consumer loyalty and random-coefficient logit model with random coefficients before price, discount and three types of state dependence. Comparing the first two models we can make a conclusion that consumer state dependence should be taken into consideration. The best model among the presented specifications is the last one. The results show that the chosen random parameters are justified, because all of them have significant estimates.

Tab. 2. Estimation results

	MNL		MNL with state dependence		RC logit with state dependence and heterogeneity			
					Mean		S.D.	
	Coef.	Std.err.	Coef.	Std.err.	Coef.	Std.err.	Coef.	Std.err.
price for 1 litre	-0.017***	0.003	-0.009***	0.002	-0.071***		0.026***	
lognorm(-price)					-4.321***	0.225	1.828***	0.195
discount	0.079***	0.002	0.075***	0.002	0.060***	0.004	0.055***	0.004
brand_state dep			2.267***	0.063	1.960***	0.101	1.227***	0.117
size_state dep			1.859***	0.091	1.647***	0.113	1.034***	0.132
flavor_state dep			1.680***	0.060	1.550***	0.085	0.990***	0.098
package size	-1.011***	0.079	-0.656***	0.077	-1.172***	0.087		
brand1	-0.475***	0.172	-0.710***	0.173	0.101	0.190		
brand2	0.647***	0.113	0.279**	0.120	0.820***	0.141		
brand3	0.023	0.179	0.036	0.174	-0.080	0.189		
brand4	0.255**	0.119	-0.078	0.131	0.540***	0.143		
brand5	-0.873***	0.315	-1.161***	0.307	-0.254	0.322		
brand6	0.416***	0.113	-0.033	0.120	0.402***	0.138		
brand7	-0.441***	0.145	-0.544***	0.152	-0.084	0.167		
brand8	-0.172	0.117	-0.778***	0.129	-0.090	0.145		
brand9	-0.009	0.193	-0.398**	0.184	0.371*	0.200		
brand10	0.281**	0.130	-0.271**	0.127	0.282*	0.170		
brand11	-0.158	0.193	-0.640***	0.178	0.053	0.211		
brand12	0.789***	0.123	0.227*	0.133	1.214***	0.157		
brand13	-0.036	0.163	-0.557***	0.165	0.425**	0.191		
flavor_mix	-0.114	0.144	-0.464***	0.152	-0.586***	0.155		
flavor_orange	-0.270*	0.150	-0.314**	0.153	-0.493***	0.158		
flavor_apple	0.284**	0.141	-0.082	0.146	-0.271*	0.152		
flavor_cherry	0.272	0.216	0.263	0.222	0.176	0.220		
flavor_peachapricot	-0.148	0.171	-0.153	0.175	-0.308*	0.181		
flavor_pineapple	-0.443**	0.193	-0.371*	0.195	-0.520***	0.200		
flavor_citrus	0.569***	0.205	0.454**	0.203	0.105	0.223		
flavor_multifruit	0.178	0.145	0.042	0.151	-0.107	0.156		
flavor_tomato	-0.269*	0.153	-0.305**	0.155	-0.507***	0.163		
flavor_grapefruit	-0.081	0.196	-0.124	0.201	-0.321	0.202		
flavor_berry	0.039	0.246	-0.052	0.251	-0.118	0.248		
# people	99		99		99			
# choices	2357		2357		2357			
# obs	505819		505819		505819			
# parameters	27		31		45			
Log likelihood	-9675		-8105		-7671			
Pseudo R2	0.123		0.265		0.305			

*p<0.05,**p<0.01,***p<0.001

The following comments refer to the random coefficient specification. The mean of price coefficient is negative and the mean of promotional effect is positive as expected. All three state dependence variables on average are positive, which corresponds to the results of the previous research of purchase behavior in consumer packaged goods markets. The estimates of the package size indicate that consumers prefer smaller sizes. The coefficients on the brand or flavor dummies reveal the increase or decrease of the utility in comparison with the base alternative. For brands, the base alternative is «no brand» group, for flavors –other flavor. Non-significant coefficient shows that on average consumers are indifferent to a brand or a flavor as compared with base-level brand or flavor.

Indeed, our analysis reveals that consumers are heterogeneous in their sensitivities to marketing-mix variables as well as the levels of state dependence. From the magnitudes of the standard deviations relative to the mean coefficients we can conclude that 86% of households in our sample prefer to make purchases with discounts. Nearby 95% of customers exhibit positive state dependence in choices of brands, package sizes and flavors. To see how these parameters are inter-related, we have estimated the correlations between price, discount and state dependence variables.

Tab. 3. Estimated elements of random coefficients covariance matrix

	price for 1 litre	discount	brand_state dep	size_state dep	taste_state dep
price for 1 litre	1.828				
discount	0.548	0.055			
brand_statedep	-0.269	-0.658	1.227		
size_statedep	-0.328	-0.697	0.392	1.034	
taste_statedep	-0.149	-0.437	0.725	0.721	0.990

diagonal - s.d.; under diagonal - significant (p>0.05) correlations

We can notice that people who are sensitive to price are sensitive to discounts too, which is logical and corresponds to results of previous research (for example, Gonul and Srinivasan, 1993). Customers, perceptive to price and promotions are less state dependent to all examined product characteristics. This finding may have important managerial implications. For example, retailers could target promotions at variety-seeking households to gain the promotional effects. Moreover, targeting promotions at highly inertial customers seems to be reasonable in the case of switching to other retailers. As far as the pricing decisions are connected with store loyalty (Sirohi, McLaughlin, and Wittink, 1998), such promotional strategies may help to retain customers. What is more, consumer state dependence parameters are correlated. It means that people tend to prefer the products of the same brands, same flavors and same sizes. This finding may be also implemented in pricing and promotional strategies.

6. Robustness checks

In order to check the robustness of our findings, we modify the current specification and compare the estimated results. The main idea is to stress the significance of modelling the random coefficients of state dependence on three characteristics – brand, size, flavor – simultaneously. We refer to the main specification further as RC logit BSF. Three models with different combinations of state dependences were additionally estimated: 1) the random coefficient logit model with state dependence on brand and size choices (further RC logit BS); 2) the random coefficient logit model with state dependence on size and flavor choices (further RC logit SF); 3) the random coefficient logit model with state dependence on brand and flavor choices (further RC logit BF).

Comparing the coefficients before random variables in different specifications we can draw a conclusion that the results of the main model are robust to the changes in specification (tab. 4). The exclusion of state dependence of any of three attributes does not change the rest of parameters greatly. The high statistical significance of all random parameters underline the reasonability of modelling the state dependence on three product attributes.

Tab. 4. Estimated results – four specifications of random coefficient logit model with different state dependences [4]

	RC logit BSF		RC logit BS		RC logit SF		RC logit BF	
Mean	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**
lognorm(-price)	-4.321***	0.225	-4.057***	0.202	-3.900***	0.231	-3.997***	0.160
discount	0.060***	0.004	0.081***	0.004	0.087***	0.005	0.082***	0.004
brand_state dep	1.960***	0.101	1.598***	0.133	-		1.823***	0.109
size_state dep	1.647***	0.113	1.398***	0.142	2.271***	0.151	-	
flavor_state dep	1.550***	0.085	-		1.540***	0.107	1.378***	0.094
S.D.	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**	**Coef.**	**Std.err.**
lognorm(-price)	1.828***	0.195	1.449***	0.146	1.537***	0.166	1.352***	0.114
discount	0.055***	0.004	0.056***	0.005	0.054***	0.005	0.049***	0.004
brand_state dep	1.227***	0.117	1.250***	0.115	-		1.100***	0.091
size_state dep	1.034***	0.132	1.112***	0.138	1.950***	0.175	-	
flavor_state dep	0.990***	0.098	-		1.029***	0.098	0.961***	0.094

*p<0.05,**p<0.01,***p<0.001

[4] The coefficients on sizes, brand and flavor dummies are not presented

The following step of our analysis is the comparison of correlations in aforementioned specifications of random coefficient logit models (tab. 5). The correlation between state dependences on any characteristics is found to be positive whatever model specification is chosen. This confirm that if consumer patter is prone to be inertial, it is likely to be inertial in every product features.

Concerning the relation between state dependences and sensitivities to promotional activities, we can notice that the more sensitive to discounts consumers are, the less inertial their behavior is. This conclusion is robust to any given specification. As for correlation between state dependences and sensitivities to price, the results are contradictory. In incomplete specifications, the sign of this correlation becomes positive, what contradicts with the results of previous research in this field. In the full model negative correlation reflects that the more elastic the demand is, the less state dependent consumer pattern is. These particularities in results stress the significance of inclusion of state dependence on brand, size and flavor choices in one model simultaneously.

Tab. 5. Comparison of correlations in different specifications of random coefficient logit models

	RC logit with state dependence on brand, size and flavor choices	RC logit with state dependence on brand and size choices	RC logit with state dependence on size and flavor choices	RC logit with state dependence on brand and flavor choices
Corr(brand_statedep; flavor_statedep)	0.725***	-	-	0.666***
Corr(brand_statedep; size_statedep)	0.392*	0.558***	-	-
Corr(size_statedep; flavor_statedep)	0.721***	-	0.676***	-
Corr(brand_statedep; discount)	-0.658***	-0.444***	-	-0.574***
Corr(size_statedep; discount)	-0.697***	-0.408**	-0.447***	-
Corr(flavor_statedep; discount)	-0.437***	-	-0.615***	-0.552***
Corr(price; discount)	0.548***	0.268***	0.013	0.157***
Corr(brand_statedep; price)	-0.269***	0.161**	-	0.354***
Corr(size_statedep; price)	-0.328***	-0.302**	0.322***	-
Corr(flavor_statedep; price)	-0.149*	-	0.425***	0.363***

*p<0.05,**p<0.01,***p<0.001

7. Conclusion

Most past research on state-dependent customer utility analyzes choices only on brand level. However, within a several dimensions of product differentiation which we observe in the marketplace, it seems to be reasonable to take other characteristics besides brands into account. This paper contributes to the investigation of consumer purchase behavior based on different product features, i.e. brands, package sizes and flavors.

The random coefficient logit model enables us to account for heterogeneity and state dependence effects. We have modeled different sensitivities to price and promotion variables alongside with different levels of state dependence on brands, package sizes and flavor. Our interest lies in the inter-relation between these random parameters. It was found that the persistence in brand choices is positively correlated with persistence in size and flavor choices. Thus, the consumer pattern is prone to be inertial or variety seeking simultaneously over all product characteristics. Moreover, the more sensitive to price and promotional activities consumers are, the less inertial their choice is in every product attribute. The results are of interest from a theoretical and managerial point of view and they can be implicated for retailer pricing and promotional policies.

We realize that customers of the retail chain may make purchases in other stores, which can bias estimation of state dependence. A promising topic for further research might be the analysis of causation of consumer heterogeneity and state dependence. Moreover, it could be useful to check whether the results are robust to other product categories. Another outlook for future research may be the investigation of how different consumer patterns influence the multi-dimensional state dependence. The segmentation based on purchase quantity or expenditure may provide researchers and practitioners with additional insights how to design efficient pricing and promotion policies.

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