Compensatory Variety Seeking in Scanner Datasets

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Maintaining strong periodic shopping trips may be not easy for households, because they face uncertainties from consumption, external shock and other schedule conflicts. While the routinization of production makes households more efficient, the routinzation of shopping trips brings little benefit. What are the implications for those households who remain strong revisit patterns? We propose a distribution-wise measure of households' revisit periodicity strength, and investigate its impacts on product choices using scanner datasets. The product-market level analysis shows that households with strong periodic revisit patterns are associated with weaker consumer inertia and have more product switches recorded. The data is consistent with the explanation that those households seek compensatory variety in product choice due to unobserved constraints in timing choice.

Keywords: periodic revisit patterns, state dependence, compensatory variety seeking, scanner data

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1. Introduction

In frequently purchased product markets, consumers[1] usually need to follow certain visiting cycles to repurchase the products. For example, a shopper can revisit stores at a specific time each week. Alternatively, she can visit stores more randomly across different days in a week. Maintaining a strong periodic pattern may not be an effortless process, because consumers are subjected to possible consumption shocks, changes of product characteristics or other unpredicted external factors. However, it is not uncommon to see consumers who restrict the repurchase occasions in narrow windows. What is the consequence of such timing choice? Will consumers with strong revisit patterns exhibit difference in product preference?

Standard economic theories that abstract away from consumers' choice contexts are not likely to provide good explanation on how timing restrictions influence product choice, because a consumer's utility maximization in a context-free world does not take restrictions in previously irrelevant choice domains to the current: such restrictions do not act on consumers' explicit monetary incentives, nor does it affect other extrinsic benefits. However, research in consumer behavior shows the availability of choice itself creates intrinsic benefit by promoting a sense of freedom or control (Schulz and Hanusa 1978, Brehm and Brehm 1981), and extra stimulation (Menon and Kahn 1995). Similarly, a lack of choices in one decision domain may lead to compensatory variety seeking in another (Levav and Zhu 2009, Yoon and Kim 2017). How do those experimental findings work in naturally occurred markets? In this paper, we investigate compensatory variety seeking using scanner data.

[1] We use "consumers" more in the introduction for better motivation, however our analysis of the scanner datasets is at the household level.

It is not new for empirical researchers to test consumer behavior theories using transaction based data. For example, it is very well documented that consumers are subjected to the status-quo bias (or "inertia"), which cannot be explained by standard economic theory (Dubé, Hitsch and Rossi 2010). However, for the very same reason, little research has investigated variety seeking preference in the field. The main challenge for an empirical strategy is that, with strong consumer inertia, transaction based data usually cannot provide additional variation to drive variety seeking preference. We provide a test of compensatory variety seeking based on choices in a relevant and important domain—the shopping time. Our thought experiment can be illustrated with two groups of households with identical characteristics and product preference. Those who have less available alternatives in shopping time are likely to switch more frequently. Controlling for potential product/ brand characteristics and random effects, a set of econometric models are estimated in hope to verify such behavioral effect from households with restrictive revisit time.

Our estimation results show that in various markets, about 10% households with highly restrictive revisit time are subjected to weaker state dependence. The magnitude of the effect varies by different brands and markets, ranging from little to as high as an 8% drop in re-purchase probability. The strongest inertia reduction happens when households allocate weekend leisure time for shopping personal consumption products that has less social use. However, no direct negative state dependence is observed for restrictive households.

Together, the current research makes several unique contributions to the literature of quantitative marketing and consumer behavior. First, we propose a new measure that is correlated with compensatory variety seeking to better test and identify variety seeking tendencies in the field. Second, we empirically test the hypothesis that households can get compensatory benefits from the mere act of choosing. Third, our study suggests that previous practice of estimating negative state dependence based on observed past choice may be problematic. Because compensatory variety seeking is based on other choice domains instead of previous choice; empirically estimating variety seeking effect may benefit from focusing more on the period before households' *switch back* to the original preferred choice, instead of focusing on the point they *switch away* from an observed one.

2. Theoretical Background

To empirically capture the effect of state dependence or variety seeking behavior using revealed preference data, conventional models of product choice usually make specific assumptions on how past consumptions enter into current utility (Seetharaman and Chintagunta 1998). Under the modeling assumption of stochastic utility maximization (McFadden 1980), a positive coefficient on past choice in those models can be interpreted as evidence of habit formation dominating variety seeking, and vice versa. Seetharaman, Ainslie and Chintagunta (1999), Seetharaman (2004), and Dubé, Hitsch and Rossi (2010) all document strong positive state dependence effects after flexibly controlling for unobserved heterogeneity and possible product characteristics (such as price and marketing campaigns). This generally strong dominating effect of structural state dependence prevents researchers from more accurately assessing inter-temporal variety seeking tendency under similar framework. [2]

However, experimental evidence suggests that variety seeking is a robust and fundamental preference related to product switch behavior (McAlister and Pessemier 1982). More importantly, variety seeking does not only serve as an end result of the maximization of the utility of consumption, it also serves other functions and generate additional benefits (Choi and Fishbach 2011). For example, households may seek for variety in product markets, in order to 1)

[2] Direct utility approach. Kim 2002 and Bah 2008 modeling variety seeking based on consumption convexity. Givon 1984 and Bawa 1990 use some additional function forms to identify satiation.

compensate for the lack of freedom and control (Levav and Zhu 2009, Yoon and Kim 2017); 2) demand for more positive social impression (Ratner and Kahn 2002), or 3) generate more stimulation and avoid (quick) satiation (Menon and Kahn 1995; Steenkamp and Baumgartner 1992). The (intrinsic) motivations of variety seeking behavior can be quite meaningful, however, such preference usually cannot be directly observed. It becomes a significant challenge to empirically test those motivations and benefit managerial practice more deeply.

To give the above intrinsic motivations a fair chance, we focus on non-durable experience foods with high level of repeated consumption and purchases. Inspired by statistical measures of distribution difference (Kullback and Leibler 1951), we propose a similar periodicity strength measure to approximate potential restrictions households face in everyday life. Given that each household makes weekly shopping visits[3] in the market, we define the periodicity, by comparing households' empirical repurchase timing choice within the seven days of each week to the discretized uniform distribution in which consumers visit grocery stores with equal probability across the seven days.[4] The intuitive explanation for households with strong periodic patterns is that alternative timing slots are inefficient (or costly) to be allocated for shopping, leaving few restrictive time slots available. Therefore, if the restriction in timing choices promotes variety seeking or reduces inertia, we view such evidence as supportive for the compensatory variety seeking.

The broad topic of timing choice and variety seeking are considered as the junction of multiple fields. Hamermesh (2005) suggests an equilibrium model to explain temporal variety seeking

[3] This assumption has been widely used in structural modeling (e.g. Erdem & Keane 1996) for nondurable experience food.
[4] The underlying assumption is that, if household does not face timing restrictions, they will visit the store uniformly given a long period of time. The further they depart from the uniform status; the higher restrictions they face.

in (consumption and production) timing choice. If households dislike routine [5], the model predicts those with higher (lower) income and education level on average would make more (less) diverse timing choices. Linking this with findings of compensatory variety thinking in the consumer goods markets (e.g. Yoon and Kim 2017), we can imagine a bigger picture where economically stuck households explore variety seeking in product choices, while others have options to seek variety in other activities. Of course, our discussion happens in markets where consumer inertia is common—the reduction of consumer inertia actually improves restrictive households' decisions. Our test provides support for choice modelers to reconsider estimating variety seeking effects using other approaches. For example, Adamowicz and Swait (2013) model variety seeking as a "strategy" of households, instead of passively followed by previous consumptions. Wang and Shankar (2017) propose to model variety seeking as a "hidden state". Those models are likely to better capture the compensatory variety seeking as a behavioral state. We expect such inter-disciplinary discussions will generate fruitful findings.

3. Data

The markets we investigate is from a recent IRI academic data set (Bronnenberg et al 2008). Four frequently purchased food and (non-alcohol) beverage categories in 2005 and 2006 are employed. We examine household choices of two top market share brands in each corresponding category, because those brands are likely to be households' first choice and are subjected to greater variety seeking switches. There are additional benefits of picking well-known products with high household exposure. Main products suffer less from the availability issue and thus it is more appropriate to assume such products are in households' choice set for all stores and weeks. Households also seem to be mostly familiar with those products and their characteristics, so that

[5] In his model, routine is more efficient for production, but less preferred by consumers; in contrast, temporal variety is more preferred, but less efficient.

learning effects are minimum. Those benefits help us rule out additional explanations for product switches.

Table 1 lists summary statistics of the selected brands. Those brands in each category take from 6% to 40% of the market share in each category. The average per unit price for each brand gives us some idea of the cost of choices in those markets.[6] Based on the most frequently purchased items, The cost is lowest for the yogurt category and is the highest for the carbonated beverage category.

[Table 1 about Here]

We employ the 2005 data to evaluate households' timing decisions associated with their shopping trips. There are 4557 households with shopping trip records in the sample. [7] To give readers some idea about households' timing choices, we plot the distribution of the shopping trips on each day of a week in Figure 1. Assuming they make weekly visits, while the top-left figure shows great dispersion at the aggregate level, at the individual (household) level, households are subjected to great heterogeneity in periodic visiting patterns. For example, Household A, B and C demonstrate increasingly concentrated (or restrictive) revisiting patterns. To characterize the restrictions on households' timing decisions, we compare the sum of the absolute difference between an individual household i's visiting frequency and a uniform benchmark, that is,

$$restrct_i \equiv \frac{7}{12}\sum_{j=1}^{7} \left|\frac{\sum_t D_{ijt}}{TD_i} - \frac{1}{7}\right|,$$

[6] The typical unit is defined as the most frequently purchased unit in each category. For example, in the carbonated beverage market, about half of the purchases are in the 144-ounce case (12 12-ounce bottles), and thus we calculate the unit price based on this volume. When the cost of the decision is high, the behavioral effect can be weaker.
[7] In the original sample, there are 5727 households. We drop 10% households with the fewest weekly visiting records. In the working sample, households have at least 39 weekly visiting records.

where j$\in \{1,2,\ldots,7\}$ represents each day for a week, $\mathrm{D_{ijt}} = 1$ if household i has yogurt shopping records in week t, and $TD_i = \sum_j \sum_t D_{ijt}$ is the total number of visiting days for household i. For each day j, we compare the probability of visiting with the uniform case where the household visit each day at equal probability (1/7). The deviations are summed up and normalized to be within unit value. The measure allows us to capture the tendency for a household to focus her shopping days within each week. For example, when $\mathrm{struc_i} = 1$, the measure suggests that households only focus on one of the seven days; when $\mathrm{struc_i} \approx 0$, it suggests that households make their yogurt purchase trips within a week almost randomly.

[Figure 1 about Here]

Figure 2 shows the distribution of the "$\mathrm{restrict_i}$" measure for households with recorded shopping trips in at least 40 weeks in the year 2005. The average structural periodicity level is around 0.22 and standard deviation around 0.14. Because the distribution is not symmetric, we also report important percentiles on a second x-axis on the top of the figure. The distributions show the majority of the households have the measure under 0.5. When a household is associated with such a relatively higher timing restriction, she can focus her main shopping trips in any one or two days of a week. This leads to different ways of restrictive choices.

[Figure 2 about Here]

[Figure 3 about here]

Essentially, "restrict_i" is a measure of how one distribution diverges from a uniform benchmark. It is similar to the Kullback-Leibler divergence (or the relative entropy), which is more commonly used in information system literature (Mackay 2003). Formally, the Kullback-Leibler divergence of our household visiting periodicity strength is defined as the weighted average of the logarithmic difference.

$$\mathrm{D}_{\mathrm{KL}}\,(P||Q) = \sum_i P(i) \cdot \log\frac{P(i)}{Q(i)},$$

where $\mathrm{P(i)}=\frac{\sum_t D_{ijt}}{TD_i}$ represents households' shopping time i's occurrence probability and $\mathrm{Q(i)} = \frac{1}{7}$ captures the idea that households can choose any day to visit—a fact that implied by households' aggregate visiting pattern. The difference between our rule-of-thumb measure and the entropy measure is that our measure punishes deviation in a more intuitive and linear way, while the later measure is formulated from the information coding perspective. The two measures are highly correlated, with the Pearson's correlation coefficient around 0.95. Therefore, we use this later measure for robustness check.

To motivate further analysis, we first provide some brand switch statistics. We use the 2005 data to calculate households' periodicity strength for shopping visits and compare statistics on brand switches in 2006 at different levels of visiting restriction. Figure 3[8] reports the local constant estimates of the households' average number of brand switches for main brands in the four IRI markets. In general, higher number of switches seems to associated with households with restrictive revisit time. But the relation is not linear: when restriction measure is less than 0.4—which accounts for about 90% of the sample—the curve is relatively flat; the rest 10% house-

[8] When drawing the figure, extreme cases (top 1% and bottom 1 %) are excluded. Those households reveal great noise in product choices.

holds (434 out of 4557) however are responsive to such restrictions. By separately plotting histogram for this group of households, Figure 4 gives us more intuition of this measurement. Compared with other households, households with restrictive timings (on average) tend to spend more time shopping during the weekend. Again, this does not mean restrictive households only choose weekend for grocery shopping, there can be households who focus more on other weekdays; but at the aggregate level, those who shop on weekend are disproportionately more among restrictive households.

[Figure 4 about here]

Restrictive households can be different from other households in predictive ways. Demographic information can potentially explain some of the variations. The IRI data provides us with a set of households' demographic information including household income, family size, education level and work time at the household level. Utilizing the variations, a straightforward OLS model gives us some basic correlational facts.[9] Family size is negatively correlated with structural periodicity as expected, because the visiting trips come from multiple members can be nosier. Household head's education level negatively affects periodicity strength, while household income level does not have a clear impact. [10] Household age seems to have a positive effect. Most occupation categories[11] are not statistically different from each other, while households with retired heads are associated with stronger periodicity. Marriage status does not show any

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[9] In Appendix Table 4, we list the detailed regression results.
[10] Education has been documented to be positively correlated with variety seeking behavior, since higher education leads to higher optimal stimulation level (Raju 1980).
[11] The IRI dataset defines household occupation in 12 categories, including: "Other", "Professional or technical", "Manager or administrator", "Sales", "Clerical", "Craftsman", "Operative", "Cleaning, food, health service worker", "Private household worker", "Retired", "Not employed".

significantly differential effects after controlling for the household family size. Overall, the above variables only explain a small proportion (about 16%) of the variations in households restrictive timing.

4. Estimation Model and Results

We pick well-received and commonly purchased brands in different markets based on market shares. Those brands are selected and summarized in Table 1. We use the data in year 2005 to calculate the "restrict" variable and that in year 2006 to test possible differences. At the brand level, the regression analysis considers full interactions of main choice determinants—the price and the state dependence dummy variable of last shopping trip choice—and Household h's demographic information variables, $\mathrm{H_h}$ (household size, income, education, age of the household heads). In addition, the model considers the effect of visiting timing restrictions ($\mathrm{restrict_h}$) on brand choice. That is,

$$Y_{hjt}^{p} = 1 \ if \ \alpha P_{jt} + \gamma State_{hjt} + H_h\beta_1 + P_{jt} \cdot H_h\beta_2 + State_{hjt} \cdot H_h\beta_3 \ldots$$

$$\ldots + \alpha_2 \cdot P_{jt} \cdot restrict_h + \gamma_2 \cdot State_{ijt} \cdot restrict_i + Z_{hjt}\beta_4 + \cdots$$

$$\ldots + \{WeeK\ Dummies\} + \alpha_h + \epsilon_{ijt} > 0$$

In the above equation, we directly model household h's choice of the target brand at store j and shopping trip t. P_{jt} represents the price index for the brand j at the corresponding shopping trip; $State_{ht}$ captures the state dependence effect; $restrict_h$ reflects household h's periodicity. We also consider control variables ($\mathrm{Z_{hjt}}$) including the price indices for the rest products on the market, past experience (cumulative effects of past consumption), the squared term of past experience, total shopping trips and weekly fixed effects. Households' previous years' total shopping trips are controlled. We estimate the above random effects bivariate logit models for different target brands on corresponding shoppers who have more than 20 relevant purchases in 2006.

Our coefficients of interest involve the interactive effects of timing restrictions on state dependence. We expect households with strong revisit restrictions are more variety seeking or are associated with reduced state dependence. We are also interested in how restrictive households respond to economic incentives; we report the effects of timing restrictions on households' price response and compare them with regular shoppers.

Marginal effects at zero as well as two important quantiles, 50% and 95%, of the restriction levels are listed in Table 2. As expected, when revisiting timing is not restrictive, all markets witness significantly positive state dependence effects. However, such strong inertia is reduced for most cases, resulting in weak or no inertia for the extremely restrictive households. This trend suggests a promising moderating effect of visiting restrictions, after controlling for household demographics. Unlike the state dependence coefficients, effects of routine strength on marginal price are more nebulous. In three brand-market pairs, the restrictive households become more price sensitive. Notice that those households are also associated with lower education level.

<Table 2 about Here>

The measure of timing restrictions in the above estimations is quite general and does not consider different restrictions households may face. In the Data section, we demonstrate that, at the aggregate level, there are disproportionately more households allocating shopping time to weekends. If this restriction is driving the result, we would expect to see similar result for a weekend shopping index. Table 3 lists the results using average percentage of weekend shopping instead of the original restriction measure: we see (weaker) decreasing trends in four out of six cases from three markets. Moreover, in the carbonated beverage market, the trends are completely reversed: households who make weekend shopping visits primarily are subjected to stronger inertia and the reversed trend is significant for Coke. Therefore, weekend shopping only accounts for a portion of effect of the periodic measure. For carbonated beverage, it has to be the case that, at the same (high) level of restrictions, households who focus their shopping trips on weekdays are more variety seeking so that they offset the reversed effects of state dependence for week end shoppers. On the one hand, weekday purchase is more relevant for personal consumption, while weekend purchase can be related to social activities. The former demands more compensatory variety. On the other hand, weekend shopping can involve larger packages of products—especially for the carbonated beverage category. The decision cost of a brand switch can be much higher.[12]

<Table 3 about Here>

Finally, we provide the exact same estimations using the more formal cross entropy measure. This measure has been widely used in data mining and for comparing distributions from the information coding perspective. In Appendix Table 7, we report the same estimation table using this measure. The removal of inertial effects happens in all brand-market cases, yet the effects are slightly weaker.

[12] This does not suggest that variety seeking only happens at quick shopping trips with minimum expenditure. As we report in the Appendix Table 6, when increasing the minimum expenditure for shopping visit to 10 US Dollars, the decreasing trend for restrictive households are preserved for most cases.

It is worth noting that the variety seeking tendency in all of the cases are not directly observed—we have been treating the weakening inertia as evidence of variety seeking during our analysis. This confirms that inertial effects, defined as the direct effect of past purchases, may be considerably stronger and dominate for most of the time. However, if the weakening of inertial is due to variety seeking, it raises question for the practice of estimating variety seeking directly based on previous choice. Because the households may face unexpected restriction in unobserved choice domains, leading to temporary compensatory variety seeking in the current choice. For better identifying variety seeking using field data, researchers may benefit from introducing extra variations related to consumption backgrounds and jointly consider timing and other major choice scenarios together.

5. Conclusion

In this paper, we investigate households' periodic purchase patterns in various non-durable experience food markets. We construct a measure of periodic strength, by which, the households' purchasing behavior can be compared in a novel dimension. We hypothesize that such visit timing decisions reflect households' restrictions in their timing choice—an important source variety; and such restriction may affect households' product choices in specific markets.

After controlling for individual and time differences, we confirm negative effects on previous choices for restrictive households. Such effect is robust controlling for households' characteristics such as income, age, education and family size. Moreover, the effect is particularly strong for products that are purchased for personal consumption, rather than social demand.

Our findings have two broader messages for modeling variety seeking preference in the field. First, when the stake of decision is not high, consumers' product choices may not be modeled as a rational decision maker with symmetric, unbiased decision errors like most economic models consider. Nor should we completely ignore the cost of decisions: in the field, they still make important tradeoffs between the cost and benefit. We should jointly consider timing decisions, and allow unobserved states where consumers are more variety seeking.

Second, variety seeking is likely to be a comprehensive measure of product experience and consumption context (timing). The periodic strength measure is more seen in data mining literature and is rarely used in consumer research. It offers a way to collect the group of households who concentrated their shopping visits in any day of the week and evaluate such group's product choice. Periodicity strength, as well as other data mining measures, provide possible ways to diagnosing products' usage and with econometric tools, we can establish more concrete evidence of variety seeking relating to each product.

Because households can occasionally get into a restrictive state and demand extra variety, providing variety becomes an effective strategy for firms to boost demand. This partly explains why many supermarkets are providing more varieties over the past several decades. Our paper shows a specific source of variety seeking due to restrictions in other choice domains and it is possible to track those households using data mining based methods. It becomes an ethical issue for firms to optimize both product choices and prices against those time of shoppers. Although opportunistic price hike against restrictive households seems to be inappropriate, sometimes, by using data mining tools, firms may not realize that they are penalizing households who are constrained and would like some choices. Without clear interpretation, data-mining driven methods seem to have unclear impact to our welfare.

Table 1 Descriptive Statistics in IRI Markets

IRI MKT	Top Sale Brand	MKT Share	Unit-Price	Std.Dev.
Yogurt	Yoplait ORG/LIT	27.40%	0.583	0.127
	Dannon L&F	11.55%	0.631	0.167
Soup	Campbells	40.46%	0.994	0.316
	Progersso	14.55%	1.060	0.369
Salty Snacks	Lays	12.97%	2.336	0.798
	Doritos	6.39%	2.568	0.667
Carbonated Beverage	Coke Classic/ Diet	16.63%	3.667	1.943
	Pepsi/ Diet Pepsi	13.14%	3.705	1.978

Figure 1 Examples of Periodic Purchase Patterns

Figure 2 Histogram for Structural Periodicity

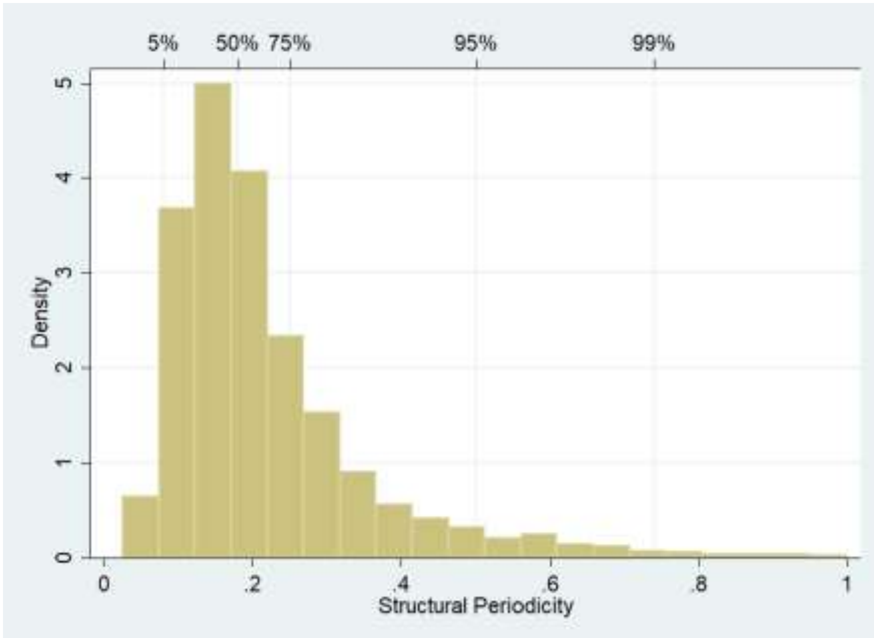

Figure 3 Product Switches and Periodic Shopping Visits

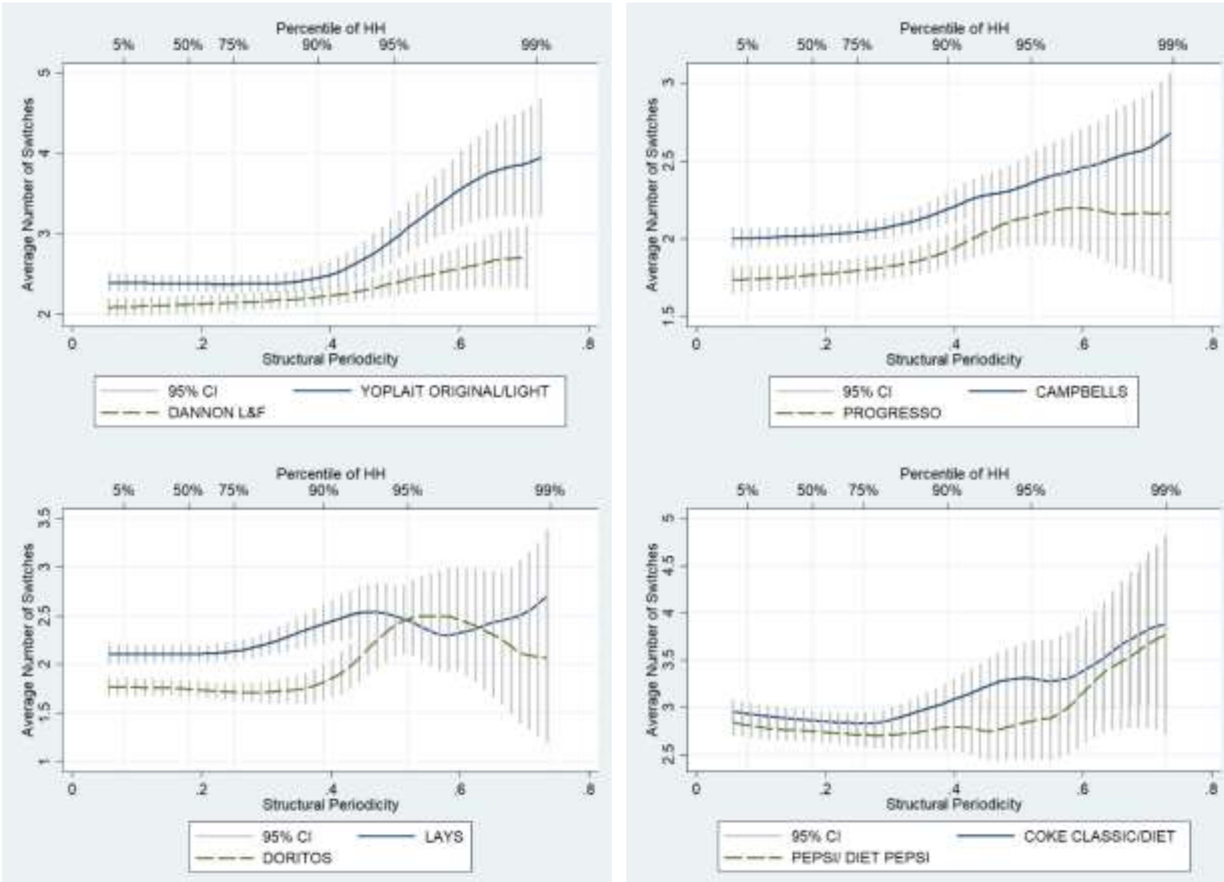

Figure 4 Group Comparison: Households' revisit timing choice (by day)

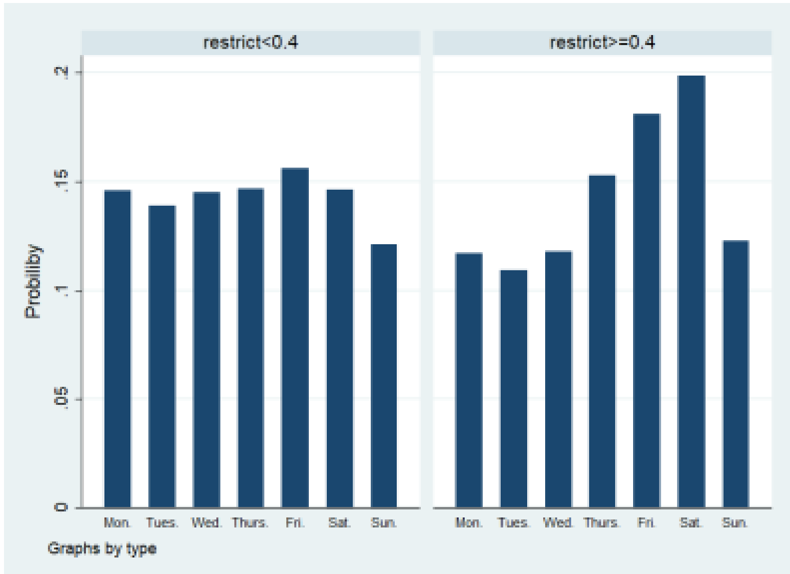

Table 2 Marginal Effect of Periodicity Strength on State Dependence and Price

		On State Dependence			On Price		
	Percentile	0th	50th	95th	0th	50th	95th
Yogurt	Yoplait	0.0741***	0.0609***	0.0345*	-0.606***	-0.600***	-0.589***
		(0.0160)	(0.00882)	(0.0161)	(0.0913)	(0.0525)	(0.121)
	Dannon	0.0602***	0.0454***	0.0230*	-0.112***	-0.131***	-0.160***
		(0.0149)	(0.00733)	(0.0102)	(0.0310)	(0.0189)	(0.0443)
Soup	Campbells	0.0934***	0.0599**	0.0114	-0.248*	-0.602***	-0.739***
		(0.0278)	(0.0212)	(0.0444)	(0.105)	(0.0885)	(0.208)
	Progresso	0.0190	0.0178*	0.0124	-0.0598***	-0.0594***	-0.0508*
		(0.0111)	(0.00722)	(0.0132)	(0.0180)	(0.0116)	(0.0216)
Salty Snacks	Lays	0.0242*	0.0118**	-0.00432	-0.0439***	-0.0556***	-0.0680***
		(0.00964)	(0.00444)	(0.00828)	(0.00665)	(0.00370)	(0.00864)
	Doritos	0.00152	0.00124	0.000786	-0.0251***	-0.0242***	-0.0222***
		(0.00532)	(0.00280)	(0.00562)	(0.00394)	(0.00233)	(0.00451)
Carbonated Beverage	Coke	0.0360**	0.0208***	0.00194	-0.0771***	-0.0599***	-0.0318***
		(0.0118)	(0.00538)	(0.00865)	(0.00812)	(0.00404)	(0.00679)
	Pepsi	0.0138**	0.00833***	-0.000155	-0.0139***	-0.0118***	-0.00805*
		(0.00443)	(0.00222)	(0.00420)	(0.00301)	(0.00165)	(0.00331)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3 Marginal Effect of Weekend Shopping on Sate Dependence and Price

		On State Dependence			On Price		
	Percentile	0th	50th	95th	0th	50th	95th
Yogurt	Yoplait	0.0557***	0.0593***	0.0636***	-0.711***	-0.631***	-0.533***
		(0.0166)	(0.00839)	(0.0159)	(0.117)	(0.0500)	(0.0833)
	Dannon	0.0583***	0.0409***	0.0259**	-0.231***	-0.146***	-0.0662*
		(0.0163)	(0.00647)	(0.00951)	(0.0530)	(0.0189)	(0.0272)
Soup	Campbells	0.117***	0.0803***	0.0362	-0.464***	-0.480***	-0.474***
		(0.0294)	(0.0158)	(0.0290)	(0.117)	(0.0671)	(0.114)
	Progresso	0.0115	0.0134*	0.0142	-0.0439**	-0.0588***	-0.0763**
		(0.00745)	(0.00561)	(0.0123)	(0.0144)	(0.0107)	(0.0234)
Salty Snacks	Lays	0.0144	0.0108*	0.00768	-0.0739***	-0.0590***	-0.0457***
		(0.0105)	(0.00431)	(0.00725)	(0.00849)	(0.00366)	(0.00552)
	Doritos	0.00942	0.00426	-0.000860	-0.0313***	-0.0240***	-0.0160***
		(0.00693)	(0.00296)	(0.00439)	(0.00493)	(0.00228)	(0.00321)
Carbonated Beverage	Coke	-0.00698	0.0128*	0.0359***	-0.0735***	-0.0578***	-0.0399***
		(0.0104)	(0.00505)	(0.0104)	(0.00919)	(0.00385)	-0.0399***
	Pepsi	0.00526	0.00584**	0.00616	-0.0112***	-0.0111***	-0.00954**
		(0.00322)	(0.00198)	(0.00438)	(0.00259)	(0.00149)	(0.00318)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Research. Forthcoming.

Appendices

Table 4 Demographic Information and Restrictions in Visiting Patterns

	Restrict
familysize	-0.00772***
	(0.00194)
hh_age	0.00732***
	(0.00193)
hh_edu	-0.00666***
	(0.00152)
combinedpret-axincomeofhh	-0.000889
	(0.000913)
hhworkhour	0.00190
	(0.00225)
count	0.00800***
	(0.000793)
totaltrips	-0.00120***
	(0.0000706)
constant	0.00746
	(0.0486)
occupation	Yes
marital stat	Yes
N	4544
R-squared	0.16

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5 The Effect of Periodicity Strength on Product Choice (Main Coefficients Shown)

	Yoplait Original/ Light	Dannon L&F	Camp- bells	Pro- gresso	Lays	Doritos	Coke Classic	Pepsi
lagchoice	1.281***	2.130***	1.127*	0.852	0.282	-0.639	0.244	0.442
	(0.367)	(0.420)	(0.552)	(0.948)	(0.234)	(0.547)	(0.202)	(0.261)
price1	-8.866***	-4.924**	-1.756	-0.922	-0.473**	-0.773**	-0.181	-0.0898
	(1.490)	(1.506)	(2.130)	(1.338)	(0.154)	(0.296)	(0.124)	(0.181)
restrict	0.325	1.662	1.015	-0.461	0.770	-1.703	-2.474***	-0.392
	(1.096)	(1.140)	(1.650)	(1.302)	(0.516)	(0.912)	(0.700)	(0.917)
lagchoice*restrict	-0.491	-0.737	-0.367	-0.412	-0.333	-0.498	-0.256	-0.275
	(0.326)	(0.407)	(0.358)	(0.630)	(0.256)	(0.519)	(0.241)	(0.299)
lagchoice*income	0.00998	-0.0260	-0.110***	-0.0570	0.00245	0.00788	-0.0359**	-0.0127
	(0.0242)	(0.0279)	(0.0268)	(0.0488)	(0.0163)	(0.0385)	(0.0137)	(0.0177)
lagchoice*hh_edu	-0.0421	-0.0623	0.0463	-0.0951	0.0404	0.0811	-0.00891	0.0150
	(0.0331)	(0.0424)	(0.0435)	(0.0766)	(0.0235)	(0.0578)	(0.0209)	(0.0260)
lagchoice*familysize	-0.142**	-0.109	0.101	0.120	-0.0652*	0.0209	0.0531	0.0202
	(0.0510)	(0.0641)	(0.0759)	(0.127)	(0.0323)	(0.0663)	(0.0300)	(0.0390)
lagchoice*hh_age	-0.0252	-0.106	-0.0765	0.0546	-0.0298	0.0750	0.0226	-0.0685
	(0.0518)	(0.0600)	(0.0708)	(0.128)	(0.0346)	(0.0809)	(0.0299)	(0.0407)
price1*restrict	-0.331	-3.041*	-2.861*	1.577	-0.629***	0.535	0.158	-0.00648
	(1.371)	(1.457)	(1.458)	(0.897)	(0.173)	(0.321)	(0.144)	(0.208)
price1*income	0.205*	0.0732	0.129	0.0820	0.0260*	-0.00854	-0.000155	0.00616
	(0.103)	(0.0983)	(0.104)	(0.0734)	(0.0109)	(0.0220)	(0.00833)	(0.0118)
price1*hh_edu	-0.0974	-0.000873	-0.0305	-0.123	0.000500	0.0464	0.00890	0.0277
	(0.143)	(0.155)	(0.172)	(0.117)	(0.0162)	(0.0320)	(0.0133)	(0.0183)
price1*familysize	0.244	0.320	-0.242	-0.285	-0.0395	-0.144***	-0.0366*	0.0158
	(0.218)	(0.229)	(0.292)	(0.189)	(0.0218)	(0.0405)	(0.0184)	(0.0269)
price1*hh_age	0.335	0.344	0.0453	-0.0799	-0.00763	0.0421	-0.0490**	-0.101***
	(0.214)	(0.217)	(0.270)	(0.179)	(0.0229)	(0.0460)	(0.0180)	(0.0275)
…	…	…	…	…	…	…	…	…
constant	3.104**	-2.220	2.123	-4.067*	-2.227***	-1.349	-2.040**	-3.143***
	(1.200)	(1.245)	(2.373)	(1.914)	(0.555)	(0.904)	(0.638)	(0.848)
Cluster	652	652	305	305	1336	1336	1505	1505
N	17823	17823	7642	7642	36830	36830	43711	43711

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6 Marginal Effect of Periodicity Strength on State Dependence and Price (shopping trips with minimum expenditure of 10 USD)

		On State Dependence			On Price		
	Percentile:	0th	50th	95th	0th	50th	95th
Yogurt	Yoplait	0.0738***	0.0606***	0.0344*	-0.603***	-0.597***	-0.585***
		(0.0160)	(0.00882)	(0.0161)	(0.0914)	(0.0526)	(0.121)
	Dannon	0.0596***	0.0451***	0.0230*	-0.112***	-0.130***	-0.158***
		(0.0149)	(0.00730)	(0.0102)	(0.0310)	(0.0189)	(0.0439)
Soup	Campbells	0.0927***	0.0605**	0.0130	-0.256*	-0.607***	-0.741***
		(0.0277)	(0.0212)	(0.0445)	(0.105)	(0.0885)	(0.208)
	Progresso	0.0181	0.0151*	0.00458	-0.0595***	-0.0590***	-0.0497*
		(0.0108)	(0.00700)	(0.0114)	(0.0179)	(0.0117)	(0.0212)
Salty Snacks	Lays	0.0244*	0.0119**	-0.00429	-0.0463***	-0.0566***	-0.0672***
		(0.00964)	(0.00444)	(0.00830)	(0.00668)	(0.00372)	(0.00860)
	Doritos	0.00652	0.00281	-0.00280	-0.0251***	-0.0216***	-0.0157***
		(0.00550)	(0.00278)	(0.00501)	(0.00385)	(0.00221)	(0.00406)
Carbonated Beverage	Coke	0.0359**	0.0208***	0.00202	-0.0765***	-0.0590***	-0.0308***
		(0.0118)	(0.00537)	(0.00862)	(0.00809)	(0.00401)	(0.00669)
	Pepsi	0.00172	0.00497*	0.0103	-0.0118***	-0.0112***	-0.0101**
		(0.00379)	(0.00214)	(0.00534)	(0.00298)	(0.00164)	(0.00350)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 Marginal Effect of Periodicity Strength on State Dependence and Price (With the Kullback-Leibler divergence measure)

		On State Dependence			On Price		
		0th	50th	95th	0th	50th	95th
Yogurt	Yoplait	0.0664***	0.0634***	0.0392*	-0.597***	-0.603***	-0.654***
		(0.0103)	(0.00898)	(0.0165)	(0.0568)	(0.0507)	(0.117)
	Dannon	0.0462***	0.0428***	0.0218*	-0.129***	-0.134***	-0.158***
		(0.00846)	(0.00713)	(0.00931)	(0.0216)	(0.0193)	(0.0408)
Soup	Campbells	0.0874***	0.0837***	0.0427	-0.406***	-0.444***	-0.651***
		(0.0194)	(0.0171)	(0.0347)	(0.0774)	(0.0697)	(0.147)
	Progresso	0.00990	0.0101	0.0118	-0.0603***	-0.0594***	-0.0471*
		(0.00627)	(0.00564)	(0.0133)	(0.0127)	(0.0112)	(0.0228)
Salty Snacks	Lays	0.0151**	0.0127**	-0.00131	-0.0545***	-0.0566***	-0.0674***
		(0.00540)	(0.00450)	(0.00846)	(0.00426)	(0.00374)	(0.00804)
	Doritos	0.00966*	0.00837*	0.000309	-0.0227***	-0.0228***	-0.0235***
		(0.00384)	(0.00325)	(0.00540)	(0.00253)	(0.00228)	(0.00440)
Carbonated Beverage	Coke	0.0240***	0.0198***	-0.00222	-0.0631***	-0.0591***	-0.0302***
		(0.00672)	(0.00553)	(0.00783)	(0.00484)	(0.00410)	(0.00616)
	Pepsi	0.00956***	0.00935***	0.00772	-0.0111***	-0.0110***	-0.00990**
		(0.00261)	(0.00229)	(0.00445)	(0.00182)	(0.00161)	(0.00311)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$