The Effect of Periodic Structure in Household Visiting Patterns

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Maintaining a strong repurchasing cycle may be not easy for households, because such routinization requires a significant amount of self-control against consumption uncertainties, external shocks and other schedule conflicts. Are households with "structural" repurchase patterns associated with better self-control, or they simply face constraints which limit their timing choices? We investigate household repurchase periodicity and its impact on product choices using scanner datasets in the Yogurt and Carbonated Beverage categories. Product-market level analysis shows that "structural households"—households with strong periodic purchase patterns—are associated with weaker consumer inertia and have more product switches recorded. However, weak evidence shows that such improved decision making can be attributed to self-control; the data is more consistent with the explanation that structural households are more easily satiated and prefer more variety in product choices.

Keywords: periodic purchase patterns, scanner data, heterogeneity, state dependence

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1. Introduction

In frequently purchased product markets, consumers usually need to follow certain visiting cycles to repurchase the products. For example, a weekly yogurt purchaser 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 them with strong periodic patterns. It is possible that consumers[1] of those households face unobserved cost or time constraints, and thus have a relatively fixed repurchase time. The limitation on the shopping time also implies that they are less able to search for better alternatives and can be associated with lower price sensitivity. Alternatively, households with fixed repurchase cycles may plan their week's shopping in advance and have better control over their subsequent consumption schedule. This later explanation implies that households view regulating repurchases beneficial. For example, by following a stable periodic pattern, they may organize their alternative activities better. No matter how a household manage to achieve a stronger repurchase periodicity (by fighting for a narrow window or executing a previous plan), those who practicing repurchase in such a periodic way over and over may demonstrate different product choice patterns. How does the "structural" periodicity correlated with purchase behavior and brand choices? What are the main explanation for households to follow a strong repurchase pattern? Do consumers obtain extra benefit if they

[1] Because our data is at the household level, the strong periodic patterns may be due to one or more purchasers of a household. We will use "household" hereafter.

choose to follow such pattern? We empirically investigate the potential behavioral effects of households' periodic purchase patterns in several scanner datasets.

A better understanding of households' (re)purchase patterns benefit marketing researchers, business practitioners, as well as policy makers. Periodicity is one of the most easily and accessible information for sellers, because repurchases happen in open public and purchase history can be collected in a less aggressive way. Such information, if proven to be predictive for purchase behavior, can be crucial for retailers and manufactures to understand the demand of individual households under an increasingly competitive packaged good markets. Therefore, this paper focuses on how periodic purchase behavior helps us learn households' revealed preference. From policy perspective, it is important to distinguish among different causes of the purchase patterns as they have different welfare implications. If the strong periodic patterns are related to time constraints or other demographic information, households are likely to be worse off against price-based marketing strategies. If strong periodic patterns are due to self-control, households may be more aware of the product or the variations of the prices.

To empirically test the effects of periodic patterns on product and brand choices, "Structural" periodicity is introduced and explained. Given that consumers are likely to make weekly purchases in the investigated markets; we focus on how repurchase time choices are deviated *within* a week. We provide rich descriptive evidence to demonstrate the correlation between previous households' purchase patterns and demographic variables as well as their later choice decisions. Next, a set of econometric models are specified in hope to capture the behavioral differences of "structural households" controlling for potential product/ brand characteristics and random effects.

Our descriptive patterns in the dataset shows that: 1) Households' periodic patterns are associated with cost-based general demographic variables. 2) "Structural" households make more product switches, and the switches are significantly improved in the yogurt category. Econometric models provide a closer look at the above possibilities. Discrete choice models with random effects report results that are generally consistent with what we expect: they are subjected to weaker state dependence. Further evidence in price responses and the main effect of structural periodicity help us test the explanation behind such improved decision making. We find that responses in both markets support a constraint-driven satiation explanation. In the yogurt market, a few households with strong repurchase structure become more price sensitive, indicating that self-control may play some roles.

The main dataset we use is the IRI scanner data set; another old ERIM scanner dataset (1986-1988) is also used so that we can compare the robustness of the results in yogurt markets 30 years ago and later. One concern with an old dataset is that yogurt buying patterns may change significantly over time. However, we are interested in the behavioral patterns that should be fundamental to a general buyer; the significance of the effect may help strengthen our view. The results we obtain are suggestive that part of the households in the sample make more cautiously repurchase choices; however, self-control plays a limited role in product choices: "structural" households do not choose healthier items with low calorie and fat content more. This leaves alternative explanations of time constraint and satiation more plausible for the observed empirical patterns. By investigating shopping revisits using classic scanner datasets, our result hopes to bridge literature on the consumer inertia, variety seeking and on self-control. Without accounting for repurchase periodicity, the state dependence in product choices may be over-estimated for "structural" households.

2. Literature

The literature is scarce regarding how households' within-period timing decisions may affect brand choices. Conventional choice models tend to assume households are passively affected by (arbitrary length of) previous purchases/ consumptions and the past behavior already affects product choices in various ways (Chandukala et al 2007). Identification of different effects of past behavior (Seetharaman 2004, Dube et al 2010) becomes the main focus. For example, using scanner datasets, Dube et al (2010) test the "structural state dependence" against other possible explanations that may lead to similar inertia behavior, and confirm the "structural state dependence" as a result of incautious habitual decision making, rather than product learning or high switch cost. Using experimental methods, the effect of routinization can be studied and such choices usually lead to more habitual decision makings. Beltsch et al (2001, 2003) demonstrate that costless routine strength significantly slow down adaption. However, from economic and marketing perspectives, the formation of routine itself may not be easy and can require additional energy to maintain, especially when temptations or external shocks are strong. In our empirical analysis, product repurchase timings can be hard to regulate. An unexpected family guest, a project with short deadline, or an immediate desire for ice cream can easily disturb one's regular schedule—if they do choose to have one. Facing uncertainties, it is important to ask what benefit a household may gain from a more regulated revisiting pattern?

On one hand, for virtue products (Wertenbroch 1998), structural repurchases help households to form a healthy life style and keep consumers from buying unhealthy snacks. On the other hand, a structural shopping pattern may be better incorporated with other activities which is more important to regulate, such as learning or working on a long term project. In addition, a byproduct of structural repurchases, implied by the strength theory of self-control (Muraven and

Baumeister 2000, Baumeister et al 2006), is that households get a good practice maintaining strong repurchase patterns and end up with better self-control and more cautious decision makings. Therefore, there may be a potential link between costly routinization (in terms of repurchase timing decisions) and the self-control ability, and such link may influence other decision domains, including product choices.

There is extensive literature in both Psychology and Economics on the topic of self-control[2]. Early studies usually consider how myopic temptations are related to self-control (Mischel et al 1972, the famous "Marshmallow test"). More recent studies demonstrate that resisting a temptation requires energy and the self-control process is governed by limited resources. Therefore, self-control depletion usually results in lower subsequent self-control performance (Muraven et al1998, Baumeister et al 2007) and can potentially lead to more unethical behavior (Gino et 2011). One interesting implication of this limited resource argument is that the function of self-control may resemble a muscle such that regular exertions of self-control may improve power strength (Muraven and Baumeister 2000, Baumeister et al 2006). Those findings have inspired recent studies of consumer buying behavior. For example, Houser et al (2008) designs a set of natural experiments utilizing items on sale next to grocery checkout aisles and demonstrates the effect of temptation based on theories introduced by Ozdenoren et al (2012). Periodicity can be related to levels of self-control: because maintaining a repurchase structure is not easy, if households cautiously follow such pattern, much self-control is required, which can affect product choices.

There is another, perhaps more intuitive explanation for structural households: households may simply face constraints, have limited number of available time slots or are exposed to less

[2] Self-control or self-discipline in this paper is broadly defined as the capacity for altering one's responses for long-term goals.

temptations. If this story is more close to the truth, (passively or costlessly) routinization can foster satiation (McAlister and Pessemier 1982), which may eventually spillover to other decision domains. Satiation is a commonly observed phenomenon in lab experiments. It is well documented that households have variety seeking preferences due to brand/ product satiation (McAlister 1982, Lattin and McAlister 1985, Fein et al 1992, etc.). However, with a purchase data set, such phenomenon is considerably weaker, mainly due to the opposite and stronger consumer inertia. For structural households, the lack of timing choice may intensify satiation, because additional attention resource can now be devoted to product themselves and product search. The increased attention may play an important role in consumer behavior. For example, Morewedge et al., 2010, Redden & Haws, 2013, Larson et al., 2014 have all documented evidence that attention accelerates satiation. Therefore, under this conjecture, we would expect structural households are more likely to be satiated and are willing to switch—which is also a cautious decision, compared to habitually falling into past options. Unlike the self-control explanation, satiation may lead to a negative state dependence and it does not require long term benefits, which are important to motivate self-control behavior.

Factors that explain household heterogeneity are of great importance in marketing applications. The adoption of mixed models (Rossi and Allenby 2005, Train 2009) has provided flexible ways to model demand in packaged good markets and achieve the segmentation goals. For example, Allenby and Lenk (1994), Gupta et al (1994) show that households' demographic information, such as household income and household size significantly correlate with households' brand choices. Shankar and Krishnamurthi (1996), Kim et al (1997), Kim et al (1999), Ainslie and Rossi (1998), Boatwright et al (2004) demonstrate that different measures of shopping patterns and characteristics may effectively predict households' price sensitivities as well as effects of other marketing strategies. The effects of marketing variables have also been related to consumption occasions. Wakefield and Inman (2003) investigate the interaction of hedonic needs and income on households' price sensitivities. Price awareness may also affect households' brand choices, as demonstrated by Binkley and Bejnarowicz (2003); they show that buyers with high opportunity costs tend to be less aware of quantity surcharges. Our paper contributes to the strand of literature by proposing a new behavioral measure to explain household choices and the effects of various marketing strategies, while controlling cross-sectional heterogeneity using random effects.

3. Data

We first investigate a recent IRI dataset; and then additional estimations are provided based on an old ERIM[3] dataset for robustness tests[4]. Two IRI categories from 2004 and 2005 are selected. The first involves the refrigerated yogurt category and because ERIM data also has this category, we can compare estimation results cross periods. The second one is the carbonated beverage category so that we can further examine possible explanations, especially whether structural consumers act differently with virtue and vice products. Products in both categories are likely to be purchased on a weekly[5] basis so that the structural periodicity measure is well defined. Approximately 2783 households in the yogurt markets and 3583 households in the soft drink market are selected into our sample, because they are frequent shoppers with visiting records in most of the weeks in a year. We collect those households' product choices in the corresponding markets, as well as

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[3] The ERIM datasets consist of household level purchase history data from year 1986 to 1988 in two mid-sized cities in US (Sioux Falls, South Dakota and Springfield, Missouri).

[4] Note that the IRI scanner datasets provide market based shopping trip information (rather than product based), so that the periodicity measure contains repurchases related to all products (See IRI Dataset Manual Version 1.5 Page 17 footnote 15, or discussions in the Appendix). We list evidence from the old data in the Appendix for those who seek for more robustness tests and discussions.

[5] This assumption has been widely used in structural modeling (Erdem & Keane 1996) for nondurable experience food. In our context, it may be generalized to bi-weekly or tri-weekly decisions. For an empty week, we treat it as an outside choice and do not count when calculating periodic patterns.

product characteristics at the shopping occasions. To avoid the simultaneity problem due to the joint decisions of timing and product choices, we use the 2004 data to calculate the periodicity measure and use the measure to predict product choices in the year 2005. *Table 1* lists summary statistics of the IRI data: two top brands and their best selling products are considered in each market. In the yogurt market, Brand Yoplait and Dannon take roughly 61% of the total market share, while Coca cola and Pepsi take about 68% of the soft beverage market in the sample. We list each brand's core products: they are well known to consumers and share similar price distributions.

[Table 1 about Here]

Assuming households make weekly decisions, we plot the distribution of the shopping trips on each day of a week in Figure 1. While the top figure shows great dispersion at the aggregate level, at the individual (household) level, households are subjected to great heterogeneity in periodic shopping patterns. For example, the household in the center figure have similarly dispersed revisiting patterns, yet the household in the bottom figure concentrates most of the purchases on Monday and Saturday. In order to characterize such periodicity for weakly purchasers, we define the following variable, by comparing the sum of the absolute difference between an individual household i's visiting frequency and a uniform benchmark, that is,

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

where $j \in \{1,2,\ldots,7\}$ represents each day for a week, $D_{ijt} = 1$ 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. A possible combination for the mid-point $\mathrm{struc_i} = 0.5$ is that households choose four out of the seven days to make grocery purchases.

[Figure 1 about Here]

This measure captures the "structure" of households' revisiting pattern within each week. In an ideal setting, we hope to compare brand and product choices of households when varying only the measure of variable "struc". However, by construction, this measure may be correlated with the total visiting frequency: in the extreme case with only one shopping visit, the "struc" becomes one, since there is no variation of visiting days. To avoid the effect of total visiting days, we explore frequent purchasers with total visiting trips covering 80% of the weeks in a year. More than half of the households meet this criterion (80% in the yogurt data and 78% in the soft drink data). In addition, in the regression analysis, we directly control for the total number of shopping trips. *Figure 2* shows the distribution of the "struc" measure for the year 2004 in the IRI yogurt data for the 2783 households[6]. The distribution shows wide heterogeneity in terms of the repurchase structure. The structural periodicity measure ranges from 0.04 to as high as 0.93. Meanwhile, the majority of the households have relatively low structural periodicity. The average structural periodicity level is 0.2, with standard deviation around 0.13; 95% of the households have structural level

[6] The two examples illustrated in Figure 1 have the measure $\mathrm{struc_i}$ equal to 0.05 and 0.50 respectively.

lower than 0.46. Because the shopping trips are not product specific, we expect that the structural periodicity level can be affected by shopping decisions for other items. In the ERIM data sets, the periodicity measure is market-specific, and thus the measure is relatively higher[7].

[Figure 2 about Here]

Admittedly, there are multiple ways to measure households' purchase periodicity, and the measures also rely on the assumption of the unit of a decision period (which is one week in our case). Readers may be curious why we care about the "structural" perspective of the periodicity pattern defined above (the ability to focus their purchases on specific schedule *within each period*), rather than the "distributional" periodicity (the ability of maintaining regular consumption *across each period*). The later measure is likely to be affected by one's consumption preference and the persistence of the preference, which is subjected to endogeneity issues and more importantly, households in our IRI data have weekly visiting trips 80% of the time, leaving us with little variations in distributional periodicity. The structural periodicity can be more innocent and effectively reflect household visiting stableness. Therefore, we focus more on buyers who have different levels of structural periodicity. Our measure of "structural" households guarantees relatively high frequency of purchases and is likely to create exogenous variations in households' periodicity.

Based on the constructed variable of $struc_i$, we first consider some important correlational facts of the measure. Because it is a household level measure, one may compare the measure with other

[7] Figure 4 in the Appendix provides the histogram for the structural periodicity measure in the ERIM data set.

demographic information. The IRI data provides us with a set of households' demographic information including household income, family size, education level and work time for both male and female heads in a household. *Table 2* reports the regression results on how demographics are related to the new constructed variable. The correlational patterns are consistent with a constraint-based explanation. For example, having full time work is positively correlated with structural periodicity, indicating that full time workers have relatively narrower shopping windows. A negative coefficient in the income measure implies that households with high opportunity cost may have a more unstable shopping schedule, especially for frequent soft drink purchasers. Household education levels are negatively correlated with "struc", which suggests they face less outside temptations. However, the demographic variables only explain around 11% of the total variations in "struc", leaving the majority part of variations unexplained. Moreover, pairwise correlations reveal weak and insignificant correlations between each demographic variable (except household size) and the structural periodicity, suggesting that the effects of periodic repurchases, if any, cannot be easily approximated.

[*Table 2* about Here]

Next, we explore the potential link between product choices and the structural periodicity measure. Previous literature concludes strong inertial effects for households in package good markets, leading to lower probability of brand switches. Because both self-control and satiation may lead to less consumer inertia, we examine product switches using IRI 2004 and 2005 data. To be specific, we use the 2004 data to calculate households' (structural) periodicities for purchase timings and compare statistics on brand switches in 2005 with the measure of structural periodicity. We plot the average number of switches from main brands in the two IRI markets (clustered at the individual household level) and demonstrate the potential differences in *Figure 3*[8]. In the 2005 yogurt market, there are significant increases in brand switches for the two major brands (Yoplait and Dannon). There is a similar trend in the 2005 soft drink market, yet with much more noise at high periodicity levels. The switch statistics are suggestive that structural households are more likely to switch--especially for virtual products. However, switching behavior can also be affected by variations of product characteristics, in the next section, we use regression models to control for product characteristics and test the robustness of the possible correlation at both market-product level.

3. Estimation Models and Results

3.1 Model Specifications

To compare more detailed product responses, we pick well-received and commonly purchased products in different markets based on market shares. Those products are selected and summarized in *Table 1*. There are additional benefits of picking well-known products with high household exposure. First, 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. Second, due to a large number of purchases, those products have more accurate price information recorded at the different time and places. Third, households are mostly familiar with those staple products, so that learning effects are minimum. Therefore, we can construct a set of binary choice scenarios and evaluate the effect of structural periodicity on product choices without worrying about the above issues.

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

We use the data in year 2004 to calculate the "struc" variable and that in year 2005 to test possible differences. At the product level, the regression analysis considers full interactions of main choice determinants (the price and state dependence dummy variable) and two forms of household type variables (the household income and household periodic purchase patterns). In addition, the models also flexibly control for possible dynamic effects (the cumulative past consumption, weekly dummies). That is,

$$Y_{hjt}^{p} = 1 \; if \; \left(1, Price1_{jt}, LagChoice_{ht}, struc_h, Income_h\right)\beta^p + \cdots$$

$$\ldots + \left(Price1_{jt}, LagChoice_{ht}\right)(struc_h, Income_h)\beta_2^p + X\beta_3^p + \cdots$$

$$\ldots + \{WK\ Dummies\} + \alpha_h + \epsilon^p > 0$$

In the above equation, we directly model household h's choice of the target product at store j and shopping trip t (with yogurt or soft drink purchases). $Price1_{jt}$ represents the price for the product at the corresponding time and place under investigation; $LagChoice_{ht}$ captures the state dependence effect; $struc_h$ reflects household h's strength level of periodic shopping patterns; $\mathrm{Income}_\mathrm{h}$ is a discrete measure of household annual income. We also consider control variables including the price indices for the composite good, past experience (cumulative effects of past consumption), the squared term of past experience, total shopping trips and weekly fixed effects. The estimation data for each selected product is processed at the household-store-trip level and thus it consists a unbalanced panel. Notice that in the above product choice regression specifications, we only consider choices of yogurt/ soft drink products in each real shopping trips, so that a reduction of state dependence cannot be due to consumption breaks during some weeks. Households' total shopping trips are controlled so that structural and non-structural households with similar shopping level can be well compared. We estimate the above random effects Logit models for different target products on both frequent yogurt and soft drink purchasers who have more than 20 relevant purchases correspondingly in 2005.

Our variables of interest involve the interacted effects of state dependence, price, as well as the main effect of the structural periodicity measure. If a household with stronger structural periodicity has better self-control and makes more cautious decisions, we should see a weaker inertia effect, a preference for healthier products, as well as more sensible price responses. If most people passively follow repurchases, we expect a satiation driven variety seeking preference, captured by reduced or even reversed state dependence. The main difference between the two explanations is that, households with significant self-control are able to resist temptations that may be harmful in the long run.

3.2 Product Choices in the IRI Markets

Table 3 lists the random effect Logit models for each of the product-market pairs. All product-market pairs witness significantly positive state dependence effects: given previous choices, households are more likely to choose the same products. The significantly positive coefficients show that households' choices in the markets may be largely affected by habitual decision making. In the soft beverage market, the models report additional lagged effects for all products, indicating a profound impact of purchases in previous time. The main effects of structural periodicity do not have a clear pattern: structural households seem to choose significantly more Pepsi brand, however, low fat and low calorie products are not significantly preferred. *Table 4* and *Table 5* show the marginal effects of the state dependence and price at different levels of structural periodicity. The upper panels of the tables show that the state dependence effects for structural households are (monotonically) reduced for all product-market pairs and the differences are significant in the all product-market pairs (P-value < 0.05). Conditional on various control variables, the clear trend of the state dependence effect suggests a promising moderating effect of structural periodicity and calls for possible behavioral explanations behind the phenomenon. While both self-control and satiation can contribute to a reduced state dependence; only satiation leads to negative state dependence. For the choice problem of Diet Coke, the significantly negative coefficient shows that satiation plays an important role.

In the lower panel of *Table 4* and *Table 5*, most price coefficients have the expected signs and the statistical significance. For the majority households (when structural periodicity level is smaller or equal than 0.5), the marginal effects of price are significant. In the yogurt markets, we observed an increasing trend of mean price sensitivities. The economic scale is worth noticing: the semi-elasticities are increased and even doubled (e.g. Dannon L&F) for structural households. For example, one percentage decrease of price for Dannon L&F yogurt leads to a 5.5 percent increase in the choice probability for households with low structural periodicity; yet leads to a 10.3 percentage point increase for those with higher structural periodicity. This number increases to 17.3 percentage points for the extremely structural households, although the statistic is marginally insignificant (P-value=0.101).

The increasing trend of marginal price is completely reversed for the soft beverage market. In *Table 5*, the marginal effects of price are decreasing with the structural periodicity. For example, the semi-elasticity of Coke Classic drops from -0.08 to -0.05, and further drops to -0.03 for the extremely structural households. Perhaps reader may find a decreasing marginal effect on price at higher structural periodicity level is more intuitive, because those households face a narrower purchase window and such constraint makes loyal households more likely to tolerate higher price. Habitual decision makers are also likely to lost track on price variations.

Compared with the soft drink market, the contradicting price responses of the yogurt market call us to consider possible fundamental market-level differences. The brand effects of soft drinks and the associated image can be considerably stronger, leading to higher willingness-to-pay in the relevant products for structural households. Yogurt is usually viewed as a healthy product; and the consumption of yogurt may not generate significant prestige value. The additional benefit in the yogurt market may provide more motivation for executing self-control and the lack of prestige value makes a brand switch less painful. To check the robustness of the pattern, we conduct additional studies in a much older data set, the ERIM dataset and discuss the result in the next subsection.

3.3 Product Choices in the ERIM Markets

The ERIM datasets are collected by A.C. Nielson from year 1986 to 1988 in two mid-sized cities in US (Sioux Falls, South Dakota and Springfield, Missouri). Again, we select the yogurt category and follow similar data preparation procedure as described in the data section. The data detail and summary statistics are provided in the Appendix (*Table 8* and *Table 9*). Importantly, in the ERIM dataset, the structural periodicity measure is market specific: the dataset only provides vising tours with recorded yogurt purchases. We limit our sample so that households with more than 20 yogurt purchases in 1986 are selected for calculating their structural periodicity[9]. The structural periodicity calculated is more dispersed, and more than 10% households have periodicity levels higher than 0.7[10]. Using the 1986 sample to calculate such measure, we estimate the product-market level choice problems as in Section 3.1.

[9] Note that in the IRI datasets, we select on shopping trips relating to all purchases, yet in the ERIM datasets, we only have yogurt related shopping trips recorded. This greatly reduced our sample.
[10] See Appendix Figure 4.

Although at a much earlier time and over a much smaller sample, *Table 6* shows that the state dependence effects for structural households in the ERIM dataset are also monotonically reduced for all product-market pairs and the differences are significant in the first three product-market pairs (P-value < 0.05). The consistent trend suggests that such inertial reduction effects are associated with fundamental preference rather than time-related shocks. The magnitude of the state dependence coefficient is significantly larger than that in the IRI sample, perhaps due to the selection requirement on heavy yogurt purchasers. Again negative state dependence is observed in one product-market pair.

The ERIM samples witness increasing price sensitivities for structural households in three out of four product-market pairs--with a much larger noise. The lower panel of *Table 6* reports such phenomenon: households whose purchase periodicity is far from both boundaries are significantly affected by price. When the households become increasingly structural, a further negative mean of the coefficients imply that at least some of the households are more aware of the price variations. On average, the price semi-elasticities are significantly larger for the old datasets. This can be caused by limited choices and relatively low income in 1980s.

[*Table 6* about Here]

4. Discussion and Limitation

One concern with our estimation result is that we used various ways of data selection rules and the results may be sensitive to different truncation rules. Specifically, we have two truncation rules in the sample: First, when calculating structural periodicity, we require households to have certain revisits in the previous year. Second, we look for serious buyers who have a certain level of product consumption in the current year. To rule out the possibility of problematic truncations, we run replications of the results using less restrictions: we test a much weaker truncation rule and cut the first truncation rule to the half of the original level[11]. Our results are largely consistent with the previous findings. Consequently, we find that for all product-market pairs considered, there are weakening trends for the inertial effects; they are unlikely to be caused by the way we truncated the data. In addition, because the estimation results are based on samples from different markets, and different time, we find the results are not caused by a temporary time shock or product related unobservables.

A more important question has to do with the main explanation behind the weakening inertia effects. In the literature review, we discussed two possible ways that structural periodicity may affect households. On one hand, households with more self-control resource may make choice decisions more cautiously and avoid habitually falling into previous choices. On the other hand, satiation in one decision domain may spill over to other domains. We have seen little evidence that a subsample of households may demonstrate better self-control; in order to better test these two explanations in the overall sample, we utilize differences between regular products and their diet versions. If self-control explain much of the effect, we expect structural households also choose more diet products due to their obvious health benefits. As discussed before, from the product-market level analysis, we already see that the main effect of structural periodicity is indefinite; and no evidence shows that the percentage choice of Diet Coke or Diet Pepsi has been increasing with variable “struc”. In one product-market pair, the coefficient of state dependence becomes even significantly negative: a negative state dependence can be better explained by satiation, rather than

[11] In the IRI data, the modified selection criterion requires 20 general shopping visits in the previous year (for calculating structural periodicity in 2004) and 5 or more product-related shopping visits in the current year (for estimating product choice in 2005).

self-control. In *Table 7*, we show another specification of the binary choice model where households make choices between diet products and regular products. Again, we fail to see evidence that healthy choices positively correlated with structural repurchase patterns. In contrast, the probability is declining (P-value < 0.01) with increasing structural periodicity and for the extremely structural households, only 34% of the choices are with diet products, compared with the group average of 54%. We find a satiation argument more relevant; especially considering the possibility that structural households require stronger flavor (of the non-diet products) for compensating timing satiation.

Our data suggests that structural households are more constrained and face limited shopping windows. This, however, may generate benefits to households. The most robust results we find is a reduction of state dependence, which potentially leads to active product switches. There are also important differences in price responses in different markets. For most households in the markets (excluding those who are extremely "structural"), estimation results on the marginal prices show that the price sensitivities are not significantly reduced. In the yogurt markets the marginal effect of price is even increased. The market specific difference is not likely to be only caused by household heterogeneity. We suspect such difference in price responses may also reflect market specific characteristics. In the beverage markets, the brand effects are considerably stronger, and structural households make compromises to purchase their favorite products. In the yogurt markets, structural households put relatively higher weights on price and brand effects are of less concern. Perhaps yogurt brands do not create as much prestige as soft drink brands and experience value is underweighted compared with health benefits (Ackerberg 2001), so that self-control may play some roles. The market specific differences are worth more investigations. For example, our analysis can be extended to other markets, and test specific conditions under which structural households become increasingly more price sensitive (or less brand loyal).

5. Conclusion

In this paper, we investigate households' periodic purchase patterns in refrigerated yogurt and carbonated beverage markets. We first construct a measure of periodic strength, by which, the households' purchasing behavior can be compared in a novel dimension. From the descriptive statistics, we find that "structural" households—households with strong periodic purchase patterns—are correlated with specific demographic information and their product choices are different from more randomly visiting shoppers. We therefore hypothesize that such timing decisions may affect product choices through two channels. On one hand, structural periodicity may reflect each household's general ability of self-control; on the other hand, they lead to satiation and call for more varieties in product choices.

We then test the effects of periodic purchase behavior by estimating product-market level choice models. After controlling for individual and time differences, we confirm significant negative effects on previous choices, indicating weakened consumer inertia for "structural households". The product level estimation results report more negative price effects in majority product market pairs for yogurt products, suggesting that a portion of "structural" households do not have less elastic demand. An older ERIM dataset confirms such findings. However, the later finding is product-specific, and in the soft drink markets, the weakening price effects (which are more intuitive) are observed.

By comparing regular soft drink products with their diet versions, we find that self-control is not the main effect driving the weakening inertia; also the correlation between regulating time and regulating diet are rather small. Satiation and higher attention resource for structural households can serve as a more plausible story and it does not impose the requirement that households resist current temptation for long term benefit.

Knowing that structural households are subjected to weaker brand preference and consumer inertia, and understanding the potential explanations behind may improve managerial decisions. For example, structural households may be targeted with more variety based marketing campaigns, while non-structural households may benefit from price-based campaigns. In addition, we should also be aware of the market-level differences in the market: structural periodicity can be interacted with distinctive price responses, which requires more sophisticated pricing strategies.

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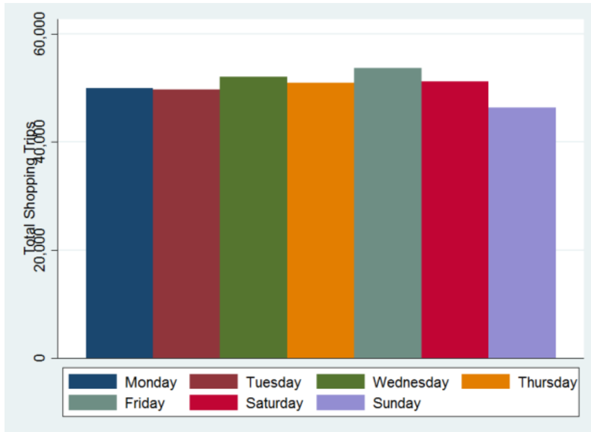
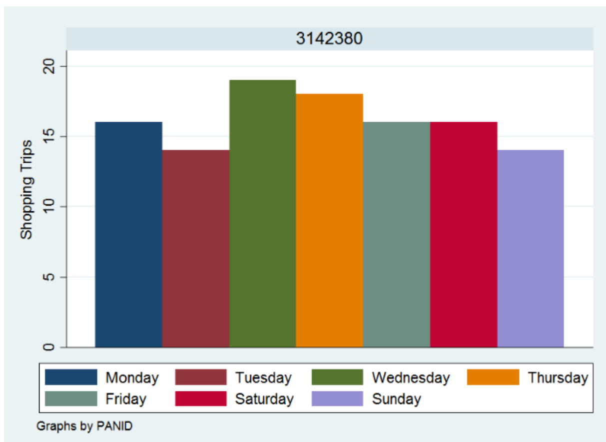
Table 1 Descriptive Statistics in IRI Markets

IRI MKT	Brand	Product	Share	Price	Std.Dev.
Yogurt	Yoplait	Yoplait Orig	13.5	1.57926	0.30965
		Yoplait Light	11.8	1.53388	0.30557
		Others	9.97	2.06631	0.53688
	Dannon	Dannon L&F	10.39	1.56058	0.35565
		Others	14.93	1.80133	0.54836
Bever-age	Coca Cola	Coke Classic	8.38	4.86058	2.49419
		Diet Coke	7.85	5.09427	2.63615
		Others	18.11	4.75103	2.25686
	Pepsi	Pepsi	6.98	4.67532	2.41698
		Diet Pepsi	6.08	5.0825	2.64769
		Others	20.17	4.86211	2.25988

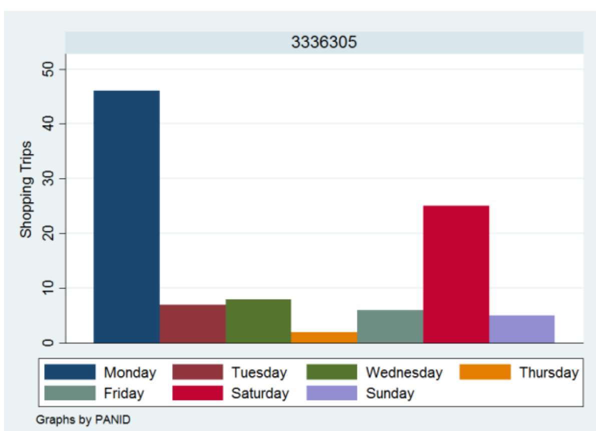
Figure 1 Examples of Periodic Purchase Patterns



A: Aggregate Counts of Visiting Day Choices



B: Individual Choices of Visiting Days



C: Individual Choices of Visiting Days

Figure 2 Histogram for Variable "struc"

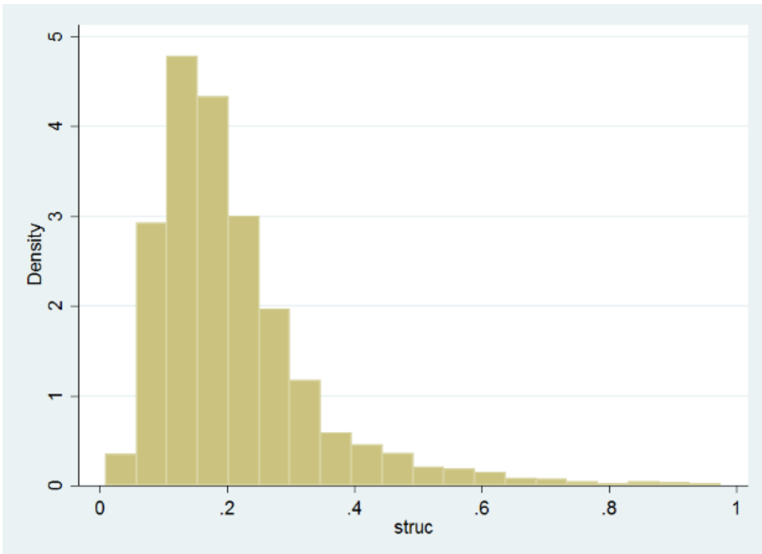
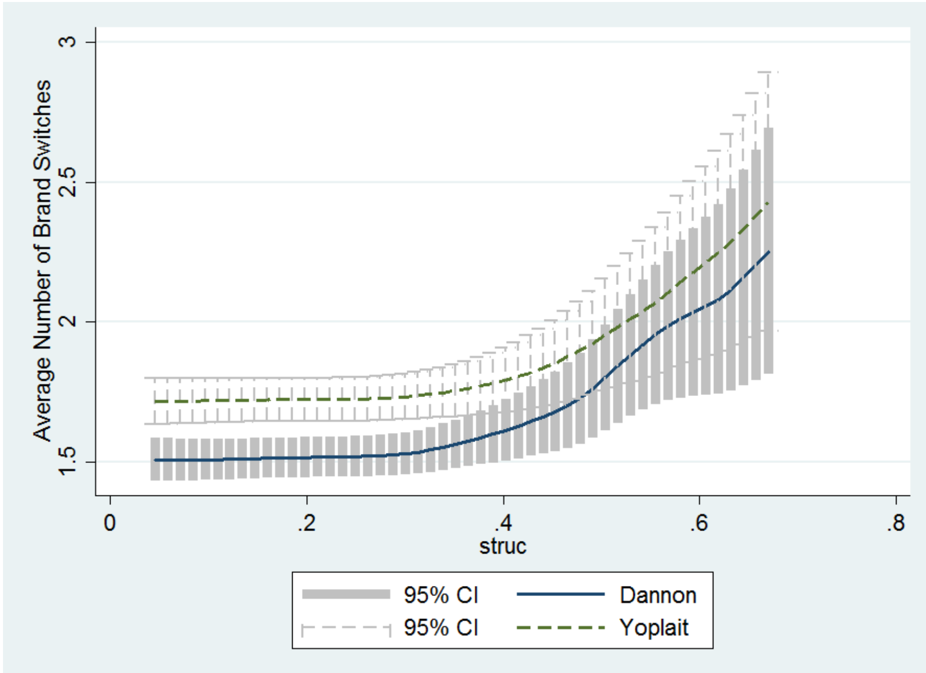


Table 2 Determinants of Structural Periodicity

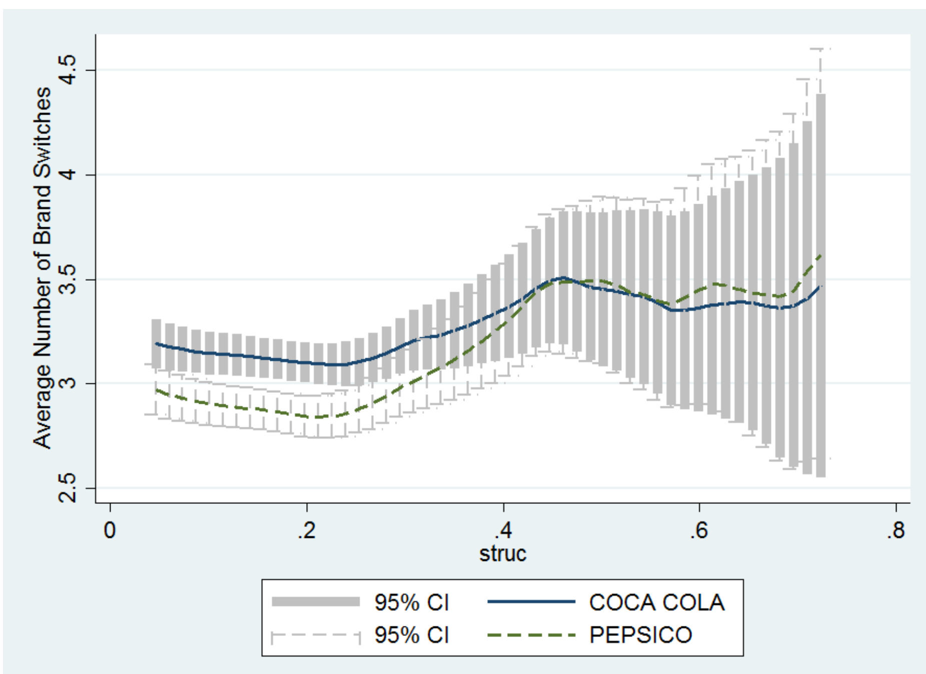
	Frequent Yogurt Purchasers	Frequent Soft Drink Purchasers
familysize	-0.00391	0.000990
	(0.00650)	(0.00243)
hh_age	0.00790	0.00477^{+}
	(0.00694)	(0.00269)
hh_edu	-0.0106^{*}	-0.00479^{**}
	(0.00420)	(0.00161)
pretaxincome	0.00218	-0.00679^{+}
	(0.00958)	(0.00370)
incomesq	-0.0000975	0.000361
	(0.000612)	(0.000240)
fulltime	0.0302^{*}	0.0108^{+}
	(0.0135)	(0.00563)
children	-0.00996	-0.0198^{**}
	(0.0176)	(0.00690)
total weeks	0.0113^{***}	0.0118^{***}
	(0.00235)	(0.000970)
total visits	-0.00231^{***}	-0.00215^{***}
	(0.000215)	(0.0000955)
_cons	-0.241^{*}	-0.156^{**}
	(0.118)	(0.0506)
occupation	Yes	Yes
marital stat	Yes	Yes
race	Yes	Yes
N	612	3456

Standard errors in parentheses
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 3 Product Switches and Periodic Shopping Patterns



A: IRI Yogurt Market 2005



B: IRI Soft Beverage Market 2005

Table 3 Product Level Choice - Random Effects Logit Model (Coefficients Shown)

	Refrigerated Yogurt			Carbonated Beverage			
	DN L&F	YPLT ORIG	YPLT LIGHT	Coke Classic	Diet Coke	Pepsi	Diet Pepsi
lagC	0.830***	0.923***	0.574***	0.268***	0.368***	0.239***	0.242***
	(0.130)	(0.119)	(0.126)	(0.0625)	(0.0702)	(0.0681)	(0.0680)
price1	-2.787***	-5.004***	-6.166***	-0.256***	-0.148***	-0.265***	-0.188***
	(0.532)	(0.545)	(0.602)	(0.0309)	(0.0330)	(0.0352)	(0.0323)
price0	3.089***	2.151*	4.182***	0.228***	0.0699	0.258***	0.243***
	(0.922)	(0.928)	(1.096)	(0.0642)	(0.0753)	(0.0663)	(0.0679)
struc	3.714	-1.630	1.221	0.730	-3.242*	2.985*	3.634**
	(2.600)	(2.562)	(2.723)	(1.348)	(1.596)	(1.403)	(1.406)
inc	0.00140	0.0799	0.0779	0.148**	0.274***	0.0492	0.0770
	(0.151)	(0.145)	(0.155)	(0.0532)	(0.0603)	(0.0600)	(0.0596)
lagC* struc	-1.350**	-1.306**	-0.441	-0.297	-0.899**	0.0896	0.0982
	(0.457)	(0.416)	(0.431)	(0.276)	(0.306)	(0.274)	(0.273)
lagC* inc	0.0741**	-0.00555	0.0431	-0.0224	-0.0725***	-0.0327*	-0.0340*
	(0.0273)	(0.0251)	(0.0266)	(0.0121)	(0.0132)	(0.0137)	(0.0136)
price1* struc	-3.731*	-1.290	0.0458	-0.0800	-0.259	-0.0429	-0.0993
	(1.731)	(1.730)	(1.840)	(0.129)	(0.144)	(0.144)	(0.133)
price1* inc	0.226*	0.174	0.315**	0.00694	-0.0114	0.0124	0.00416
	(0.108)	(0.113)	(0.122)	(0.00579)	(0.00597)	(0.00681)	(0.00620)
price0* struc	-1.708	6.199	-1.381	-0.340	0.546	-0.724*	-0.791**
	(3.259)	(3.467)	(3.888)	(0.292)	(0.349)	(0.288)	(0.295)
price0* inc	-0.216	-0.269	-0.425	-0.0319**	-0.00808	-0.0255*	-0.0239
	(0.195)	(0.196)	(0.227)	(0.0117)	(0.0132)	(0.0124)	(0.0128)
exp	-0.00842	0.0559	0.0553	0.0267*	0.0672***	0.0723***	0.0709***
	(0.0342)	(0.0300)	(0.0308)	(0.0131)	(0.0134)	(0.0139)	(0.0139)
exp_sq	-0.000148	-0.00143	-0.00180	-0.000731	-0.00232***	-0.00206***	-0.00198***
	(0.00124)	(0.000984)	(0.000940)	(0.000412)	(0.000410)	(0.000410)	(0.000411)
tvisits	-0.00155	0.00405	0.00569	0.00103	-0.000460	0.000691	0.000819
	(0.00303)	(0.00274)	(0.00312)	(0.00114)	(0.00135)	(0.00123)	(0.00123)
const	-3.957***	-2.488**	-2.021*	-3.119***	-2.698***	-3.116***	-3.333***
	(0.878)	(0.852)	(0.897)	(0.369)	(0.421)	(0.394)	(0.393)
WK fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clus-ters	618	618	618	3511	3511	3511	3511
N	16874	16874	16874	64819	64819	64819	64819

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

Table 4 Product Level Choice in IRI Yogurt Market (2005)- Random Effects Logit Model with Continuous Measure of Household Periodic Structure (Marginal Effects Shown)

	DANNON LIGHT N FIT	YOPLAIT ORIGINAL	YOPLAIT LIGHT
LagChoice			
struc=0	0.0382***	0.0486***	0.0231**
	(0.0108)	(0.0113)	(0.00741)
struc=0.5	0.00715	0.0184	0.0154*
	(0.00667)	(0.0104)	(0.00752)
struc=1	-0.0204	-0.0334	0.00649
	(0.0172)	(0.0301)	(0.0166)
Price1			
struc=0	-0.0950***	-0.209***	-0.210***
	(0.0266)	(0.0432)	(0.0453)
struc=0.5	-0.182***	-0.359***	-0.238***
	(0.0492)	(0.0781)	(0.0630)
struc=1	-0.311	-0.595*	-0.270
	(0.190)	(0.262)	(0.168)
Clusters	618	618	618
N	16874	16874	16874

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

Table 5 Product Level Choice in IRI Soft Beverage Market (2005)- Random Effects Logit Model with Continuous Measure of Household Periodic Structure (Marginal Effects Shown)

	COKE CLASSIC	DIET COKE	PEPSI	DIET PEPSI
LagChoice				
struc=0	0.0260***	0.0197**	0.0129***	0.0127***
	(0.00676)	(0.00609)	(0.00388)	(0.00383)
struc=0.5	0.000937	-0.00495*	0.00748	0.00767
	(0.00346)	(0.00207)	(0.00401)	(0.00407)
struc=1	-0.00349	-0.00408	0.00359	0.00396
	(0.00337)	(0.00221)	(0.00774)	(0.00809)
Price1				
struc=0	-0.0154***	-0.00682**	-0.00761***	-0.00725***
	(0.00290)	(0.00219)	(0.00171)	(0.00155)
struc=0.5	-0.00837***	-0.00486***	-0.00796***	-0.00806***
	(0.00202)	(0.00138)	(0.00212)	(0.00204)
struc=1	-0.00442	-0.00240	-0.00819	-0.00875
	(0.00245)	(0.00143)	(0.00479)	(0.00484)
Clusters	1590	1590	1590	1590
N	46176	46176	46176	46176

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

Table 6 Product Level Choice in ERIM Markets (1987)- Random Effects Logit Model with Continuous Measure of Household Periodic Structure (Marginal Effects Shown)

	Sioux Falls		Springfield	
	YPLT ORIG	DN LF FOB	YPLT ORIG	DN LF FOB
LagChoice				
struc=0	0.202**	0.163+	0.113	0.300**
	(0.0649)	(0.0889)	(0.0763)	(0.102)
struc=0.5	0.0667*	0.0570*	0.0210	0.251***
	(0.0292)	(0.0274)	(0.0165)	(0.0466)
struc=1	0.00104	-0.0107	-0.102 Δ	0.183163+
	(0.0315)	(0.0347)	(0.0616)	(0.0955)
Price1				
struc=0	-0.887**	-0.172	-0.0463	-0.240
	(0.274)	(0.152)	(0.0544)	(0.240)
struc=0.5	-0.366**	-0.387*	-0.173*	-0.562**
	(0.127)	(0.154)	(0.0687)	(0.183)
struc=1	-0.0263	-0.697	-0.583	-0.970+
	(0.190)	(0.507)	(0.411)	(0.560)
Clusters	91	91	61	61
N	3411	3411	2477	2477

Standard errors in parentheses
+ P<0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7 Probability of Choosing Diet Products

	Prob of Choosing Diet Product
struc=0	0.599***
	(0.0301)
struc=0.5	0.455***
	(0.0429)
struc=1	0.340***
	(0.0898)
N	18688

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

Appendix

A. ERIM Data Summary

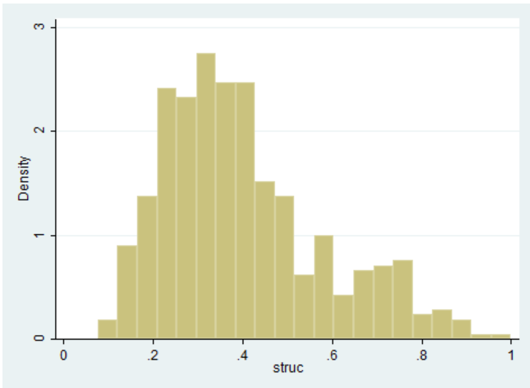
The ERIM dataset is collected by A.C. Nielson. The ERIM datasets consist of household level purchase history data from year 1986 to 1988 in two mid-sized cities in US (Sioux Falls, South Dakota and Springfield, Missouri). Approximately 1400 households (households who have more than 10 shopping trips over around 138 weeks) are selected into our sample. There is data on households' product choices, product characteristics in different categories (Ketchup, Dry Detergents, Canned Soup and Yogurt) as well as the household demographic information. Moreover, the shopping trip information can be used to describe households' periodic purchase patterns. We focus on the Yogurt category where the storage problem may be the weakest due to the products' high storage cost and short expiration date. *Table 8* provides us with brand level descriptive statistics.[12] Compared with Springfield, Sioux Falls has witnessed two local brands with significant market share (30.51%) and yet lower prices. Moreover, the two markets are also different in the dominant brands. In Sioux Falls, the local brand Nordica has slightly higher market share, compared with Yoplait and Dannon, while households seem to purchase Dannon much more frequently in Springfield. The histogram of the structural periodicity measure is provided in *Figure 4* and product level descriptive statistics are listed in *Table 9*. We discuss the estimation results on the ERIM dataset in the main text and list the results in *Table 6*.

[12] The brand abbreviations YPLT is for Yoplait; WW for Weight Watcher; DN for Dannon; NDC for Nordica; WBB for Well's Blue Bunny; CTL for CTL.

Table 8 ERIM: Descriptive Statistics: Brand Level

	Sioux Falls				Springfield		
Brand	Share	Price	Std. Dev.	Brand	Share	Price	Std. Dev.
YPLT	18.29%	0.58	0.11	YPLT	12.80%	0.64	0.12
WW	6.76%	0.45	0.04	WW	5.46%	0.46	0.07
DN	15.61%	0.44	0.07	DN	44.96%	0.43	0.10
NDC	19.35%	0.37	0.07	CTL	13.30%	0.28	0.09
WBB	10.60%	0.28	0.05	OTHR	23.48%	0.23	0.06
CTL	16.22%	0.27	0.03				
OTHR	13.17%	0.30	0.09				

Figure 4 ERIM: Histogram for Variable "struc"



Structural Periodicity in Yogurt Purchases (1986 Data)

Table 9 ERIM Descriptive Statistics: Product Level

	Yogurt Market: Yoplait ORIG		Yogurt Market: Dannon LF	
	Sioux Falls	Spring-field	Sioux Falls	Spring-field
Price	.567	.621	.445	.423
Std. Dev.	.090	0.093	.065	.096
Market Share	13.79%	5.89%	9.91%	24.18%
Shopping Trips	4173	1334	2920	4098

B. Estimation with Different Truncation Rules

Table 10 Product Level Choice in IRI Yogurt Market--Robustness Test

	DANNON LIGHT N FIT	YOPLAIT ORIGINAL	YOPLAIT LIGHT
LagChoice			
struc=0	0.0381***	0.0479***	0.0308***
	(0.00729)	(0.00799)	(0.00640)
struc=0.5	0.0226**	0.0305***	0.0200***
	(0.00736)	(0.00821)	(0.00607)
struc=1	0.00833	0.0154	0.0121
	(0.0156)	(0.0164)	(0.0112)
Price1			
struc=0	-0.162***	-0.282***	-0.278***
	(0.0226)	(0.0324)	(0.0334)
struc=0.5	-0.221***	-0.297***	-0.206***
	(0.0344)	(0.0431)	(0.0352)
struc=1	-0.291**	-0.314**	-0.151*
	(0.105)	(0.109)	(0.0660)
Clusters	2502	2502	2502
N	36295	36295	36295

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

Table 11 Product Level Choice in IRI Soft Drink Market--Robustness Test

	COKE CLASSIC	DIET COKE	PEPSI	DIET PEPSI
LagChoice				
struc=0	0.0182***	0.0161***	0.00986**	0.00978**
	(0.00501)	(0.00453)	(0.00312)	(0.00308)
struc=0.5	0.00415	-0.00312	0.00977**	0.0101**
	(0.00373)	(0.00181)	(0.00357)	(0.00362)
struc=1	-0.000744	-0.00366*	0.00970	0.0105
	(0.00446)	(0.00175)	(0.00756)	(0.00801)
Price1				
struc=0	-0.0175***	-0.00788***	-0.00959***	-0.00690***
	(0.00241)	(0.00181)	(0.00156)	(0.00133)
struc=0.5	-0.0105***	-0.00530***	-0.00838***	-0.00671***
	(0.00202)	(0.00122)	(0.00179)	(0.00161)
struc=1	-0.00620*	-0.00282*	-0.00752*	-0.00670
	(0.00281)	(0.00134)	(0.00374)	(0.00354)
Clusters	3253	3253	3253	3253
N	64294	64294	64294	64294

Standard errors in parentheses

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