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Store Choices of Rural Grocery Shoppers Using an Attribute Screening Model

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Store Choices of Rural Grocery Shoppers Using an Attribute Screening Model

Independent and locally owned grocery stores represent a critical piece of the infrastructure that sustains America's rural communities, providing food, supporting jobs, and generating taxes. Yet, these independently-owned grocery stores struggle to remain in business. In many rural communities, convenience stores, gas stations or dollar stores become the only retail food outlet, supplying high priced, nutritionally diminished foods (Bitler and Haider, 2009; Ford, 2009; Morris et al., 1992; Morton and Blanchard, 2007; Ver Ploeg, 2009). The elderly and poor make up high proportions of 2.4 million rural citizens that live in "food deserts" (Bitto et al., 2003; Whitacre et al., 2009). The USDA defines food deserts in terms of the portions of people who are at economic disadvantage and have low access to a supermarket or large grocery store.

Commercial viability of rural grocery stores will depend on consumers' shopping behavior and their demand for grocery stores in their communities. The few available studies on rural consumers suggest that their choices are similar to their urban counterparts, but have unique dimensions. The Center for Engagement and Community Development at Kansas State University, which leads the Rural Grocery Initiative, surveyed customers of five rural grocery stores in Kansas to develop a cumulative profile of a typical customer of rural groceries (Clark, Tsoodle, and Kahl, 2008). Most (81%) of the respondents identified "getting weekly/monthly groceries" as a primary reason for visiting the chain grocery store, where they spent more on less frequent trips than at the local store, for which "picking up a few essential/emergency items" was the primary reason for visit. Based on simulations of shopping trips of rural Kansas households, Amanor-Boadu (2009) illustrated that the success of a shopping location depends on attracting a sufficient customer base, which in turn depends on perceived value including product prices and product mix. Webber,

Sobal, and Dollahite (2010) conducted in-depth interviews with food shoppers of rural households in upstate New York and concluded that there was a wide variability in relationships these shoppers had with the stores, which affected how shoppers perceived their food choice, access, and availability.

This paper contributes to the literature by furthering our understanding of rural households' choices of grocery stores using data from a uniquely designed survey, applying a method that allows for the possibility that households eliminate from consideration stores where one or more attributes lie outside some acceptable range. Screening out alternatives based on attribute ranges is a behavioral phenomenon first modeled in random utility frameworks in the fields of transportation and marketing (e.g., Elrod et al., 2004; Gilbride and Allenby, 2004; Huber and Klein, 1991; Swait, 2001; Cascetta and Paploa, 2001). This literature has uncovered evidence, obtained from a range of datasets on different goods, that agents have a systematic tendency to screen out alternatives on the basis of one or more attributes.

Our approach is based on the attribute non-attendance models presented by Scarpa et al. (2009) and Hensher et al. (2011). The model accounts for the heterogeneity in preferences across shoppers as well as the possibility that some shoppers care about a greater number of store attributes than others. Some shoppers may compare stores using all relevant attributes (distance from home, pricing, product selection, ownership structure, staffing), while others only consider some of these dimensions. Shoppers in the latter category may screen out stores that don't meet their criteria on the few dimensions they consider. For example, a shopper who only cares about the breadth of product selection will always choose a large store over smaller one, even if the smaller store has other attributes that are desirable. If present in households' choices over shopping

venues, this type of screening has potentially important implications for the viability of small-scale grocery outlets.

Data for this study were collected in June 2013 from a survey of all postal patrons in four rural counties in Kansas and Nebraska. In each of the county, there were at least two independent and locally owned grocery stores in a community with less than 2,500 people. The survey elicited data on store choices, store attributes, and household characteristics. From the list of grocery stores identified by the respondents, we are able to construct a set of all possible choices for a county resident. The store attributes focused on distance from home or place of work, pricing (everyday low pricing vs. promotional discounts on selected items), business ownership (independent and locally owned vs. a national or regional franchise), familiarity with people (acquaintance with the store owner/manager and/or employees vs. none), and product offering (limited/adequate selection of mostly discount brands, limited/adequate selection of mostly national name brands, or expansive/full selection of national name and discount brands).

Our empirical analysis suggests that certain segments of shoppers focus on particular attributes and that the presence of certain attributes cannot make up for the absence of others. For a total customer base made up of mixtures of these segments, store owners must accommodate the tension in finding a mix of attributes that are attractive to key cohorts while still maintaining a large enough customer base from all cohorts.

Model

The model is built on the random utility framework, but relaxes the standard assumption that all agents derive utility from an alternative as a continuous function of its attributes. Continuous utility implies smooth tradeoffs between attributes, or *compensatory* decision rules in which the

presence of a desirable attribute can compensate for an undesirable one. Much experimental evidence from many decision domains, however, suggests that individuals often use *non-compensatory* decision rules during choice tasks. One manifestation of non-compensatory behavior is that agents ignore one or more attributes during comparisons, or attribute non-attendance (Scarpa et al., 2009).

Attribute non-attendance may either reflect agents' underlying preferences, if an attribute is truly of zero value, or the pattern left behind from their information processing strategies. In the latter case, agents may derive some utility from all attributes but only focus on those they care the most about to narrow their alternatives. Whatever the origin, attribute non-attendance can be accommodated in a random utility choice framework by restricting the marginal utility associated with the ignored attribute to be zero. This is a straightforward estimation restriction in the case of a linear utility function, but the modeling challenge is that the number of possible restrictions is large. The standard random utility model assumes that all agents exhibit "total attendance" to all attributes (TA agents). To capture all possible forms of non-attendance, the model must also consider agents that do not attend to one attribute (NA-1 agents), as well as NA-2 agents, NA-3 agents, and so on. Moreover, if the alternatives have K attributes, every group of NA-n agents (n =1, …, K) has distinct subgroups, each of which ignores a unique combination of the n out of the K attributes available. Here, we consider only TA agents and NA-1 agents, as higher-dimension models were not supported by our data.

Following Scarpa et al. (2009), we adapt the latent-class logit model (Boxall and Adamowicz, 2002; Train, 2003) to capture the behavior of NA-1 agents alongside TA agents. Let the alternatives (stores) available to each individual be indexed by j and let the latent classes

representing different preferences be indexed by c. For an individual in class c, the utility obtained from store j is

(1) $U_{jc} = V_{jc} + \varepsilon_{jc}$,

where V_{jc} is a linear function of store j's attributes ($\mathbf{x}_j$) and ε_{jc} is a disturbance term encapsulating unobserved factors that are known to the individual but are random to the researcher. The probability that an individual in class c chooses store j, P_{jc}, follows the well-known logit formula, which assumes that each individual chooses the store that maximizes utility and that ε_{jc} follows an extreme value type I distribution:

(2) $$P_{jc} = \frac{e^{V_{jc}}}{\Sigma_j e^{V_{jc}}}$$

Classes in the model are defined such that the first class is made up of TA agents and the remaining classes are NA-1 agents. If information on K attributes is presented for each store, then the full version of the model has $K + 1$ classes. To simplify notation, we now index the classes by $k = 0, 1, \ldots, K$, where $k = 0$ indicates the TA agents and $k = 1, 2, \ldots, K$ indicates NA-1 agents who ignore the kth attribute. Let $\boldsymbol{\beta}_{(k)}$ denote a vector of utility coefficients the kth element is restricted to equal zero if $k = 1, \ldots, K$, and $\boldsymbol{\beta}_{(0)}$ has all unrestricted elements. From (1), the utility of choosing j for class k then becomes

(3) $U_{jk} = \boldsymbol{\beta}'_{(k)}\, \mathbf{x}_j + \varepsilon_{jk}, \quad k = 0, 1, \ldots, K.$

As class membership is unobserved (latent), the probability of belonging to a class must be inferred from the individual's stated choices. The model also relies on the logit formula to estimate class membership probabilities. Combining all the components, the unconditional probability that alternative j is the utility-maximizing choice for an individual is

(4) $$P_j = \sum_k \left(\frac{e^{\boldsymbol{\theta}'_k \mathbf{z}}}{\Sigma_k e^{\boldsymbol{\theta}'_k \mathbf{z}}} \right) \left(\frac{e^{\boldsymbol{\beta}'_{(k)} \mathbf{x}_j}}{\Sigma_j e^{\boldsymbol{\beta}'_{(k)} \mathbf{x}_j}} \right),$$

where the first term in parentheses is the probability that the individual belongs to class k, the second term is the probability of choosing j conditional on belonging to class k, $\mathbf{z}$ is a vector of individual characteristics, and $\boldsymbol{\theta}_k$ is a vector of class-membership parameters to be estimated. The unconditional probability is thus a mixture of the class membership probabilities and the conditional choice probabilities.

Data

Data were gathered from selected counties in Kansas and Nebraska that included case study locations, which were identified as part of a larger study. The locations were selected to represent communities with populations of 2,500 or below and a grocery store, and represent one of the three strategies the overall study had identified as the study focus (Procter et al., 2012). Data for the current analysis were obtained from a survey mailed to all valid postal addresses in the home counties of the case communities. Chautauqua and Clark Counties are located in the southeastern and southwestern parts of Kansas, both bordering Oklahoma. Republic and Smith Counties are in the north central part of Kansas, both bordering Nebraska, with one county (Jewell) in between. Republic County and Thayer County in Nebraska share a border.

A total of 9,143 surveys were mailed out on May 31, 2013, with the counts by county as follows: Chautauqua (1,618), Clark (880), Republic (2,409), Smith (1,827), and Thayer (2,409). The cover letter requested a response by June 21, 2013 using an enclosed postage paid envelope. A total of 1,445 surveys were returned, for a response rate of 13.5%. Response rates varied by county with the lowest (13.3%) from Chautauqua County, the highest (18.6%) from Republic County and the remaining counties between 15% and 15.6%.

Summary statistics of the respondents are shown in table 1. More than three out of four respondents were female (78.6%), and the average respondent's age was 60 years. A third of the respondents had a bachelor's degree. The respondents were asked to identify their employment status, and those who self-identified as working were asked to indicate whether they worked within or outside their community. A slight majority (52.2%) indicated that they were currently working, with 37.9% (72.6% of those working) working in their community and working 14.3% outside. The annual household income, calculated as the mid-point of the ranges presented to the respondents in the survey, averaged $58,251.

The survey included a short series of selected questions to measure social capital, based on the short form of the Social Capital Community Benchmark Survey (2002). Some of the responses were included in the current analysis. More than half (56.3%) of the respondents attended religious services (not including weddings and funerals) at least once a week during the past 12 months; 28% indicated that they volunteered at least once a week during the past 12 months. In terms of public meetings (to discuss town or school affairs) and club or organizational meetings, 20.4% and 43.9% indicated that they attend these respective types of meetings at least once a month during the past 12 months. As a collective measure of civic engagement, the variable *ENGAGED* was created if the respondent had been active in at least two of these areas, which corresponded to 46.2% of the respondents. In addition, about 42% responded that they had friends from their community over to their home at least once a month, and 43% indicated they trusted people in their community "a lot."

The respondents were asked to complete a series of choice tasks related to their preferences for grocery shopping venue. The following attributes were included: distance to the store, pricing, ownership, knowing people at the store, and product offering. Table 2 summarizes the attributes

and their levels considered. A full factorial design implies 48 store profiles. But, given the very limited space on the survey and to minimize the respondent burden for maximum rate of response, we proceeded with the smallest reasonable design size suggested by SAS of 12 profiles, which were presented to the respondents in a series of 4 tasks with 3 options each.

Results

The starting point of our empirical analysis was a full specification latent classes representing TA agents as well as all agents that are AN-1 with respect to each attribute. With $K = 5$ attributes in the stated choice questions (table 2), the full model has 6 latent classes. No restrictions were imposed on the first class representing TA shoppers. For each of the remaining AN-1 classes, the coefficient(s) on one of the attributes in table 2 were restricted to equal zero. In all AN-1 classes except for the last one, a single coefficient was restricted, while in the last class the coefficients on both *ADEQNA* and *FULLSEL* were set to zero to represent non-attendance to product offering.

The results of the full model had a very small estimated share of the sample in certain classes, however, and in two classes the coefficients on all but a single attribute were not statistically different from zero. Alternative models with fewer classes yielded improved AIC fit measures relative to the full model. Thus, the data provide no strong evidence that the shoppers in our sample are distributed across all possible AN-1 groups.

Our preferred specification has four classes (table 3). The estimated coefficients on the store attributes differ substantially across classes, indicating distinct preference patterns. Class 1, making up about 10 percent of the sample, represents shoppers with a clear preference for locally owned independent grocers. As expected, shoppers in this (and all other) classes are averse to greater distances to shopping locations, but the relative coefficients on *MILES* and *INDLOC* imply

that these shoppers would be willing to travel up to 2.317/0.046 ≈ 50 additional miles to a locally owned grocer over a franchise grocer that is equivalent in all other dimensions. The coefficients on the individual characteristics indicate that shoppers in this category tend to be older and have a large degree of trust in their communities.

The second class, which is AN-1 with regard to store pricing, also has a clear preference for independent local grocers. This group desires a relationship with the store staff and a full selection of products. Shoppers in this group tend to be younger individuals who actively cultivate friendships, and make up about 14 percent of the sample. The estimated utility coefficients imply that individuals in this group would drive an additional 15.5 miles to a store that is independently owned, and would be willing to travel 14.8 additional miles if they also know the staff at that store. To get a full product selection (versus a store that has an adequate selection of discount brands) they would travel an additional 9.7 miles.

Class 3 individuals are AN-1 with regard to store ownership. Their shopping choices are driven heavily by pricing and product offering, and they prefer to shop "anonymously" without knowing any staff members at their store. They are also the least averse to traveling among the four classes with an estimated coefficient on *MILES* of -0.015. They would be willing to travel up to 44.3 miles to a store that has every-day low pricing (over one with only promotional discounts) and an additional 44.6 miles if the store has a full product selection. If all else is equal between two stores, they would be willing to travel an additional 17 miles to avoid the store where they know a staff member. These individuals tend to be younger, less engaged in community activities, and do not work in the community.

The fourth class is AN-1 with respect to product offering. Individuals in this class are the most averse to traveling and value every-day low pricing. However, the practical significance of

the latter effect is small. The high aversion to distance among these shoppers implies that their willingness to travel to obtain every-day low pricing is only 1.7 miles. The estimated coefficient on independent, local ownership is positive and implies a willingness to travel of 5.1 miles, although the effect is not statistically significant. This group can be described as "neighborhood shoppers," as they tend to choose the store closest to them. They are the base group in the class selection model, so the estimated coefficients in the bottom half of the table are relative to this class. This comparison implies that class 4 is less involved in their community than classes 1 and 2, who have strong preferences for local ownership, but are more involved than the price-convenience shoppers in class 3. Class 4 is also the largest group, accounting for 49 percent of the sample.

Our estimates provide insight on the most effective business strategies for independent grocers. A key set of measures for the grocer is the effect of different store attributes on the size and composition of the store's customer base. These measures can be extracted from our model as marginal effects (discrete effects in the case of dummy coded attributes). Marginal and discrete effects within each class are equivalent to those of a standard conditional logit model, where the effect of any attribute in a given alternative is in general a function of all attributes in all alternatives in the choice set. Thus a base set of alternatives and attributes must be specified, and marginal/discrete effects are computed relative to this base.

We calculated marginal and discrete effects for six different base specifications, as shown in tables 4 and 5. In all cases, we consider a choice set with only two store alternatives. The first store in each choice set is a locally owned independent store that is 5 miles away from a given shopper. As the base case, we assume that this store does not have every-day low pricing, nor staff who knows the shopper, and has a product selection of discount brands. The second alternative is

a competing store that varies across cases by store type and travel distance. The cases in table 4 represent a large retailer as a competing store, such as Wal-Mart. These competitors feature every-day low pricing and a full selection of products, but are not independently owned and are assumed not to have staff who know the shopper. The cases in table 5 represent a "dollar store" as a competitor (e.g., Dollar General). The attributes of dollar stores are similar to large retailers, except that the product selection is limited to national brands. These two types of competitors are the most prevalent for independent grocers in the rural Great Plains.

The middle columns in each table report the unweighted marginal/discrete effects by class. For *MILES*, the only continuous attribute, the marginal effect is computed using the standard conditional logit derivate, $\frac{\partial P_j}{\partial x} = P_j\left(1 - P_j\right)\beta_x$, where P_j is the probability of choosing alternative j, x is the continuous attribute in alternative j, and β_x is the coefficient on x. For the remaining discrete attributes, the discrete effects are the calculated change in the probability of choosing the local alternative from equation (2), when the attribute in question is switched from 0 to 1 while all other attributes are held constant at their base values. The rightmost columns report these effects weighted by the share of individuals in each class from table 3. The overall effect in the final column measures the total change in the customer base (change in market share), which is the sum of the weighted effects.

First consider the top panel of table 4, where the local store and the competing large retailer are both 5 miles away from the shopper. Even in the base case when the local store does not attempt to compete with the retailer on pricing or selection, and the shopper does not know the staff at the store, the local grocer would capture 97% of class 1 shoppers and 68% of class 2 shoppers. Only 20% of class 3 shoppers will come to the local store, however, and 64% of class 4 shoppers will come. While the store captures dominant shares in three of the four segments, the overall market

share is a more modest 57%. The overall share is somewhat smaller because the store commands the greatest loyalty from the smaller segments (classes 1 and 2, which collectively account for 24% of the customer base).

The marginal effect of the *INDLOC* attribute is large especially in classes 1 and 2, which indicates their loyalty to independent locally owned stores. In class 2, where 68 out of every hundred shoppers go to the local store, fully 46 of them come primarily because of its ownership structure. The overall effect of *INDLOC* is 19.5 percentage points out of the 57 percent market share, implying that about 1/3 of the store's customer base is drawn to the store because of local ownership. However, the store can improve its position by changing other attributes. If shoppers know the staff in the store, market share would increase by an estimated 7.1 percentage points, mostly driven by the effects on classes 2 and 4. While class 2 has a stronger preference for knowing the staff compared to class 4, class 2 is a much smaller customer segment so the weighted effect is actually larger for class 4. The next most effective strategies for this store would be to offer every-day low pricing and a full selection of products, which would raise overall market share by 6.5 and 5.9 percentage points, respectively.

The most effective strategies change somewhat as the competitor is further away from the shopper. Proximity to the shopper gives the local store a near complete customer share in classes 1, 2, and 4, leaving class 3 as the only segment from which a large number of additional shoppers can be attracted. Thus, as the competitor is further away, the most effective strategies for attracting more customers is driven by the preferences of class 3. These customers are the segment who by definition do not pay attention to ownership structure and would need to be attracted by other store features. Accordingly, the most effective strategies when the large retailer is further away are every-day low pricing and a full product selection. Interestingly, having a staff that knows the

customers would result in a small decrease in total market share, because class 3 shoppers prefer anonymity. This highlights the tension in finding a set of attributes that is attractive to the most loyal shoppers while also attracting convenience shoppers.

Table 5 shows that the local store is in a more advantageous position when competing against a dollar store. Predicted market shares for the local store are higher at every distance compared to the large retail cases. This result is driven by the fact that dollar stores have a product offering of national brands, which is not a preferred offering for any market class (table 3). The most effective strategies for the local store are similar to that for the large retailer, however. At every distance, the locally owned store can attract customers by offering every day low pricing or a full selection of products. If the competitor is nearby, having staff that know shoppers is also effective.

Conclusions

This paper has applied a recently developed choice/selection model to analyze the rural household's grocery store choices. Shoppers were found to fall within distinct market segments, most of which ignore particular store attributes when choosing shopping destinations. Two of these segments, collectively accounting for about one-fourth of the customer base, are highly loyal to independent, local grocers and one of these segments ignores the store's pricing strategy. These shoppers, in fact, are willing to travel significant distances to shop and locally owned grocery stores. Their preference for these stores is enhanced further if they personally know the store staff or if the product selection is broadened. Another segment, however, ignores the ownership of the local store and will only be drawn to it if it has features allowing for convenient shopping. A

fourth and final segment is strongly averse to traveling to shop and will chose whichever store is nearest to home.

The presence of these distinct segments that exhibit non-attendance to certain store features have important implications for independent local stores. The best strategy to enlarge the customer base depends importantly on the distance shoppers must travel to the store in question as well as to competing stores. If the competing store is far away, the local store will capture a number of customers not because of its local ownership but because of customers' aversion to travel. If the competing store is nearby, then many customers will come to the local store purely because it is local and independently owned.

Finally, depending on the local store's objectives and the costs of changing store features, the managers must balance the preferences of different customer groups. As the loyal cohorts represent only about 25% of customers, there is much potential for expanding the customer base by adding store features that attract individuals in the remaining cohorts. In some cases, however, the features needed to attract these groups will be unwelcome changes to the loyal groups.

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Table 1. Descriptive Statistics from Survey

Variable	Description	Mean	St. Dev.	Observations
FEMALE	Female respondent (dummy)	0.786	0.410	1418
AGE	Respondent age (years)	59.565	15.320	1418
BPLUS	Bachelor's or higher degree (dummy)	0.332	0.471	1408
WORKIN	Work in the community	0.379	0.485	1445
WORKOUT	Work outside the community	0.143	0.350	1445
HINC	Annual household income ($ thousand)	58.251	47.795	1275
CHURCH	Attend church weekly (dummy)	0.563	0.496	1445
VOLUNTEE	Volunteer weekly (dummy)	0.280	0.449	1445
PUBLICMT	Attend public meetings monthly (dummy)	0.204	0.403	1444
CLUBMTG	Attend club meetings monthly (dummy)	0.439	0.496	1445
ENGAGED	Sum of preceding 4 variables ≥ 2 (dummy)	0.462	0.499	1444
FRIENDS	Had friends over monthly (dummy)	0.419	0.493	1445
TRUST	Trust people in community "a lot" (dummy)	0.429	0.495	1444

Table 2. Attributes and Levels in Stated Choice Experiment

Attribute	Levels	Variables and codes
Distance to store	5 miles	*MILES* = 5
	30 miles	*MILES* =30
Pricing	Everyday low pricing	*ELP* = 1
	Selected items on promotional discount	*ELP* =0
Ownership	Local and independent	*INDLOC* = 1
	Part of a franchise	*INDLOC* = 0
Know staff	Know owner/manager and/or employees	*KNPEOP* = 1
	Know no one in particular	*KNPEOP* = 0
Product offering	Adequate selection of mostly national brands	*ADEQNA* = 1, *FULLSEL* = 0
	Full selection of national and discount brands	*ADEQNA* = 0, *FULLSE* = 1
	Adequate selection of mostly discount brands	*ADEQNA* = *FULLSEL* = 0

Table 3. Estimation Results

	Class 1		Class 2		Class 3		Class 4	
Variable	Coef.	Coef/st err	Coef.	Coef/st err	Coef.	Coef/st err	Coef.	Coef/st err
Choice attributes in utility function								
MILES	-0.046 **	-2.52	-0.131 ***	-3.81	-0.015 ***	-3.50	-0.172 ***	-5.72
ELP	-0.211	-0.31	0		0.677 ***	7.57	0.296 ***	3.85
INDLOC	2.317 *	1.75	2.034 ***	3.41	0		0.877	1.50
KNPEOP	1.680	1.31	1.897 ***	3.43	-0.259 **	-2.39	0.399	0.68
ADEQNA	-0.359	-0.56	0.336	1.45	-0.037	-0.32	0	
FULLSE	-0.863	-1.06	1.270 ***	3.88	0.681 ***	6.72	0	
Individual characteristics in class probability model								
Intercept	-4.230 ***	-3.48	1.803	1.25	1.516 **	2.18	0	
FEMALE	-0.129	-0.64	0.090	0.16	-0.106	-0.53	0	
AGE	0.028 ***	2.1	-0.054 ***	-2.68	-0.030 ***	-3.23	0	
BPLUS	-0.001	-0.83	0.000	-0.07	0.000	0.17	0	
WORKIN	0.280	0.78	-0.156	-0.26	-0.515 **	-2.00	0	
WORKOUT	0.479	0.99	-1.558	-1.54	-0.365	-1.17	0	
HINC	0.000	-0.27	0.001	0.55	0.000	-1.19	0	
ENGAGED	0.427	1.27	-0.801	-1.41	-0.598 ***	-2.86	0	
FRIENDS	-0.054	-0.18	1.005 *	1.72	0.331	1.51	0	
TRUST	0.953 ***	2.56	-0.043	-0.2	-0.041	-0.19	0	
Avg. Class Prob	0.105		0.143		0.259		0.493	
AIC	1.354							
McFadden R^2	0.392							

Asterisks denote significance at the: * 90%, ** 95%, and *** 99% levels of confidence

Table 4. Marginal Effects for an Independent Store Competing Against a Large Retailer

	Base Attributes		Marginal/Discrete Effects by Class				Weighted Marginal/Discrete Effects				
Item	Local store	Competitor	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 4	Overall
Competing Store 5 miles away											
MILES	5	5	-0.001	-0.028	-0.002	-0.040	0.000	-0.004	-0.001	-0.019	-0.024
ELP	0	1	-0.007	0	0.131	0.065	-0.001	0	0.034	0.032	0.065
INDLOC	1	0	0.222	0.463	0	0.215	0.023	0.066	0	0.106	0.195
KNPEOP	0	0	0.026	0.253	-0.039	0.086	0.003	0.036	-0.010	0.042	0.071
ADEQNA	0	0	-0.013	0.068	-0.006	0	-0.001	0.010	-0.002	0	0.007
FULLSE	0	1	-0.041	0.202	0.132	0	-0.004	0.029	0.034	0	0.059
Base share of customers			0.967	0.682	0.205	0.641	0.102	0.098	0.053	0.316	0.568
Competing Store 20 miles away											
MILES	5	20	-0.001	-0.008	-0.003	-0.007	0.000	-0.001	-0.001	-0.003	-0.005
ELP	0	1	-0.004	0	0.145	0.010	0.000	0	0.037	0.005	0.042
INDLOC	1	0	0.130	0.272	0	0.052	0.014	0.039	0	0.026	0.078
KNPEOP	0	0	0.013	0.052	-0.045	0.013	0.001	0.007	-0.012	0.006	0.004
ADEQNA	0	0	-0.007	0.017	-0.007	0	-0.001	0.002	-0.002	0	0.000
FULLSE	0	1	-0.022	0.043	0.146	0	-0.002	0.006	0.038	0	0.042
Base share of customers			0.983	0.939	0.244	0.959	0.103	0.134	0.063	0.473	0.774
Competing Store 35 miles away											
MILES	5	35	0.000	-0.001	-0.003	-0.001	0.000	0.000	-0.001	0.000	-0.001
ELP	0	1	-0.002	0	0.155	0.001	0.000	0	0.040	0.000	0.040
INDLOC	1	0	0.071	0.056	0	0.004	0.007	0.008	0	0.002	0.018
KNPEOP	0	0	0.007	0.008	-0.050	0.001	0.001	0.001	-0.013	0.001	-0.011
ADEQNA	0	0	-0.004	0.003	-0.008	0	0.000	0.000	-0.002	0	-0.002
FULLSE	0	1	-0.011	0.006	0.156	0	-0.001	0.001	0.041	0	0.040
Base share of customers			0.992	0.991	0.289	0.997	0.104	0.142	0.075	0.491	0.812

Table 5. Marginal Effects for an Independent Store Competing Against a Dollar Store

	Base Attributes		Marginal/Discrete Effects by Class				Weighted Marginal/Discrete Effects				
Item	Local store	Competitor	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 4	Overall
Competing Store 5 miles away											
MILES	5	5	-0.001	-0.028	-0.002	-0.040	0.000	-0.004	-0.001	-0.019	-0.024
ELP	0	1	-0.012	0	0.164	0.065	-0.001	0	0.042	0.032	0.073
INDLOC	1	0	0.308	0.429	0	0.215	0.032	0.061	0	0.106	0.200
KNPEOP	0	0	0.043	0.128	-0.056	0.086	0.004	0.018	-0.014	0.042	0.051
ADEQNA	0	1	-0.021	0.039	-0.008	0	-0.002	0.006	-0.002	0	0.001
FULLSE	0	0	-0.064	0.106	0.165	0	-0.007	0.015	0.043	0	0.051
Base share of customers			0.947	0.845	0.345	0.641	0.099	0.121	0.089	0.316	0.626
Competing Store 20 miles away											
MILES	5	20	-0.001	-0.003	-0.004	-0.007	0.000	0.000	-0.001	-0.003	-0.005
ELP	0	1	-0.006	0	0.167	0.010	-0.001	0	0.043	0.005	0.048
INDLOC	1	0	0.194	0.139	0	0.052	0.020	0.020	0	0.026	0.066
KNPEOP	0	0	0.022	0.021	-0.060	0.013	0.002	0.003	-0.016	0.006	-0.004
ADEQNA	0	1	-0.011	0.007	-0.009	0	-0.001	0.001	-0.002	0	-0.002
FULLSE	0	0	-0.035	0.018	0.168	0	-0.004	0.003	0.044	0	0.042
Base share of customers			0.973	0.975	0.399	0.959	0.102	0.139	0.103	0.473	0.818
Competing Store 35 miles away											
MILES	5	35	-0.001	0.000	-0.004	-0.001	0.000	0.000	-0.001	0.000	-0.001
ELP	0	1	-0.003	0	0.167	0.001	0.000	0	0.043	0.000	0.043
INDLOC	1	0	0.111	0.023	0	0.004	0.012	0.003	0	0.002	0.017
KNPEOP	0	0	0.011	0.003	-0.063	0.001	0.001	0.000	-0.016	0.001	-0.014
ADEQNA	0	1	-0.006	0.001	-0.009	0	-0.001	0.000	-0.002	0	-0.003
FULLSE	0	0	-0.018	0.003	0.168	0	-0.002	0.000	0.043	0	0.042
Base share of customers			0.986	0.996	0.455	0.997	0.104	0.142	0.118	0.491	0.855