MAR
Articles in Advance, pp. 1–22
ISSN 0732-2399 (print)—ISSN 1526-548X (online)

http://dx.doi.org/10.1287/mksc.2013.0775

Category Positioning and Store Choice: The Role of Destination Categories

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We focus on destination categories, so named because they have the greatest impact on where households choose to shop and, more generally, on how category positioning (e.g., long-run merchandising policies) affects which store a household chooses. We propose a reduced-form model-based analytical approach to identify categories that fill the destination role. Our approach determines which categories are most important to shoppers' store choice decisions and helps determine in which categories the retailer provides superior value. In addition, our approach allows us to understand the impact of the retailer's long-run merchandising policy decisions on the value it provides. Previous store choice research focused on the effects of pricing, assortment and other merchandising decisions at the store level but did not consider the effect of specific categories on

the meaning of a destination category. First, being the primary provider helps the retailer become the

retailers welcome larger basket sizes and/or basket expenditures. However, interviews with category managers at large retailers revealed that higher category purchase quantities are associated with other

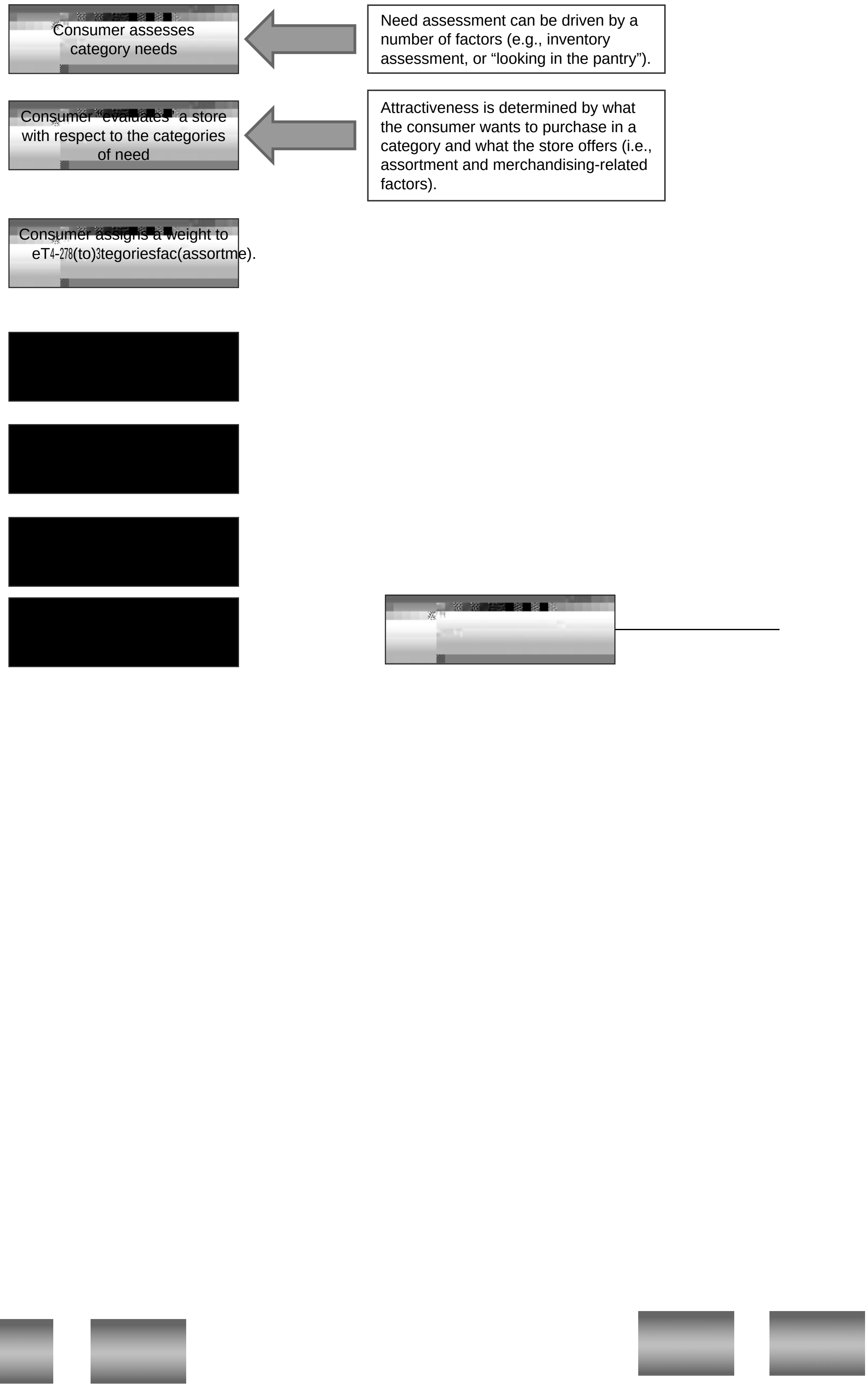
Table 1 (Cont'd.)

Category	BI-LO	Food Lion	Harris Teeter	Winn-Dixie	Walmart
Shampoo	76	47	48	90	236
Batteries	66	36	58	75	252
Pickles/relish/olives	108	94	138	137	52
Margarine/spreads/butter	101	107	102	144	84
Dinner sausage	130	94	118	188	50
Deodorant	73	53	71	81	212
FZ desserts/topping	84	115	124	180	43
Shortening and oil	119	110	97	111	65
Baking needs	122	100	113	95	82
SS dinners	148	129	91	105	56
Toaster pastries/tarts	156	83	123	89	86
Air fresheners	80	70	71	84	191
Toothbrush/dental accessories	68	36	47	59	247
Food and trash bags	77	87	98	81	112
Spaghetti/Italian sauce	117	103	137	128	52
Sanitary napkins/tampons	78	72	85	49	180
Seafood—SS	127	107	99	114	60
Peanut butter	106	110	100	104	80

Note FZ, frozen; RFG, refrigerated; SS, shelf stable.

retail chains in the Charlotte, North Carolina market. These chains and product categories will be the focus of the empirical analysis that follows in §8. CDIs can vary markedly across retail chains, as is the case for the ve retail chains shown in Table 1. Although CDIs can undoubtedly identify store-by-category dif-

Figure 1 Conceptual Frameworks: (A) Conceptual Consumer Model and (B) Conceptual Modeling Framework



4.1. Conceptual Shopper Model

As depicted in panel A of Figure 1, the process begins with the shopper recognizing one or more category needs. He or she then, either consciously or unconsciously, evaluates each store's offering in the categories of need. In essence, this involves an evaluation of what the shopper wants to purchase and what the store offers. It is important to note that this evaluation re ects what the shopper knows before choosing a store—each store's long-run category assortment and merchandising policies, not the actual displays and (unadvertised) prices, which are only observable after choosing the store. In addition, the shopper weighs the importance of individual categories in satisfying his or her needs. These importance weights re ect the fact that certain categories may have a greater impact on store choice. At this point, the shopper is in a position to assess the total basket utility that he or she would derive from purchasing at each store under consideration. To determine which store to visit, the shopper compares the store-speci c total basket utility with store-speci c shopping costs. The shopper then chooses the store that maximizes his or her net utility, which in turn determines which in-store stimuli he or she sees and hence whether category purchases are consummated. Recall that only the household's category purchases (incidence) are observed, not the household's category needs or the store-speci c category value. In our model, category needs and store-speci c category value are identi ed by the household's category purchases.

4.2. Conceptual Modeling Framework

The modeling framework shown in panel B of Figure 1 adds further speci city to the shopper model described above. In the gure, ovals depict inherently unobservable factors (i.e., constructs) and squares depict observable variables. W a9ET BT 1 0 0 .707a(ppesTwe8s)] TJ ET BT 1 0 0 1 57.785508(ar)18(en-po8(tsimidof)-45

5. Model Forms

5.1. Category Incidence Model

The indirect utility for household h purchasing category c on trip t (at store s) can be written as

$$U^C_{hsct} = V^C_{hsct} + \varepsilon^C_{hsct} \quad (1)$$

where V^C_{hsct} denotes the deterministic component of utility. Consistent with our conceptual modeling framework, we partition the deterministic component of the utility of purchasing in the category in terms of category needs, in-store factors, and store-specific category value as follows:

$$\begin{aligned} V^C_{hsct} = {} & \alpha_{hsct} + \beta_{0hc} + \beta_{1hc}\mathrm{Time}_{hsct} + \beta_{2hc}\mathrm{Qnty}_{hsc,t-1} \\ & + \beta_{3hc}\mathrm{Time}_{hsct}\ \mathrm{Qnty}_{hsc,t-1} + \beta_{4hc}\mathrm{FAdv}_{hsct} \\ & + \beta_{5hc}\mathrm{WKEnd}_{hct} + \beta_{6hc}\mathrm{Price}_{sct} + \beta_{7hc}\mathrm{Disp}_{hsct} \end{aligned} \quad (2)$$

In Equation (2), the first five covariates relate to factors that influence a household before shopping and which assist in determining the household's category needs:

Time = The number of days since the household last purchased in the category.

Qnty = Quantity purchased in a category on

attribute dimensions. Note also that (1) AdvF and DispF are incorporated in the merchandising score but only as long-term frequencies (see Ainslie and Rossi 1998), and (2) in deriving the store locations ($\bullet_{sd}$) and category ideal points ($\bullet^{I}_{hcd}$), we remove the baseline category purchase frequencies (f_{0hc}) so that the impact of assortment and merchandising is independent of how often the household purchases in the category. We establish the conditions for identi cation of the spatial parameters below (proofs are available in the Web appendix).

Finally, we would argue that the merchandising and product assortment variables (and their de ni- tions) that appear in Equation (5) reasonably capture a retailer's merchandising and product assortment decisions and are similar to the operationalizations used by others (e.g., Boatwright and Nunes 2001, Briesch et al. 2009); however, we recognize that these covariates may not be re ective of how households encode category information or form impressions about categories. For example, Hoch et al. (1999) present an interesting approach to capturing how households perceive the "variety" of an assortment. Their approach, however, is best suited to studies that consider a small number of items per category, unlike the present study, because it is based on computing the psychological distance between all items in a category (i.e., all pairwise comparisons).[11] We discuss this limitation of the current study further in §10.

5.1.2. Identi cation Conditions for Spatial Parameters. To identify the spatial parameters, i.e., store locations ($\bullet_{sd}$) and category ideal points ($\bullet^{I}_{hcd}$), we use category purchase incidence data along with a number of identifying constraints. In this section we provide general identi cation conditions. Conditions for identi cation of a k-dimensional solution rely on the identifying restrictions associated with the k ƒ 1 dimensional solution (see the Web appendix for proofs).

Condition 1. The weights for the dimensions are set to ƒ 1 for all dimensions. This identi es the scale of the map and ensures that all dimensions have the same scale.

Condition 2. One store is located at the origin (or the stores are centered at the origin; i.e., the sum of the store positions on each dimension add to 0). This restriction provides translational invariance for the stores and helps identify the category intercepts.

Condition 3. One category is located at the origin (or the categories are centered at the origin; i.e., the sum of the category positions on each dimension add to 0). This restriction provides translational invariance for the categories and helps identify the category intercepts and other store positions.

Condition 4. For each dimension d, $\bullet_{4s}$

[11] Another interesting approach is presented by Morales et al. (2005), who capture how a consumer organizes category assortment internally. We thank a reviewer for raising this issue and pointing us to the work of Hoch et al. (1999) and Morales et al. (2005).

de category positionss

To develop such a measure, we first consider the extent to which categories should be weighted differently in determining the impact that a category has on store choice. As discussed in §4, it is reasonable to expect that certain categories will have more weight in driving store choice; for example, categories such as carbonated beverages, which have high purchase frequency and relatively high dollar value are perhaps more likely to affect store choice decisions than categories such as salt, which have low purchase frequency and low dollar value (ACNielsen 2006). Letting ω_{hc} denote the weight that household h places on category c, we can write

$$\omega_{hc} = \exp(\theta_c + \gamma_{c1}\$Spend_{hc} + \gamma_{c2}APT_{hc} + \gamma_{c3}\$Spend_{hc} \times APT_{hc} + \xi_{hc}) \quad (1)$$

where $Spend denotes the household's average dollar spend in the category and APT denotes the average time between purchases in the category. In estimating ω_{hc}, we mean center both covariates and therefore expect that both covariatesihctherefore

where ˆ denotes the global set of store choice and category incidence parameters, è denotes the parameter covariance matrix, and f4ˆ —è5 is the distribution of the parameter vector ˆ conditional on the covariance matrix è.[15] We assume that this distribution is multivariate normal. To account for heterogeneity across household purchase incidence and store choice decisions, we use a continuous distribution with the parameter covariance matrix è. To reduce the dimensionality of the covariance matrix è

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Table 3 Category Descriptive Statistics

	Penetration	Share of	Average prices

shopper chose the store he or she visited most often. On 69% of single-category trips, however, the shopper chose the store with the highest CDI (recall that CDI measures the extent to which retailers get more or less than their fair share of category sales). Thus, without the confounding effects of other categories in the market basket, we find that shoppers were almost twice as likely to choose the store "specializing" in the category as their favorite store, which strongly suggests that specific categories do indeed affect store choice.[19]

8. Results

We began by fitting several models and progressively increasing the number of dimensions specified for the latent multiattribute space. We stopped increasing the number of latent attribute dimensions when the BIC and CAIC information-theoretic statistics indicated that the improvement in log likelihood from adding an additional dimension did not compensate for the increase in model complexity.

8.1. Model Fit

Table 5 provides goodness-of-fit statistics for both in-sample and out-of-sample results. First, we see that all of the proposed models fit better than the baseline model. Recall that these proposed models include a spatial representation for the attraction parameter. Thus, the superior fit of the proposed models suggests that the relative positions of stores and category ideals in perceptual space may provide insights into the role of categories and category merchandising in store choice decisions and enable retailers to make their stores more attractive by better accommodating shoppers' preferences.

In terms of in-sample fit, the three-dimensional solution has lower BIC and CAIC information-theoretic statistics than either the two- or four-dimensional solutions. Table 5 also reports in- and out-of-sample log likelihoods along with hit rates. In terms of hit rates, all of the models perform equally well, although the three-dimensional solution provides the highest hit rates in and out of sample. The three-dimensional solution also yields the lowest out-of-sample log likelihood. Given that the three-dimensional solution fits the data best, we will focus on this solution in the remainder of our analyses and discussion.[20]

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Table 7 Impact of Household (HH) Demographics on the Importance of a Category

Category	Elderly (65+)	HH size	HH income	College or above	Married	Children in HH	Ethnicity (Caucasian)	No. of signi cant parameters
1 Carbonated beverages							Sƒ	1
3 Cold cereal							Sƒ	1
6 Salty snacks				ƒS		SC		2
11 Crackers	CS							1
12 Luncheon meats				ƒS				1
14 Total chocolate candy					CS			1
15 Dog food	ƒS							1
17 FZ pizza	CS							1
21 Coffee	CS			SC				2
22 RFG salad/coleslaw				CS				1
23 Pet supplies						SC		1
25 Wine	ƒS					Sƒ	Sƒ	3
27 Vegetables					CS			1
28 Toilet tissue			ƒS					1
31 Total nonchocolate candy	ƒS							1
33 Paper towels				ƒS		SC		2
34 Household cleaner			CS		Sƒ			2
36 Internal analgesics			ƒS					1
37 Dough/biscuit dough—RFG			CS		Sƒ			2
38 Frankfurters		CS	Sƒ			SC		3
39 Vitamins	CS							1
41 Yogurt		ƒS		SC		SC		3
42 Bottled water							Sƒ	1
45 Pastry/doughnuts			ƒS					1
48 FZ plain vegetables					ƒS			1
50 Snack nuts/seeds/corn nuts		CS						1
51 Baking mixes			ƒS		SC			2
52 Bottled juices—SS				CS				1
53 Skin care			CS			Sƒ		2
56 Canned meat			ƒS	SC		SC		3
63 Shampoo	CS						SC	2
67 Dinner sausage				ƒS				1
68 Deodorant		CS				Sƒ		2
73 Toaster pastries/tarts							SC	1
74 Air fresheners		ƒS				SC		2
76 Food and trash bags	CS							1
77 Spaghetti/Italian sauce						CS		1
79 Seafood—SS		ƒS				SC		2

Notes FZ, frozen; RFG, refrigerated; SS, shelf stable. "CS" indicates a statistically signi cant positive relationship; "ƒS" indicates a statistically signi cant negative relationship.

associated with one or more of the household demographic variables under consideration. Among the statistically signi cant relationships, we nd that elderly households (65 years of age or older) place greater importance on crackers, breakfast meats, coffee, and vitamins, for example, whereas households with children place more importance on yogurt, paper towels, frankfurters, salty snacks, spaghetti, and Italian sauce. In general, although we nd signi cant covariation between interhousehold category importance and household demographics, the relationships were for the most part weak; household demographics accounted for less than 2% of the variation in category importance and, across all comparisons, about 20% of the possible relationships were statistically signi cant at the $p < 0.10$ level and less than 10% at the $p < 0.05$ level.

8.2.4. Store Positions and Long-Run Merchandising Parameters. We nd that all of the store position parameters are statistically signi cant across all three latent attribute dimensions. Interestingly, although there is a demonstrable relationship between physical geography and the derived perceptual store distance (i.e., we nd that approximately 22% of the variation in the perceptual distances between stores is explained by median travel time) nearly four- fths of the variation in perceptual store distances is not explained by the geographic location of the stores.

The long-run merchandising parameters were estimated for each of the three latent attribute dimensions. We nd that 20 of the 27 mean parameter estimates are signi cant. There is not much intuition in the store positioning or long-run merchandising parameters, however, because of the dimensionality of our model. As a consequence, we have left a detailed discussion of these parameter estimates for the Web appendix.

Table 8 Decomposition of BaskUtil Category Utilities

Rank	Category	BI-LO	Food Lion	Harris Teeter	Winn-Dixie	Walmart	Average	Sales rank
1	Carbonated beverages	7.717	6.029	6.946	7.115	2.854	6.132	1
2	Salty snacks	3.245	2.865	3.443	2.917	1.481	2.790	6
3	Fresh bread and rolls	1.922	1.578	2.151	1.758	0.747	1.631	5
4	RFG salad/coleslaw	0.897	1.117	1.734	1.363	0.406	1.104	22
5	Crackers	0.984	0.939	1.525	0.791	0.537	0.955	11
6	Beer/ale/alcoholic cider	1.045	1.246	1.069	0.784	0.210	0.871	7
7	Yogurt	0.941	0.476	1.389	0.690	0.408	0.781	41
8	Cold cereal	0.905	0.690	0.920	0.879	0.379	0.754	3
9	Coffee	0.598	0.612	0.920	0.710	0.340	0.636	21
10	FZ breakfast food	0.536	0.551	0.736	0.504	0.160	0.498	54
11	Toilet tissue	0.538	0.446	0.533	0.651	0.282	0.490	28
12	Cups and plates	0.495	0.283	0.711	0.508	0.297	0.459	60
13	Milk	0.564	0.450	0.573	0.504	0.202	0.459	8
14	Dough/biscuit dough—RFG	0.541	0.376	0.450	0.539	0.168	0.415	37
15	FZ dinners/entrees	0.475	0.443	0.610	0.368	0.174	0.414	4
16	Deodorant	0.368	0.257	0.351	0.210	0.708	0.379	68
17	Pastry/doughnuts	0.312	0.423	0.617	0.352	0.189	0.378	45
18	Wine	0.375	0.444	0.304	0.310	0.088	0.304	25
19	Bottled water	0.290	0.127	0.523	0.181	0.272	0.279	42
20	Laundry detergent	0.261	0.286	0.337	0.217	0.224	0.265	26
21	Ice cream/sherbet	0.243	0.260	0.392	0.260	0.064	0.244	16
22	Dish detergent	0.217	0.187	0.286	0.305	0.212	0.241	58
23	Toaster pastries/tarts	0.262	0.178	0.262	0.350	0.114	0.233	73
24	Canned meat	0.328	0.251	0.186	0.285	0.112	0.233	56
25	FZ desserts/topping	0.196	0.242	0.324	0.295	0.058	0.223	69
26	Internal analgesics	0.190	0.194	0.282	0.213	0.177	0.211	36
27	Snack nuts/seeds/corn nuts	0.175	0.131	0.298	0.154	0.160	0.183	50
28	FZ novelties	0.230	0.189	0.260	0.170	0.037	0.177	32
29	Baking mixes	0.190	0.173	0.190	0.213	0.053	0.164	51
30	Cold/allergy/sinus tablets	0.147	0.103	0.182	0.126	0.247	0.161	46
31	Seafood—SS	0.164	0.142	0.218	0.140	0.055	0.144	79
32	Bottled juices—SS	0.157	0.144	0.163	0.137	0.062	0.132	52
33	FZ appetizers/snack rolls	0.139	0.118	0.225	0.102	0.051	0.127	61
34	FZ meat	0.115	0.075	0.228	0.082	0.038	0.108	57
35	Batteries	0.051	0.043	0.060	0.031	0.164	0.070	64
36	Soup	0.080	0.069	0.090	0.074	0.025	0.068	20
37	Cookies	0.074	0.069	0.100	0.051	0.040	0.067	10
38	Total nonchocolate candy	0.046	0.047	0.060	0.040	0.066	0.052	31
39	Vegetables	0.059	0.051	0.056	0.065	0.015	0.049	27
40	Paper towels	0.048	0.029	0.044	0.049	0.025	0.039	33
41	Pickles/relish/olives	0.041	0.036	0.059	0.045	0.011	0.039	65
42	Cigarettes	0.031	0.053	0.014	0.025	0.008	0.026	2
43	Household cleaner	0.023	0.018	0.030	0.021	0.033	0.025	34
44	Shampoo	0.019	0.016	0.018	0.016	0.047	0.023	63
45	Natural cheese	0.027	0.019	0.029	0.027	0.008	0.022	9
46	Dry packaged dinners	0.024	0.019	0.023	0.018	0.009	0.019	35
47	Margarine/spreads/butter	0.021	0.016	0.022	0.025	0.007	0.018	66
48	Soap	0.013	0.015	0.014	0.013	0.032	0.017	43
49	Shortening and oil	0.018	0.016	0.023	0.021	0.006	0.017	70
50	SS dinners	0.020	0.023	0.016	0.015	0.007	0.017	72
51	Dog food	0.019	0.015	0.019	0.017	0.013	0.016	15
52	Luncheon meats	0.021	0.017	0.019	0.021	0.005	0.016	12
53	FZ pizza	0.020	0.015	0.026	0.011	0.007	0.016	17
54	Processed cheese	0.019	0.014	0.016	0.016	0.006	0.014	24
55	FZ seafood	0.025	0.015	0.015	0.012	0.004	0.014	29
56	Toothbrush/dental accesories	0.014	0.013	0.011	0.006	0.025	0.014	75
57	RFG fresh eggs	0.013	0.012	0.016	0.015	0.004	0.012	62
58	Toothpaste	0.008	0.007	0.015	0.005	0.016	0.010	44
59	Cat food	0.013	0.009	0.013	0.009	0.007	0.010	19
60	RFG juices/drinks	0.013	0.010	0.014	0.010	0.003	0.010	40
61	Frankfurters	0.010	0.008	0.011	0.011	0.003	0.009	38
62	Breakfast meats	0.009	0.009	0.010	0.010	0.003	0.008	13

Table 8 (Cont'd.)

Rank	Category	BiLo	FoodLion	Harris Teeter	Winn-Dixie	Walmart	Average	Sales rank
63	Spaghetti/Italian sauce	0.007	0.009	0.013	0.008	0.003	0.008	77
64	Skin care	0.002	0.003	0.004	0.003	0.023	0.007	53
65	Peanut butter	0.009	0.007	0.008	0.007	0.004	0.007	80
66	Canned/bottled fruit	0.008	0.005	0.009	0.007	0.002	0.006	49
67	Spices/seasonings	0.005	0.006	0.008	0.004	0.003	0.005	59
68	Total chocolate candy	0.005	0.004	0.007	0.003	0.007	0.005	14
69	Baking needs	0.005	0.004	0.007	0.005	0.003	0.005	71
70	FZ bread/FZ dough	0.004	0.003	0.005	0.004	0.001	0.004	55
71	Snack bars/granola bars	0.004	0.003	0.003	0.003	0.003	0.003	30
72	Dinner sausage	0.003	0.003	0.003	0.003	0.001	0.002	67

Table 9 Effective Merchandising Findings

Utility rank	Category	BI-LO	Food Lion	Harris Teeter	Winn-Dixie	Walmart	% effectively merchandising

distance mapping could be used to evaluate merchandising effectiveness at the category level and to suggest approaches to improving merchandising effectiveness category by category. Fourth, the efficacy of our model for selecting destination categories could be tested experimentally, either by matching stores of a given retailer within a geographic market or by comparing stores across geographic markets for the same retailer. Finally, the framework we have developed could be extended to address the question of how much shoppers buy; i.e., purchase quantity.[30]

Acknowledgments
The authors thank Information Resources, Inc. for providing the data used in this paper. Any mistakes or omissions are the sole responsibility of the authors.

Electronic Companion
An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/mksc.2013.0775.

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