Destination Categories and Store Choice

Richard A. Briesch, William R. Dillon, and Edward J. Fox
Cox School of Business
Southern Methodist University

May 2010

Abstract

Our objective in this work is to identify and understand "destination categories," defined as those that, after controlling for location, prices and feature advertising, increase a shopper's probability of choosing a store. A secondary objective is to extend the literature concerning the influence of product assortment on store choice decisions by isolating the differential impact, if any, of specific product categories (80 total categories) across retail formats (grocery and a mass merchandiser supercenter). To investigate these issues, we formulate a modified logit store choice model that captures differential category effects by incorporating a spatial model that positions categories and stores in multi-attribute space so that a category's *destination-ness* for a store determines its proximity. We identify destination categories for six retailers in the Charlotte, North Carolina market as well as the categories that are most influential in store choice decisions (i.e., high leverage). We find that the high leverage categories tend to be purchased frequently, consume a high share of household spending and be fresh/refrigerated or frozen categories. We also find that Food Lion's assortment decisions in these high-leverage categories are more likely to draw shoppers to its stores while Lowe's assortment decisions generally have the opposite effect. Further, we find that Wal-Mart tends to price its destination categories higher than other categories while most other retailers price categories independent of *destination-ness*.

Retail practitioners have long recognized that categories play different roles (e.g., destination, routine, seasonal and convenience) and have differential importance to shoppers' store choice decisions (Blattberg et al. 1995). Moreover, Dhar et al. (2001) note that retailers develop expertise in particular categories and, once developed, category expertise becomes part of the organization's intellectual capital.

While there is a growing body of literature concerning the effects of category assortment and related factors on store choice, this literature has focused almost exclusively on the store choice decision without considering category purchase decisions. Accordingly, the influence of specific categories on the store choice decision has not received much attention. The belief that specific categories generate traffic by attracting shoppers to a store is widely held by retailers though much of evidence to support the existence so called "destination categories" is anecdotal (see, Blattberg et al. 1995, p. 23).

Objectives

Our objective in this work is to identify and understand "destination categories," defined as those that, after controlling for location, prices and feature advertising, increase a shopper's probability of choosing a particular store.[1] Both retailers and manufacturers have an interest in determining which categories have a greater or lesser influence on store choice. Retailers are interested in this issue because it affects category merchandising, advertising and pricing decisions; manufacturers are interested in this issue because it supports their category expertise, hence their ability to advise retailers as a "category captain" (cf. Blattberg et al. 1995). A secondary objective is to extend the literature concerning the influence of product assortment on

[1] We will have more to say about how destination categories should be defined in a later next section.

store choice decisions by isolating the differential impact, if any, of specific product categories (80 total categories) across retail formats (grocery and a mass merchandiser supercenter).

To investigate these issues, we formulate a modified logit store choice model that captures differential category effects by incorporating a spatial model. In the spatial model, categories and stores are positioned in multi-attribute space so that a category's *destination-ness* determines its proximity to a store.

We estimate the model using a multi-outlet scanner panel dataset containing information about the purchases of 357 households in 80 categories across six retailers over a 104 week period. We identify the extent to which each of the major store chains in the Charlotte, North Carolina market area has developed specialized category expertise (i.e., destination categories). For traditional grocery retailers, these categories primarily include perishable (fresh, refrigerated and frozen) goods; for Wal-Mart Supercenters, these products primarily include non-grocery products and, interestingly, candy. We further identify the categories that exert the greatest leverage on store choice decisions across all retailers, finding that leverage is concentrated in a few categories. Among these high-leverage categories are some of the retailers' highest revenue categories—milk, fresh bread & rolls, beer, carbonated beverages and cigarettes—as well as lower revenue categories such as fresh eggs, ice cream/sherbet and frozen meat. We are also able to determine which retailers are assorting these high leverage categories most effectively to attract shoppers to their stores.

The rest of the paper is organized as follows. We begin by briefly reviewing the extant literature and positioning our work relative to this literature. Next we discuss the concept of a destination category and argue that, while it may be easy to describe, it may be far more difficult to measure directly. In the course of that discussion, we present a number of propositions about destination categories that can be subjected to empirical testing. We then formulate the general model, discuss its rationale vis-à-vis extant models, and describe the store choice and category incidence component models. This is followed by a discussion of how the store choice and category incidence model intercepts are parameterized. The next section is devoted to estimation issues, specifically parameter identification. We then describe the data and the covariates used to estimate the model. Next, we describe our approach to testing the destination category propositions and discuss empirical findings. Modeling results then follow. After discussing parameter estimates, we present a policy analysis which calibrates the impact of categories on store choice. We conclude with a discussion of our findings including which assortment-related factors have the greatest impact on *destination-ness* as well how effectively each retailer has assorted those categories shown to have the greatest impact on store choice.

Background and Contribution

Explaining store choice decisions has been of great interest to academics and practitioners alike; however, the vast majority of research in this area has focused on what factors influence a consumer's decision on where to shop. With this focus in mind, researchers have addressed a wide variety of issues such as explaining store choice behaviors in terms of marketing activities—price promotions, feature and display, retail/price formats (HILO vs. EDLP), shopping basket sizes and composition, travel distance, prior shopping experiences, the need for variety, shoppers' fixed and variable costs, cherry-picking, household characteristics and more recently store-category loyalty and category assortments.[2]

[2] Representative papers include: Reilly 1931; Baumol and Ide 1956; Huff 1964; Arnold, Ma and Tigert 1978; Arnold, Roth and Tigert 1981; Arnold and Tigert 1982; Arnold, Oum and Tigert 1983; Bell, Ho and Tang 1998; Bell and Lattin 1998; Rhee and Bell 2002; Fox and Hoch 2005; Briesch, Chintagunta and Fox 2009.

Because our focus is on the existence of and role played by destination categories, the recent work investigating the influence of category assortments on store choice and the phenomenon of store-category loyalty deserve some attention.

What We Know About Category Assortments

The role which category assortment plays in store choice has been the subject of some debate. While several studies fail to find a positive relationship between assortment size and category sales in grocery stores (Broniarczyk et al. 1998; Dreze et al. 1994; Boatwright and Nunes 2001), others find that assortment size positively affects the probability that shoppers will patronize a particular retailer (Fox et al. 2004). However, there is a growing body of evidence that larger assortments are not universally preferred (Broniarczyk et al. 2006; Chernev et al. 2003; Chernev and Hamilton 2009) and that assortment preferences are heterogeneous (Broniarczyk et al. 1998; Briesch et al. 2009). Moreover, the recent findings of Chernev and Hamilton (2009) and Briesch et al. (2009) demonstrate that the influence of product assortment on store choice is more nuanced than previously thought. The ability of larger assortments to attract shoppers to a particular store varies greatly by household, is correlated with travel distance, and depends on the attractiveness and the composition of the assortment with respect to the brands, sizes and the number of SKUs. For example, small assortments can attract shoppers if sufficiently attractive; increasing the number of brands offered will likely increase a shopper's probability of choosing a particular retailer but increasing the number of SKUs may not.

Store-Category Loyalty

Two studies have investigated the degree to which shoppers are store-category loyal; that is, households shop at specific stores in order to make purchases in particular categories. Dhar et al. (2001) suggest that there are categories for which consumers have strong store-category preferences and shop at a specific retailer when purchasing in these categories whenever possible. Using a controlled store experiment, they demonstrate that retailers can induce consumers to be store-loyal for specific products through cross merchandising programs.

Zhang et al. (2010) estimate a store loyalty model at the category level with a view toward demonstrating that store loyalty is a category-specific household trait and that it is quite common for households to be loyal to different stores in different categories. Using a scanner panel dataset that contains the purchases of 1321 households in 284 categories across 16 stores over a 53 week period, they find that shopping at multiple stores is pervasive, and, of those who shop at multiple stores, almost all are to some degree store-category loyal—they make all of their purchases exclusively at the same store for at least one of their regularly purchased product categories. These authors find that store-category loyalty is, among other factors, positively influenced by category dollar share of requirements, store visit frequency, breadth, uniqueness and relevance of SKUs in the assortment, and perceived price advantage.

Contribution

Our primary focus is not on modeling store choice *per se*, or, for that matter, on the role of product assortments in store choice decisions. Rather, our objective is to assess the *destination-ness* of specific categories; that is, the extent to which the attractiveness of specific categories increases the probability of choosing a store. As such, we need to investigate factors thought to influence store choice, including product assortments; however, our modeling approach differs from previous store choice/loyalty studies in a number of important ways.

1. Compared to Zhang et al. (2010) we are not interested in store-category loyalty — that is, we do not model the probability that a household makes *all* of its purchases in a given category exclusively at a particular store. In addition, we adopt a model form that

explicitly considers category incidence and allows household and category parameters to vary across categories. Consequently, our store choice probabilities are explicitly informed by category purchases.

2. Compared to Bell et al. (1998) and Briesch et al. (2009) we do not adopt a *shopping list* metaphor or a *need-based* approach to category incidence. By not conditioning on a shopping list or on category needs, we capture all purchase incidences and therefore can account for impulse purchases and the effects of in-store merchandising and, in addition, can accommodate basket-splitting behaviors, i.e., when shoppers make purchases at different stores on the same day. Because we incorporate a spatial model of household preferences in which stores and categories are positioned in multi-attribute space, we also are better able than either of the prior studies to assess the extent to which different categories drive store choice across retail formats. We show how the locations of a given store and category in multi-attribute space reflect the degree to which the category is a destination; in other words, the closer a category is positioned to the store, the greater the *destination-ness* of the category for that store. We also derive a new measure, [*C*]ategory [*L*]everage [*I*]n [*P*]atronage [*D*]ecisions to determine how much leverage specific categories exert in shoppers' store choice decisions. Finally, we explicitly model both store choice and category incidence and consider a much larger number of categories and retail formats than either of the cited studies.

Substantively, we find that the categories that are most influential in store choice decisions (i.e., highest *CLIPD*) tend to be fresh/refrigerated or frozen, purchased frequently and consume a high share of household spending. We also find that Food Lion's assortment decisions in the most influential categories are more likely to draw shoppers to its stores while Lowe's assortment decisions generally have the opposite effect. Further, we find that Wal-Mart tends to price its destination categories higher than other categories while most other retailers price categories independent of *destination-ness*.

Destination Categories and Category Leverage

The concept of a destination category is seemingly very simple and can be defined either from the perspective of the shopper or the retailer; for the shopper, a category is a "destination" if it increases that shopper's probability of choosing a store; for the retailer, a category is a "destination" if it attracts shoppers to its stores. Although these definitional perspectives are rather intuitive, destination categories may well be easier to describe then to measure. Consider, for example, the following two illustrative self-reports:

"I buy all of my pasta and pasta sauce at Winn Dixie, but little else."

"I buy almost all of my weekly household grocery needs at Winn Dixie because they stock my favorite brands of pasta and pasta sauce."

In both instances, it is clear that the reason for shopping at Winn Dixie is the strong preference for specific pasta and pasta sauce brands so these categories qualify as destination categories. However, in the case of the first shopper, Winn Dixie captures only a small percentage of this household's grocery requirements while, for the second shopper, Winn Dixie captures almost all of this household's grocery requirements. Moreover, using household panel data it is likely that even crude methods of analysis would point to pasta and pasta sauce as destination categories for the first shopper, whereas identifying pasta and pasta sauce as destination categories in the case of the second shopper would be more challenging.

Identifying destination categories on the basis of store scanner data may also be difficult. Consider Table 1 which presents the Category Development Index (*CDI*) across 80 product categories for six retail chains in the Charlotte, North Carolina market. These chains and product categories will be the focus of the empirical analysis which follows in a later section. At an aggregate level, *CDI* reflects the preference of shoppers to purchase specific categories at one retailer (rather than at others) and is defined as the retailer's share in a particular category divided by its overall market share, multiplied by 100 (e.g., Dhar et al. 2001). While *CDI*s can vary markedly across retail chains, as is the case for the six retail chains shown in Table 1, *CDI* does not necessarily measure whether the category actually attracts shoppers to a particular store. For example, categories in which the retailer gets more than its fair share (*CDI* > 100) might be purchased coincidently with categories that actually influenced the store choice decision (see e.g., Manchanda et al. 1999) or coincidently with other purchases that were made because of advertised prices. More importantly, *CDIs* provide no diagnostic information that can explain why certain categories have a stronger impact on a shopper's decision to make a category purchase at a particular store, which is the focus of this paper.

Place Table 1 about here

If a destination category increases the probability of choosing one store (i.e., draws traffic to that store), that category must necessarily decrease the probability of choosing competing store(s). Identifying categories that affect store choice probability, whether or not they are destination categories, is important to retailers' category merchandising, advertising and pricing decisions; it is also important to manufacturers that supply those categories because they often advise retailers on those decisions. We therefore expand our investigation of destination categories to consider the overall effect of categories on store choice across retailers in a market, which we call category leverage.

Propositions

Notwithstanding the challenge that identifying destination categories presents, there are a number of intuitive and verifiable propositions that should be observed if destination categories exist. The following propositions are based on the premise that, if stores do indeed develop expertise in particular categories and if such expertise varies by store and by category, then we should observe the following[3]:

Proposition 1: Households that are attracted to particular stores because of the product offerings (i.e., assortments) in specific categories will make purchases in different categories at different stores on the same day/week.

Proposition 2: Households that purchase at multiple stores on the same day/week will show (non-random) patterns of store choice and category purchasing over time – households will purchase at different stores on the same day/week with purchase incidences reflecting the complementary nature of the stores shopped.

Proposition 3: Destination categories imply store specialization; they are not confined to the household's favorite store. Stated differently, store loyalty is not the driving force behind destination categories.

In the empirical application section later in the paper, we will assess the extent to which these propositions are observed in our sample of households. While these propositions cannot unambiguously demonstrate category *destination-ness*, if these behaviors are indeed manifest in the shopping behaviors of households in our dataset, we are in a better position to argue for the existence of destination categories.

[3] The following propositions focus on households who make category purchases at different stores. We do not mean to imply that households that make all of their purchases at one store do not exhibit category destination behaviors, but simply that, as mentioned previously, all else the same, it is more difficult to propose straight-forward empirical metrics that can provide evidence of the *destination-ness* of a category.

Model Formulation

General Model Form

Consistent with Bell et al. (1998) and Briesch et al. (2009), we assume that the decision as to which store to visit is dependent upon store-specific characteristics (e.g., pricing, store locations) as well as the attractiveness of all categories to the consumer:

Store Visit = f (store characteristics and *attractiveness of all categories).*

In this research we assume that category attractiveness is a function of merchandising activity, consumer need for the category as well as the *destination-ness* of the category for the chosen store. If we knew the attractiveness of categories *a priori*, then a store choice model consistent with the specification shown above could be estimated directly. However, because we do not know how consumers evaluate the attractiveness of categories, we use incidence models conditional on the shopper visiting the store to estimate each category's unobserved attractiveness.

Denoting the probability of household h (h =1,2,...,H) purchasing a subset of the total categories C, conditional on visiting store s (s =1,2,...,S) on trip t (t =1,2,...,T) as $\Pr(C \mid y_{hst} = 1)$, the joint probability of household h purchasing the set of categories C at store s on trip t, denoted as $\Pr(y_{hst} = 1 \cap C)$, can be expressed as:

$$\Pr(y_{hst} = 1 \cap C) = \Pr(y_{hst} = 1)\Pr(C \mid y_{hst} = 1). \tag{1}$$

The two components of the joint probability shown in equation 1 will be referred to as the store choice model and the category incidence model, respectively. We note that, in theory, this model could be estimated in two steps (although less efficiently), where the category incidence model is estimated in the first step to calculate the category attractiveness for each store, and then the store choice model is estimated in the second step. Besides efficiency concerns, one of the many problems associated with the two-step approach is that household heterogeneity is tacitly assumed to be unrelated across the two steps. Therefore, we use a single step (i.e., simultaneous) estimation approach.

To account for heterogeneity across household purchase incidence and store choice decisions, we use a continuous distribution with the parameter covariance matrix Σ. We utilize a mixed logit model to estimate the store choice probabilities (Train 2003). Let θ denote the set of category incidence and store choice model parameters. Now the probability that we observe household h purchasing a subset from the set of categories C at store s on trip t can be written as

$$\Pr(y_{hst}=1 \cap C|\theta,\Sigma)=\Pr(y_{hst}=1|\theta,\Sigma)\times\prod_{c\in c_h}[\Pr(y_{hcst}=1|y_{hst}=1,\theta,\Sigma)^{y_{hcst}}(1-\Pr(y_{hcst}=1|y_{hst}=1,\theta,\Sigma))^{1-y_{hcst}}]$$

where y_{hcst} = 1 if household h purchases in category c at store s on trip t, and 0 otherwise.

Model Rationale

Our store choice model differs significantly from the forms used by Bell et al. (1998) and Briesch et al. (2009). Bell et al. used a shopping list metaphor whereas Briesch et al. used a needs-based approach to category incidence; in both cases store choice is conditional on "intentions," as evinced by an unobserved shopping list or by unobserved category needs. These intentions are then used to calculate the estimated cost of visiting each store, which is part of the indirect utility. Both of these studies take a *cost minimization* approach in order to calculate the probability of choosing a particular store; our model adopts a *utility maximization* approach, which, in general, is more parsimonious.[4]

While conditioning store choice on category purchase would at first appear to be consistent with the notion that destination categories are those in which a household's mere

[4] Note that utility maximization is the dual problem of cost minimization.

intention to purchase (in the category) drives the household to a particular store, there are several problems with this approach. In the case of the shopping list metaphor, households are presumed to have constructed a list of planned purchases, which is not directly observable, and all items that are purchased by the household are tacitly assumed to be on the shopping list. Moreover, everything on the shopping list is tacitly assumed to be purchased. Adopting a needs-based approach to category incidence, on the other hand, is also limiting because it cannot account for impulse purchases or the effects of in-store merchandising. More limiting from a destination category perspective is that, under either approach, it is not possible to account for category purchases at different stores on the same day-i.e., basket-splitting. In such cases, variable costs are difficult to assign since it is impossible, in a strict sense, to split a shopper's total basket across different stores if the underlying assumption is that there is one shopping list and one set of category needs that motivated the household to shop on a given day. Further, both approaches require an estimate of the expected quantity purchased in order to calculate the cost of visiting each store.

In contrast, our model form does not require quantity estimates as we do not calculate category cost, but rather category attractiveness. Category attractiveness enters the store choice model as a covariate and is estimated at the time the store visit is made and the category purchases are observed. We also directly account for unplanned/impulse purchases due to in-store merchandising and promotions, behaviors which we feel must be controlled for in order to develop a sound measure of category *destination-ness*. While our model form requires (via the conditioning argument) that a household be in a store in order to make a purchase, the conditioning is used only to estimate the attractiveness of the categories, i.e., *it is not assumed to be part of the household decision process*. Finally, as demonstrated in the policy analysis which follows, although we explicitly model the relationship between *ex-post* category purchasing and store choice we are able to estimate the extent to which specific categories draw households to specific stores.

Store Choice and Category Incidence Models

Store Choice Model: The indirect utility for household h selecting store s on trip t is:

$$u_{hst} = v_{hst} + \varepsilon_{hst} \,. \tag{2}$$

The deterministic component, v_{hst} , is defined in terms of the intrinsic attractiveness of the store to the household (τ_{hst}), a set of household and store-related covariates (X_{hst}), and a *category attractiveness (CA)* term:

$$v_{hst} = \tau_{hst} + X_{hst}\,\beta_m + \kappa CA \,, \tag{3}$$

where

$$CA = \ln\left(\sum_{c \in S(C)} \exp(v_{hct})\right).$$

The category attractiveness term given by $\ln\left(\sum_{c \in S(C)} \exp(v_{hct})\right)$ captures the attractiveness of the set of categories available in store s (represented by $S(C)$). v_{hct} will be defined in the category incidence section below. Under the usual assumption that the error terms ε_{hst} have Gumbel distributions, the probability that household h will visit store s on trip t is given by:

$$P(y_{hst} = 1 \mid \theta, \Sigma) = \frac{\exp(v_{hst})}{\sum_{j=1,S} \exp(v_{hjt})} \,. \tag{4}$$

The household and store-related covariates will be defined shortly.

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

$$u_{hct} = v_{hct} + \varepsilon_{hct}, \tag{5}$$

where v_{hct} denotes the deterministic component of utility; v_{hct} is defined in terms of the category intercepts, $\varphi_{hct|s}$, and a set of household, store and category-related covariates, Z_{hsct}, relevant to category incidence:

$$v_{hct} = \varphi_{hct|s} + Z_{hsct}\gamma\ . \tag{6}$$

The set of household, store and category covariates, which includes price, display, feature and "category needs" also will be defined in a later section. Assuming a binary logit model for the distribution of ε_{hct}, the probability that household *h* purchases in category *c* on trip *t* conditional on choosing store *s* can be written as

$$P(y_{hct} = 1 \mid s) = \left(1 + \exp\left(-v_{hct}\right)\right)^{-1}. \tag{7}$$

Different specifications for the model intercepts τ_{hst} and $\varphi_{hct|s}$ are possible (see, e.g., Elrod and Keane 1995; Erdem 1996). As discussed in the next section, we use a vector model decomposition for the store choice model intercepts, τ_{hst}, and an ideal-point representation for the category incidence model intercepts, $\varphi_{hct|s}$, parameterized in terms of the spatial distance between the household's perception of store *s*'s offering in category *c* on trip *t* and the household's ideal point for category *c*--in other words, the distance between what the store provides and what the household wants.

Spatial Representations

To understand the extent to which retailers have developed expertise in particular categories, we use store choice and category purchase data to infer store position locations and category ideal points in multi-attribute space, as well as the extent to which a store's management of assortment and other factors hypothesized to affect *destination-ness* (we will refer to these collectively as "*destination-ness* factors") translates its position closer to or farther away from category ideal points. The proximity of the store's position, adjusted for *destination-ness* factors, to a category ideal point reflects the *destination-ness* of the category for that store. The adjusted store position locations and category ideal points are derived from a reparameterization of τ_{hst} and $\varphi_{hct|s}$, the store choice and category incidence model intercepts, respectively.

In describing our approach we will drop the time (*t*) subscript for notational convenience and assume a two-dimensional latent multi-attribute space (D=2) with K *destination-ness* factors which are denoted by x_k.

Store choice model intercepts: We adopt a vector model representation for the store intercept parameters. Letting τ_{hs} denote the perceived attractiveness of store s for household h we can write the factor analytic representation for τ_{hs} as

$$\tau_{hs} = L_{sd}\Pi^{(0)}_{hd} = \pi^{(0)}_{h1} l_{s1} + \pi^{(0)}_{h2} l_{s2}, \tag{8}$$

where $\boldsymbol{L}_{sd}$ denotes a matrix of store positions (i.e., loadings) and $\Pi^{(0)}_{hd}$ denotes a matrix of household factor scores which are constrained to have equal mean values across dimensions; i.e, $\sum_{h=1}^{H} \pi^{(0)}_{h1} / H = \sum_{h=1}^{H} \pi^{(0)}_{h2} / H$. This constraint is used for identification purposes and has the salutary benefit of defining the scale of the d-dimensional latent multi-attribute space to be the same on all D dimensions (Erdem 1996). In the following, we will use τ_{hsd} to denote the perceived attractiveness of store s on dimension d for household h.

Category incidence model intercepts: The parameterization of the conditional category incidence model intercepts is intended to capture the notion of *destination-ness*. To accomplish this, we first compute a linear composite (i.e., principal component) of *destination-ness* factors in order to reduce the number of estimated parameters needed to develop the *destination-ness* measure. We define the linear composite as

$$A_{hsc} = Y_{sc} W_h = w_{h1} y_{sc1} + w_{h2} y_{sc2} + ... + w_{hk} y_{sck},$$

where w_{hk} are household-specific component weights. Next, we use these linear composites to translate the store's position in the latent multi-attribute space toward or away from the category ideal point, thereby capturing the extent to which the store's merchandising decisions affect the category's *destination-ness* for that store. The category incidence model intercepts ($\varphi_{hc|s}$) can then be written as

$$\varphi_{hc|s} = I_{scd} \Pi_h^{(1)} = \pi_h^{(1)} (l_{s1} + A_{hsc}\gamma_{h1} - l_{c1})^2 + \pi_h^{(1)} (l_{s2} + A_{hsc}\gamma_{h2} - l_{c2})^2, \tag{9}$$

where $\Pi_h^{(1)}$ denotes a matrix of household factor scores and I_{scd} denotes the squared Euclidean distances, i.e., distances between the location, in latent multi-attribute space, of the store translated to account for *destination-ness* factors ($l_{sd} + A_{hsc}\gamma_{hd}$), and the category ideal points (l_{cd}). Notice that the role of $A_{hsc}\gamma_{hd}$ is to translate the position of store s on dimension d based on the perceived attractiveness of store s's merchandising decisions in category c– this is how retailers directly affect *destination-ness*.

As we discuss in the identification section to follow, all of the attribute dimension loadings (the $\boldsymbol{L}$'s) , factor scores (the $\Pi^{(\bullet)}$'s) and latent dimension importance weights (the γ_{hd}'s) are estimated simultaneously by the appropriate use of identifying normalizations, identifying constraints and reduced-form utility representations (McFadden 1986).

Estimation

Likelihood

We can write the likelihood for the store choice and category incidence models as:

$$\mathcal{L}=\prod_{h=1}^{h}\int_{-\infty}^{\infty}\prod_{t=1}^{T}\prod_{s=1}^{S}\Pr\left(y_{hst}=1\cap C\,|\,\theta,\Sigma\right)^{y_{hst}}f(\theta\,|\,\Sigma)\partial\theta\,, \tag{10}$$

where θ denotes the global set of store choice and category incidence parameters and Σ denotes the parameter covariance matrix. The parameters in equation 10 can be estimated using simulated maximum likelihood. Here we use a mixed logit estimation procedure (see, Train 2003, Chapter 6) with Halton sequences for the numerical integration implemented with a quasi-Newton algorithm and user-supplied (i.e., analytic) gradients. In estimating the model we vary the number of latent dimensions and use fit heuristics and out-of-sample diagnostics to determine the number of dimensions to retain. To reduce the dimensionality of the covariance matrix Σ we use a two-factor structure of the Cholesky including parameters for unique components of the variance (see, e.g., Briesch et al. 2009; Hansen et al. 2006).

Identification

It is well known that spatial ideal point models suffer from indeterminacies. In this section, we discuss the constraints used to identify the spatial parameters in the store choice and category incidence equations. Our general approach is to first provide conditions which identify the store spatial positions from the store choice equations and then use the identified store positions to identify the category positions (and destination parameters) using the category incidence equations.

Store Positions

R1: The number of dimensions (D) is less than the number of stores (S), $D \leq S$-1.

Intuitively, this restriction comes from standard factor analysis, where the number of factors is constrained by the number of variables in the analysis and there are only S-1 intercepts defined in the multinomial logit model.

R2: For each dimension d, the sum of the positional parameters equals zero, i.e.,

$$\forall d, d = 1..D, \sum_{s=1}^{S} l_{sd} = 0 .$$

Erdem (1996) notes that this is equivalent to placing one store at the origin to provide translation invariance. The benefit of this restriction is that it places the origin in the middle of the stores, centering the positional map.

R3: One store is placed at location {1,0} which identifies the scale of the positional map. We note that because we are using continuous distributions, the factor scores $\pi_{hd}^{(0)}$ can be written as $\pi_{hd}^{(0)} = \pi_{d}^{(0)} + \zeta_{hd}^{(0)}$, where $\pi_{d}^{(0)}$ is the mean response and $\zeta_{hd}^{(0)}$ is the zero centered unobserved household-specific response. The restriction that $\pi_{1}^{(0)} = \pi_{2}^{(0)}$ identifies the scale for both dimensions and provides rotational invariance.

Category Positions

Similar to the identification of the intercept in a linear regression, identification of the category positions is done assuming that the assortment factor (A_{hsc}) is zero, e.g., each of the composite elements is mean centered.

R4: The category positional parameters are identified by constraining the sum of the positional parameters to be zero for each dimension *d*, i.e.,

$$\forall d, d = 1..D, \sum_{c=1}^{C} l_{cd} = 0 .$$

Erdem (1996) notes this constraint is equivalent to placing one category at the origin which ensures translation invariance. This restriction, coupled with the identification of the store positions, identifies the scale of the positioning map. When one category is constrained to be at the origin, the scale is identified from the category's intercept at each store. Rotational invariance comes from the identification of the store parameters and the constraint that the factor scores (i.e., $\pi_h^{(1)}$) are the same for each dimension. Finally, identification of the term $A_{hsc}\gamma_{hd}$ comes from cross-sectional (between store and category) as well as inter-temporal variation. Identification of γ_{hd} is achieved by setting the weight for one of the components of A_{hsc} to one.

Data and Covariate Definitions

We use a multi-outlet panel data set from Charlotte, North Carolina that covers a104-week period between September 2002 and September 2004. Panelists recorded all packaged and non-packaged goods purchases using in-home scanning equipment so their purchase records are not limited to a small sample of grocery stores; purchases made in all grocery and non-grocery stores are included. This is important since packaged goods purchases are frequently made outside of grocery stores. Households are included in the sample if at least 80 percent of their purchases were made at the six store chains (five supermarkets, one mass merchandiser supercenter) for which we have geolocation data and if they spent at least $10 every month.[5] The resulting data set included 357 families with a total of 57,755 shopping trips. Descriptive statistics for these households are provided in Table 2. We use the first 26 weeks as an initialization period to identify categories purchased by each household as well as to identify the inter-temporal variables for the categories, which left 37,438 shopping trips. We used the middle 52 weeks as an estimation sample and the final 26 weeks as a validation sample.

Place Table 2 about here

We have detailed price information for 289 categories. From those categories we selected the top 80 based upon total dollars spent in the category; this resulted in excluding only categories which were not substantial, i.e., in which fewer than 10% of the households purchased. The 80 categories selected together comprise more than 75% of the average market basket (excluding products not tracked by *UPC*). Table 3 presents penetration rates and share-of-wallet for each category along with the price index for each retail chain. Store statistics are shown in Table 4; this table provides trip and spend share, travel time from home to the closest store of the retail chain and (aggregate) category indexed measures for price and each of the seven assortment and related variables that are hypothesized to affect *destination-ness*.

Place Tables 3 and 4 about here

Covariates

Table 5 provides definitions for all of the store choice, category incidence and destination-related covariates used in estimating the model. In the table, we use **x***'s* to denote store choice covariates, **z**'s to denote category purchase incidence-related covariates, and **y**'s to represent merchandising factors that affect *destination-ness*. Note that among the factors that are

[5] The last criterion was used to ensure that panelists were faithful in recording their purchases and remained in the panel for the entire 104 week period.

posited to affect *destination-ness* are several assortment variables along with the frequency of promotions and the average inter-purchase time. These latter two covariates have been hypothesized to affect store traffic and the role that categories play in the store choice decisions; i.e., merchants believe that destination categories, by definition, are those associated with short average inter-purchase times (i.e., more frequent shopping), while frequency of promotions provide an indicator of shoppers' expectations concerning future promotions in a category and thus may have longer-term consequences for store choice decisions (cf. Mela et al. 1997). Finally, note that we have added to the set of assortment factors investigated by Briesch et al. (2009), the *proportion of unique private label items* and the *proportion of unique national brand items*.

Place Table 5 about here

Empirical Results: Propositions

We begin our analysis by revisiting the three propositions introduced earlier. For each proposition, we investigate the extent to which the empirical data on household shopping behaviors lends support to the existence of destination categories. Although we do not have the luxury of asking our households to participate in controlled experiments, we can identify groups of households who have exhibited specific shopping behaviors which may prove informative in understanding the extent to which they visited a store with a specific category purchase in mind; for example, as discussed below, shoppers who visited two or more stores on the same day and shoppers who made a single category purchase at a store can provide some insights into category *destination-ness*. We are not suggesting that the analysis and findings provided in this section stand as strong arguments for the existence of destination categories, rather that simple analysis of households' store and category shopping behaviors may provide some preliminary insights. As we will see, the empirical shopping behaviors of our households do indeed support the possible existence of destination categories; however, our analysis in this section does not rule out alternative explanations. A stronger test of the existence of destination categories will be provided by our formal model which controls for a number of putative covariates such as price, display, feature, etc.

Proposition 1

This proposition speculates that households shop at multiple stores on the same day/week in order to take advantage of the category-specific expertise that retailers have developed. If this proposition is at all tenable, then we should observe households visiting multiple stores on the same day/week and the number of categories purchased and dollar spending levels should vary across retailers.

Findings: Table 6, part A presents the distribution of stores shopped on the same day or during the same week for households in our data set. As can be seen in the table, almost 16% of the trips were made to 2 or more stores on the same day. The incidence of multiple store visits in a given week increases to a little over 54%.[6] In part B of the table, we present the same day/week relative store spend and relative number of categories purchased reported in terms of the number of stores visited. We see that households who made purchases at two stores on the same day spend about four times more at one store than the other, and purchased in about four times the number of categories.[7] For households purchasing in multiple stores in one week we see a

[6] In computing these incidences we excluded visits to the same store.
[7] Relative spend and relative no. of categories purchased percentages were computed as follows: 1) for each household compute the dollar spend/no. of categories purchased for each pair/triplet, etc. of stores visited; 2) compute the total spend and no. of categories purchased (by summing across the appropriate set of stores); 3) compute relative quantities (step 1/step 2); 4) identify which store in the pair/triplet, etc. received the largest spend

similar pattern. As households shop at more stores on the same day or during the same week the relative distribution become more skewed, reflecting even more disproportionate spending and categories shopping behavior. Finally, we investigated whether households who visited two or more stores on the same day/week purchased in different or the same categories. Across all 80 categories, the percentage of unique category purchases (i.e., non-overlapping) was very high (> 90%).

Comment: The incidence of visiting multiple stores on the same day or in the same week is higher than what would be expected due to chance; perhaps more important to this proposition, however, is the skewed relative dollar spend and number of categories shopped. If households shop at multiple stores to take advantage of category-specific expertise then, all else the same, we would expect households to purchase in more categories and spend greater dollar amounts at certain stores and less at others. In addition, the data strongly suggest that when households visit different stores on the same day or during the same week, they do purchase in different categories.

Place Table 6 about here

Proposition 2

According to *Proposition* 2 households shop at different stores on the same day/week when purchasing in specific categories because of the assortments offered and consequently will tend to visit the same stores on a fairly consistent basis.

Findings: For stores visited on the same day/week, Table 7, part A presents the probabilities of visiting the same pair/triplet, etc. of stores. As can be seen from the table, the

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and no. of categories purchased; 5) for households who shopped at more than two stores compute average spend and no. of categories purchased across stores, excluding the store identified in step 4; and 6) compute mean relative spend and no. of categories purchased for the store identified in step 4) and for the set of remaining stores.

likelihoods of consistent same stores-same day/week visits (over the household's purchase history) are larger than what would be expected due to chance; for example for those households visiting two stores on the same day the likelihood of visiting the same two stores over the household's purchase history is about .35. In the case of households who visited more than three stores on the same day, the likelihood of consistent store choices increases to about .61 for households who visited three stores on the same day, and to almost .82 for households who purchased in four or more stores on the same day.[8]

Table 7, part B presents log odds ratios computed from the joint table of stores visited in the same week. For a given pair of stores (e.g., Bi-Lo and Food Lion) a statistically significant negative log-odds ratio indicates that a household is more likely to shop at both stores during the same week as compared to making two visits to the *same* store (either Bi-Lo or Food Lion) in the same week. From the table we see that five of the fifteen log-odds ratios are statistically significant and negative, three are statistically significant and positive, and seven are statistically non-significant.

Comment: The same stores-same day/week probabilities as well as the same week log-odds ratios suggest that, for some households at least, the choice of which stores to visit is not random and consequently implies that households are visiting specific set of stores for specific reasons. Interestingly, as the number of stores visited in a day/week increases, so does the likelihood that the household will visit the same set of stores over time, which again would suggest distinctive patterns of store complementarities. Finally, it is also interesting to note that three of the five statistically significant negative log-odds ratios involve across retail format pairs, (i.e., Wal-Mart and a grocery retailer).

[8] Admittedly the incidence of 4+ stores shopped on the same day is small; we present this comparison for completeness.

Place Table 7 about here

Proposition 3

This proposition hypothesizes that category expertise, independent of store loyalty, is a driving force behind store choice decisions. To investigate this proposition, we limit our analysis to trips on which the household purchased in a single category. In the case of these trips, we will assume that the household initiated the trip for the purpose of buying in that category alone; as such, single-purchase trips provide a sharper lens to evaluate category *destination-ness*.

Findings: Table 8 shows three metrics which are informative in characterizing store choice and category purchase behaviors. The first column gives the percentage of times single category purchase trips were consummated at the households' *favorite store*; i.e., the store they visited most frequently. The second column, *CSSL*, gives the percentage of times the single category purchase was consummated at the store which had the highest category-specific store loyalty – *CSSL* is the proportion of the household's category requirements purchased at a particular store (Bell et al. 1998). The third column, *CDI*, gives the percentage of times the single category purchase was consummated at the store which had the highest category development index—a proxy measure of category expertise. From the table, we see that shoppers consummated a single category purchase at the households' favorite store 38% of the time.[9] We find a higher likelihood that the household consummated the single category purchase at the store with the highest category-specific store loyalty (41%) but a much higher likelihood that the single category was purchased at the store with highest *CDI* in that category—58% of the time.

Comment: When a household makes a single category purchase at a store, we can assume that that category drove the store visit. By comparing the *favorite store/CSSL*

[9] Interestingly, the incidence of single purchases at the household's favorite store is about the same as for multiple category purchases.

percentages and the *CDI* percentages, we can conclude that households are more likely to purchase at a store which has category expertise than at the store where they purchase most often (both in general and in that category). For trips that involve a single category purchase, households are more likely than not to choose the store with specialized expertise in that category.

Place Table 8 about here

Modeling Results

Model Fit

Fit statistics for three model specifications are shown in Table 9. The models differ in the number of dimensions specified for the multi-attribute *destination-ness* space. The table reports the in-sample AIC, BIC and CAIC information-theoretic statistics and the in and out-of-sample log-likelihoods along with hit rates for each model specification. We see from the in-sample fits that all three information criteria point to the three-dimensional solution. Although this model does not yield the highest in-sample hit rate, all three model specifications perform similarly on this measure. In the hold-out sample, we compare log-likelihoods and hit rates. Out-of-sample log-likelihoods also indicate that the model with three dimensions is preferred to both the two and four dimensional solutions. Once again, out-of-sample hit rates are high for all three models. For these reasons, the remaining analyses will focus on the three-dimensional model specification.

Place Table 9 about here

Parameter Estimates

Table 10 presents parameter estimates for the store choice, category incidence and *destination-ness* equations. The first set of parameter estimates gives the mean parameter values, whereas the second set gives the heterogeneity standard errors.

Focusing first on the *store choice model*, we see that all of mean parameter estimates are statistically significant (p-value <.10). The *state dependence* mean parameter estimate is negative, suggesting that on average households systematically switch between stores. The *travel time* mean parameter estimate is also negative; i.e., all else the same, households prefer to shop at stores which are closer as opposed to farther away. The mean parameter value for the *CA* term, which measures the attractiveness of a store based upon the utility derived by the household from the categories shopped, is statistically significant and positive.

With respect to heterogeneity, we see that all of the standard deviations for the store choice covariates in the right-most panel of Table 10 are statistically significant (p < .10) except for travel time. This suggests that households are more homogeneous when it comes to travel time (distance) response as compared to the other covariates.

Turning next to the *category incidence model*, we see that all of the covariates are statistically significant (p-value < .10), with the exception of *lag quantity x lag time* which suggests, on average, the absence of significant stock pressure (cf. Assuncao and Meyer 1990). The *lag time* since last purchase is positive, suggesting that the more time that has elapsed since the last purchase in a category, the more likely the household will purchase in the category. The *lag quantity* parameter mean value is negative suggesting that the greater the quantity purchased in a category, the less likely the household is to purchase in the category on a successive trip. The *price*, *feature* and *display* parameter mean values all have the appropriate algebraic signs. The spatial mean parameter values associated with the category incidence model intercepts (the γ_{hd}'s) are all statistically significant as is the mean value associated with the household *factor scores* (the $\pi_h^{(1)}$'s) which reflect household merchandising preferences.

Five of the seven (estimable) mean parameter values associated with the *destination-ness* composite (the w_{hk}*'s*) are statistically significant; we see that in general assortment is a positive function of *favorite brand* (by design), *number of unique private labels*, *average inter-purchase time*, and *number of unique national brands*, and a negative function of *number of UPCs/brand* and *number of brands*. These parameter estimates are consistent with those reported by Briesch et al. (2009) with the exception of *number of brands* which has a negative algebraic sign. This difference can be explained by the two additional covariates, namely, *number of unique private label brands* and the *number of unique national brands*, both of which are positive and statistically significant. These estimates suggest that the previously found positive effect from the number of brands dissipates when controlling for *unique items* (brands and private labels) as well as *favorite brand*. Collectively, these estimates suggest that it is the availability of *favorite brands* and *unique items*, rather than the *number of brands*, that increases store choice probability.

Turning to heterogeneity of the category incidence covariates, we see that four of the seven standard deviations in the right-most panel of Table 10 are statistically significant ($p<.10$). It appears that households are homogeneous in their response to *lag time*, *lag quantity* and *display*. Interestingly, we find significant heterogeneity in *lag quantity x lag time* despite a non-significant parameter mean, suggesting that stock pressure can be important in the store and category purchase decisions of some households. It is also interesting to note that there appears to be relatively strong heterogeneity in household's *price* and *feature* responses – the standardized betas for these covariates are -5.33 and 6.21, respectively. With the exception of *number of brands* and *number of unique national brands*, all of the standard deviations associated with the *destination-ness* variables are statistically significant ($p<.10$). In terms of relative variability, it is interesting to note that there is far more heterogeneity among households in their responses to the *number of unique private labels* and *average inter-purchase time* than in responses to the other *destination-ness* covariates.

Place Table 10 about here

The reparametization of the store and category model intercepts yields a reduced-space (3 dimensional) representation of store position locations and category ideal points. Figure 1A shows the store locations for each of the six retailers. Our interest is in the *destination-ness* of a category and the degree to which the assortment decisions made by each store moves the store closer to or farther away from the category ideal point, and in so doing increases/decreases the probability of choosing a store. For example, in Figure 1B we have shown the translated store positions based upon each stores' assortment decisions in the milk category. We see that Food Lion's, BiLo's and Winn Dixie's milk-related assortment decisions (based on the average values over time for each assortment factor) move each of these stores closer to the ideal point for milk, whereas the assortment decisions made by Lowes and Harris Teeter move them farther away; stated differently, the assortment decisions of Food Lion, BiLo and Winn Dixie have increased the *destination-ness* of milk for their stores while Lowe's and Harris Teeter's assortment decisions have reduced the *destination-ness* of milk for their stores. In the next section we extend our analysis to these and other policy issues in greater detail.

Place Figure 1 about here

Policy Analysis

To assess the influence of specific categories on store choice, we use the parameter estimates in Table 10 and the derived spatial positions of categories and stores to compute two conditional store choice probabilities: $\Pr(y_{hst} = 1|C_{ht} = \hat{c})$ and $\Pr(y_{hst} = 1|C_{ht} = \hat{c}\text{-}c)$, where C_{ht}

represents the "average" household, c is the single category of interest and $\hat{c}$ includes all categories.[10] The former probability is the "baseline" probability which conditions on every category with the average observed purchase probability while the latter probability conditions on all categories *except* the category of interest. Note that this policy simulation does not condition on the purchase of these categories *per se*, but rather on the estimated attractiveness (or absence of that attractiveness) of those categories at each store.

The change in store choice probability due to category c reported in Table 11 is computed by taking the difference

$$\Pr(y_{hst} = 1 \mid C_{ht} = \hat{c}) - \Pr(y_{hst} = 1 \mid C_{ht} = \hat{c} - c).$$

Baseline store choice probabilities are reported in the first row of the table. The remaining rows show the percent change in expected store choice probability due to the category of interest. We find that for 41/80 categories, the category of interest increases the expected probability of choosing BiLo; in contrast, the probability of choosing Lowes is increased for only 27/80 categories.

Place Table 11 about here

Which categories draw shoppers to each store chain? The expected probability of choosing BiLo is increased most by refrigerated fresh eggs (+2.8%), milk (+2.3%) or carbonated beverages (+1.6%). The increased probability of choosing BiLo comes primarily at the expense of Food Lion for eggs (-1.7%) or at the expense of Wal-Mart Supercenter for carbonated

[10] We demonstrate the impact of a category on store choice probabilities by omitting it from a full basket, rather than adding it to an empty basket, so that our policy analysis more accurately reflects baseline store choice probabilities. There are two other salutary benefits that deserve mention. First, our approach ensures that low-share stores are not affected by each category in a way that overstates its leverage and makes comparison with higher-share stores difficult. Second, our approach takes the household's basket as given and consequently controls for whatever cross-category basket-related correlations that may exist.

beverages (-2.7%) and milk (-1.5%). The expected probability of choosing Food Lion is increased most by fresh bread & rolls (+1.4%), carbonated beverages (+1.3%) or (canned) vegetables (+1.0%). The increased probability of choosing Food Lion comes primarily from Wal-Mart Supercenter for fresh bread & rolls (-1.7%), carbonated beverages (-2.7%) and vegetables (-1.8%). The expected probability of choosing Harris Teeter is increased most by refrigerated fresh eggs (+2.7%), milk (+2.2%) or spices/seasoning (+1.3%). The increased probability of choosing Harris Teeter comes primarily at the expense of Food Lion for eggs (-1.7%) and spices/seasoning (-0.4%) or at the expense of Wal-Mart Supercenter for milk (-1.5%). The expected probability of choosing Lowes is increased most by refrigerated salad/cole slaw (+9.7%), fresh bread & rolls (+4.8%), frozen poultry (+3.2%), vegetables (+3.2%) or frozen bread/frozen dough (+3.2%).[11] For all of these categories, the gains come from Wal-Mart Supercenter: -1.1% for refrigerated salad/cole slaw, -1.7% for fresh bread & rolls, -0.6% for frozen poultry, -1.8% for vegetables or -0.7% for frozen bread/frozen dough. The expected probability of choosing Winn Dixie is increased most by refrigerated salad/cole slaw (+3.1%), milk (+3.0%) or luncheon meats (+2.2%). For all of these categories, the gains also come from Wal-Mart Supercenter: -1.1% for refrigerated salad/cole slaw, -1.5% for milk or -1.3% for luncheon meats. Finally, the expected probability of choosing Wal-Mart Supercenter benefits most from total chocolate candy (+3.4%), total non-chocolate candy (+3.0%), soap (+2.2%) or vitamins (+2.0%). Wal-Mart's gains come primarily at the expense of Harris Teeter for chocolate candy (-2.1%), non-chocolate candy (-1.7%) and vitamins (-1.0%) or at the expense of Lowes for soap (-1.6%).

While the categories that most increase store choice probabilities may seem ad hoc, some

[11] The relatively large magnitudes of changes in the expected probability of choosing Lowes are primarily due to the small number of stores and low baseline choice probability of the chain.

patterns emerge. Shoppers are more likely to choose BiLo, Harris Teeter, Lowes or Winn Dixie due to perishable categories (i.e., fresh, refrigerated or frozen). Food Lion is more likely to be chosen because of dry grocery (i.e., shelf stable) categories plus fresh bread & rolls. Wal-Mart Supercenters are more likely to be chosen for non-grocery categories and candy. Overall, the expected choice probabilities of Wal-Mart Supercenter and, to a lesser extent, Food Lion are most negatively affected by categories that benefit the other retailers.

Discussion

The primary objective of this research is to identify categories that draw shoppers to retailers' stores. The preceding policy analysis shows that certain categories increase the probability that shoppers choose some stores while decreasing the probability that they choose others. Identifying such categories is clearly important to retailers. Manufacturers also have an interest in whether the categories they supply affect store choice because the knowledge can enhance their category expertise and their ability to advise retailers as "category captains;" i.e., making advertising, merchandising and pricing recommendations to retailers (cf. Blattberg et al. 1995). We therefore construct a new measure, [*C*]ategory [*L*]everage [*I*]n [*P*]atronage [*D*]ecisions, to determine how much leverage specific categories exert in shoppers' store choice decisions.

Category Leverage Analysis

The impact of categories on store choice is captured by the term $\varphi_{hc|s}$ which is the squared distance between category *c*'s ideal point and store *s* (translated to reflect the store's merchandising and assortment decisions in the category) in multi-attribute space (see equation 9). $\varphi_{hc|s}$ enters the store choice equation through the *CA* term, $\ln\left(\sum_{c \in S(C)} \exp(v_{hct})\right)$, where it appears as an additive component of v_{hct} (see equation 6). Given the nature of our choice model, the relative variation in $\varphi_{hc|s}$ across stores in the choice set captures the category's differential effect (i.e., leverage) on store choice decisions. To measure relative variation, we first determine $\varphi_{hc|s}$ for each of the six stores (assuming category assortment and related variables are at average levels for store *s* across time) then compute the coefficient of variation of $\varphi_{hc|s}$ across stores. The coefficient of variation is reported for all 80 categories in Table 12 as the *CLIPD* measure of category leverage.

Place Table 12 about here

The table shows that category leverage in store choice is highly skewed; *CLIPD*>1 for two categories, *CLIPD*>.75 for five categories and *CLIPD*>.5 for only fifteen categories—(1) milk, (2) fresh bread & rolls, (3) cigarettes, (4) beer/ale/alcoholic cider, (5) carbonated beverages, (6) refrigerated salad/cole slaw, (7) dinner sausage, (8) frozen bread/frozen dough, (9) refrigerated fresh eggs, (10) frozen meat, (11) ice cream/sherbet, (12) frozen poultry, (13) wine, (14) frozen novelties and (15) [canned] vegetables. Among the highest leverage categories are four of the five highest-ranking categories in terms of sales, yet so are the 54th, 55th, 62nd and 71st ranking categories. Consistent with the received wisdom in grocery retail that fresh products are important determinants of store choice, five of the fifteen high-leverage categories are fresh and/or refrigerated (note that fresh product categories without *UPC*s are not tracked in our syndicated dataset). The other categories include five frozen and three "sin" categories—cigarettes, beer and wine.

Why do these categories have more leverage in the store choice decision? To answer this question, we regress the category *CLIPD* measures on variables reflecting category (1) reach (*penetration rate*), (2) frequency (*average interpurchase time*), and (3) monetary value (*average* *household SOW*), as well as dummy variables for (4) *fresh/refrigerated* and (5) *frozen* categories. Together, these five predictors explain a substantial amount of the variation in *CLIPD* across the 80 categories (R^2=.55). The coefficients of all predictors are significantly different from zero. The *average household SOW* coefficient is positive and significant (p-value=.007); the *penetration rate* and *average interpurchase time* coefficients are negative and significant (p-value=.043 and p-value=.002, respectively). Higher purchase frequency (lower *interpurchase time*) and higher spending in a category would be expected to make that category more important to the shopper and her store choice decision. Interestingly, higher penetration negatively affects category leverage in store choice decisions, perhaps because high penetration categories receive more merchandising support from stores without those categories being relatively more important to individual households. The dummy variables for fresh/refrigerated and frozen categories both have positive and significant coefficients (p-value=.001 for both coefficients). *Ceterus paribus*, the *CLIPD* leverage measure for a fresh/refrigerated category is .155 higher than the baseline, while *CLIPD* for a frozen category is .145 higher.

Assortment Decisions and *Destination-ness*

We now use $\varphi_{hc|s}$, the squared distance in multi-attribute space that reflect category *destination-ness*, to investigate how retailers' actual assortment decisions affect *destination-ness*. Specifically, we compute a baseline $\varphi_{hc|s}$ for each store *s* and category *c*, assuming that the store has average levels of assortment and related variables (i.e., *number of brands*, *SKUs/brand*, *sizes/brand*, *number of unique private labels and national brand SKUs*, *proportion of favorite brands*, *frequency of promotion*) for that category across the six stores. This baseline $\varphi_{hc|s}$ is subtracted from the estimated $\varphi_{hc|s}$, then the difference is divided by the baseline $\varphi_{hc|s}$ to capture the percent of category *destination-ness* that is attributable to the retailer's assortment decisions.

Negative percentages imply that the retailer's assortment decisions reduce $\varphi_{hc|s}$ and so increase category *destination-ness*; positive percentages imply the opposite. We compute these percentages for the fifteen highest leverage categories and report the results in Table 13.

Place Table 13 about here

In 14/15 high leverage categories, Food Lion's assortment decisions reduce $\varphi_{hc|s}$ (-25% on average) and so increase category *destination-ness* compared to the other stores' assortment decisions. In contrast, in 14/15 high leverage categories Lowes' assortment decisions increase $\varphi_{hc|s}$ (64% on average) and so reduce the *destination-ness* of those categories compared to other stores' assortment decisions. These results are consistent with the summary statistics for assortment variables reported in Table 4, in particular Lowes' uniformly low levels of these variables. The other four retailers assort some categories to increase their *destination-ness* better than the average retailer, but not so for other categories. Consider Wal-Mart Supercenters, whose assortment decisions in cigarettes, refrigerated salads and wine increase the *destination-ness* of these categories when compared to other retailer's decisions but whose assortment decisions in other categories such as ice cream/sherbet and frozen novelties do not. Harris Teeter's assortment decisions substantially reduce the *destination-ness* of milk, fresh bread & rolls and cigarettes when compared to other retailer's decisions but its assortment decisions in frozen meat, ice cream/sherbet, frozen novelties, wine and beer increase the *destination-ness* of these categories. Overall, we find substantial differences in the extent to which retailers' assortment decisions help make high-leverage categories into destination categories for their stores.

The same category cannot draw shoppers to all retailers (without drawing shoppers away from some others); however, we did find a few cases in which the same category had a substantial positive effect on store choice for more than one store chain. For example, fresh eggs and milk substantially increase the probability of choosing BiLo but also of choosing Harris Teeter. Thus, we find that the same category can attract customers to more than one retailer, a finding that has implications for retailers' selection of destination categories.

Perhaps our most surprising finding is that the categories with the most positive effect on the choice of Wal-Mart Supercenter stores are chocolate and non-chocolate candy. This finding belies the reputation of the supercenter format as focusing on non-grocery items and general merchandise. Stated differently, supercenters may not be viewed as specializing in grocery products to the same extent as supermarkets. It is clear why Wal-Mart Supercenter is preferred by shoppers buying in this category, however. Wal-Mart has far more brands (143 index), *SKU*s per brand (122 index) and sizes per brand (117 index) and carries a higher proportion of unique *SKU*s (0.52) and favorite brands (0.47) compared to any other store chain. It appears that Wal-Mart has effectively made chocolate and non-chocolate candy destination categories, in part because of its extensive product assortment decisions.

Pricing Strategies and *Destination-ness*

Given our findings about how categories affect the probability of choosing stores, we now consider how retailer prices are related to the category's effect on store choice. To determine the nature of the relationship we compute the correlation between the category's effect on store choice (from Table 11) and its average price (category price index computed from average category price in Table 3) for each of the six store chains in our dataset. We find that pricing strategies vis-á-vis category *destination-ness* vary widely among retailers. The average correlation across categories for Wal-Mart Supercenter is +0.22, implying that it charges higher (lower) prices in categories that customers prefer (prefer not) to buy at their stores. Wal-Mart therefore seems to price in a way that compensates for shopper's preference to buy particular categories at its stores; stated differently, Wal-Mart appears to be "smart" about how it prices in these categories. The average correlations for BiLo, Harris Teeter and Lowes are +0.04, +0.02 and -0.02, respectively, implying that these retailers price categories independent of shoppers preference to purchase them at the retailer's stores. Curiously, the average correlation is -0.37 for Winn Dixie and -0.24 for Food Lion, implying that these retailers price lower (higher) in categories that shoppers prefer (prefer not) to buy in their stores. Such a strategy would seem to ignore shopper's willingness to tradeoff price against their preference to purchase a category at their stores, perhaps "leaving money on the table."

***CDI* Revisited**

Recall that *CDI* is an indexed measure of the retailer's share of category sales compared to its overall market share--a *CDI* above 100 indicates that shoppers buy more of the focal category than of other categories at the retailer. Clearly, one possible reason for a high *CDI* is that shoppers prefer to shop at that retailer for the category (other explanations for a higher *CDI* were proffered in the introductory section). We now consider whether *CDI* does in fact reflect the differential impact of a category on store choice. To address this question, we compute the correlation between *CDI* (from Table 1) and changes in store choice probability due to incidence of each of the 80 categories (from Table 11). We find that the correlation between changes in store choice probability and *CDI* is 0.43. This suggests that while *CDI* is correlated with category influence on store choice, it explains less than 20% of that influence.

In closing we should emphasize that our analysis of store choice is limited by the scope and scale of the data. We used data from a single geographic market over a two-year period, with a sample of 357 households. While this sample is sufficient for inference, generalizing our results would require data from other markets and time periods. Notwithstanding this limitation, our analysis has demonstrated how and why categories have a differential impact on store choice.

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FIGURE 1
Store Locations and Impact of Assortment Decisions

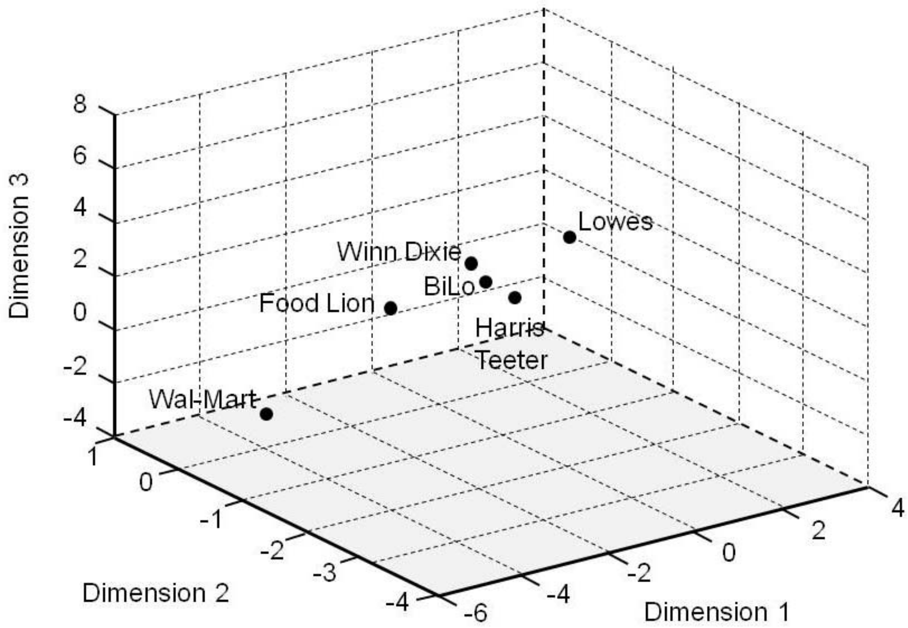

Figure 1A
Store Locations

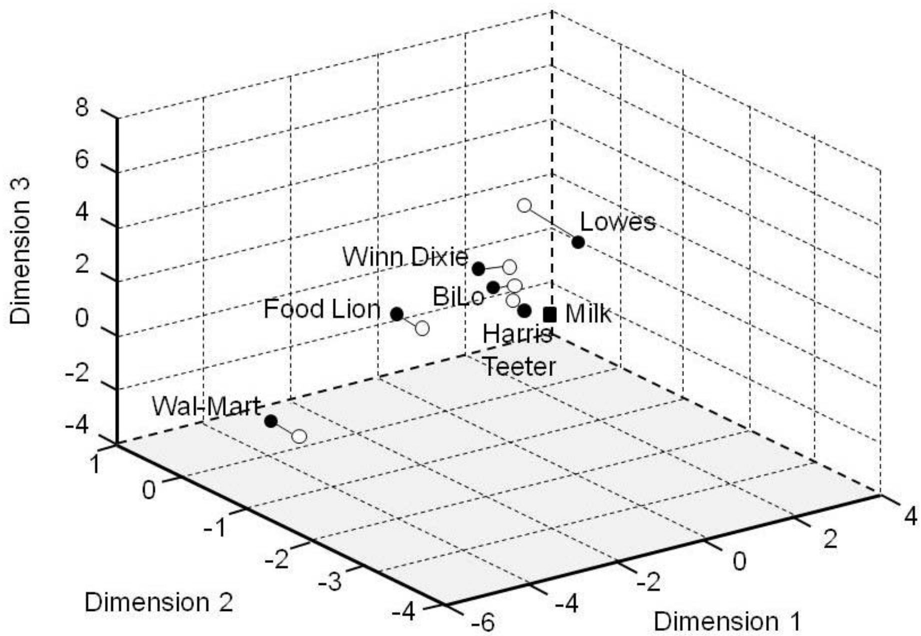

Figure 1B
Impact of Assortment Decisions

TABLE 1
Category *CDIs*

Category	BiLo	Food Lion	Harris Teeter	Lowes	Winn-Dixie	Wal-Mart
CARBONATED BEVERAGES	116	100	118	97	117	70
CIGARETTES	95	227	8	21	50	50
COLD CEREAL	102	92	132	97	96	83
FRESH BREAD & ROLLS	97	94	1	125	109	66
BEER/ALE/ALCOHOLIC CIDER	97	155	68	136	86	60
FZ DINNERS/ENTREES	103	116	120	71	105	63
SALTY SNACKS	110	103	117	96	107	75
NATURAL CHEESE	120	103	118	100	126	62
MILK	120	104	108	138	115	67
LUNCHEON MEATS	117	124	94	97	134	56
CRACKERS	89	106	113	85	91	91
COOKIES	87	96	132	87	106	84
BREAKFAST MEATS	105	106	115	108	145	60
TOTAL CHOCOLATE CANDY	64	66	85	61	66	192
DOG FOOD	108	101	68	152	78	122
CAT FOOD	126	124	66	159	95	80
FZ PIZZA	143	102	133	122	78	52
SOUP	110	109	127	137	107	51
ICE CREAM/SHERBET	104	112	148	129	107	33
FZ POULTRY	97	81	156	108	100	76
RFG SALAD/COLESLAW	137	95	125	123	131	53
PET SUPPLIES	35	32	26	23	55	311
COFFEE	110	99	101	149	126	79
PROCESSED CHEESE	134	115	94	111	125	59
LAUNDRY DETERGENT	101	99	110	107	75	99
VEGETABLES	128	127	109	103	121	42
WINE	61	135	112	136	72	68
TOILET TISSUE	104	98	100	97	99	102
FZ SEAFOOD	220	79	113	50	207	27
PAPER TOWELS	84	100	96	123	119	107
FZ NOVELTIES	116	115	123	115	111	41
DRY PACKAGED DINNERS	129	105	93	224	89	71
SNACK BARS/GRANOLA BARS	101	84	94	29	79	143
TOTAL NON-CHOCOLATE CANDY	53	77	60	62	99	193
INTERNAL ANALGESICS	85	55	52	69	96	213
HOUSEHOLD CLEANER	70	74	92	84	81	164
FRANKFURTERS	122	115	114	126	134	43
DOUGH/BISCUIT DOUGH - RFG	106	103	134	116	121	54
RFG JUICES/DRINKS	92	100	144	127	101	61
SOAP	60	62	56	103	89	209
YOGURT	78	67	176	107	76	94
TOOTHPASTE	76	50	96	73	93	186
BOTTLED WATER	82	47	150	91	78	142
VITAMINS	41	27	24	15	23	335
COLD/ALLERGY/SINUS TABLETS	74	46	56	44	53	245
PASTRY/DOUGHNUTS	104	95	158	65	76	66
CANNED/BOTTLED FRUIT	99	105	135	129	98	60
FZ PLAIN VEGETABLES	130	96	154	106	94	44
SALAD DRESSINGS - SS	130	109	110	138	113	55
SKIN CARE	36	20	33	24	29	329
BAKING MIXES	136	106	106	116	121	60
BOTTLED JUICES - SS	91	125	109	101	107	63
SNACK NUTS/SEEDS/CORN NUTS	76	98	95	64	87	129
FZ MEAT	102	60	225	58	91	50
FZ BREAD/FZ DOUGH	96	121	135	85	126	38
FZ BREAKFAST FOOD	84	118	125	162	112	49
CANNED MEAT	151	114	70	110	142	67
DISH DETERGENT	77	80	132	138	95	105
CUPS & PLATES	80	80	89	113	125	135
SPICES/SEASONINGS	109	99	116	108	110	78
SHAMPOO	72	46	47	123	87	231
RFG FRESH EGGS	118	92	121	122	132	69
FZ APPETIZERS/SNACK ROLLS	96	99	115	122	169	62
BATTERIES	66	35	54	49	72	258
PICKLES/RELISH/OLIVES	112	94	141	94	141	53
MARGARINE/SPREADS/BUTTER BLE	98	105	99	119	137	80
FZ DESSERTS/TOPPING	77	112	122	168	171	41
SHORTENING & OIL	119	109	99	148	115	67
DEODORANT	66	52	67	63	79	218
SS DINNERS	150	126	89	83	108	52
DINNER SAUSAGE	132	92	121	89	194	45
TOASTER PASTRIES/TARTS	173	78	116	103	76	86
BAKING NEEDS	114	102	112	79	92	87
FOOD & TRASH BAGS	79	89	106	136	88	118
SANITARY NAPKINS/TAMPONS	85	69	76	123	49	182
AIR FRESHENERS	70	71	64	92	88	190
SPAGHETTI/ITALIAN SAUCE	116	104	134	101	126	49
SEAFOOD -SS	138	109	96	125	120	63
POPCORN/POPCORN OIL	114	98	111	171	83	82
TOOTHBRUSH/DENTAL ACCESORIES	64	38	52	51	58	261

TABLE 2
Household Descriptive Statistics

	Mean	*Std Dev*
Number of Households	357	
Monthly Spending	216.0	107.22
Spending per Trip	35.0	13.36
Number of Trips	165.7	64.96
Trip Share of Non-included Stores	14%	0.07
Spend Share of Other Stores	11%	0.06

TABLE 3

Category Descriptive Statistics

Category	Penetration Rate	Share of Wallet	Average Price						Av. Quantity	Av. Purchase Days
			BiLo	Food Lion	Harris Teeter	Lowes	Winn-Dixie	Wal-Mart		
CARBONATED BEVERAGES	97.5%	5.14%	7.38	7.27	8.74	8.37	7.54	6.87	1.26	25.29
CIGARETTES	24.4%	4.34%	28.84	28.26	29.59	28.85	29.12	30.06	0.84	52.41
COLD CEREAL	94.7%	2.62%	2.85	2.84	3.01	2.93	3.11	2.48	1.66	40.87
FRESH BREAD & ROLLS	98.3%	2.42%	1.22	1.19	1.43	1.19	1.23	1.11	1.55	18.34
BEER/ALE/ALCOHOLIC CIDER	32.5%	2.37%	20.78	20.67	20.66	20.39	20.73	20.90	0.60	78.43
FZ DINNERS/ENTREES	81.8%	2.35%	2.76	2.72	3.01	2.99	2.84	2.51	2.23	55.20
SALTY SNACKS	95.8%	2.34%	4.80	4.83	5.21	4.86	4.94	4.38	1.04	29.39
NATURAL CHEESE	93.0%	1.83%	5.84	5.75	6.40	5.90	6.25	5.16	0.98	41.49
MILK	98.0%	1.83%	0.06	0.06	0.06	0.06	0.06	0.05	4.08	19.34
LUNCHEON MEATS	88.0%	1.65%	4.08	3.76	4.53	4.28	3.82	3.58	1.03	47.91
CRACKERS	95.2%	1.64%	3.62	3.47	3.92	3.65	3.56	3.00	1.18	42.92
COOKIES	91.9%	1.60%	2.93	2.77	3.27	2.89	2.81	2.47	1.22	46.60
BREAKFAST MEATS	85.4%	1.51%	4.02	3.91	4.26	3.83	3.88	3.49	1.25	61.23
TOTAL CHOCOLATE CANDY	91.0%	1.32%	6.11	5.97	6.66	6.40	6.39	5.49	1.02	59.96
DOG FOOD	50.7%	1.27%	0.11	0.11	0.12	0.11	0.12	0.10	6.51	52.40
CAT FOOD	34.5%	1.21%	0.67	0.65	0.69	0.68	0.74	0.60	3.85	45.14
FZ PIZZA	58.5%	1.17%	2.17	2.06	2.32	2.10	2.12	1.83	2.00	79.45
SOUP	96.4%	1.17%	1.61	1.55	1.66	1.70	1.68	1.41	1.94	42.39
ICE CREAM/SHERBET	84.9%	1.12%	0.28	0.28	0.31	0.31	0.28	0.24	4.11	63.80
FZ POULTRY	59.1%	1.09%	2.42	2.28	2.47	2.40	2.47	2.06	2.70	87.76
RFG SALAD/COLESLAW	86.3%	1.03%	2.25	2.56	3.05	2.49	2.46	2.11	1.02	52.11
PET SUPPLIES	51.3%	1.02%	4.40	4.68	5.55	4.18	4.78	4.38	1.49	95.71
COFFEE	68.6%	1.02%	2.20	2.21	2.34	2.29	2.26	2.00	1.21	80.74
PROCESSED CHEESE	87.7%	0.98%	3.39	3.23	3.54	3.43	3.43	3.18	1.04	59.74
LAUNDRY DETERGENT	86.8%	0.88%	0.14	0.13	0.14	0.14	0.14	0.12	4.83	75.47
VEGETABLES	96.4%	0.84%	0.84	0.80	0.89	0.87	0.84	0.68	2.36	38.46
WINE	19.9%	0.84%	1.55	1.55	1.56	1.53	1.58	1.53	1.49	99.95
TOILET TISSUE	92.2%	0.82%	0.05	0.05	0.06	0.06	0.06	0.05	6.95	61.60
FZ SEAFOOD	47.3%	0.79%	2.91	2.64	3.04	3.00	2.76	2.53	1.61	106.65
PAPER TOWELS	83.8%	0.75%	0.67	0.65	0.69	0.68	0.67	0.59	2.11	82.43
FZ NOVELTIES	54.1%	0.75%	1.12	1.08	1.17	1.15	1.11	0.98	2.24	82.31
DRY PACKAGED DINNERS	73.4%	0.74%	2.81	2.69	2.96	2.96	3.00	2.48	1.23	78.71
SNACK BARS/GRANOLA BARS	52.9%	0.74%	8.60	8.56	9.15	9.02	9.14	7.63	0.87	86.68
TOTAL NON-CHOCOLATE CANDY	82.9%	0.73%	5.87	5.66	6.16	5.85	5.79	5.24	0.89	74.21
INTERNAL ANALGESICS	61.6%	0.70%	5.84	4.57	5.42	5.51	5.46	4.92	1.18	115.06
HOUSEHOLD CLEANER	81.2%	0.70%	0.95	0.94	1.01	0.99	1.01	0.87	1.87	81.27
FRANKFURTERS	68.6%	0.67%	3.02	2.88	3.34	3.25	3.14	2.31	1.50	83.61
DOUGH/BISCUIT DOUGH - RFG	76.8%	0.66%	2.46	2.35	2.65	2.62	2.52	2.15	1.49	73.37
RFG JUICES/DRINKS	75.6%	0.65%	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	50.42	63.44
SOAP	77.9%	0.64%	3.69	3.60	3.94	3.88	3.74	3.34	1.44	90.40
YOGURT	54.9%	0.63%	2.12	2.07	2.18	2.23	2.04	1.91	1.71	66.14
TOOTHPASTE	76.2%	0.62%	29.67	29.12	30.57	31.92	30.69	28.54	0.48	103.21
BOTTLED WATER	45.9%	0.62%	1.47	1.47	1.61	1.53	1.56	1.27	1.55	88.25
VITAMINS	41.2%	0.61%	0.06	0.05	0.05	0.05	0.05	0.05	8.71	109.71
COLD/ALLERGY/SINUS TABLETS	37.3%	0.59%	1.03	0.97	1.11	1.09	1.16	0.86	2.80	126.86
PASTRY/DOUGHNUTS	57.4%	0.58%	3.47	3.39	3.59	3.42	3.37	3.17	0.99	84.20
CANNED/BOTTLED FRUIT	84.0%	0.58%	0.84	0.82	0.90	0.88	0.86	0.73	1.75	70.27
FZ PLAIN VEGETABLES	68.9%	0.57%	1.44	1.43	1.68	1.58	1.66	1.21	1.70	81.23
SALAD DRESSINGS - SS	78.2%	0.57%	2.26	2.19	2.38	2.34	2.39	1.89	1.34	82.57
SKIN CARE	35.3%	0.53%	23.51	29.11	27.30	22.78	26.27	22.14	0.39	143.82
BAKING MIXES	83.2%	0.52%	1.13	1.09	1.21	1.15	1.19	0.93	1.56	68.12
BOTTLED JUICES - SS	77.9%	0.51%	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	45.87	70.92
SNACK NUTS/SEEDS/CORN NUTS	55.5%	0.51%	3.47	3.47	4.06	4.04	3.69	3.28	1.14	101.19
FZ MEAT	42.3%	0.50%	4.18	4.19	4.88	4.32	4.48	3.79	2.03	100.11
FZ BREAD/FZ DOUGH	61.1%	0.49%	1.58	1.54	1.62	1.63	1.59	1.38	1.50	90.98
FZ BREAKFAST FOOD	51.0%	0.49%	3.17	3.10	3.38	3.33	3.30	2.73	1.23	91.06
CANNED MEAT	56.6%	0.49%	1.70	1.70	1.78	1.78	1.84	1.61	1.23	93.77
DISH DETERGENT	83.2%	0.47%	0.57	0.56	0.61	0.59	0.60	0.50	2.00	88.19
CUPS & PLATES	61.9%	0.47%	2.35	2.21	2.34	2.45	2.43	2.49	1.32	99.23
SPICES/SEASONINGS	80.4%	0.47%	3.13	3.12	3.17	2.84	3.08	2.62	0.56	94.74
SHAMPOO	59.9%	0.45%	2.87	2.79	3.13	3.07	2.79	2.56	1.15	119.75

TABLE 3

Category Descriptive Statistics *cont.*

Category	Penetration Rate	Share of Wallet	Price Index BiLo	Price Index Food Lion	Price Index Harris Teeter	Price Index Lowes	Price Index Winn-Dixie	Price Index Wal-Mart	Av. Quantity	Av. Purchase Days
RFG FRESH EGGS	96.9%	0.45%	0.01	0.01	0.01	0.01	0.01	0.01	7.92	38.94
FZ APPETIZERS/SNACK ROLLS	37.5%	0.44%	4.66	4.24	5.10	4.71	5.02	3.98	1.41	126.43
BATTERIES	55.5%	0.44%	0.15	0.16	0.17	0.15	0.16	0.15	4.76	132.93
PICKLES/RELISH/OLIVES	72.5%	0.43%	0.87	0.82	0.97	0.87	0.85	0.73	1.17	91.42
MARGARINE/SPREADS/BUTTER BLE	87.4%	0.43%	0.79	0.76	0.84	0.83	0.78	0.65	1.38	61.13
FZ DESSERTS/TOPPING	61.3%	0.43%	2.96	2.87	3.16	2.98	3.01	2.39	1.05	97.84
SHORTENING & OIL	81.2%	0.43%	0.43	0.42	0.45	0.44	0.46	0.38	1.80	97.16
DEODORANT	62.7%	0.42%	2.75	2.69	2.98	2.75	3.01	2.65	1.29	124.29
SS DINNERS	62.2%	0.42%	1.46	1.43	1.59	1.55	1.47	1.31	1.69	86.06
DINNER SAUSAGE	43.7%	0.42%	3.11	3.24	3.59	3.53	3.31	2.68	1.60	108.87
TOASTER PASTRIES/TARTS	40.6%	0.41%	1.83	1.80	1.91	1.88	2.00	1.62	1.45	95.96
BAKING NEEDS	71.4%	0.40%	2.48	2.40	2.55	2.51	2.68	2.18	1.10	98.89
FOOD & TRASH BAGS	85.2%	0.39%	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	0.00[a]	30.85	76.88
SANITARY NAPKINS/TAMPONS	43.4%	0.39%	0.52	0.52	0.55	0.54	0.55	0.50	2.84	100.68
AIR FRESHENERS	49.3%	0.39%	2.49	2.51	2.67	2.76	2.49	2.34	1.53	105.98
SPAGHETTI/ITALIAN SAUCE	70.3%	0.38%	0.59	0.59	0.65	0.63	0.62	0.53	2.16	83.31
SEAFOOD -SS	64.4%	0.38%	5.85	5.17	6.82	5.45	5.45	4.73	1.05	88.27
POPCORN/POPCORN OIL	59.9%	0.38%	2.53	2.33	2.81	2.61	2.56	2.13	1.36	112.71
TOOTHBRUSH/DENTAL ACCESORIES	47.3%	0.38%	2.78	2.52	2.80	2.44	2.61	2.64	1.41	136.07

[a] Exact prices are not shown given that the price per unit is less than $0.01.

TABLE 4
Store Descriptive Statistics

	Store Descriptive Statistics					
	BiLo	*Food Lion*	*Harris Teeter*	*Lowes*	*Winn-Dixie*	*Wal-Mart*
Loyalty	9.9%	26.4%	15.7%	3.0%	8.5%	36.5%
	(0.25)[a]	(0.37)	(0.31)	(0.14)	(0.23)	(0.43)
Trip Share	11.6%	32.9%	17.9%	3.2%	9.0%	25.4%
	(0.32)	(0.47)	(0.38)	(0.18)	(0.29)	(0.44)
Distance	20.46	9.41	17.79	41.41	17.32	41.96
	(20.09)	(7.52)	(13.17)	(29.60)	(17.02)	(26.71)
Price	189.66	184.91	204.90	195.36	194.34	170.36
	(8.03)	(7.59)	(8.05)	(5.83)	(8.70)	(5.32)
Number of UPCs	54.85	64.45	58.14	38.38	53.01	58.89
	(5.43)	(5.47)	(5.34)	(4.89)	(6.43)	(4.89)
Number of brands	56.35	58.34	58.67	37.12	46.07	71.17
	(5.76)	(5.02)	(6.07)	(5.83)	(6.08)	(6.28)
Number of brand sizes	54.97	59.34	55.84	46.44	53.74	57.39
	(3.94)	(3.61)	(3.59)	(4.30)	(4.65)	(3.73)
Percent unique private labels	8.34	8.67	7.86	5.62	10.32	6.39
	(1.42)	(1.04)	(1.14)	(1.94)	(1.98)	(0.91)
Percent unique national brands	9.67	9.20	10.68	9.33	7.60	16.30
	(2.20)	(2.00)	(2.08)	(3.49)	(2.30)	(1.98)
Favorite brand present	23.13	28.78	25.68	14.32	20.37	28.47
	(19.28)	(20.00)	(19.63)	(16.17)	(18.53)	(20.32)
Frequency of promotions	21.39	16.60	16.40	6.01	12.81	31.42

[a]Numbers in ( ) give standard deviations.

TABLE 5
Model Covariates

Variable	Description
x_1	Natural logarithm of the travel time (in minutes) plus one from the centroid of the households zip+4 to the store.
x_2	State dependence. Binary variable set to one if household visited this store on previous day where a shopping trip occurred.
z_1	Time (in days) since the household last purchased in this category.
z_2	Quantity purchased in this category on the last visit.
z_3	Mean centered interaction of z1 and z2.
z_4	Category price. This is calculated a long-run market share of each UPC divided by the share of the UPCs carried in the store.
z_5	Display. Long-run share weighted average of UPCs on display.
z_6	Feature. Long-run share weighted average of UPCs feature advertised.
y_1	Favorite brand present. This calculated on a household-level. The purchase share of the top three brands for the household in this category are calculated. This variable is then the sum of the shares times a binary indicator variable set to one if the brand is sold in this store during this period.
y_2	Number of UPCs per brand minus one. Number of UPCs per brand in store s during period *t* for category *c* divided by average number of UPCs per brand carried by all stores over all periods in category *c*. This variable is made relative to brands to reduce colinearity with the number of brands and centered at the expected value (one).
y_3	Number of brands minus one. Number of brands carried in store *s* in period *t* divided by the average number of brands carried by all stores in all periods. This variable is mean centered.
y_4	Number of brand sizes per brand minus one. Number of brand sizes per brand for category *c* in store *s* and period *t* divided by the average number of brand sizes per brand for all stores over all periods. This variable is mean-centered. Computing brand sizes per brand helps to reduce colinearity with the number of brands.
y_5	Percent of house-brand *UPC*s.
y_6	Frequency of promotion. Moving average of the previous four weeks of whether or not there was a promotion in the category (cf. Mela et al. 1997).
y_7	Average inter-purchase time. Average number of days between purchases for this category divided by 100.
y_8	Percent of unique national brand *UPC*s.

TABLE 6
Proposition 1: Empirical Results

Part A: Distribution of Number of Stores Visited

	No. Stores	Frequency	%
Same Day			
	1	42794	84.4%
	2	6878	13.6%
	3+	1033	2.0%
Same Week			
	1	19380	45.8%
	2	17572	41.6%
	3	4641	10.9%
	4+	660	1.7%

Part B: Relative Dollar Spend and Number of Categories Purchased

			2 Stores	3 Stores	4+ Stores	5+ Stores
Same Day						
	Spend					
		Store A	0.6847	0.5414	0.4171	
		Store B	0.3153	0.2293	0.0981	
		Ratio[a]	3.9802	2.7363	4.2510	
	Category Purchased					
		Store A	0.6993	0.5686	0.4223	
		Store B	0.3007	0.2157	0.0925	
		Ratio	3.7794	3.2451	4.8850	
Same Week						
	Spend					
		Store A	0.6939	0.5886	0.4607	0.4333
		Store B	0.3061	0.2057	0.1284	0.0886
		Ratio	2.7073	3.3425	5.8400	6.6728
	Category Purchased					
		Store A	0.7295	0.6127	0.4656	0.4352
		Store B	0.2705	0.1926	0.1259	0.0867
		Ratio	3.6860	4.0151	6.0111	6.9522

[a] Ratios reflect the relative dollar spend and number of categories shopped computed by dividing dollar spend/number of categories shopped for the store receiving the largest dollar spend/number of categories shopped by the dollar spend/number of categories shopped for all remaining stores. See footnote #7

TABLE 7

Proposition 2: Empirical Results

Part A: Number of Stores Visited

No. of Stores Visited	Same Day	During Same Week
2	0.3464	0.2502
3	0.6066	0.4091
4+	0.8182	0.6628

Part B: Log Odds Visiting Same Stores/Same Week

	BiLo	Food Lion	Harris Teeter	Lowes	Winn Dixie	Wal-Mart
BiLo		0.04879	0.322083	2.721295[b]	0.371564	-2.12026[b]
Food Lion			-1.89712[b]	1.61343[b]	0.329204	-1.04982[a]
Harris Teeter				-4.07454[b]	0.95935	-1.56065[b]
Lowes					2.785011[b]	0.955511
Winn Dixie						0.173953

[a] $p<.05$
[b] $p<.01$

TABLE 8
Proposition 3: Empirical Results

Single Category Purchase trips		
Favorite Store	*CSSL*	*CDI*
0.3809	0.4097	0.5831

CSSL = category-specific store loyalty
CDI = category development index

TABLE 9
Model Fit Summary

		Dimensions		
		(2)	(3)	(4)
Estimation Sample				
	Households	357	357	357
	#of Trips	25,387	25,387	25,387
	Log Likelihood	-248,930	-246,514	-246,462
	# parameters	248	337	425
	Hit Rate	92.4%	92.3%	92.4%
	AIC	498,355	493,702	493,774
	BIC	500,374	496,446	497,234
	CAIC	500,622	496,783	497,659
Hold Out Sample				
	Households	357	357	357
	# of Trips	12,051	12,051	12,051
	Log Likelihood	-116,018	-115,060	-115,261
	Hit Rate	92.7%	92.7%	92.8%

TABLE 10
Model Parameters

		Mean			Heterogeneity Standard Deviation		
		Value	Std Err	p-Value	Value	Std Err	p-Value
Store Choice Model							
κ	*CA*	2.17	0.092	0.014	1.528	0.043	0.009
$\pi_1^{(0)}$	Factor Score (d1)	-0.391	0.008	0.006	1.059	0.195	0.058
$\pi_2^{(0)}$	Factor Score (d2)	-0.391	c	na	3.411	0.289	0.027
$\pi_3^{(0)}$	Factor Score (d3)	-0.391	c	na	1.528	0.059	0.012
β_1	Travel Time ln(Distance) (x1)	-0.901	0.020	0.007	0.347	1.675	0.435
β_2	State Dependence (x2)	-0.065	0.019	0.091	0.407	0.013	0.010
Category Incidence Model							
$\pi_h^{(1)}$	Factor Score	-0.028	0.001	0.009	0.009	0.001	0.020
	Lag Time (z1)	0.174	0.043	0.077	0.126	0.086	0.191
	Lag Quantity (z2)	-0.546	0.099	0.057	0.192	1.144	0.447
	Lag Quantity x Lag Time (z3)	0.628	0.360	0.166	0.734	0.215	0.091
	Price (z4)	-1.566	0.02	0.004	0.294	0.015	0.016
	Feature (z5)	0.649	0.022	0.011	0.104	0.031	0.093
	Display (z6)	0.479	0.020	0.014	0.111	0.672	0.448
γ_{h1}	Destination (d1)	-0.200	0.006	0.010	0.033	0.010	0.096
γ_{h2}	Destination (d2)	-0.170	0.01	0.009	0.021	0.014	0.091
γ_{h3}	Destination (d3)	0.220	0.006	0.009	0.081	0.008	0.030
Destination Factor							
	Favorite Brands (y1)	1	c	na	0	c	na
ω_1	# Brands (y3)	-7.352	0.204	0.009	1.264	0.445	0.108
ω_2	# *UPC*s/Brand (y2)	-9.174	0.470	0.016	3.248	0.296	0.029
ω_3	# Sizes/Brand (y4)	0.911	0.656	0.199	1.716	0.348	0.064
ω_4	Unique Private Label Items (y5)	29.277	1.185	0.013	4.142	1.030	0.078
ω_5	Frequency of Promotion (y6)	-0.485	0.180	0.113	1.237	0.383	0.096
ω_6	Avg Interpurchase Time (y7)	18.853	0.626	0.011	2.547	0.698	0.085
ω_7	Unique National Brand Items (y8)	26.97	1.012	0.012	2.003	1.276	0.181

c = Constrained parameter
na = Not applicable

TABLE 11
Percent Change in Expected Choice Probabilities

	BiLo	FoodLion	Harris Teeter	Lowes	Winn Dixie	Wal-Mart
Baseline Choice Probabilities	11.6%	32.9%	17.9%	3.2%	9.0%	25.4%
CARBONATED BEVERAGES	1.6%	1.3%	0.7%	1.6%	0.4%	-2.7%
CIGARETTES	-0.3%	0.6%	-0.8%	0.0%	-0.3%	-0.1%
COLD CEREAL	0.0%	-0.3%	0.0%	0.0%	-0.5%	0.5%
FRESH BREAD & ROLLS	-0.2%	1.4%	-1.5%	4.8%	1.8%	-1.7%
BEER/ALE/ALCOHOLIC CIDER	0.1%	0.1%	0.5%	0.0%	0.3%	-0.4%
FZ DINNERS/ENTREES	0.3%	0.8%	-0.2%	-1.6%	0.1%	-1.0%
SALTY SNACKS	-0.1%	0.6%	0.7%	-1.6%	-1.1%	-0.5%
NATURAL CHEESE	0.6%	0.1%	1.0%	1.6%	-0.2%	-0.8%
MILK	2.3%	-1.2%	2.2%	1.6%	3.0%	-1.5%
LUNCHEON MEATS	1.2%	0.1%	-0.4%	0.0%	2.2%	-1.3%
CRACKERS	-1.1%	0.2%	-0.3%	-1.6%	-1.2%	0.8%
COOKIES	-1.0%	0.5%	-0.3%	-1.6%	-1.1%	0.4%
BREAKFAST MEATS	0.1%	0.3%	0.2%	1.6%	1.1%	-0.8%
TOTAL CHOCOLATE CANDY	-1.9%	-0.9%	-2.1%	-3.2%	-2.0%	3.4%
DOG FOOD	-1.1%	-0.1%	-1.3%	-1.6%	-1.4%	1.5%
CAT FOOD	-0.5%	0.6%	-0.4%	0.0%	-1.3%	0.1%
FZ PIZZA	0.3%	0.4%	0.4%	0.0%	-0.3%	-0.7%
SOUP	1.2%	0.8%	1.2%	0.0%	-0.2%	-1.9%
ICE CREAM/SHERBET	0.7%	0.5%	1.2%	0.0%	0.5%	-1.5%
FZ POULTRY	0.5%	0.0%	0.6%	3.2%	0.4%	-0.6%
RFG SALAD/COLESLAW	-0.9%	0.1%	0.7%	9.7%	3.1%	-1.1%
PET SUPPLIES	-0.9%	-0.7%	-1.0%	-1.6%	-0.7%	1.8%
COFFEE	-0.7%	0.4%	0.0%	0.0%	0.1%	-0.1%
PROCESSED CHEESE	0.5%	0.2%	0.7%	0.0%	0.2%	-0.8%
LAUNDRY DETERGENT	-0.8%	0.0%	-0.5%	-1.6%	-1.1%	0.9%
VEGETABLES	0.9%	1.0%	0.3%	3.2%	0.2%	-1.8%
WINE	-0.2%	0.1%	0.0%	0.0%	-0.2%	0.0%
TOILET TISSUE	-0.5%	-0.2%	-0.5%	-1.6%	-0.2%	0.7%
FZ SEAFOOD	0.4%	0.1%	0.4%	1.6%	0.2%	-0.6%
PAPER TOWELS	-0.8%	0.0%	-0.2%	-1.6%	-0.5%	0.6%
FZ NOVELTIES	0.3%	0.2%	0.7%	1.6%	0.3%	-0.7%
DRY PACKAGED DINNERS	0.1%	0.2%	-0.1%	0.0%	-0.2%	-0.3%
SNACK BARS/GRANOLA BARS	-0.5%	-0.1%	-0.3%	-1.6%	-0.3%	0.6%
TOTAL NON-CHOCOLATE CANDY	-1.6%	-0.9%	-1.7%	-1.6%	-1.6%	3.0%
INTERNAL ANALGESICS	-0.3%	-0.1%	-0.2%	0.0%	-0.3%	0.4%
HOUSEHOLD CLEANER	-1.0%	-0.5%	-0.8%	-1.6%	-1.1%	1.6%
FRANKFURTERS	0.5%	-0.2%	0.3%	1.6%	0.5%	-0.3%
DOUGH/BISCUIT DOUGH - RFG	0.4%	-0.1%	0.9%	1.6%	1.0%	-0.7%
RFG JUICES/DRINKS	0.4%	0.1%	0.8%	1.6%	1.1%	-1.0%
SOAP	-1.5%	-0.6%	-1.5%	-1.6%	-1.2%	2.2%
YOGURT	0.5%	-0.4%	1.2%	0.0%	0.5%	-0.3%
TOOTHPASTE	-1.0%	-0.6%	-1.0%	-1.6%	-1.1%	1.9%
BOTTLED WATER	-0.5%	-0.4%	-0.5%	0.0%	-1.0%	1.2%
VITAMINS	-1.0%	-0.8%	-1.0%	0.0%	-0.8%	2.0%
COLD/ALLERGY/SINUS TABLETS	-0.4%	-0.5%	-0.6%	0.0%	-0.6%	1.2%
PASTRY/DOUGHNUTS	0.1%	0.0%	0.1%	0.0%	-0.1%	-0.1%
CANNED/BOTTLED FRUIT	0.7%	0.3%	0.8%	1.6%	0.0%	-1.0%
FZ PLAIN VEGETABLES	0.9%	0.3%	0.4%	1.6%	-0.3%	-0.9%
SALAD DRESSINGS - SS	0.7%	0.1%	0.6%	1.6%	0.3%	-0.8%
SKIN CARE	-0.5%	-0.3%	-0.4%	0.0%	-0.2%	0.8%
BAKING MIXES	0.7%	0.1%	0.2%	1.6%	1.2%	-1.0%
BOTTLED JUICES – SS	-0.1%	0.7%	-0.4%	-1.6%	-0.1%	-0.5%
SNACK NUTS/SEEDS/CORN NUTS	-0.5%	0.2%	-0.4%	0.0%	-0.4%	0.3%
FZ MEAT	0.3%	-0.1%	0.6%	0.0%	0.4%	-0.4%
FZ BREAD/FZ DOUGH	0.6%	-0.1%	0.3%	3.2%	1.1%	-0.7%
FZ BREAKFAST FOOD	0.3%	0.1%	0.2%	0.0%	0.3%	-0.5%
CANNED MEAT	0.4%	0.0%	0.1%	0.0%	0.2%	-0.3%
DISH DETERGENT	-0.5%	-0.4%	-0.1%	-1.6%	-0.2%	0.7%
CUPS & PLATES	0.0%	-0.1%	-0.1%	0.0%	-0.1%	0.2%
SPICES/SEASONINGS	0.6%	-0.4%	1.3%	1.6%	-0.1%	-0.3%
SHAMPOO	-0.8%	-0.7%	-1.1%	-1.6%	-0.8%	1.7%
RFG FRESH EGGS	2.8%	-1.7%	2.7%	1.6%	-0.7%	-0.3%
FZ APPETIZERS/SNACK ROLLS	0.2%	0.1%	0.0%	1.6%	0.1%	-0.4%
BATTERIES	-0.3%	-0.3%	-0.3%	0.0%	-0.4%	0.7%
PICKLES/RELISH/OLIVES	0.3%	0.1%	-0.2%	1.6%	1.2%	-0.6%
MARGARINE/SPREADS/BUTTER BLE	0.1%	0.1%	-0.3%	1.6%	1.1%	-0.5%
FZ DESSERTS/TOPPING	0.1%	0.2%	-0.1%	0.0%	0.4%	-0.5%
SHORTENING & OIL	0.4%	0.2%	0.5%	1.6%	1.0%	-0.9%
DEODORANT	-0.4%	-0.2%	-0.4%	0.0%	-0.4%	0.6%
SS DINNERS	0.5%	0.0%	0.4%	0.0%	0.4%	-0.6%
DINNER SAUSAGE	0.5%	-0.1%	0.2%	1.6%	0.5%	-0.4%
TOASTER PASTRIES/TARTS	0.2%	-0.1%	0.1%	0.0%	-0.3%	0.1%
BAKING NEEDS	-0.3%	-0.1%	-0.1%	0.0%	-0.1%	0.2%
FOOD & TRASH BAGS	-0.9%	-0.2%	-1.0%	-1.6%	-0.8%	1.3%
SANITARY NAPKINS/TAMPONS	-0.7%	-0.4%	-0.5%	-1.6%	-0.5%	1.1%
AIR FRESHENERS	-0.5%	-0.2%	-0.4%	0.0%	-0.5%	0.8%
SPAGHETTI/ITALIAN SAUCE	0.5%	0.0%	0.1%	1.6%	0.7%	-0.6%
SEAFOOD –SS	0.2%	0.2%	0.2%	1.6%	1.2%	-0.8%
POPCORN/POPCORN OIL	-0.9%	0.3%	-0.7%	0.0%	-0.6%	0.6%
TOOTHBRUSH/DENTAL ACCESORIES	-0.3%	-0.1%	-0.2%	0.0%	-0.2%	0.3%

TABLE 12
Category Leverage In Patronage Decisions (*CLIPD*)

CLIPD	Category	Sls Rnk	*CLIPD*	Category	Sls Rnk
1.20	MILK	9	0.35	FZ DESSERTS/TOPPING	67
1.06	FRESH BREAD & ROLLS	4	0.34	COLD CEREAL	3
0.93	CIGARETTES	2	0.33	BREAKFAST MEATS	13
0.75	BEER/ALE/ALCOHOLIC CIDER	5	0.33	TOOTHPASTE	42
0.73	CARBONATED BEVERAGES	1	0.32	TOTAL CHOCOLATE CANDY	14
0.66	RFG SALAD/COLESLAW	21	0.32	DEODORANT	69
0.62	DINNER SAUSAGE	71	0.32	FZ PIZZA	17
0.59	FZ BREAD/FZ DOUGH	55	0.31	TOTAL NON-CHOCOLATE CANDY	34
0.58	RFG FRESH EGGS	62	0.31	SPICES/SEASONINGS	60
0.58	FZ MEAT	54	0.31	SKIN CARE	50
0.56	ICE CREAM/SHERBET	19	0.31	MARGARINE/SPREADS/BUTTER BLE	66
0.55	FZ POULTRY	20	0.30	PROCESSED CHEESE	24
0.53	WINE	27	0.30	AIR FRESHENERS	76
0.53	FZ NOVELTIES	31	0.30	DOUGH/BISCUIT DOUGH - RFG	38
0.51	VEGETABLES	26	0.30	BOTTLED JUICES - SS	52
0.49	LUNCHEON MEATS	10	0.29	INTERNAL ANALGESICS	35
0.48	FZ SEAFOOD	29	0.29	SHAMPOO	61
0.46	CAT FOOD	16	0.29	PASTRY/DOUGHNUTS	46
0.46	FZ APPETIZERS/SNACK ROLLS	63	0.29	SOAP	40
0.45	SALAD DRESSINGS - SS	49	0.28	SNACK BARS/GRANOLA BARS	33
0.45	FZ DINNERS/ENTREES	6	0.28	TOOTHBRUSH/DENTAL ACCESORIES	80
0.44	RFG JUICES/DRINKS	39	0.28	CRACKERS	11
0.44	SALTY SNACKS	7	0.27	COOKIES	12
0.43	SEAFOOD -SS	78	0.27	HOUSEHOLD CLEANER	36
0.42	NATURAL CHEESE	8	0.25	COLD/ALLERGY/SINUS TABLETS	45
0.42	SOUP	18	0.24	CANNED MEAT	57
0.42	SANITARY NAPKINS/TAMPONS	75	0.23	SNACK NUTS/SEEDS/CORN NUTS	53
0.42	FZ BREAKFAST FOOD	56	0.23	LAUNDRY DETERGENT	25
0.40	BAKING MIXES	51	0.23	BOTTLED WATER	43
0.40	PET SUPPLIES	22	0.22	FOOD & TRASH BAGS	74
0.40	FRANKFURTERS	37	0.21	POPCORN/POPCORN OIL	79
0.39	SHORTENING & OIL	68	0.21	DRY PACKAGED DINNERS	32
0.38	FZ PLAIN VEGETABLES	48	0.20	TOASTER PASTRIES/TARTS	72
0.38	DOG FOOD	15	0.19	COFFEE	23
0.37	SS DINNERS	70	0.18	BATTERIES	64
0.37	YOGURT	41	0.18	PAPER TOWELS	30
0.37	PICKLES/RELISH/OLIVES	65	0.17	DISH DETERGENT	58
0.37	VITAMINS	44	0.14	TOILET TISSUE	28
0.36	CANNED/BOTTLED FRUIT	47	0.13	BAKING NEEDS	73
0.35	SPAGHETTI/ITALIAN SAUCE	77	0.13	CUPS & PLATES	59

TABLE 13

Category Assortment Decisions and *Destination-ness*

Sales Rank	Category	CLIPD	Percent Change in $\varphi_{hc\|s}$ Bilo	Food Lion	Harris Teeter	Lowes	Winn Dixie	Wal-Mart
9	MILK	1.20	-60%	-32%	86%	259%	-61%	-7%
4	FRESH BREAD & ROLLS	1.06	11%	-33%	30%	50%	-12%	-1%
2	CIGARETTES	0.93	-53%	-83%	91%	142%	-23%	-14%
5	BEER/ALE/ALCOHOLIC CIDER	0.75	-36%	-33%	-14%	114%	-7%	-5%
1	CARBONATED BEVERAGES	0.73	-11%	-26%	-5%	20%	89%	-6%
21	RFG SALAD/COLESLAW	0.66	104%	-1%	-5%	-3%	-20%	-12%
71	DINNER SAUSAGE	0.62	-6%	-9%	12%	11%	13%	-3%
55	FZ BREAD/FZ DOUGH	0.59	-3%	2%	6%	8%	-15%	1%
62	RFG FRESH EGGS	0.58	-21%	-17%	-16%	62%	48%	-8%
54	FZ MEAT	0.58	-7%	-14%	-31%	106%	-5%	3%
19	ICE CREAM/SHERBET	0.56	-18%	-27%	-25%	39%	17%	20%
20	FZ POULTRY	0.55	4%	-11%	-1%	15%	3%	0%
27	WINE	0.53	-7%	-40%	-23%	92%	21%	-14%
31	FZ NOVELTIES	0.53	-9%	-21%	-15%	17%	10%	17%
26	VEGETABLES	0.51	-17%	-30%	-2%	23%	34%	6%