Variety and the Cost of Search in Supermarket Retailing

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Abstract

Prices for similar products often differ between retail outlets, leading consumers to actively search for products that meet their needs at the lowest possible price. Search costs have essential implications for retail pricing behavior, because it is generally not optimal for consumers to become perfectly informed about all prices and all available products in a multi-product retail environment when search is costly. We examine the link between search costs and product variety offered by multi-product retailers. When consumers are faced with a large number of goods on each shopping occasion, this raises the number of prices consumers need to compare across retailers, which can raise search costs. Yet, the net benefits of search can rise within a category when retailers offer wider product assortments, because packing products more densely in an attribute space allows consumers to more easily find a product that matches their desired specifications, hampering price comparison across retailers. In this study, we develop an empirical method designed to test how search costs change with product variety in a multi-product retail setting. We consider a hierarchcial process in which consumers search among stores and then among brands and compare the model fit to a model in which consumers search only among brands. We find statistically significant search costs exist both for search among stores and for search among brands within a store. We also find that search costs rise in variety, a finding that suggests both store and brand consideration sets are limited in size.

Keywords: consumer search, variety, retail prices, attribute search, market power.

JEL Classification: D12, D83, L13, L81.

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1 Introduction

It is well understood that retailers can have market power when search is costly, even in homogenous product markets (Burdett and Judd 1983). There is considerable evidence that search costs are, in fact, meaningful in numerous retail environments (Mehta, Rajiv, and Srinivasan 2003), including online formats (Brynjolfsson and Smith 2000; Clay, Krishnan, and Wolff 2001; Hong and Shum 2006; Moraga-Gonzalez and Wildenbeest 2008; Kim, Albuquerque, and Bronnenberg 2010; de Los Santos, Hortacsu, and Wildenbeest 2012). Yet little evidence exists on the extent of consumer search costs in retail settings in which consumers purchase multiple products at once. When consumers select among multiple products on a given shopping occasion, for instance at a supermarket, the search experience requires consumers to jointly search for desired brands within each store and for low prices among stores.

In this paper, we consider the link between retail product variety provision and consumer incentives to search. Given the on-going debate regarding the desirability of deeper assortments (Iyengar and Lepper 2000; Boatwright and Nunes 2001; Oppewal and Koelemeijer 2005), it is important to understand how variety impacts consumer incentives to search over both product attributes and prices. A retailer that decides to offer greater product variety increases the number of products consumers must search to find brands that match their tastes, raising search cost over brands. But greater variety provision also increases the odds that a product selected by a consumer matches more closely in attributes with the product the consumer would purchase with a rival retailer, increasing the benefits of search.

Existing empirical research on search costs typically considers the consumer search effort to be a single-product process, as when consumers compare prices across retailers for a particular book title or computer game that is common across both retailers. Such models have proven useful in explaining retail price dispersion in settings with costly consumer search (Hong and Shum 2006; Wildenbeest 2011). Yet, an important characteristic of multi-product retailers is that consumers are required to search among multiple brands, some of which are store-specific, and compare multiple prices across stores. Consumers typically purchase multiple items at once in a supermarket, are confronted with a wide array of products from which to choose. Comparison is often difficult not only due to the presence of store brands, but because some stores stock unique sizes, variants, or formulations specifically to prevent direct comparison. Consumers purchasing more than one product at a time from a supermarket thus engage in two dimensions of search, undergoing costly search effort to select both among stores and among products within a given store. Retail assortment decisions, therefore, can have a fundamental effect on both forms of search, so it is important to understand how changes in product variety influence consumer search over brands in conceiving how consumers search over prices and stores.

We develop an empiricial model of consumer search that focuses on the effect of product variety on changes in the propensity of consumers to search. Consumers in our model search over stores and brands, so we are able to examine how product variety affects consumers' incentive to search. We consider search as a joint process over products and prices in a nested empirical environment where consumers search over retail stores, and then over brands within the selected retailer in a hierarchical manner. Specifically, we consider a model in which consumers planning to make a purchase from a product category first choose a retailer on the basis of location, cleanliness, quality of service, perception of overall price level, and other store-level attributes (Smith 2004), and then choose their desired brand from among available products in the category, or categories, of interest (Bell and Lattin 1998). Modeling consumer search as a hierarchical process allows us to examine how consumer incentives to engage in both forms of search vary with the depth of assortment offered by retailers. Controlling for changes in consumer search effort over brands in response to changes in variety is important for understanding the role of consumer search over stores in multi-product settings, which in turn has important implications for retail price-setting.

We frame our model around the assumption that consumers must undertake costly search activities to resolve uncertainty surrounding their selection of retailer and brand when making supermarket purchases. When choosing among retailers, consumers may be uncertain about the availability of parking, the stock of key products held in the store, the length of cashier lines and the particular set of brands promoted through in-store specials on a given shopping occasion. When choosing among brands, consumers are unlikely to know the exact price they would pay for a similar shopping basket obtained from a rival supermarket (Dickson and Sawyer 1990; Degeratu, Rangaswamy, and Wu 2000; Mojir, Sudhir, and Khwaja 2013), and the set of goods contained in the shopping basket is likely to differ by retailer. Indeed, Point of Purchase Advertising International (2012) reports that 76% of consumers' purchases are the result of unplanned, in-store decisions, a feature that complicates price comparison across retailers. To account for this feature of consumer search behavior, we model brand and store search decisions as a nested, two-step processes.

Previous research has considered the role of search over prices and product quality. Mehta, Rajiv and Srinivasan (2003) introduce search as a mechanism to resolve both price and quality uncertainty regarding purchases of consumer packaged goods (liquid detergent and ketchup). While consumers are willing to pay for search to resolve price uncertainty, they eliminate quality uncertainty over time through a dynamic learning process. Moraga-Gonzalez, Sandor and Wildenbeest (2011) examine consumer search in the automobile market where consumers are fully aware of the measurable attributes of an automobile such as price, horsepower, color and weight, but are uncertain about some of the more aesthetic aspects of the vehicle's "fit", for instance experience attributes like transmission smoothness and handling. Search costs are random in their model, reflecting the fact that searching for a new car involves a multi-step process of driving to dealerships, locating a specific model, and finding a salesperson. For products that are frequently purchased at a supermarket, it is likely that consumers readily understand experience-attributes after initial purchase and consumption, and we consequently model uncertainty as deriving from prices and the quality of the match that is available from the assortment at a given retailer. Search costs are random in our model to account for the fact that products selected from one supermarket may not be available at the rival supermarket, as in the case of private labels, and this random element of consumer choice adds complexity to the process of price comparison.

Our model contributes to the literature on search with endogenous consideration sets. In this literature, the size and composition of consumers' decision sets are determined by comparing the costs and benefits of adding another product to the list of products to search (Stigler 1961; Roberts and Lattin 1991; Andrews and Srinivasan 1995; Ben-Akiva and Boccara 1995; Mehta, Rajiv, and Srinivasan 2003).[1] Traditional discrete-choice models of demand (Berry, Levinsohn, and Pakes 1995; Nevo 2001) implicitly assume each consumer's consideration set includes all available products or, equivalently, that search costs are zero (Moraga-Gonzalez, Sandor, and Wildenbeest 2011); however, under costly search, it may be prohibitively costly for consumers to become fully informed of the prices and availability of products at different retailers. Goeree (2008)

[1] The endogeneity of choice sets has also been incorporated into empirical models of recreation demand and transportation (Haab and Hicks 1997; von Haefen 2008; Hicks and Schnier 2010).

argues that it is consumers' limited amount of information regarding alternatives that bounds the size of consideration sets, and shows how this lack of measurement introduces bias in traditional, zero-search cost models of demand. Here, we allow both consideration sets – the store consideration set and the brand consideration set – to vary endogenously based on the net benefits of search at each choice-level.

A number of authors have shown the manner in which consumers search to be important. Weitzman (1979) and Stahl (1989, 1996) consider sequential processes for search, in which consumers search through products according to a rank-ordering of preference and select the first product they discover that meets their tolerance level at an acceptable price. Kim, Albuquerque, and Bronnenberg (2010) consider a sequential search process, in which search activity stops, and a choice is made, when a suitable product is found. De los Santos, Hortacsu, and Wildenbeest (2012) compare sequential and non-sequential alternatives by exploiting a unique data set in which they observe consumers' search processes, and find evidence to support the non-sequential model of search in an online retail context. Moreover, Honka and Chintagunta (2013) estimate a mixture model that includes sequential and non-sequential components, and find that the non-sequential segment dominates the sequential segment. We design our model along the lines of this recent empirical evidence by framing consumer search using a fixed-sample size rule.

By accounting for costly search in our demand model, we not only remove a potential source of bias, but also gain insight on how the net benefits of consumer search are influenced by retailer variety decisions. In particular, there is much concern among retailers regarding how the number of products offered in each category influences equilibrium search-and-choice behavior (Iyengar and Lepper 2000; Boatwright and Nunes 2001; Borle et al. 2005; Oppewal and Koelemeijer 2005; Briesch, Chintagunta, and Fox 2009; Ratchford 2009; Scheibehenne, Greifeneder, and Todd 2010). Our framework encompasses several possible channels through which variety can influence the net benefits of consumer search. First, providing greater product variety increases the number of potential choice comparisons consumers are required to make, complicating the process of forming consideration sets and commensurately raising search costs. A growing body of theoretical and experimental research finds that deeper assortments cause consumers to be overwhelmed by the number of choices they are required to make (Klemperer and Padilla 1997; Lehmann 1998; Schwartz 2004; Diehl and Poynor 2010; Kuksov and Villas-Boas 2010), which implies that search costs rise in variety.

Second, greater variety increases the likelihood of finding an acceptable preference-match, which lowers the cost of search. Yet, offering more products increases the likelihood of finding similar brands at other retailers, which facilitates price comparison, and reduces the cost of searching among stores. The net effect of variety on search costs, therefore, is an empirical question.

Our framework helps disentangle the identification problem that is inherent in any empirical investigation of the relationship between variety and search. Most empirical models of consumer search assume search costs rise linearly with the number of products considered, and, therefore, impose a strict assumption as to how the net benefits of search change in the size of the consideration set (Hong and Shum 2006; Wildenbeest 2011; de Los Santos, Hortacsu, and Wildenbeest 2012). At the same time, utility rises in the size of the consideration set due merely to the inherent love of variety embodied in any logit model of demand (Petrin 2002; Ackerberg and Rysman 2005). In our model, we retain the assumption that *total* seach costs rise in the number of products considered, but also allow the *marginal* return to search to depend on product variety. In this way, we allow for a sharper identification of the two forms of search cost that underlie the net benefits to search. Moreover, we allow search costs to vary across households according to differences in the opportunity cost of time, relative proximity to retail stores, or in ability to adapt to greater complexity of the retail environment. Mehta, Rajiv, and Srinivasan (2003) allow search costs to vary with a set of demographic variables in order to form practical conclusions regarding the profile of a "shopper" who likes spending time in the store, or an individual who just wants to get into the store and back out with as little time spent as possible. We similarly control for sources of variation in household search costs to better identify the effect of product variety on the net benefits of search.

Our analysis contributes to the consumer search and retailing literatures in a number of ways. First, we estimate search costs in a nested, multi-product environment.[2] This environment is both realistic and likely revealing as a typical shopping trip involves search for stores, and then among brands within the chosen store. Second, we extend the existing econometric methods of identifying price distributions for single products into a multi-product framework. Third, we empirically examine the effect of increasing variety on the equilibrium search cost, and the net benefits of search. Although consumers are not likely to search through all items

[2] While all search models are, by definition, multi-product, we use this term to differentiated search among single-product firms from search among multiple firms that each sell multiple products. We show below that this distinction is important.

retailers stock in a particular category, a "high variety" retailer is more likely to stock many products that are close substitutes within each category than a retailer with lesser variety. How the incentives to search vary with assortment depth is a key, practical question faced by retailers. By modeling consumer search behavior in a multi-product, differentiated-product environment, we provide insights that are particularly relevant to the food retailing industry as online shopping radically changes both search costs, and potential retail variety (Nielsen 2011).

We find that the net benefits to search, defined as the difference between the higher utility associated with variety, and the cost of searching, decrease in equilibrium as variety rises. The reason is that deeper assortments facilitate better matches between consumers and brands, reducing the net benefit of search in the market equilibrium. Consumer search intensity decreases in response to greater product variety and less active search, in turn, is likely to imply greater market power for retailers. Thus, a key strategic implication of our findings is that retailers have a clear incentive to increase product variety, because increasing assortment depth deters search, improving retail margins. Moreover, we find that search costs are separable between stores and between brands within stores. This finding suggests that many types of consumer decisions are subject to a multi-stage, consideration-set formation process: Whether shopping for insurance, cars, hotels, restaurants, or cheese, consumers appear to follow a hierarchical search process to simplify the inherently difficult task of comparing across multiple dimensions at once. Our analysis indicates that both types of search cost are significantly different from zero, with magnitudes that are relatively large on a per-unit basis. Aggregated over an entire shopping basket, and over a number of shopping trips, the net benefits of search are sufficiently large that they substantially impact consumers' behavior. Indeed, the magnitude of search costs suggests that consumer search costs are roughly equivalent in terms of importance with in-store promotion and coupon activity as a driver of consumer sales.

The remainder of the paper is organized as follows. In the first section, we derive an econometric model of nested search in which consumers first choose stores, and then brands within stores, while stores compete in prices and assortments. In the second section, we describe the household-panel data used for the analysis, and explain why understanding search in consumer packaged good categories is critically important to not only the retailing function, but manufacturer conduct as well. We follow with a presentation of our estimation results, and discuss some of the primary implications of our findings, both for retailing, and for search more generally. The final section concludes, and offers a suggestion of what research questions remain.

2 Empirical Model of Nested Search and Search Costs

2.1 Overview

The observation that consumers search over limited and endogenous consideration sets before making a purchase decision represents a fundamental change in demand analysis (Mehta, Rajiv and Srinivasan 2003; Goeree 2008; Koulayev 2010). We extend the empirical search model of Moraga-Gonzalez, Sandor, and Wildenbeest (2011) and De los Santos, Hortacsu, and Wildenbeest (2012) in order to estimate the net benefits to search across two dimensions of search: Between and within retail stores. To maintain tractability, we assume consumers engage in two, separate search activities in finding the appropriate store, and then in identifying the brand that best meets their needs within the selected store. We use this model to test our second hypothesis, namely that the net benefits to search over brands decreases in variety. The goals of our empirical analysis are: (i) to obtain estimates of the net benefits of searching between stores and brands; (ii) to examine whether these net benefits rise or fall in product variety; and (iii) to obtain refined estimates of consideration-set size that take into account the limited nature and endogeneity of choice sets (Koulayev 2010) under conditions of costly search (Kim, Albuquerque, and Bronnenberg 2010). We begin by estimating search costs in a non-nested framework, and then extend this initial model into a nested environment in order to test our maintained hypothesis against a simpler, more parsimonious alternative.

2.2 Brand Search

The primitives of our model are consumer utility, search cost, and a set of heterogeneous consumer and product attributes. We initially assume consumers search among brands only and are indifferent as to what store they are purchased from. Consumers are indexed by $i = 1, 2, ..., I$ and brands $j = 1, 2, ..., J$. Utility depends on brand fixed-effects, μ_j, brand attributes that are both observed by the econometrician (x_j), and those that are not (ξ_j),a shelf price that varies by brand (p_j),and a random term capturing individual heterogeneity in the actual price paid, competing brands the consumer may notice when in the store, in-store merchandising, whether children are present, or other factors that reflect the realities of a “shopping” experience (ε_{ij}). We assume consumers face uncertainty in both product attributes and shelf prices, and are not fully aware of any in-store promotions, or other things that may influence their in-store decision. Consumers have an implicit understanding of the distribution of these factors prior to their arrival in the store, which implies consumer utility (gross of search effort) can be written as:

$$u_{ij} = \mu_j + x_j\beta + \alpha_i p_j + \xi_j + \varepsilon_{ij}, \tag{1}$$

where the marginal utility of income (α_i) is assumed to vary over individuals. Consumers do not know the ultimate price they will pay for each brand, nor what other factors may influence their choice decision, but are aware of how these random elements are distributed, and therefore can form expectations of the net utility from shopping. Following Mehta, Rajiv and Srinivasan (2003) and Moraga-Gonzalez, Sandor, and Wildenbeest (2011), we assume these random elements are Type I Extreme Value (EV) distributed, and consumers shop (search) in order to resolve their uncertainty regarding these random parts of their shopping experience. Consumers use a fixed-sample, or non-sequential, search strategy in that they first decide on a subset of brands ($B \in J$) to consider within the category, and then choose from among the searched brands (de Los Santos, Hortacsu, and Wildenbeest 2012; Honka and Chintagunta 2013).

The consumer's consideration set is determined by maximizing the net benefits of search (NB_{iB}), or the maximum expected utility less the cost of searching:

$$NB_{iB} = E\left[\max_{j \in B}\{u_{ij}\}\right] - k \cdot c_i, \tag{2}$$

where c_i is the net cost of searching over brands (a composite of matching cost and search cost), and k is the number of brands searched. In order to test our hypothesis that the net benefits of search vary with variety, we allow search costs to depend on a set of individual attributes and the total number of brands available according to: $c_i = z_i\eta + n\lambda$, where n is the number of brands offered by the store, z_i is a vector of individual attributes, and η and λ are parameters to be estimated. Assuming consumers are only able to evaluate the net benefits of search up to a mean-zero random error term (ν), which we also assume to be EV distributed with scale parameter σ_v, the probability the consumer selects a subset B_i is given by:[3]

[3] Note that we normalize the scale parameter to 1 without loss of generality.

$$P_{iB_i} = \frac{\exp(NB_{iB})}{\sum\limits_{B' \subseteq B} \exp(NB_{iB'})}, \tag{3}$$

where B' indicates all other subsets. Once the consideration set is chosen, the consumer selects the brand from this group that maximizes her utility. With the distributional assumption for the utility obtained from shopping, and defining mean utility for brand j as $\psi_j = \mu_j + x_j\beta + \alpha p_j + \xi_j$, the expectation in (2) has a closed form given by:

$$E\left[\max_{j \in B}\{u_{ij}\}\right] = I_B = \log\left(\sum_{j \in B} \exp\left[\psi_j\right]\right), \tag{4}$$

where the parameters of this distribution are found using maximum likelihood, simultaneous with the parameters of the search-cost function.

The conditional purchase probability, that is, the probability the consumer chooses brand j from the consideration set B, is found by maximizing the utility in (1) conditional on draws from the distribution of unobserved heterogeneity governing: $\alpha_i\tilde{}N(0,1)$ such that: $P_{ij|B} = \Pr(u_{ij} > u_{ik} \forall k \neq j \in B_i)$. The combined probability of forming a consideration set, and searching for the best brand is then given by: $P_{ijB} = P_{iB}P_{ij|B}$ so the log-likelihood function to be maximized is given by:

$$LLF = \sum_i \log P_{ijB} = \sum_i \log P_{iB}P_{ij|B} \tag{5}$$

which is evaluated using simulated maximum likelihood methods. To this point, the combined search-and-purchase model reflects very standard assumptions regarding how consumers form consideration sets, and choose from the brands they comprise. In a retail supermarket context, however, the fact that rival stores compete in both prices and non-price attributes means that this simple description of the search process is not complete. In the next section, we account for non-zero substitution among stores.

2.3 Brand and Store Search

In the nested model, we extend the above framework to consider the possibility that consumers search first between stores, and then among brands within each store.[4] Rather than assume preferences among

[4] This hierarchical interpretation is for convenience only and is not necessary for the GEV distributional assumption to be valid (Cardell 1997; Train 2003).

stores and brands are distributed Generalized Extreme Value (GEV) as is the standard approach (Bell and Lattin 1998), we assume that the nested choice is instead driven by the distributional assumption regarding consumers' knowledge of actual prices paid, and other features of their shopping experience that determine the actual utility obtained. In the non-nested model above, we assumed consumers knew the distribution of these random factors up to a Type I Extreme Value distribution. When considering choices over multiple stores, however, it is reasonable to assume instead that consumers' understanding of the quality of their shopping experience is instead GEV distributed. Our implicit assumption is that consumers may know that some stores tend to offer lower prices, in general, than others, or that the prices in some stores are more highly correlated than others. For example, everyday-low-price (EDLP) stores offer prices that are likely to be more highly correlated than in stores that have relatively high shelf prices, but offer frequent promotions (HILO stores). Similarly, some stores offer many competing brands in a category, while other stores offer a more limited selection. Stores are indexed by $s = 1, 2, 3, ...S$ and utility now depends not only on individual attributes and element of the brand-marketing mix, but store-and-individual attributes that affect store choice. Define the utility from purchasing from a specific store, s, as:

$$u_{ijs} = \psi_j + \psi_s + \xi_{js} + \varepsilon_{ijs}, \tag{6}$$

where the mean utility of store-choice, ψ_s,depends on a set of store attributes (store size, location, cleanliness, quality of fresh produce, for example), so now the form of the net benefit function is again driven by our assumption regarding the distribution of the uncertainty consumers face in choosing among brands, and between stores.

In the nested case, consumers now search both among stores, and among brands within the store. The optimal consideration set, therefore, is determined by again maximizing the net benefits of search, which now consist of the benefits of searching among stores and brands, and incurring the costs of both search activities. Define the net benefits of store-and-brand search as the sum of the benefits of searching among stores and brands, or $NBS_{iBR} = NB_{iB|R} + NS_R$, where again $B \in J$ and $R \in S$, and where R is a subset of the total number of stores available to be searched, less the cost of search.[5] Therefore, the maximum expected utility less both store and brand search costs is:

[5] The brands offered in all stores are the same, so the set of brands is the same in each store.

$$NBS_{iBR} = NB_{iB|R} + NS_R = E\left[\max_{j \in B|R, s \in R}\{u_{ijs}\}\right] - k_B \cdot cb_i - k_S \cdot cs_i, \tag{7}$$

where cb_i is the net cost of searching among brands, k_B is the number of brands searched, cs_i is the cost of searching among stores, and k_S is the number of stores searched. The cost of searching among brands is again allowed to depend on a set of individual attributes and store variety so that: $cb_i = z_i\eta_b + n_s\lambda$, while the cost of store-search depends on individual attributes and distance to the store: $cs_i = z_i\eta_s + d_i\varphi$ where d_i is defined as the distance between consumer i and the store being searched, and φ is the marginal cost of distance.[6]

Again assuming consumers incur random errors in evaluating the net benefits of searching stores and brands, which we now assume to be GEV distributed, the probability the consumer selects a subset of brands B_i,conditional on searching a subset of stores, and a subset of stores R_i is given by:

$$P_{iB_iR_i} = P_{iB_i|R_i}P_{R_i} = \frac{\exp(NB_{iB|R})}{\sum\limits_{B' \in B|R} \exp(NB_{iB'|R'})} \frac{\exp(NS_R)}{\sum\limits_{R' \in R} \exp(NS_{R'})}, \tag{8}$$

where R' indicates all other subsets of stores. Define the inclusive value of all brands in subset B conditional on store R as $IV_{j \in B|R} = \log(\sum\limits_{j \in B} \exp\left[\psi_{j|s}\right])$ so that, assuming the random elements in (6) are GEV distributed, we write the expected maximum utility of searching stores and brands as:

$$E\left[\max_{j \in B|R, s \in R}\{u_{ijs}\}\right] = IV_{j \in B|R} + \log\left(\sum_{s \in R} \exp\left[\psi_s + \sigma_s IV_{j \in B|R}\right]\right), \tag{9}$$

where σ_S measures the correlation between brands within each store. In order for (9) to represent a well-defined model of choice, we require that $0 \leq \sigma_S \leq 1$. If $\sigma_S = 1$, then there is perfect correlation in preferences among brands in each store, and they are regarded as perfect substitutes. On the other hand, if $\sigma_S = 0$, then there is no correlation among brands and the model collapses to a logit form.

Again, we form the likelihood by multiplying the probability of choosing a store consideration set by the conditional probability of choosing a specific store, and then the brand-choice probabilities described above. As a result, the combined probability for the nested-search model is given by: $P_{ijBR} = P_{iB|R}P_{ij|BR}P_{iR}P_{is|R}$ so the log-likelihood function to be maximized is given by:

[6] The search cost expressions do not include constant terms because they are not separately identifiable from the constant terms in the demand equations.

$$LLF = \sum_i \log P_{ijBR} = \sum_i \log P_{iB|R} P_{ij|BR} P_{iR} P_{is|R}, \tag{10}$$

which is again evaluated using simulated maximum likelihood (Train 2003).

Comparing the nested with the non-nested specification allows us to test the hypothesis that consumers indeed follow a nested search process for frequently purchased consumer products. Moreover, estimating both models allows us to test the hypothesis that the net benefits of search over brands decreases in the variety offered by the store. If greater product variety decreases the net benefit of search (i.e. raises the net cost), then this supports the notion that consumer search intensity decreases in product variety. Lower search intensity, in turn, has implications for how rapidly prices adjust (Tappata 2009): If consumers do not search, then retail prices adjust slowly. In the next section, we describe the data we use to estimate the model described here.

3 Data and Estimation Methods

Our data are from the IRI research data set (Bronnenberg, Kruger, and Mela 2008). We use household panel data from Eau Claire, WI for the years 2009 - 2011, focusing on purchases from the ready-to-eat cereal category, and Infoscan (store-level) data over the same period in order to impute missing prices in the household panel data. Household data is necessary for our analysis because we model the costs of searching between and within stores on an individual level, and require household-level variation in search costs to identify the model.

There are a number of reasons why cereal provides an excellent context with which to study. First, many researchers choose durable-good product categories or services for which search is more obvious, whether it is automobiles (Moraga-Gonazalez, Sandor, and Wildenbeest 2011), insurance (Honka 2010), or hotels (Koulayev 2012). Search is important for frequently-purchased products such as cereal, however, because consumers spend more time purchasing food than virtually any other good, the attributes of food are obviously salient for an increasingly health-conscious consumer-market, and the pace of change in branded foods. Indeed, manufacturers introduce new products every month, retailers change their stocking plan weekly, and consumers demand variety from day-to-day. In dynamic retail markets, consumers cannot know what alternatives are offered each week, and what promotions are offered. Cereal is a good example of one such market. Second, the cereal category is dominated by two manufacturers, Kelloggs and General Mills, who are well-known to behave strategically through both prices and product introductions (Nevo 2001). Consumers have no incentive to search unless retail prices and product assortments vary from week to week. Third, because cereal is manufactured from basic farm commodities, cereal is an ideal market to study price response as manufacturers faced wildly-fluctuating input prices over the sample period. As a consequence, wholesale prices, and hence retail promotions, exhibit significant variation in our data set. Fourth, cereal is an important category to retailers, so represents somewhat of a "flagship" that embodies a retailers' overall pricing strategy. If a retailer claims to operate some form of everyday-low-price (EDLP) strategy, then cereal prices will generally be lower than in competitors, and more stable. In sum, if consumers do indeed search for consumer packaged goods, and they are cereal consumers, they are likely to be searchers.

In panel data, it is necessary to have data on prices for not only the product that was purchased, but those that were not purchased as well. Both the household-purchase and store-level contains a masked store code that allowed us to merge both data sets by store, week, and UPC. By combining the household and store-level data sets, we observe the complete set of prices, and other marketing mix variables, for all UPCs available on a given purchase trip. We include only households who purchase cereal from the two most popular stores in the data set (IRI keys 257871 and 1085053) because the other stores do not provide price information to IRI, so we are unable to impute price for non-purchased items in a consistent way. We account for other stores these consumers may have searched by including an outside option for the upper-level, store-choice model.

We estimate both the nested and non-nested search models using a two-stage approach, first estimating household-specific cereal preferences in the first stage, and the cost of search in the second. In the econometric model described above, each household faces consideration sets that consist of $2^N - 1$ elements if there are N brands to choose from. In consumer packaged good categories such as the one considered here, the number of cereal brands stocked at any given time by a traditional supermarket is between 250 and 400 (Richards and Hamilton 2013), and even if we restrict attention to only subcategories such as children's, family, or adult cereals, the number seriously considered by each household could still easily exceed two dozen. We focus on the top 20 brands in the entire category, which covers over 85% of all cereals sold, so this means that a typical household would face over 1.0 million different consideration sets. Clearly, a problem of this magnitude is empirically intractable. However, Honka (2010) argues that the range of consideration sets can be drastically simplified if we realize that consumers will not evaluate consideration sets that consist of brands that are dominated by others that we know to be preferred.[7] That is, if a store stocks cereals A, B, and C, and the consumer prefers A to B, and B to C, then the only consideration sets that will be plausibly considered consist of {A}, {A,B}, and {A, B, C} and not {B}, {C}, or {B, C}. If we can first order the individual products according to each consumer's preference, therefore, we reduce the number of consideration sets from $2^N - 1$ to N. In this way, the problem is now tractable for even relatively large categories.

The first-stage model consists of household-level mixed logit and random-parameter nested-logit models. Specifically, in the non-nested case, the first-stage utility model in (1) is written as:

$$u_{ij} = \mu_{ij} + \alpha_i p_j + \beta_1 fea_j + \beta_2 dis_j + \beta_3 pro_j + \beta_4 loy_{ij} + \beta_5 inv_i + \beta_6 st_1 + \beta_7 st_2 + \xi_j + \varepsilon_{ij}, \quad (11)$$

for consumer i and brand j, where the arguments of utility are defined as follows:

μ_{ij} = preference for brand j by consumer i,

p_j = shelf price of brand j,

fea_j = a binary indicator variable that equals 1 when brand j is featured,

dis_j = a binary indicator variable that equals 1 when brand j is on display,

pro_j = a binary indicator variable that equals 1 when brand j is on promotion,

loy_{ij} = a binary indicator variable that equals 1 when household i is defined to be loyal to brand j,

inv_i = category inventory held by household i on the date of purchase,

st_s = a binary indicator variable that equals 1 if the brand is purchased in store s,

ξ_j = set of unobserved brand attributes,

[7] Honka (2013) follows Chade and Smith (2006) who show that if the utility-distributions of a set of products can be ranked according to a first-order stochastic dominance criteria, then calculating the expected utility from each choice, and ranking them accordingly, will describe a consumers' simultaneous search process. A rule such as this is necessary in the absence of sequential search as described by Weitzman (1979). Vishwanath (1992) develops a ranking rule based on second-order stochastic dominance that uses reservation utilities instead of expected utilities. We follow Honka (2013) and rank cereals by their expected utility.

ε_{ij} = iid random error term.

We calculate inventory in a relatively simple way. First, we use the entire data set to calculate the average consumption rate (at the category level) of each household. We then estimate the initial amount on hand from the observed consumption rate, and the date of the first purchase. We then calculate a running inventory by adding new purchases, and subtracting consumption over the entire sample period. Loyalty, on the other hand, is defined in repeat-purchase terms. That is, a household is deemed loyal to a specific brand if it is purchased on the previous shopping trip. Both of these calculation methods are well-accepted in the literature (Lattin and Bucklin 1989; Bucklin and Lattin 1991).

Allowing the marginal utility of income to vary randomly over households is essential in that we are able to order brand preferences for each household over all brands. In the specification of utility (11), the marginal utility of income (price parameter) is modeled as a random-normal variate with location parameter defined as a function of a set of demographic variables (z_{mi}):

$$\alpha_i = \alpha_0 + \alpha_1 inc + \alpha_2 hhs + \alpha_3 age + \alpha_4 edu + \alpha_5 mar + \sigma_\alpha \nu_i,\ \nu_i \sim N(0,1), \tag{12}$$

where the arguments of the random-parameter functions are as follows:

α_0 = mean marginal utility of income,

inc = household income,

hhs = household size,

age = age of household head,

edu = education level (number of years) of household head,

mar = marital status of household,

ν_i = random normal variate.

By allowing the price and preference parameters to vary by household, we are able to recover a unique ranking across all brands, greatly simplifying the search-cost estimation routine. Assuming the random error term in (11) is iid Type I Extreme Value, the probability of choosing brand j does not have a closed-form expression, but is found by integrating over the distribution of consumer heterogeneity as in:

$$\Pr(j=1)=\int\frac{\exp(\mu_{ij}+\alpha_i p_j+x_j\beta+\xi_j)}{\sum_k\exp(\mu_{ik}+\alpha_i p_k+x_k\beta+\xi_k)}f(\alpha)d\alpha, \tag{13}$$

for all brands j.

In the nested demand model, the arguments of the conditional brand-choice component are defined as in equations (11) and (12). Store-choice, however, depends on store attributes, a vector of household-attributes, and an inclusive value term that represents the inherent attractiveness of the brands offered by each retailer. In the absence of detailed data on store size, cleanliness, and other factors thought to be important in determining store choice, we allow for store-specific fixed effects so that store-utility is written:

$$u_{ijs}=\gamma_1 st_1+\gamma_2 st_2+\gamma_3 inc+\gamma_4 hhs+\gamma_5 age+\gamma_6 edu+\gamma_7 mar+\sigma_s iv_{ij|s}+\xi_{js}+\varepsilon_{ijs}, \tag{14}$$

where each of the arguments are as defined above, and: $iv_{ij|s}=\log(\sum_j\exp(\mu_{ij}+\alpha_i p_j+x_j\beta+\xi_j))$. The probability that household i purchases brand j from store s is now given by the product of the conditional probability of purchasing brand j in store s and the probability of choosing to shop in store s, or:

$$\Pr(j=1,s=1)=\int\left(\frac{\exp(\mu_{ij}+\alpha_i p_j+x_j\beta+\xi_j)}{\sum_k\exp(\mu_{ik}+\alpha_i p_k+x_k\beta+\xi_k)}\right)\left(\frac{\exp(iv_{ij|s}+y_s\gamma+\xi_s)}{\sum_r\exp(iv_{ij|r}+y_r\gamma+\xi_r)}\right)f(\alpha)d\alpha. \tag{15}$$

Identifying the cost-component of the net benefit of search requires that choice, and the nature of the search process vary across households. From the data presented in tables 1 and 2, it is evident that there is considerable variation in cereal market shares, over households, stores, and over time. Although there is no threshold that defines the amount of choice-variation that is sufficient to identify the parameters of our combined search-and-demand model, we infer from the easy convergence of our model that the data are adequate. The cost of search, on the other hand, depends largely upon the difficultly of the search process. We proxy this effect by including the number of unique items (UPCs) over which consumers may search, or the variety offered by each store. Not only does a larger variety mean that there are likely to be more brands within the specific type of sub-category considered by each household, but the cereal aisle is likely to be physically larger for high-variety stores compared to the alternative. By including variety, we proxy the cognitive, or mental processing, costs consumers incur when weighing the costs and benefits of each brand, or each store (Roberts and Lattin 1991). With respect to variety, the data in table 3 show that Store 1 offers substantially less variety than Store 2, and the number of UPCs offered varies considerably over time. If search costs are indeed influenced by variety, our data should be able to identify the hypothesized effect.

The net benefits of store-search, on the other hand, are likely to be influenced by the opportunity cost of time, which we proxy by modeling store-search cost as a function of income, and by the distance consumers must travel to reach each store. By the data in table 3, it is evident that income varies widely over our sample households. Distance, however, is not included directly in our data set. Because the household-panel data contains the ZIP code of each panel member, we are able to locate each consumer in our data in an approximate way. That is, without specific street addresses, we assume each household is located at the center of each associated ZIP code. We obtained the street addresses for the two sample stores from public records, and calculated the distance between each household and each store using the latitude / longitude coordinates associated with each and the GEODIST function in SAS 9.2 By the data presented in table 3, we find considerable variation in the distances between the sample households, and each store. Therefore, our data contain more than enough variation to identify the choice parameters, and the costs of searching among brands and stores.

[tables 1, 2 and 3 in here]

4 Results and Discussion

In this section, we first summarize some stylized facts from our data and then present the first-stage demand-model results for both the nested and non-nested models, and then compare the net benefits of search estimated from each. For each stage of the estimation process, we compare the results using a battery of specification tests in order to determine whether consumers do indeed search in a nested, relative to a non-nested way.

Observational evidence, that is stylized facts available even without estimation, exists for both search within each store and search among stores. Within each store, if we observe consumers switching among brands, even if induced by price changes or promotional activity, then it is clear that they are at least considering other brands while in the store. The data in table 4 show that the modal consumer purchased fully seven different brands over the sample period, so consumers typically search among several brands over a period of time. Further, just over 51% of all households only shopped at one store during the sample period, while the remainder made at least one purchase at both. These summary data, however, do not control for variation in preferences, distance, or other factors that may explain the fact that consumers typically consider multiple brands and more than one store. Therefore, we next present econometric estimates of our brand and store-choice models.

[table 4 in here]

We first compare demand estimates from a non-nested model of brand choice to one that assumes consumers choose stores and brands according to a hierarchical process. The demand estimates for the non-nested model (from equation (5)) are in table 5, while the nested estimates (from equation (10)) are in table 6. We compare the net benefits of search from both models in table 7. Within each specification, we test for the importance of unobserved heterogeneity by comparing a fixed-coefficient version of the maintained model to a random-coefficient specification. For the non-nested model reported in table 5, the chi-square statistic comparing the fixed and random-coefficient specifications is 5,851.8 while the critical chi-square statistic with 21 degrees of freedom is 32.671. Therefore, we reject the fixed-coefficient version of the non-nested model in favor of the random-coefficient version and conclude that unobserved heterogeneity is likely important. As a second, less formal, test of the random-coefficient specification, note that full 2/3 of the standard deviation estimates in the random coefficient model are significantly different from zero. Restricting these coefficients to zero, as the fixed-coefficient model does, would clearly be a misspecification of the brand-preference model.

In the random coefficient model, we find that there is a distinct preference ordering among the brands: Cheerios, Life, Frosted Flakes, and Reeses' Puffs are the most preferred cereals, while Special K, Lucky Charms, Frosted Mini-Wheats, and Pebbles are the least preferred. If we were to rank cereals according to their reservation utility (Vishwanath 1992), these parameters would guide the construction of our consideration sets. However, as described above, we use expected utilities instead so these parameters are only suggestive of the rankings used in the search cost model. Further, we find that each of the Feature, Display, Promotion, and Loyalty variables are positive and significantly different from zero, as expected, and Inventory has a negative effect on purchase probability, also as expected. Price-response also depends on observed heterogeneity, as measured by a set of demographic variables. Of these estimates, 3 out of 5 are statistically different from zero (at a 5% level), and imply that older, more wealthy, married individuals have less elastic demands than others, while Household Size and Education are not important determinants of price response.

[table 5 in here]

Comparing this specification to the nested choice model results in table 6, the chi-square (likelihood ratio, LR) test statistic is 18,597.8; hence, we reject the non-nested model in favor of the nested logit store-and-brand choice model. As in the non-nested case, we prefer the random coefficient to the fixed-coefficient specification as unobserved heterogeneity is evidently important in store choice. In this model, we fix the Price, Feature, Display, and Promotion parameters to be equal between the two stores, but allow the brand-preference parameters to vary by store. Notice that the preference ordering is slightly different between the two stores (Cheerios is preferred to Private Label in Store 2, but not in Store 1), but cereals that are generally preferred in one store are also preferred in the other. This finding highlights the importance of modeling search store-by-store. If the preference ranking differs across stores and households, consideration sets for households that frequent each store are likely to be quite different. In the store choice model, we define Store 2 as the outside option, so normalize the utility of this choice to zero. Consequently, the parameters reported in table 6 refer to the marginal effects on the probability of choosing Store 1. In this case, wealthier, older, and married couples are less likely to choose Store 1 and more likely to choose Store 2. The significance of the scale parameter ($\sigma_S = 0.4413$) suggests that there is positive correlation in the utility obtained from cereals within each store, but they are not perfect substitutes. The fact that it is significantly different from zero indicates that consumers do substitute among stores: Supermarkets do not operate entirely as local monopolists so consumer search behavior among stores is likely to be important.

[table 6 in here]

Estimates of the net benefits of searching among brands also differ when we assume consumers are indifferent as to their choice of store, compared to a nested store-choice model. The estimates of the search-cost part of the net benefit functions from both the non-nested (equation (5)) and nested (equation (10)) are shown in table 7. When focusing on brand-search only (Non-Nested Model columns in table 7), we find that variety has a significant, negative effect on the net benefit of search.[8] Namely, if the store stocks an additional

[8] Note that, as in Mehta, Rajiv, and Srinivasan (2003), constant terms in the search-cost function are not separately identified from the brand-preference constants.

cereal UPC, the net benefits of search fall by nearly \$ 0.04 / oz. These estimates are comparable to others in the literature who focus on a similar class of goods (Mehta, Rajiv, and Srinivasan 2003) and are indeed economically significant. Relative to the retail prices shown in table 1, the costs of searching are important and form a substantial component of the net benefits of searching for, and purchasing, the cereal in question. Ideally, a test of the "choice overload" hypothesis (Kuksov and Villas Boas 2010; Diehl and Poynor 2010) would involve estimating a quadratic in variety and determining whether or not a finite optimal quantity exists. However, the quadratic specification does not converge in either the nested or non-nested model, so we assume our negative, linear result represents an accurate, local approximation to a decreasing net-benefit function in which greater product variety reduces the marginal benefit of searching. The implication of this result is that, in the neighborhood of assortments offered by the retailers in our data, consumers are likely to search less intensively when facing greater variety, which supports the prediction of our theoretical model. Less intensive search also means more market power – if consumers are not searching for better deals, then they are likely to pay prices that are "too high" relative to the competitive ideal.

[table 7 in here]

Modeling search as a hierarchical process confirms these results when consumers first search for stores, and then for brands (table 7). Greater product variety causes the net benefits of searching for brands to fall, albeit at a slightly lower rate than in the non-nested case ($0.0344 < 0.0395$ and $0.0305 < 0.0395$). The net benefit of searching for stores also falls in the opportunity cost of time, which we proxy by household income. Because income is normalized into units of \$10,000 per household, the estimate in this table implies that an extra \$10,000 of income raises the unit-cost of searching over stores by roughly \$0.015 per oz of cereal. It is intuitive that search costs should also rise in the distance between households and the stores (Moraga-Gonzalez, Sandor, and Wildenbeest 2011); however, the positive point estimate for this distance-effect is not statistically different from zero. Our data describes shopping behavior in a relatively small city (67,000 people), so the distances involved may not be large enough to be considered economically significant by the shoppers in our sample. In a larger city, with perhaps many sample members in the suburbs, distance may play a more important role in store search costs. Nonetheless, to the extent that much of the burden of consumer search is in terms of cognition and decision-making, our finding that income dominates distance in determining the net benefits of both brand and store search is consistent how we conceive of the cost of search. More importantly, our findings suggest that consumers do indeed face a two-stage process in searching for brands. Because the store-search costs are statistically significant, we can conclude that shoppers face two types of cost when they are searching for brands: The cost of searching for the appropriate store, and the cost of searching for particular items within the chosen store.

Based on our estimates in table 7, we infer the probability that consumers search a particular number of brands, a particular number of stores, as well as the cost-component of the net benefits of searching at each level. These results are shown in table 8. In Store 1, only 41% of consumers consider only one brand (or, alternatively, there is a 41% probability that a particular consumer searches only one brand), while nearly 51% of consumers in Store 2 do so. A nearly identical 28.5% of consumers search two brands in each store, while 15.6% search three brands in Store 1, and 12.5% search three brands in Store 2. Comparing the estimates across stores, it appears that consumers in Store 1 are more likely to search a larger number of brands than the consumers in Store 2. Store 1 has a relatively smaller product assortment than Store 2, which is consistent with the prediction of the model that the net benefit of search is decreasing in product variety. Moreover, this notion is borne out by examining the right-most column in table 8: The net benefit of searching among brands in Store 1 is fully 25% higher than the cost of searching in Store 2. We also find that nearly 63% of consumers search only one store, while 37% search both stores. Given the lack of statistical significance of the distance coefficient, it is perhaps surprising that more consumers do not exercise the option to search in both stores; however, the fact that our estimated store-search costs are nearly as high as brand search costs suggests that many consumers may be deterred simply by the difficulty of engaging in multi-product search.

[table 8 in here]

The implications of our research are clear. First, the observation that consumers engage in a hierarchical search process for cereal brands suggests that considering search frictions only in the market for brands, as in Mehta, Rajiv, and Srinivasan (2003), captures only important aspect of the story. From a macroeconomic perspective, if search really is important to the rate at which cost increases are passed through to retail prices, as suggested by the analysis of Tappata (2009), then there are many opportunities for barriers to search to impede search efficiency. On the other hand, Bakos (1997), Anderson and Renault (1999, 2000), Chen and Hitt (2003), Kuksov (2004), and Cachon, Terwiesch, Yu (2008) suggest that lower search costs may be associated with higher prices as consumers search more intensively for the brands they prefer. If that is indeed the case, then our findings suggest that the relatively high search costs in supermarket retailing may instead be an impediment to their exercise of market power. Lacking the ability to search freely among stores and among brands in a traditional supermarket-format, consumers may simply fall into habitual purchase patterns and do not bother considering something that may be new, innovative, and perhaps provide a better product match. Third, to the extent that the net benefits of search fall in product variety, supermarket managers who have an interest in raising the net benefits of search in order to attract custom and induce shoppers to purchase may wish to consider moving to a limited-assortment format wherein only the most popular brands are stocked. The intuition that variety represents a source of market power (Borle et al. 2005; Briesch, Chintagunta, and Fox. 2009; Trindade 2012) derives from more traditional models of demand that consider only the *gross* benefits of search, not the *net* benefits of search that we capture here that account for the fact that consideration sets are both limited in size and endogenously determined.

Extended our results beyond the market for food, there is an implicit assumption among many policy-makers that creating a market for a good or service, such as healthcare insurance, will automatically create efficiencies and lead to a competitive result. Our finding that search costs are important for even mundane, well-understood products such as cereal can help inform the discussion over creating markets for inherently complicated products or services. If consumers consider only a few brands of cereal each time they go to the store, then they will likely shop even less intensively when faced with a dozen insurance-product choices, each with a unique combination of coverages, co-pays, premiums, and other restrictions.

5 Conclusions

In this study, we investigate whether consumers search among stores and then products for frequently-purchased consumer goods, or simply search among brands. We also test whether the net benefits of search rise or fall in the depth of assortment, or variety, offered by retailers. In this sense, we offer a nested and a non-nested test of the "choice overload hypothesis." Reaching a plausible answer to this question is critically important not only for retail practice, but for the conduct of the retailing function more generally. If it is the case that consumers costlessly find the items in their weekly shopping basket, then the process of shopping-and-purchasing everyday food items is more efficient than once thought – even more efficient than many e-commerce channels, if current research is correct.

We find that consumers do indeed appear to search among stores, and then among brands once in the store. Because searching for stores is costly, our findings suggest that supermarket retailers have a source of market power in addition to those already identified in the literature (Cotterill 1986). Once in the store, however, the net benefits of searching among brands fall in the depth of assortment, or variety, offered by the store. While reducing search intensity may be a source of market power when searching among stores, reducing search in the store may cut both ways. To the extent that consumers may not be aware of substitute products selling at more competitive prices, the retailer may be better off. However, if the "choice overload" hypothesis is true in its most extreme form, if the cost of search rises too far, consumers may not make a choice at all, so the retailer may lose a sale. Moreover, there are a number of theoretical studies that show how greater search intensity may, in fact, result in higher prices if consumers have a preference for product diversity.

More generally, our results imply that traditional demand models – models that implicitly consumers consider all products in the data set – are incorrect in a fundamental way. Instead, most consumers only really consider two or three products so the opportunities for substitution are far more limited than previously thought. Retailers' and manufacturers' notions of the elasticity of demand facing their products is considerably higher than is truly the case.

If search is costly, then the retailing function is considerably less competitive and efficient than is generally thought to be the case. If retailers are competitive, then changes in wholesale prices will be passed along to consumers on a one-to-one basis and the rate of food inflation simply becomes a matter of the state of competition in food manufacturing, and the behavior of production costs. With costly retail search, however, an extra intervening layer means that estimates of cost pass-through cannot consider retailers as passive brokers between manufacturers and consumers. Retailers may have an important role in determining the rate of food price inflation.

Our findings are subject to a number of limitations. Future research in this area would benefit from considering food retailers in larger markets, where distance may be more important than in the small-market considered here. Estimating the search model in a wider range of categories may also uncover some heterogeneity in search costs due specifically to differences in the types of products consumers are searching for. Further, our demand model embodies an implicit assumption that consumers have a preference for variety. However, if this is indeed the case, then a model that explicitly recognizes the multiple-discrete nature of consumer packaged good (CPG) purchases (Dube 2004) may be more appropriate. Finally, our findings are subject to the usual weaknesses in panel data such as this. Because IRI imputes the prices for products that consumers did not purchase, but may have considered, our description of the range of competitive products may be in error.

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Table 1: Summary of Non-Nested Data

	Vol Share (%)		Volume (M oz)		Feature (%)		Display (%)		Promotion (%)		Price ($/oz)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
GM Cheerios	0.215	0.411	5.696	15.145	0.323	0.468	0.432	0.495	0.733	0.443	0.241	0.058
Private Label	0.061	0.240	1.576	7.394	0.114	0.317	0.121	0.326	0.318	0.466	0.227	0.028
K Raisin Bran	0.019	0.136	0.415	3.522	0.180	0.384	0.150	0.357	0.413	0.492	0.226	0.049
K Frosted Mini-Wheats	0.016	0.125	0.345	3.338	0.152	0.359	0.125	0.331	0.346	0.476	0.207	0.036
Q Cap N Crunch	0.031	0.174	0.794	5.775	0.191	0.393	0.183	0.387	0.399	0.490	0.196	0.038
K Rice Krispies	0.030	0.170	0.549	3.784	0.074	0.261	0.229	0.420	0.222	0.416	0.197	0.038
K Special K	0.014	0.118	0.236	2.248	0.239	0.426	0.463	0.499	0.646	0.478	0.229	0.065
G Chex	0.036	0.187	0.995	6.043	0.210	0.407	0.455	0.498	0.671	0.470	0.169	0.045
P Honey Bunches of Oats	0.036	0.187	0.909	5.876	0.119	0.324	0.121	0.326	0.221	0.415	0.182	0.029
K Frosted Flakes	0.060	0.237	1.120	5.659	0.191	0.393	0.356	0.479	0.575	0.494	0.248	0.051
G Cinnamon Toast Crunch	0.043	0.203	1.225	7.012	0.111	0.315	0.249	0.433	0.359	0.480	0.168	0.036
Q Life	0.079	0.270	1.570	6.481	0.143	0.350	0.126	0.331	0.304	0.460	0.254	0.046
G Lucky Charms	0.016	0.125	0.535	5.375	0.022	0.147	0.025	0.156	0.238	0.426	0.159	0.031
G Reeses Puffs	0.064	0.245	1.588	7.266	0.060	0.237	0.141	0.348	0.543	0.498	0.227	0.044
P Shredded Wheat	0.027	0.163	0.612	4.335	0.069	0.254	0.213	0.409	0.549	0.498	0.237	0.055
K Corn Flakes	0.023	0.151	0.593	4.921	0.031	0.174	0.052	0.223	0.312	0.463	0.207	0.037
P Grape Nuts	0.138	0.345	4.392	14.753	0.050	0.217	0.461	0.499	0.759	0.428	0.155	0.049
K Froot Loops	0.032	0.176	0.769	5.228	0.095	0.293	0.297	0.457	0.673	0.469	0.191	0.044
P Pebbles	0.042	0.200	1.020	5.756	0.097	0.297	0.251	0.434	0.639	0.480	0.196	0.038
Q Oatmeal Squares	0.016	0.125	0.433	4.181	0.069	0.253	0.063	0.243	0.385	0.487	0.235	0.047

Note: G = General Mills, K = Kelloggs, P = Post, and Q = Quaker Oats.

Table 2: Summary of Choice Data by Store

	Store 1						Store 2					
	Vol Share (%)		Price ($/oz)		Promotion (%)		Vol Share (%)		Price ($/oz)		Promotion (%)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
GM Cheerios	0.053	0.225	0.245	0.039	0.853	0.354	0.093	0.290	0.225	0.036	0.674	0.469
Private Label	0.014	0.118	0.224	0.023	0.281	0.449	0.028	0.166	0.233	0.025	0.341	0.474
K Raisin Bran	0.004	0.062	0.241	0.039	0.529	0.499	0.006	0.079	0.217	0.031	0.359	0.480
K Frosted Mini-Wheats	0.005	0.069	0.215	0.032	0.579	0.494	0.004	0.061	0.198	0.026	0.223	0.416
Q Cap N Crunch	0.005	0.073	0.201	0.025	0.474	0.499	0.012	0.108	0.189	0.030	0.375	0.484
K Rice Krispies	0.007	0.083	0.218	0.029	0.418	0.493	0.015	0.120	0.171	0.011	0.109	0.312
K Special K	0.004	0.062	0.221	0.057	0.843	0.363	0.005	0.070	0.213	0.026	0.549	0.498
G Chex	0.011	0.104	0.166	0.035	0.861	0.346	0.013	0.115	0.161	0.023	0.579	0.494
P Honey Bunches of Oats	0.011	0.106	0.195	0.024	0.502	0.500	0.011	0.105	0.169	0.005	0.073	0.260
K Frosted Flakes	0.017	0.131	0.248	0.039	0.859	0.348	0.025	0.157	0.224	0.021	0.436	0.496
G Cinnamon Toast Crunch	0.011	0.103	0.171	0.025	0.589	0.492	0.022	0.146	0.155	0.010	0.257	0.437
Q Life	0.029	0.169	0.277	0.031	0.381	0.486	0.027	0.163	0.233	0.012	0.278	0.448
G Lucky Charms	0.004	0.060	0.155	0.015	0.157	0.364	0.006	0.078	0.149	0.015	0.290	0.454
G Reeses Puffs	0.015	0.121	0.238	0.036	0.395	0.489	0.029	0.167	0.221	0.032	0.656	0.475
P Shredded Wheat	0.005	0.073	0.242	0.053	0.495	0.500	0.009	0.096	0.235	0.045	0.612	0.487
K Corn Flakes	0.005	0.072	0.211	0.029	0.233	0.423	0.011	0.105	0.197	0.031	0.368	0.482
P Grape Nuts	0.046	0.211	0.148	0.029	0.782	0.413	0.059	0.237	0.147	0.031	0.758	0.428
K Froot Loops	0.008	0.087	0.208	0.046	0.655	0.475	0.015	0.120	0.180	0.026	0.691	0.462
P Pebbles	0.009	0.096	0.206	0.040	0.580	0.494	0.017	0.130	0.188	0.026	0.700	0.458
Q Oatmeal Squares	0.002	0.043	0.251	0.041	0.171	0.377	0.007	0.081	0.224	0.045	0.522	0.500

Note: G = General Mills, K = Kelloggs, P = Post, and Q = Quaker Oats.

Table 3: Summary of Demographic and Choice Data

	Units	Mean	Std. Dev.	Minimum	Maximum	N
Income	$000 / yr.	56.3518	36.1528	5.0000	125.0000	15,101
Household Size	#	2.5161	1.1816	1.0000	6.0000	15,101
Black	%	0.0045	0.0670	0.0000	1.0000	15,101
Hispanic	%	0.0032	0.0564	0.0000	1.0000	15,101
Asian	%	0.0043	0.0657	0.0000	1.0000	15,101
White	%	0.9880	0.1091	0.0000	1.0000	15,101
Age	years	58.0906	10.8207	29.5000	69.5000	15,101
Education	years	12.5411	2.1531	6.0000	18.0000	15,101
Marital Status	% Single	0.0630	0.2429	0.0000	1.0000	15,101
Number of Shopping Trips	#	24.9329	15.2957	10.0000	105.0000	15,101
Store 1	%	0.3805	0.4855	0.0000	1.0000	15,101
Store 2	%	0.5919	0.4915	0.0000	1.0000	15,101
Volume Purchased	oz	25.3723	19.9730	1.3008	252.0000	15,101
Consumption Rate	oz	0.6709	0.4011	0.1025	2.4118	15,101
Number Brands: Store 1	#	250.9097	15.8375	186.0000	275.0000	15,101
Number Brands: Store 2	#	353.5829	7.8247	338.0000	380.000	15,101
Distance to Store 1	miles	2.3933	3.1205	1.2274	89.6697	15,101
Distance to Store 2	miles	2.7561	4.9350	1.5495	145.7904	15,101

Note: Distance calculated from centroid of household ZIP code to exact store address. Store brands are UPCs.

Table 4: Households Searching Multiple Brands and Stores

# Brands	% of HH	# Stores	% of HH
1	0.69%	1	51.44%
2	3.71%	2	48.56%
3	7.02%		
4	12.24%		
5	12.65%		
6	14.99%		
7	15.13%		
8	9.90%		
9	9.35%		
10	4.95%		
11	3.85%		
12	2.34%		
13	1.24%		
14	0.96%		
15	0.28%		
16	0.28%		
17	0.14%		
18	0.00%		
19	0.14%		
20	0.14%		

Source: IRI household panel data set.

Table 5: Non-Nested Demand Estimates

	Fixed Coefficient		Random Coefficient			
	Estimate	t-ratio	Estimate	t-ratio	Std. Dev.	t-ratio
GM Cheerios	3.0702*	11.2133	3.7592*	12.0437	1.0571*	17.8806
Private Label	2.3574*	8.6125	2.9178*	9.3069	0.8304*	9.4011
K Raisin Bran	1.2411*	4.4466	1.8348*	5.7716	0.1406	0.6368
K Frosted Mini-Wheats	1.0091*	3.6079	1.6338*	5.0643	0.5085*	3.4073
Q Cap N Crunch	1.4088*	5.1237	1.9437*	6.1586	0.4840*	4.3805
K Rice Krispies	1.4984*	5.4489	2.1490*	6.8627	0.5029*	4.8783
K Special K	0.6283*	2.2303	1.2047*	3.7443	0.2899*	2.4495
G Chex	1.002*	3.6643	1.4891*	4.8003	0.0890	0.7403
P Honey Bunches of Oats	1.6048*	5.8711	2.1405*	6.8756	0.3922*	4.6880
K Frosted Flakes	2.2855*	8.3073	3.0839*	9.9075	0.1294	1.7055
G Cinnamon Toast Crunch	1.4392*	5.2844	1.9667*	6.3726	0.2863*	4.3438
Q Life	2.8792*	10.4839	3.5764*	11.4945	0.1249*	2.0139
G Lucky Charms	0.766*	2.7594	1.5673*	5.0117	0.2342*	2.3186
G Reeses Puffs	2.2594*	8.2574	3.0599*	9.8920	0.0160	0.2735
P Shredded Wheat	1.5019*	5.4252	2.2572*	7.2094	0.0725	0.8682
K Corn Flakes	1.4162*	5.1243	2.1333*	6.8244	0.0289	0.3494
P Grape Nuts	1.9888*	7.3697	2.7262*	8.9480	0.1101*	2.6403
K Froot Loops	1.2265*	4.4642	1.8136*	5.8223	0.1859*	2.5389
P Pebbles	1.1515*	4.1082	1.6531*	5.1548	0.2431*	2.3397
Price	-9.5817*	-37.1542	-19.0680*	-9.2104	1.0156*	4.5760
Feature	0.5384*	18.8120	0.6203*	18.4668		
Display	0.7616*	27.9486	0.8229*	25.4689		
Promotion	0.1794*	6.2530	0.2491*	7.1622		
Loyalty	1.8333*	78.6149	1.5190*	50.9390		
Inventory	0.1215	1.1890	-0.2824*	-2.3051		
Store 1	-0.3953	-1.4264	-0.5290	-1.6878		
Store 2	-0.5881*	-2.1687	-0.7167*	-2.3408		
Price (Inc)			0.0244*	4.3186		
Price (HHSize)			0.2526	1.2323		
Price (Age)			0.0866*	4.0734		
Price (Ed)			-0.0036	-0.0397		
Price (Marital)			5.8321*	7.9312		
LLF	-27,416.1		-24,490.2			
Chi-Square	10,969.9		24,179.8			
AIC/N	4.451		4.02			

Note: A single asterisk indicates significance at a 5% level. Estimates by maximum likelihood or simulated likelihood.

Table 6: Results of Nested Model

	Fixed Coefficient Estimates				Random Coefficient Estimates							
	Store 1		Store 2		Store 1				Store 2			
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Std. Dev.	t-ratio	Estimate	t-ratio	Std. Dev.	t-ratio
GM Cheerios	0.4567*	3.0231	1.2886*	9.8276	0.0091	0.0436	2.1127*	20.9739	1.6542*	11.5147	1.6955*	28.2536
Private Label	-0.6405*	-4.0189	0.2899*	2.0894	0.3894	1.8027	0.2848	1.5223	1.2806*	9.0887	0.8331*	13.0539
K Raisin Bran	-1.8391*	-7.9546	-1.0875*	-6.3686	-1.1432*	-2.8497	0.1754	0.4551	-0.5298*	-2.1740	0.8624*	6.9453
K Frosted Mini-Wheats	-1.3412*	-7.5573	-1.8150*	-9.0691	-7.3627*	-7.9508	7.0453*	12.1565	-0.6066*	-2.1749	0.6742*	2.7791
Q Cap N Crunch	-1.9160*	-9.4941	-0.9953*	-6.9113	-2.6483*	-3.4691	1.8046*	3.9473	-0.5148*	-2.9988	1.1428*	10.9674
K Rice Krispies	-1.7204*	-8.6391	-0.9915*	-7.4504	-1.3225*	-3.3275	0.6656	1.8316	-1.1038*	-4.5204	1.2074*	9.7710
K Special K	-2.5610*	-11.0933	-1.3360*	-7.6698	-1.7976*	-4.7679	0.2835	0.7980	-0.4444	-1.7882	0.6419*	2.7389
G Chex	-2.5365*	-14.3006	-1.3353*	-10.0671	-1.7525*	-6.4166	0.5997*	2.6871	-2.0839*	-8.9438	2.5643*	18.3953
P Honey Bunches of Oats	-1.3215*	-8.1832	-0.8462*	-6.4997	-1.1567*	-3.7364	0.8645*	3.6922	-2.5657*	-6.7811	2.7615*	14.8868
K Frosted Flakes	-0.4535*	-2.7542	0.0526	0.3702	-0.7124*	-1.9693	2.0339*	8.4987	1.2887*	9.3588	0.0622	0.4733
G Cinnamon Toast Crunch	-2.1176*	-12.3475	-0.6409*	-5.6712	-2.1494*	-5.2386	1.1932*	3.4121	-1.8314*	-5.3265	2.0004*	10.7065
Q Life	0.4952*	3.0392	0.4369*	3.0645	0.5139*	2.0167	0.2403	0.6007	0.0561	0.2623	2.3172*	21.6036
G Lucky Charms	-2.4908*	-11.9143	-2.1359*	-12.5760	-2.2351*	-4.8226	0.1455	0.1497	-1.7632*	-6.1295	1.2217*	7.2985
G Reeses Puffs	-0.3334*	-2.1772	0.2166	1.6214	-0.0059	-0.0227	0.9261*	3.8056	0.8764*	4.9767	1.1682*	10.3785
P Shredded Wheat	-1.5507*	-7.8748	-0.7262*	-4.5939	-0.5737	-1.7911	0.4021	1.2031	-0.6092*	-2.1525	1.4752*	8.5380
K Corn Flakes	-1.8852*	-8.7363	-1.3498*	-8.3414	-1.2979*	-2.9031	0.3943	0.6478	-0.6459*	-2.6751	0.3349	0.9907
P Grape Nuts	-0.8984*	-7.9582	-0.3050*	-2.9704	-0.7030*	-3.8637	1.2748*	10.0370	0.0066	0.0511	1.2926*	18.7415
K Froot Loops	-1.5854*	-9.2654	-0.8550*	-6.3611	-1.1290*	-3.5437	0.9900*	4.1464	-0.3351	-1.6888	0.8939*	6.5598
P Pebbles	-1.5312*	-8.9770	-0.7384*	-5.4226	-1.6903*	-4.2350	0.9769*	3.4415	-0.0655	-0.3900	1.0285*	7.6984
Q Oatmeal Squares	-2.8022*	-7.1003	-1.5127*	-8.1648	-2.3938	-0.8416	1.0866	0.3939	-1.1784*	-3.8744	0.3664	1.3642
Store 1	0.4324*	7.4874			0.4078*	5.5871	0.1856	1.8839				
Price	-13.9273*	-28.9495			-22.7478*	-10.5461	5.7193*	25.9732				
Feature	0.2946*	7.6879			0.3490*	5.7543						
Display	0.6425*	17.3649			0.7200*	12.3351						
Promotion	0.1730*	4.1358			0.1772*	2.6105						
Price (Inc)					0.0085	1.4679						
Price (HHSize)					0.2961	1.6437						
Price (Age)					0.0626*	3.1988						
Price (Ed)					-0.0135	-0.1304						
Price (Marital)					1.5042*	2.6068						
Store Choice Estimates:												
Constant	18.8551*	40.5957			47.4874*	12.5390	4.0203*	22.82187				
Income	-0.0179*	-27.1212			-0.04734*	-11.218						
HH Size	-0.0569*	-2.6827			-0.0811	-0.6912						
Age	-0.0418*	-17.4895			-0.1072*	-6.6501						
Education	0.0574*	5.6607			0.0554	0.8211						
Marital	-0.5082*	-7.0948			-1.7292*	-3.76167						
σ_S	0.1809*	40.3795			0.4413*	13.1378						
LLF	-19,541.98				-15,191.29							
Chi-Square	2,804.43				23,531.05							
AIC/N	5.397				4.211							

Note: A single asterisk indicates significance at a 5% level. All estimates by maximum likelihood or simulated maximum likelihood.

Table 7: Net Benefits of Search Model Estimates

		Non-Nested Model			Nested Model			
		Model 1:			Model 1:		Model 2:	
		Estimate	t-ratio		Estimate	t-ratio	Estimate	t-ratio
Brand Search:	Variety	0.0396*	2.3866	Variety, Store 1	0.0344*	3.4104	0.0470	1.0979
				Variety, Store 2	0.0305*	4.4941	0.0316*	3.8396
Store Search:	N.A.			Income	0.0161*	4.3281	0.0188*	2.2509
				Distance			0.0033	0.0407
	LLF	-266.8867		LLF	-26,539.8		-26,539.4	
	Chi-Square	205.8846		Chi-Square	2,793.8		2,793.0	
	AIC	535.7734		AIC	53,085.58		53,086.71	

Note: A single asterisk indicates significance at a 5% level. Note that positive parameter estimates imply lower net benefits of search.

Table 8: Consideration Set Probabiliites and Search Cost Estimates

	Brand Consideration Sets		Store Consideration Sets		Search Costs	
	Store 1	Store 2				
One Brand	0.4097	0.5089	One Store	0.6258	Store 1	0.0086
Two Brands	0.2859	0.2856	Two Stores	0.3742	Store 2	0.0108
Three Brands	0.1562	0.1248			Store Search	0.0089
Four Brands	0.0784	0.0501				
Five Brands	0.0374	0.0193				
Six Brands	0.0175	0.0072				
Seven Brands	0.0081	0.0026				
Eight Brands	0.0037	0.0009				
Nine Brands	0.0017	0.0003				
Ten Brands	0.0008	0.0001				
Other	0.0006	0.0001				

Note: Search costs are on a per oz basis. Search probabilities based on model estimates.