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Consumer Choice Behavior in Online and Traditional Supermarkets: The Effects of Brand Name, Price, and other Search Attributes

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Abstract

Are brand names more valuable online or in traditional supermarkets? Does the increasing availability of comparative price information online make consumers more price-sensitive? We address these and related questions by first conceptualizing how different store environments (online and traditional stores) can differentially affect consumer choices. We use the liquid detergent, soft margarine spread, and paper towel categories to test our hypotheses. Our hypotheses and the empirical results from our choice models indicate that: (1) Brand names become more important online in some categories but not in others depending on the extent of information available to consumers – brand names are more valuable when information on fewer attributes is available online, (2) Sensory search attributes, particularly visual cues about the product (e.g., paper towel design), have lower impact on choices online, and factual information (i.e., non-sensory attributes, such as the fat content of margarine) have higher impact on choices online (3) Price sensitivity is higher online, but this is due to online promotions being stronger signals of price discounts. The combined effect of price and promotion on choice is weaker online than offline.

Key Words: Brand value; Choice models; e-commerce; Grocery products; Internet marketing; Price sensitivity

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1. Introduction

There is increasing interest in understanding the effects of computer mediated shopping environments (Hoffman and Novak 1996). An issue of particular interest to both practitioners and academics is in determining whether there are systematic differences in consumer choice behavior between online and regular (offline) stores, and if there are differences, in understanding the reasons for these differences. Put another way, will the same person exhibit different choice behavior online and offline, and if so, why? Identifying and understanding these differences is important for formulating marketing strategies, especially for online marketers.

We address these questions by first proposing a general conceptual framework to articulate how various factors influence online and offline choices. Although there are many factors that affect online choice behavior, we focus specifically on assessing whether brand names have more impact on choices online or offline, and whether price and other search attributes have higher impact online or offline. We empirically evaluate the implications of our conceptual framework by analyzing consumer choices in Peapod, an online grocery subscription service, headquartered in Skokie, IL,[1] and in traditional supermarkets belonging to the same grocery chain operating in the same geographical area.

Few papers have explored how consumer behavior online differs from consumer behavior offline. Exceptions are a conceptual paper on Interactive Home Shopping by Alba et al. (1997) and an experimental study by Burke et al. (1990). Alba et al. point out that a key difference between online and offline shopping is the ability of online consumers to obtain more information about both price and non-price attributes. More information on prices could increase consumer price sensitivity for undifferentiated products. At the same time, having more information on non-

[1] Peapod offers an online grocery subscription service in seven metropolitan areas. It was founded in 1989 and started offering its services in the Chicago area in 1990. In each of its served markets, Peapod is affiliated with a local grocery store from which the items are delivered to consumers. Peapod's prices correspond exactly to the prices at the affiliated store. In addition, Peapod may offer some of its own promotions.
Consumers shop for, and place their orders online. Peapod delivers the items to consumers within a consumer-specified half-hour time slot. There is a monthly fee to be a member of this service (currently, $4.95) as well as delivery fees at $4.95 per delivery and 5% of the grocery amount ordered.

price attributes could reduce price sensitivity for differentiated products. Therefore, these authors suggest that an important research question is "What are the true dynamics of price sensitivity in this environment?" We need empirical research to understand how these implications are moderated by type of product, the power of the brand name, and the attributes for which information is available online.

Burke et al. (1990) tracked the purchases made by 18 consumers in a traditional supermarket over a 7-month period. Two months later, the same group of consumers participated in laboratory experiments wherein market conditions identical to the in-store environment were created on a computer system for several product classes of interest. Each subject made online purchases in the simulated store during the same weeks in which that subject had made in-store purchases. A comparison of online purchases versus in-store purchases revealed systematic differences when information relevant to choice decisions was not equivalently available in both store types. Specifically, product-size information is often not conveyed realistically in online stores. Consequently, there were greater discrepancies between the online and offline choice shares for the various product sizes, with larger sizes being purchased more frequently online. At the same time, there were no significant differences in the effects of promotions when the online store presented promotion information graphically in a manner that resembled promotions in the regular store. The authors report mixed results with regard to purchases of store brands. For some product categories (e.g., paper towel and tuna), the proportion of purchases of store brands was greater online than in the traditional supermarkets, whereas in other categories (toilet tissue and soft drinks), the proportion of purchases of store brands was smaller online. They attribute these results to unspecified product-class differences. While the reported results are interesting, these authors do not provide any overall conceptual framework to understand and predict differences between online and offline choice behavior.

In the next section, we propose a conceptual framework to help us assess the relative impact of brand names, prices, and other search attributes on consumer choices within a specific product category. Using this framework, we derive specific hypotheses about potential differences we might expect between online and offline choice behavior. In Section 3, we describe the characteristics of our panel data and our methodology for testing the hypotheses. In Section 4, we describe the results of our empirical analyses in three product categories: liquid detergent, soft light margarine spread, and paper towel. In Section 5, we summarize the main insights from our study and suggest further research opportunities in this area.

2. Conceptual Framework and Hypotheses

Information availability and search: We start with a conceptual framework to articulate how differences in ***information available for decision making*** online and offline influence consumer choices. When choosing among alternatives, consumers are faced with a "mixed" choice task situation (Lynch et al., 1988). Consumers make their choices using prior information already available in their memories as well as information they obtain from the external environment. When searching for information in the external environment (e.g., online store), consumers focus on those relevant attributes that are available and are diagnostic (Dick et. al, 1990). To the extent that relevant information is missing in the external environment, or if search costs for acquiring relevant information are higher than expected benefits, consumers will rely more on their prior information (Ratchford 1982).

If information on an attribute is not already known to the consumer and the expected benefits of search are high relative to search costs, consumers will first try to search for that information. On the other hand, if the expected benefits are high but search costs are also high (in a given medium), then consumers may try to infer the value of that attribute. A common method of inference, especially in low-involvement product categories like groceries, is the "halo effect," whereby consumers infer attribute values based on their overall evaluations of that product (e.g., "I Can't Believe It's Not Butter!" is a good brand. Therefore, it must be low in fat. Here, fat content is an attribute for which information may be more costly to obtain offline than online)[2].

In both the online and offline media, some attribute information relevant for decision making may not be readily available (i.e., search costs for those attributes are high). This occurs, either because information on an attribute is simply not accessible in a given medium (e.g., the scent of a detergent or softness of paper towel are difficult to discern online) or the information can only be obtained with considerable effort (e.g., generating a comparative listing of the nutritional facts of different brands of margarine is more effortful offline than online).

Information integration: We now propose a mechanism by which consumers integrate all the ***information actually available to them*** (including prior information in their memories and any information obtained through search) into overall product evaluations and preferences. Information integration theory (see, for example, Anderson 1971, 1981; Bettman, Capon, and Lutz, 1975) offers a specific mechanism to describe how individuals integrate separate pieces of available information into an overall index of preference. In the context of product evaluations, this theory suggests that consumers assign importance weights and scale values (utilities) to product attributes for which information is available at the time of decision making, and then combine these weights and values according to some rule (e.g., adding, averaging) to come up with an overall evaluation. The "averaging" rule has found substantial support as an information integration mechanism (e.g., Troutman and Shanteau 1976; Johnson and Levin 1985; Busemeyer 1991):

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[2] In this paper, we are concerned only about information availability that is a consequence of the medium in which consumers make choices. Thus, we are concerned only with situations in which information availability affects all choice alternatives. In the more general case, where information may be missing only for specific choice alternatives (e.g., we do not know the quality of the private label brand), consumers may use inference rules other than the "halo effect" (see, for example, Alba and Hutchinson 1987, Ross and Creyer 1992, and Burke 1992). Alternative inference rules include the following: (1) Similarity-based inference, in which consumers infer information about an attribute value using the overall similarity of that choice alternative to other alternatives (e.g., Promise margarine should have roughly the same fat content as the other *leading* margarine brands); (2) Within-attribute inference, such as assigning an attribute value to a choice alternative equal to the average value of that attribute across the other choice alternatives (e.g., the fat content of Promise margarine will be equal to the average fat content in the product category); (3) Attribute correlations, in which consumers use their prior knowledge of the correlations between an attribute of interest and other attributes (e.g., inferring the quality of a color laser printer based on its print speed). Johnson and Levin (1985) suggest that the averaging model may not adequately represent consumers' evaluations if the attributes are negatively correlated. However, this inference rule is likely to apply only in high-involvement decision situations, where consumers are knowledgeable about the attributes.

$$W(X_1,\ldots,X_n) = \alpha_1 U_1(X_1) + \cdots + \alpha_n U_n(X_n)$$
$$\sum_{i=1}^{n} \alpha_i = 1 \quad \text{and} \quad \alpha_i \geq 0. \tag{1}$$

where

$W(X_1,\ldots,X_n)$ is the overall evaluation (value) of a product;
$\alpha_1,\ldots,\alpha_n$ are the importance weights of attributes 1, 2, …n;
$U_1(X_1)\ldots U_n(X_n)$ are the utilities assigned to attributes 1,2,…,n with attribute levels specified as $X_1,\ldots,X_n$; and
$\sum_{i=1}^{n} \alpha_i = 1$ is the "averaging" rule

Accordingly, if X_n is not available in consumers' memory or in the external environment, α_n will become zero, and the importance weights for one or more of the remaining attributes (α_1, α_2, …,α_{n-1}) will increase (Huber and McCann 1982). Note that α_i's sum to 1. In particular, under the "halo effect" argument, the importance weight attached to brand name will increase. Dick et al. (1990) experimentally evaluated consumers' inference processes when information is unavailable. They find that when their subjects had limited availability of attribute information, they inferred brand attribute values consistent with their prior evaluations. In the limit, we can conceive of situations where the brand name becomes the surrogate for all the attributes for which information is missing or costly to obtain. Conversely, when information about new attributes become available, the importance of existing attributes, particularly the brand name, is diminished.

We note here that if attribute information is unavailable only for a specific alternative, then it is likely that such information will be unavailable in both the online and offline environments (e.g., information that the private label brand is actually manufactured by the same company that makes the leading brand). Also, information about experience attributes (e.g., how a product tastes to a given customer; the absorbency of a brand of paper towel) are unavailable ***both*** online and offline, and have to be typically ascertained by product use, i.e., if they exist, they are in the memories of consumers. We assume that information unavailable in both media would have no systematic differential impact on product evaluations in either medium.

Information Availability in Online and Offline markets

In this subsection, we use the above conceptualization to articulate how the store environment (online versus offline) influences information availability, and consequently consumer choices. We describe how consumer search costs and strategies are different in online and offline markets, focusing on differences between Peapod and regular supermarkets, and relating these differences to information availability when consumers make choices.

Differences in search costs: We start by partitioning search attributes[3] into four categories: (1) brand name, (2) price, (3) sensory attributes, and (4) non-sensory attributes (excluding brand name). By sensory attributes, we mean those attributes that can be directly determined through our senses, particularly, touch, smell, or sound, ***before*** we purchase the product, i.e., they are *searchable* sensory attributes. For example, the design of a paper towel is a sensory attribute, whereas the taste of a food item is not. By non-sensory attributes, we mean those attributes that can be conveyed reasonably well in words (e.g., nutritional information). Thus, all non-sensory attributes are search attributes. We consider price as a separate search attribute because it varies across purchase occasions unlike other product-specific (non-sensory) attributes that are relatively stable across purchase occasions.

An important difference between online and offline markets is that for attributes for which information can be obtained in both media search costs are typically lower online than offline (see, for example, Bakos 1997). Other things equal, information that is easier to search will be more "available," and hence, will have a larger influence on overall product evaluation (see, for example, Kisielius and Sternthal, 1984). Several studies have also demonstrated that when information is presented in a suitable format (e.g., brand $\times$ attribute matrix) as in Peapod, it facilitates both consumer information acquisition and comprehension (e.g., Bettman and Kakker 1977; Russo et al. 1986). In online markets, it should take roughly the same amount of effort (time) to obtain information on every listed attribute. At least, this is the case in Peapod. An

[3] Note that information on experience attributes (e.g., taste) and credence attributes (e.g., health benefits) have to be inferred by consumers (e.g., from their own memory) in both online and offline markets.

example screen display from Peapod is shown in Figure 1. All listed attributes, such as price, size, fat content, and calories can be sorted and searched with about the same amount of effort. On the other hand, when information is obtained offline, search costs may vary by attribute. For example, in the traditional grocery store it is somewhat easier to search by price or unit price (e.g., find the product with the lowest price, or find products that are on promotion), than it is to search by nutritional information (e.g., find the margarine with the lowest level of fat). If there are attributes that many consumers won't typically search in the traditional stores because of high search costs, but information about them is available in the online store, then we should expect price importance to go down online. If there are no such search attributes, price importance may actually increase because price search is somewhat less effortful online than offline.

Figure 1 here

We also assume that search costs for obtaining information about the non-sensory attributes listed in the online market are lower online than offline. At the same time, search costs for obtaining information about sensory attributes should be higher online than offline. Thus, we expect offline consumers to have more information available about sensory attributes when making choices, thereby making the importance weights for sensory attributes higher offline than online. Likewise, we expect importance weights for non-sensory attributes to be higher online.

The total amount of information available in a shopping environment varies by product category. For product categories that have a large number of sensory attributes (e.g., fruits and vegetables) the offline environment has more total information available to facilitate consumer choices. For product categories which have a large number of non-sensory attributes (e.g., industrial products) the online environment will offer more total information than the offline environment. As suggested earlier by the "halo effect" argument, when the total information available about price, sensory attributes, and non-sensory attributes is large, the importance weight given to brand is reduced. Thus, in some product categories the importance weights given to brands may be higher online than offline; yet in other categories the reverse will be true.

Differences in search strategies: Many online stores, including Peapod, allow consumers to customize their shopping environment to make it more convenient for them to shop online. This may reduce the availability of price information relative to non-price information. For example, consumers in Peapod can generate and use "personal lists"[4] of their most frequently purchased items, items purchased on a previous purchase occasion, or items selected on other self-selected criteria (e.g., "party list"). An example of a personal list is given in Figure 2. Personal lists allow consumers to search within a restricted consideration set, instead of searching the entire category. Thus, competitive products not on the personal list are removed from consideration when consumers search using this feature. This is likely to insulate consumers' frequently purchased products from price competition. In sum, the use of personal lists should further dampen the importance weight of price online, relative to other attributes. In Peapod, we can track whether consumers purchased an item using their personal lists or whether they purchased it by "browsing" the aisles (we refer to the latter as category-based purchase). This type of tracking allows us to do separate analyses of category-based purchases, to more clearly assess the effects of price in the online market.

Figure 2 here

In summary, recall from our earlier discussion that attribute-information that is not available at the time of decision making will have smaller impact on overall evaluation. Conversely, when the information on a relevant attribute is easier to access, that attribute should have a larger impact on evaluation. In this section, we pointed out several important differences between online and offline information availability: (1) Typically, more information on sensory attributes is available offline and more information on non-sensory attributes is available online; (2) Search costs are lower online for the attribute information that are displayed, the difference being more pronounced for non-price attributes; (3) Some convenience features (e.g., personal lists) available online may shift consumer focus from price to non-price attributes.

[4] This is akin to the use of bookmarks to store Internet sites of interest to a user.

Hypotheses

We now state our specific hypotheses about the differential effects of the online medium, based on the conceptual framework and arguments presented in the previous two subsections:

H1a: ***Sensory search attributes will have smaller impact online than offline.***

H1b: ***Non-sensory attributes will have larger impact online than offline.***

These hypotheses follow directly from the arguments of the previous subsection. Attributes for which less information is available will have lower impact on product evaluations.

H2: ***Brand names have greater impact on choices in store environments where less total information is available for facilitating consumer choices.***

We derive H2 using the following reasoning: When the total available information decreases, the importance weight attached to brand name increases (note that the brand name information is equally available both online and offline). The brand name becomes a surrogate for attribute information that is missing or costly to acquire. For product categories with few sensory search attributes (e.g., margarine), it is likely that more information is available online than offline and brands becomes less important online than offline. For categories with some sensory attributes (e.g., paper towels), we can expect more information to be available offline than online, and thus, brands become more important online than offline.

H3: ***To the extent that attributes listed in the online store are relevant for choice, price will have smaller impact on choices in online supermarkets than in traditional supermarkets.***

Information search (for the attributes listed in the display) is less effortful online than offline. Further, all attributes listed online are searchable with approximately equal effort. Thus, online, we should expect relatively more non-price information to be available at the time the consumer makes choice decisions. According to the information integration theory, as information on more attributes becomes available, the relative importance weights of the attributes already available (either in the internal memory of consumers or in the external environment), including price, should decrease. Further, when consumers use the personal list feature, there is reduced availability of competitive price information (specifically, the current prices of brands not on the personal list are not available), which also diminishes the importance of price online. On the other hand, if the product category has a large number of sensory attributes for which information is not available online, the importance weights of the available attributes, including brand name and price, may increase. However, due to the "halo effect" argument we presented earlier, it is likely that the effects of missing sensory information will be to enhance the value of the brand, rather than to increase price sensitivity. Thus, on balance, we expect that the combined effects of all these factors would be to reduce price sensitivity online, leading to our hypothesis.

Past research suggests that loyal customers are less price sensitive (see, for example, Narayandas 1998). We note here that although Peapod members are loyal to the service (i.e., many of our panelists buy most of their groceries from Peapod), this should have little effect on price sensitivity in a particular product category, say detergents. In fact, most consumers shop for most of their groceries in a single supermarket. Progressive Grocer (1995) estimates that, on average, households typically spend about 75% of their budgets in one primary supermarket, about the same as Peapod's members.

For testing our hypotheses, we use data from three product categories for which we were able to obtain information from both Peapod and comparable regular supermarkets: Detergent, Margarine, and Paper Towel (we describe our data in more detail in the next Section). These three categories have been previously used in academic research. Detergents and paper towels are categories with frequent price promotions, while paper towels is also one of the most frequently purchased categories. Nutritional information (fat) should be an important attribute in the margarine category. If our hypotheses are valid, we would expect the following results in each category:

- <u>Liquid detergent</u>: Here, the search attributes that affect choice include brand name, price, promotion, and brand-specific attributes (e.g., refill package, scent). Detergent is a heavily promoted category in traditional supermarkets with frequent features and displays. However, in the Peapod store, promotions involve only price cuts - there are no features (e.g., store fliers) or "end of aisle" displays. Some variables that affect choice, such as package visuals and scent[5], are difficult to discern online. This category contains some sensory attributes that are not as readily available online as offline, namely, refill package (these have a different kind of package design than regular packages) and scent (the detergent boxes are not sealed, and hence offline consumers may be able to make some assessment of the scent if they wish to). Therefore, we expect refill packages and scent to have lower impact on choice online (H1a). However, we do not expect these effects to be strong because these attributes are unlikely to be important in influencing consumer choice. Because some sensory attributes are missing online, we expect brand names to have stronger influence on choices online than in traditional supermarkets (H2). Finally, we expect prices to have smaller impact online than offline because of the reasons outlined earlier (H3).

- <u>Margarine</u>: In the soft-margarine category there are no searchable sensory attributes that affect consumers' perception of quality (Steenkamp, 1986). The major search attributes that influence choice are brand name, price/promotion, and nutritional information (fat content). In traditional supermarkets, consumers may use the brand name to infer relative fat content, whereas online, the exact fat content of each SKU is displayed on the screen (see Figure 1). Thus, we should expect fat content information to have more impact online than offline. Because of the online availability of easy-to-search nutritional information, we expect that more total information about attributes is available online than offline. Thus, non-sensory attributes should have more impact online (H1b), while brand name should have less impact online (H2). Because more total information is available online, prices should have relatively lower impact on choices online (H3). Note that information on experience attributes (e.g., taste) and credence attributes (e.g., health benefits) are missing both online and offline.

[5] Because detergent containers are not sealed, the scent of a detergent could be ascertained before purchase offline and, thus, is a sensory attribute.

- Paper Towel: In the paper towel category, we can use brand name, price/promotion, and some brand-specific attributes (e.g., plain white versus design, paper size) as explanatory variables. Some sensory search attributes (e.g., the exact design on the towel, its softness) are missing online. Therefore, we expect paper towels with designs (a sensory attribute) to have lower impact on choice online, where the actual designs cannot be easily seen (H1a), and for brand names to have higher impact online (H2). Finally, we expect lower price sensitivity online (H3).

3. Methodology for Testing Hypotheses

Description of data: To fully understand the differences in choice behavior induced by the shopping medium, we would ideally need to conduct a randomized experiment in which some people are assigned to shop online and some are assigned to shop offline over an extended period of time. Such an experiment would be expensive and impractical. A realistic and practical alternative is to use longitudinal field data from separate samples of online and offline shoppers, but account for self-selection differences between these samples in the methodologies we use for data analyses. This approach is quite common in many scientific fields where random assignments are not possible (e.g., labor economics; see Heckman 1976, 1979).

Not surprisingly, the composition of people who shop online is different from the composition of people who shop offline. To account for these sample differences, we do the following: (1) On aggregate, we try to match the samples on the education levels of the shoppers, an observable criterion, that differentiates between early adopters of the online shopping medium and the shoppers in traditional stores. Several surveys suggest that the online population is highly educated. For example, over 50% of those surveyed by the "GVU surveys" (www.gvu.gatech.edu/user_surveys) have college education or higher. (2) We incorporate within the model a term to account for the fact that household income may affect price sensitivity; (3) Even for these matched samples, and after accounting for observable differences, there may remain important unobservable differences (e.g., in value of time) that influence store choice. To address this issue, we develop a new methodology to correct for selectivity bias in a choice model with unobserved heterogeneity. We formulate a two-stage choice model in which customers first choose the store type in which they shop (online versus offline), and then make brand choices within their chosen store environment. In our estimation, we allow the first-stage errors to correlate with the unobserved heterogeneity distribution of parameters in the second stage. In what follows, we describe our methods in greater detail.

For our study, we use two of the most comprehensive data sets currently available. The first data is from Peapod, where we tracked about 300 subscribers in the Chicago suburban area from May 1996 to July 1997[6]. The second data set is from IRI for 1,039 panelists who shopped in the same grocery chain in the same geographic area, although not in the same supermarket as the Peapod subscribers. (The supermarket from which Peapod customers are served is not part of the sample of supermarkets that IRI uses to collect its panel data.) These data were collected between September 1995 and November 1997 from three stores. Two of these supermarkets are located in the same part of the metropolitan area as the Peapod store and all are in relatively affluent areas. For the IRI data, we have individual-level demographic information for all the panelists. For the Peapod data, we have aggregate demographics based on a survey conducted by the company, and we have individual-level demographic data for only about 40% of the panelists. For the remaining individuals, income data was imputed as the overall average for Peapod consumers in the Chicago area.

Table 1 summarizes some demographic information for the two samples that we used in our analyses. An examination of Table 1 suggests that Peapod households are, on the average,

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Table 1 here
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[6] These panelists are a subset of active Peapod households that do a majority of their grocery shopping through Peapod. The average order size for these panelists is around $125, about five times $23.5, the size of the average order in a regular grocery store. The average Peapod "visit" lasts 23 minutes in our sample (with improved modem speeds, this has probably declined). In comparison, a visit to a regular store lasts about 1 hour (Bauer, 1995). An average order in Peapod contains 42 items, and the average number of visits per month is 2.2. Consumers visit regular grocery stores about 7.9 times per month on the average (Food & Beverage Marketing, August 1998).

younger, better educated, and more affluent than the US population. Also, a larger proportion of Peapod households have children. To get some comparability between the samples used in the analyses, we use education as a matching criterion and retain only those IRI households with at least one member having graduated from college (denoted as IRI (H-E)). It was important to match on the education criterion because only about 20% of the IRI sample had some college education compared to about 95% in the Peapod panel. With regard to income, the Peapod sample is much more affluent, even when compared to the IRI (H-E) sample.[7] These income differences could induce differences in choice behavior, because higher income households face substantially different budget constraints. To account for the effects of budgetary considerations on price sensitivity, we include a price-income interaction term in our models (see Kalyanam and Putler 1997). This is described in the subsections below.

Two-Stage Choice Model: Consumer price sensitivity is likely to be a function of income, an observable characteristic of the household. However, other variables that remain unobserved by the researcher are also likely to affect price sensitivity. When these unobserved variables do not affect the choice of store type (online vs. offline), they would have the same distribution in the Peapod and IRI (H-E) samples and, thus, cannot be a source of differences in behavior between samples. However, it is likely that some of the unobserved variables may also affect store choice. For example, some households where both adults are employed may have a higher "opportunity cost of time," due to availability of overtime work opportunities. To save time, these households are more likely to shop online, ***and*** are also more likely to be *less* price sensitive than other households with the same observable demographics (e.g., income). As a result, this self-selection along unobserved characteristics during store choice may be responsible for differences in price sensitivities between online and offline samples. This self-selection bias must be removed before we can attribute differences in parameter estimates to differences in the store environment.

[7] Although there are some differences in category definitions and the times at which the income data were collected for the three groups in Table 1, it is nevertheless clear that Peapod members are significantly more affluent. Unfortunately, we do not have any psychographics information (e.g., price sensitivity), or information on computer skills or interest (e.g., subscription to a computer magazine) for the respondents in either sample.

The outcome of store choice (i.e., shop online or offline) provides information about those unobservable characteristics that may affect price sensitivities in brand choices. This potential relationship is captured in a two-stage choice model. In the first stage, we use a binary probit model of store choice (online versus offline), with utility for shopping online vs. offline being a function of household income. In the second stage, we use a multinomial logit model of brand choice with observed and unobserved heterogeneity. For reasons mentioned above, the errors from the binary probit model are likely to be correlated with the *unobserved* heterogeneity in price sensitivity (i.e., heterogeneity *not* induced by differences in observed characteristics, such as income) during brand choice. We remove self-selection bias by taking this correlation into account in the estimation procedure (described below).

Our methodology contains two novel aspects, which distinguish it from previously proposed methods dealing with self-selection (Heckman 1976, 1979; Lee 1983; Trost and Lee 1984). The previous methods incorporate a simple regression model (i.e., with fixed coefficients) in the second stage. This approach, with a second-stage regression model, has also been used in Marketing (e.g., Krishnamurthi and Raj 1988). In contrast, in the second stage, our method accommodates a multinomial choice model with unobserved heterogeneity. Also, while the previous methods simply allow correlations between errors of the two stages, our method performs bias correction on specific parameters (e.g., price sensitivity). As described below, we have to use more sophisticated estimation methods to estimate our two-stage model.

First Stage Choice Model: The store choice model is a binary probit with the following structure:

$$U_{online,i} = \gamma_0 + \gamma_1 \cdot HHI_i + \xi_i \qquad (2)$$

$U_{online,i}$ is the utility that consumer i gets from shopping online, rather than offline; HHI_i is household income of consumer $_i$, ξ_i is standard Normal error. Consumer i chooses to shop online if and only if $U_{online,i}>0$. This model is estimated on the joint data from the IRI and Peapod samples, separately from, and prior to estimating the second stage, and yields the point estimates

$\hat{\gamma}_0$ and $\hat{\gamma}_1$. Conditional on store choice, error ξ_i comes from a truncated standard Normal distribution, such that

$$\xi_i > -\hat{\gamma}_0 - \hat{\gamma}_1 \cdot HHI_i$$

if consumer i shops online and

$$\xi_i < -\hat{\gamma}_0 - \hat{\gamma}_1 \cdot HHI_i$$

if consumer i shops offline. This constraint will be applied in the second stage choice model.

Second Stage Choice Model: To formulate the brand choice model, we follow Russell and Kamakura (1993) and first decompose brand value (BV) into two components: a tangible component (BTV) and an intangible component (BIV). The tangible value can be directly attributed to levels of measurable attributes (e.g., fat per serving), while the intangible value cannot be captured by the measured attributes. The impact of brand name on choice is captured by the intangible value.

Let J and K be the number alternatives and brands, respectively, in the choice set. **First**, consider product categories where each alternative in a choice set is associated with a distinctly different brand (i.e., there is no distinction between a brand and a choice alternative and J=K). This is the case in our analysis of the margarine category. Then, brand *j*'s utility during choice occasion *n* is specified by a linear utility function (for ease of exposition, we suppress household subscript *i*):

$$U_{jn} = BIV_j + BTV_j + \boldsymbol{\beta} \cdot \boldsymbol{X_{jn}} + e_{jn} \qquad j=1,\ldots,J \qquad (3)$$

where $\boldsymbol{X}_{jn}$ is a vector of marketing variables (e.g., price, promotion) or household income (e.g., price $\times$ income), $\boldsymbol{\beta}$ is a row vector of consumer sensitivities, and e_{jn} is the random component of U_{jn}. By relating the tangible component to measurable attributes, equation (4) becomes:

$$U_{jn} = BIV_j + \mathbf{g}.\mathbf{A}_j + \boldsymbol{\beta} \cdot \boldsymbol{X_{jn}} + e_{jn} \qquad (4)$$

where $\mathbf{A_j}$ is a vector of attributes (e.g., fat content, presence of bleach), **g** is a row vector of consumer sensitivities to those attributes. Let *R* be the number of brand-specific attributes included in the analysis (i.e., the sizes of $\mathbf{A_j}$ and $\mathbf{g}$). Because of standard identification constraints, only J-1-R brand-specific coefficients (i.e, BIV_j's and elements in $\mathbf{g}$) can be identified. Following Kamakura and Russell (1993), we impose:

$$\sum_j BIV_j = 0 \tag{5}$$

and

$$\sum_j BIV_j \cdot A_{jr} = 0; \quad r=1,\ldots,R \tag{6}$$

The identification constraints in (5) and (6) ensure that brand intangible values are orthogonal to brand-specific attributes. Kamakura and Russell (1993) estimate the parameters sequentially, with sensitivities to marketing mix variables estimated first, and brand intangible values and sensitivities to product attributes estimated second. We, however, estimate all the coefficients simultaneously. This approach allows us to derive the statistical properties (based on asymptotic standard errors and/or likelihood ratio tests) of the brand intangible values and sensitivities to product attributes.

Second, consider product categories where there are several choice alternatives for each brand (i.e., J<K). Alternatives belonging to the same brand *k* now share that brand's intangible brand value BIV_k (which replaces BIV_j in equations (3) - (4)). If $J\text{-}K \geq R$, as is the case in the detergent and paper towel categories, all coefficients in the model are identified except for one brand intangible value. To identify the model, we set the brand intangible value of the brand with the largest market share to zero.

Note that in the utility specification given in (4), we cannot identify the importance weights of the information integration model, α_i, as specified in (1). The α parameters are subsumed within the coefficients given in (4).[8] There are also other factors that prevent us from directly estimating and comparing the importance weights across the online and offline models: (i) the information integration model specified in (1) does not have an error term, which we need for

[8] Specifically, for linear utility models, the ith component of (1) is $\alpha_i U_i(X_i) = \alpha_i(s_i X_i) = (\alpha_i s_i)X_i$, where s_i is a scaling factor for the utility measure. The corresponding term in the measurement model (4) is given by $\beta_i X_i$, so that β_i captures the effect of both α_i and s_i.

estimating choice models. (ii) The basic information integration model also does not incorporate heterogeneity in preference structures, which we incorporate in our choice models. For these reasons, we will compare the relative importance of attributes online and offline using other measures, such as the estimated proportion of households exhibiting positive vs. negative coefficients for a specific attribute, or their responses to identical promotions. We must point out that the purpose of our analysis is not to test the information integration theory, but only to test the implications of this theory as summarized in our hypotheses. For this objective, our approach is appropriate.

Modeling Heterogeneity: We consider two types of heterogeneity: brand intercept heterogeneity (referred to as preference heterogeneity by Papatla (1996)) and response heterogeneity. The former characterizes the distribution of brand intercepts (i.e., brand intrinsic values) across consumers whereas the latter characterizes the distributions across consumers of such factors as price sensitivity and response to brand-specific attributes. We include intercept heterogeneity in all our models. We selectively include response heterogeneity in our models when both the online and offline samples are large enough to yield reliable estimates.[9]

We assume a multivariate Normal distribution of parameters and IID extreme value errors. This yields a heterogeneous logit model, which we estimate using simulated maximum likelihood method (Erdem 1996). However, in our case we also need to account for, and estimate the correlation of first choice errors with unobserved heterogeneity in price sensitivity in the second stage. We accomplish this by making random draws from the distribution of heterogeneity, which in fact, is the basis for simulated maximum likelihood estimation. Specifically, we obtain draws from the simulated heterogeneity distribution for price sensitivity through rejection sampling, such that the realizations of our random draws are consistent with the corresponding store choice error. A pair {price sensitivity coefficient, store choice error} is drawn from their unconditional bivariate Normal distribution. If the draw yields a valid store choice error (i.e., $\xi_i > -\hat{\gamma}_0 - \hat{\gamma}_1 \cdot HHI_i$ for

[9] Heterogeneity-related parameters capture differences across individuals, rather than across choice occasions. Thus, we need larger samples of panelists to assess heterogeneity along more dimensions. In our models, we ensured that there were at least ten panelists for each heterogeneity-related parameter.

consumers shopping online and $\xi_i < -\hat{\gamma}_0 - \hat{\gamma}_1 \cdot HHI_i$ for consumers shopping offline), the corresponding price sensitivity is retained. Otherwise that particular realization is discarded. We continue the process until we obtain the desired number of price sensitivities (here, 50). This procedure yields estimates that are corrected for self-selection bias for the population parameters (i.e., the means and covariance matrix of the Multivariate Normal distribution)[10].

4. Results

Brand switching: Table 2 presents the brand switching percentages in the three product categories for the IRI and Peapod data. To facilitate interpretation, in Table 2 we report two sets of percentages for Peapod for each product category. In Peapod, we first report results that include all purchases regardless of whether the consumer purchased using the personal list or whether the consumer purchased by browsing the category aisles. We then report results based only on category-based purchases.

Table 2 here

For all three categories, a striking result from Table 1 is that there is less brand switching online than in traditional supermarkets. At first glance, this may appear to be the result of the personal list feature of Peapod, which allows members to place orders for their favorite products without having to browse the category aisles. However, there is less switching in Peapod, as compared to IRI (H-E), even when consumers browse a category to make their choices. Brand switching differences are, therefore, probably due to stronger point-of-purchase influences in traditional supermarkets, or because of sample differences between Peapod and IRI (H-E) samples. We conclude that: 1) there is less overall brand switching in Peapod than in traditional supermarkets, and 2) there is less brand switching when consumers use personal lists than when they don't.

[10] Because the likelihood function is nonlinear, the bias in the absence of correction would affect all the coefficients in the model, not just price sensitivities.

We now analyze consumer choices in each category and assess whether the three hypotheses proposed in Section 2 are supported by our results.

Liquid Detergent

To specify the choice model to test our hypotheses, we included the following variables: 1) Brand name, 2) Unit price, 3) Promotion[11], and 4) Several category-specific attributes. The category–specific attributes that the consumers could assess in both online and traditional supermarkets are: 1) whether the detergent is scent free, 2) whether a bleaching agent is added, 3) whether the detergent is a refill package, and 4) the size of the package. After eliminating SKU's that had a low number of choices in both types of stores, we were able to retain over 70% of the choices observed in our data sets. We allowed most coefficients, including brand intercepts, to vary across consumers, but we kept the coefficients for brand-specific attributes (e.g., refill package) common across consumers. This allowed us to incorporate consumer heterogeneity, while still having sufficient data points to estimate the heterogeneity distribution, especially for Peapod's category-based purchases.

Tables 3 and 4 summarize the results. In Table 3, we present the coefficients of the choice model, and in Table 4, we summarize the brand intercepts and other related information we use to assess the value of brand names.

Insert Tables 3 and 4 here

The first three columns under "Peapod" in Table 3 contain summaries of our analyses of the Peapod data. In Column 1, we summarize the bias-corrected estimates that are based on all the purchases made at Peapod by the respondents. In Column 2, we summarize bias-corrected estimates based only on purchases that the respondents made while browsing the category (i.e., excluding personal-list based purchases). For comparison purposes, in Column 3 we also report

[11] In Peapod, the only promotions in the categories of interest were price cuts (as described in Figure 2). Recently, Peapod has begun including banner ads that appear in the appropriate category aisles (e.g., an ad for Colgate toothpaste in the toothpaste aisle). For the regular stores, IRI records both Features and Displays, which we include in our analysis of the IRI data.

the estimates obtained when we do not correct for selection bias (i.e., with correlations between first stage errors and price sensitivities constrained to zero). Because the model uncorrected for bias is nested in the bias-corrected model, and has one less parameter (the correlation coefficient), we can use a likelihood ratio test to assess the effectiveness of the correction for bias (Δ(LL) = 18 >> 6.63 = $\chi^2_{0.01}(1)$). This test, along with the statistical significance of the correlations between store choice errors and price sensitivities confirm that bias-correction was necessary and significantly alters the results. Moreover, since these correlations are positive, all else being equal, households shopping online are less price sensitive than the entire population of households with high education. The result for the IRI High-Education sample, reported in the last column, reveals a much weaker selectivity bias, with a correlation coefficient of –0.43. This suggests that the selection bias associated with IRI (H-E) panelists occurs in the expected direction, i.e., they are slightly more price sensitive than the entire population of high-education shoppers.

Sensory attributes: We now compare the coefficients for category-specific attributes in the Peapod and IRI (H-E) models.[12] We see that online consumers are less likely to buy "Refill" packages, which are more difficult to discern online – refills have a different type of package that is more readily obvious offline. These results are consistent with our arguments about sensory attributes, thereby supporting hypothesis H1a. Interestingly, consumers are equally likely to buy scent free detergents online and offline. According to H1a, we should expect scent free detergents to be more appealing online because consumers cannot ascertain the smell of a detergent online even if they wished to. The lack of differential effects on this attribute suggests that scent is not an important attribute influencing choice in this category, probably because visual cues are more salient than olfactory cues in traditional supermarkets. Recent research suggests that about two-thirds of all stimuli reach the brain through the visual system (Kosslyn, 1994).

[12] We also included product size as a control variable in the analysis. We find that Peapod consumers are much more likely to buy larger size packages, a result also replicated in the paper towel category in terms of their purchases of multi-packs. Possible reasons for this result include: (i) A greater proportion of Peapod households have children, (ii) Peapod delivers the products – consumers may be more reluctant to buy larger packages if they have to carry them home, and (iii) Size cues may be difficult for consumers to discern online, which is the explanation provided by Burke et al. (1992).

Brand name impact: A visual inspection of Table 4 suggests that actual market shares in Peapod are typically lower than in the IRI (H-E) data for low-share brands (e.g., All, Store brand). Intuitively, this suggests that brand names have more impact online than offline in this category. To assess the effects of brand names formally, we use the brand intercepts reported in the table. These intercepts are measured relative to the largest-share brand (Tide), which happens to be the same in both Peapod and IRI (H-E) data. By using the highest-share brand as the base, we can improve the reliability of the intercept estimates with reference to the baseline. To facilitate comparison of the intercepts across models, we compute an index called "Net Market Share," which is the market share of a brand computed from household-specific brand intercepts. It represents the market share attributable just to a brand name, net of the effects of marketing mix variables and the tangible attributes of the brand. Specifically, the net market shares are based on the theoretical distribution of brand intrinsic values of each model. The net market share of brand *i* represents the percentage of consumers in the market for whom $BIV_i > BIV_j$ for all $j \neq i$. We compute these values by simulating 10,000 consumers based on the heterogeneity distributions of brand intercepts.

Net Market Shares provide us an intuitively appealing way to compare the effects of brand names on consumer choices across models. If brand names have no effect on choice (net of brand-specific attributes and marketing mix variables), then Net Market Shares should be equal to (100/J) for each brand j, with a standard deviation of Net Market Shares across brands being equal to 0. On the other hand, if brand names have maximal impact, then one of the brands should have a Net Market Share equal to 100, while the remaining J-1 brands have Net Market Shares equal to 0, giving a maximum standard deviation of Net Market Shares equal to $\frac{100}{J}\sqrt{J-1}$.

We observe that Net Market Shares are large for stronger brands like Tide when compared to weaker brands such as Arm & Hammer. The standard deviation of Net Market Shares in Peapod is equal to 13.5 (all purchases) and 14.0 (category-based purchases). At the same time, the standard deviation of Net Market Shares in IRI (H-E) is only 6.3, suggesting that brand names have much stronger impact on choices online than offline. Thus, we find compelling support for hypothesis H2.

Price effects: To identify the differences between online and offline price sensitivities, we have to compare the Peapod (All purchases) model with the IRI (H-E) model. This is because, even in a traditional supermarkets, a significant proportion of consumers make planned purchases (Bauer 1995), i.e., they pick products from their "shopping lists" without browsing the entire category, in a manner akin to "personal list" shopping of Peapod consumers.

In choice models, the coefficients for the same variable across models cannot be directly compared because coefficients of a model are scaled by the variance of the errors (Swait and Louviere,1993). However, ratios of coefficient estimates from the same model are scale-independent and can be compared across models. Since Promotion in Peapod is roughly equivalent to Feature in traditional stores, the ratio of these pairs can be used to understand the differences in reactions to price promotions across the two markets. Using ratios for their mean effects, we see that Price is more important than Promotion online (the ratio of their means is –2.27/1.76= -1.29), but far less important than Feature in traditional stores (the ratio of their means is –0.87/2.04= -0.43). When we consider only category-based purchases in Peapod, price impact is slightly higher, as we would expect (Price/Promotion ratio = -2.30/1.47 = -1.56).

At first glance, the above results suggest that Peapod consumers are more price sensitive than offline shoppers, and we should reject H3. However, these results do not necessarily mean that the online medium (Peapod) makes consumers more price sensitive. Shoppers tend to respond to the ***joint*** effect of price discount and promotions (i.e., Price discount and promotion in Peapod; Price discount with Feature and/or Display in offline stores). Our findings indicate that online consumers respond better to the price discount itself, whereas consumers in traditional stores rely more on Feature as an indicator of a good deal. This result is consistent with our search cost framework – in traditional stores, it is easier to search for deals based on featured products (features being reasonable, but not perfect indicators of price discounts), whereas online it is equally easy to sort on (unit) price or on the promotion indicator (see Figure 1). The data suggest that promotions are stronger signals of price cuts in Peapod than in traditional stores. The correlation between price and promotion in the detergent category in Peapod is –0.69. In contrast, in the IRI data, the correlation between price and feature is –0.18 and the correlation between price and display is also –0.18. This suggests that in Peapod, the price sensitivity results may be partly due to a confounding of price and promotion effects. To compare the overall impact of price promotions in the two store environments, we must take into account the joint effects of price and promotion in Peapod and the joint effect of price, feature, and display in traditional stores. For this purpose, we conducted a simulated experiment using model estimates.[13] To facilitate comparison across store environments, we compute the responsiveness (i.e., changes in market shares) to identical price promotions in the two environments, when the population is described by bias-corrected parameters of each model. The results are summarized in Table 3 under the heading "Market share gain from price promotion."[14] We observe that the combined effects of price and promotion is substantially higher in the IRI (H-E) sample than in the Peapod sample, suggesting that overall price sensitivity is lower online than offline.

Also of interest, comparing the bias-corrected and uncorrected coefficients, we see that price impact is smaller when we do not correct for bias (Price/Promotion ratio =-0.45/1.24 = -0.32 versus a ratio of –1.29 for the bias corrected coefficients). This suggests that if Peapod members were to resemble the high-education segment in the general population, they would be more price sensitive than the current members. At the same time, the uncorrected price sensitivity is lower than the IRI (H-E) sample (Price/Promotion ratio equals -0.32 in Peapod versus -0.43 in IRI).

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[13] The use of simulated experiments to assess the practical implications of the coefficients of a choice model is standard (see, for example, Erdem 1996).

[14] "Market share gain due to price promotion" is reckoned in terms of the ***absolute*** change in own market share when own price is discounted by 50¢ per 100oz container and the product is featured in Peapod (featured and put on display in IRI). For each alternative, we first compute its market share, when all alternatives are held at their average prices. Next, we compute the change in market share when an alternative is put on promotion, while all other alternatives remain at their average prices. We repeat this computation for each alternative. The number reported is the average market share change across the alternatives, weighted by their market shares at average prices. The market shares themselves are computed from a sample of 1,000 households with model coefficients being drawn randomly from the estimated heterogeneity for each model (i.e., with a mean of –2.27 and standard deviation of 1.17 for the Price coefficients under the Peapod model with bias correction). All households are endowed with the average income in the IRI (H-E) sample.

Thus, with the current membership base, online price sensitivity is somewhat lower than offline price sensitivity. We also note that without the bias correction, we would have a smaller gain in market share from online promotions (11.0 versus 16.5). As expected, the price×income coefficients are positive suggesting that people with higher incomes are willing to buy higher priced products.

Summarizing the above analysis, if we redefine "price sensitivity" as "promotion induced price sensitivity," we see that price sensitivity is smaller online than offline. Overall, while we do not find direct support for H3 as stated, our broader interpretation of price sensitivity suggests that H3 is in fact, supported.

In summary, in the detergent category, we find support for H1and H2, and indirect support for H3.

Light Margarine Spread

The choice model used to test our hypotheses, included the following variables: 1) Brand name and, 2) Fat[15]. We allowed both brand intercepts and the fat coefficient to vary across consumers. In spread margarine category, brand names typically convey general fat content information (e.g., Promise, Promise Light, and Promise Ultra suggest varying levels of fat content). Federal laws regulate the use of such adjectives as "Light" and "Fat free" to describe products. Hence, such labels convey meaningful information to consumers. However, within a subcategory (e.g., light margarine), all brand names and associated labels convey the same information about fat content. To better assess the impact of fat on choice, beyond what consumers learn from brand names alone, we restrict the analysis to light margarine spread. We retained all the choices in this sub-category. Unlike the detergent category, in this subcategory each brand retained had only one choice alternative. Tables 5 and 6 summarize the results. In Table 5, we present the coefficients of the choice model, and in Table 6 we report brand intercepts and other related information needed to assess the value of brand names.

[15] Promotional activity and Price do not impact choices in this category in any of our models.

Insert Tables 5 and 6 here

Non-sensory attributes: With regard to hypothesis H1b, Table 5 shows that fat content, on the average, negatively influences choice in Peapod, although the standard deviation of the heterogeneity distribution is large suggesting that for many consumers, fat had positive impact on choice. On the other hand, in the IRI (H-E) model, the mean effect of fat on choice is positive. At first glance, the positive sign may seem to be counterintuitive. However, there is a perfectly compelling explanation --fat is a surrogate for "taste," something not observable in either the online or traditional supermarkets. Thus, it appears that consumers generally prefer to buy the tastier (i.e., fattier) spreads. In traditional supermarkets, consumers purchase margarine spreads that are closer to their intrinsic preference for better taste, while in online store they overcome their intrinsic preferences and purchase brands with lower fat content (e.g., Fleischmann). The non-sensory attribute, fat, has a significant impact in the online market, supporting hypothesis H1b.

Brand name impact: Table 6 summarizes the actual and net market shares for assessing the value of brand names. The actual market shares for the four brands are quite different in the two store types, with a much greater proportion of online purchases for Fleischmann margarine, which has lower fat content. The differences in market shares for Brummel & Brown require further explanation. This is a new product, introduced only in November 1994, when some of the Peapod panelists had already been members for several months. The market share for Brummel & Brown in Peapod is 14.9% of category-based purchases and 35% of personal-list based purchases, combining to give an overall share of 25.9 when all purchases are considered. Thus, we see that its share of personal list-based purchases is about the same as its share in IRI (H-E) market. This suggests that the online market environment does not help generate trial, but once consumers put a product on their personal lists (perhaps after a careful evaluation), they tend to repeat purchase at a higher rate. This also suggests that an online environment may not be a good medium to test market new product concepts by placing them on virtual shelves.

The standard deviation of net market shares is 7.57 in Peapod (all purchases) and 11.81 in IRI (H-E) sample. Thus, we find support for H2. The differential effects of brand name is not strong, and we suspect is probably due to brand names not being major determinants of choice in this category, in comparison to the unobserved taste factor.

Price effects: Because price is insignificant in both Peapod and IRI models, we cannot assess the validity of hypothesis H3 in this category. In retrospect, the lack of a price impact in this category is not surprising. These products are used as spreads and not for cooking. Because spreads are not mixed with other ingredients, their taste is directly discernable and should be an important determinant of choice. This suggests that price may not be a major factor in purchase.

Summarizing our findings for the margarine category, we were unable to test H3, and found support for H1 and H2.

Paper Towel

The choice model used to test our hypotheses included the following variables: 1) Brand name, 2) Unit price per 100 sq. ft., and 3) Promotion. In addition, we included several category-specific attributes, namely, whether the paper towel was plain white or whether it had printed designs, and whether the consumer can tear off half a sheet instead of a whole one (Select-Size). For these two attributes there is differential information online versus offline. Peapod customers know if an alternative has a print design or is white. However, the design of the print, which is observable offline, remains unobserved by Peapod shopper. Similarly, Peapod customers know if a certain paper towel allows tearing off half-sizes, but do not know what the size of the full-size sheet is. Thus, some customers may be concerned that half-sizes may be too small for their needs. Given these conditions, one would expect these two attributes to be less important online than offline. After eliminating SKU's that had a low number of choices in both types of stores, we could retain over 75% of the observed choices in our data sets. We allowed brand intercepts and all coefficients relevant to our hypotheses to vary by consumers. Tables 7 and 8 summarize the results. In Table 7, we present the coefficients of the choice model, and in Table 8, we summarize the brand intercepts and other related information to assess the value of brand names.

Insert Tables 7 and 8 here

Sensory attributes: The effects of category-specific attributes on choice are what we hypothesized. Online consumers are more likely to avoid print designs and select-size alternatives than consumers in traditional markets are (see sign, magnitude and statistical significance of coefficients in Table 7). These differences become less pronounced when consumers purchase by browsing the category aisles, which is not surprising since in that case they seem to pay increased attention to price promotions (see differences in market share gains due to price promotion in Table 7). The heterogeneity distribution for printed design has a large standard deviations (Peapod mean = 1.87, standard deviation = 4.91; IRI (H-E) mean = 0.32, standard deviation = 1.43), suggesting considerable heterogeneity in preferences for this attribute. In sum, the results for paper towel support hypothesis H1b. Of interest is the fact that half-sheet paper towels were introduced only in June 1992, and some Peapod members may not have become familiar with it through offline purchases. This may also account for its lower preference online, similar to the lower market share online for the relative newcomer Brummel & Brown in the margarine category.

Brand name effects: The actual market shares and the net market shares for the four brands are quite different for the two store types. Unlike detergent, the store brand does well in this category in both Peapod and in traditional supermarkets. The standard deviation of net market shares are: 13.11 in Peapod (all purchases), 22.08 in Peapod (category-based purchases), and 10.06 in IRI (H-E). This indicates clearly that brand names are more valuable online than in traditional supermarkets, providing strong support for H2. Of interest is the result that Viva has significantly higher Net Market Share than actual share in all three models. In a recent review of paper towels, Consumer Reports rated Viva the best paper towel (Consumer Reports, 1998). This provides face validity to our measure of brand value computed from Net Market Share.

Price effects: The results here mirror what we found in the detergent category. Bias corrected Price/Promotion ratio is higher in Peapod than in IRI (< -100 versus –1.1). Also, as expected, income dampens price sensitivity (Price×Income coefficient is positive). Also, as in the detergent category, it appears that Promotion is a better signal of price cuts in Peapod than in IRI (H-E). The correlation between promotion and price is –0.61 in Peapod, whereas the correlations in the IRI (H-E) sample are –0.35 between price and feature and –0.09 between price and display. We also see that "Market share gain due to price promotion" is higher offline than online (26.5 in IRI and 14.1 in Peapod). In sum, as in the detergent category, we find only indirect support for H3.

Summarizing our findings for the paper towel category, we found support for H1 and for H2, but only indirect support for H3.

5. Discussion and Conclusions

In Table 9, we summarize our key findings. In Table 9a, we summarize our category-specific hypotheses, and in Table 9b, we report the overall nature of the support we found for our hypotheses. Except for H3, where we found only indirect support, our analyses and results support our hypotheses. We submit that neither the hypotheses nor the implications are obvious a priori.

Insert Table 9 here

Many executives are very concerned that online consumers will focus on price and this will result in strong price competition (See for example, the Booz Allen survey reported in Financial Times, February 9, 1998). At first glance, our results seemed to support this contention. But, further analyses indicated a more complex story, at least with respect to grocery products. First, people currently online may not be as price sensitive as the general population. Even if the online population becomes comparable to the general population, the ***combined*** effects of price and promotion seem to be stronger in regular stores than in online stores. Even after accounting for the fact that online promotions are better signals of price reductions, we find that offline promotions induce larger changes in brand choices. This is partly because of the low correlation between point-of-purchase (POP) activities and price in traditional supermarkets. It is likely that consumers in the traditional supermarkets are buying featured products even when there is little price reduction. Note also that we have "covaried out" the income effects when computing the market share changes due to price promotion. Thus, the price sensitivity coefficients reported in the paper are NOT induced by differences in income across the two samples. Nevertheless, we need controlled field studies in online markets to tease out these effects more precisely – a challenging task we leave for future research.

There is also concern in some quarters that online markets would "commoditize" brands, thereby reducing the value of brand names (Burke 1997). Several executives have suggested to us that online markets make it more difficult to differentiate products, and will therefore reduce the value of brand names. Our study suggests that brands can have more or less impact online than in traditional supermarkets depending on the extent of relevant information available for making choices in these markets. When more total information about product attributes is available online, brand names become less valuable. This is particularly likely if the product category contains few sensory attributes (e.g., margarine). Based on our results, we expect brand names will be more important online in product categories that are differentiated on brand image and other attributes that do not lend themselves to be easily summarized by an online store (e.g., fashion products). On the other hand, brand names will be less important online for functional products (e.g., fax machines, computers) for which online stores can give detailed attribute information, as well as comparative information, online.

Finally, our results clearly suggest that sensory attributes, particularly visual cues, will influence choice to a lesser extent online than offline. This implies that marketers who rely strongly on visual cues to influence offline purchases of their brands, may be disappointed by the level of online sales that they are able to generate.

We see the contributions of this paper along three dimensions: (1) We developed a conceptual framework that will help researchers to better articulate how and why online choices may differ from offline choices. (2) We have proposed a few methodological innovations to help researchers empirically compare offline and online data, even though the two samples may not be equivalent. In particular, our two-stage choice modeling framework and new concepts, such as net market shares, can be applied in other studies. (3) Finally, as the first large-scale study of online choice behavior using field data, we were able to offer several novel insights about how search attributes differentially affect choices online and offline. Even though our results did not fully support H3, they do indicate that there are systematic differential effects of brand name, price, and other search attributes online.

An important limitation of our study is that it lacks experimental control, making precise inferences infeasible. We had to exclude random assignment for a longitudinal data collection effort of this type from considerations of both cost and practical feasibility. An important issue not addressed by our research is choice behavior in online markets that are not subscription services like Peapod. The broader Internet market (essentially all sellers linked to the Internet) or online shopping malls, enable consumers to search across sellers to find the products and prices that best meet their needs. In these types of online markets, search can both expand and narrow the consideration sets of some consumers, and the information sources that they use while making choices. Some research initiatives are currently underway to explore consumer decision making and choices in these situations. In particular, several recent studies explore issues related to online price sensitivity (Lynch and Ariely 1998; Shankar, Rangaswamy, and Pusateri 1999, Brynjolfsson and Smith 1999).

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Table 1
Comparison of Sample Demographics

Education	% of Primary Peapod Members	% of IRI Households Selected (Hi-Education)	% of US Population (18+)
High school or less	9	0	52
Some College	25	0	26
College graduate	39	50	15
Post-graduate	27	50	7

Age	% of Primary Peapod Members	% of IRI Panel Selected (Hi-Education)	% of US Population (18+)
18-34	37	8	33
35-54	51	55	39
> 54	12	37	28

Children	% of Peapod Households	% of IRI Households Selected (Hi-Education)	% of US Households
Yes	53	39	34

Household Income (′000 $)	% of Peapod Households	% of IRI Households Selected (Hi-Education)	% of US Households
< 50	18	56	65
50 – 99	41	25 (50 – 75K)	26
> 99	41	19 (> 75K)	9

Notes: (1) Peapod data were collected in late 1997. The summary here is based on about 5,600 Chicago area members who chose to fill out an online survey on demographics. Note that the education level is with respect to the primary shopper in the household.

(2) Each selected IRI household had made at least one purchase of margarine, detergent, or paper towel during the course of our study. The Hi-Education household had at least one member with college education or higher. The IRI income data is collected when a member joins the panel and is updated periodically. The data reported here are from an earlier time period than for the census data.

(3) The US statistics are based on Census Bureau reports for 1996 (www.census.gov).

Table 2
Brand Switching Percentages

	Liquid Detergent	Margarine	Paper Towel
Peapod			
All purchases	13.3 (752)	3.2 (281)	5.5 (2078)
Category-based purchases	24.7 (296)	3.7 (107)	11.3 (761)
IRI (H-E)	41.5 (647)	7.7 (248)	28.3 (1458)

Note: Brand switching percentage is determined by examining each choice made by a panelist and determining whether the brand purchased was different from the brand purchased by that panelist on the previous purchase occasion. Brand switching is not the same as switching between choice alternatives, because a brand may have several SKU's. The numbers in parentheses indicate the total number of choices from which a reported percentage was calculated. In calculating the switching percentages, we have to exclude the first choice of each individual.

Table 3: Summary of Model and Coefficients for Liquid Detergent

Variable	Peapod			IRI (H-E) (Bias Corrected)
	Bias Corrected		Uncorrected All Purchases	
	All Purchases	Only category-based purchases		
# of individuals	146	125	146	121
# of choices	898	421	898	765
# of alternatives	26	26	26	26
# of brands	9	9	9	9
Average Income($ ‘000)	118.0	110.0	118.0	55.3
Price ($/100oz) – Mean – Std. Dev.	-2.27 (0.42) 1.17 (0.13)	-2.30 (0.65) 1.05 (0.16)	0.10 (0.30) 0.01 (0.09)	-0.87 (0.24) 0.59 (0.09)
Price*Income($ ‘0,000) – Mean – Std Dev.	0.13 (0.03) 0.03 (0.01)	0.13 (0.06) 0.04 (0.02)	-0.01 (0.03) 0.09 (0.01)	0.03 (0.04) 0.11 (0.02)
Promotion (0/1) – Mean Only in Peapod – Std. Dev.	1.76 (0.25) 0.90 (0.25)	1.47 (0.31) 0.76 (0.38)	1.63 (0.26) 0.52 (0.21)	
Feature (0/1) – Mean Only in IRI – Std. Dev.				2.04 (0.16) 0.65 (0.13)
Display (0/1) – Mean Only in IRI – Std. Dev.				1.23 (0.14) 0.47 (0.12)
Scent free (0/1)	0.15 (0.08)	0.30 (0.13)	0.16 (0.03)	0.25 (0.11)
Refill (90oz) (0/1)	-0.76 (0.11)	-0.88 (0.19)	-0.76 (0.06)	-0.45 (0.17)
LL	-1794.3	-950.9	-1803.3	-1502.2
Corr(Price Coeff, Store Choice Error)	0.76 (0.07)	0.89 (0.13)		-0.43 (0.24)
Market share gain due to price promotion	16.5	15.0	11.0	26.3

Notes: (1) For variables for which we estimated heterogeneity distributions, we report both the estimated means and standard deviations of the distributions (Mean, Std. Dev.).

Table 4: Brand Value Analysis for Liquid Detergent

	Actual Market Share	Average Price	Std. Dev. Of Price	Brand Intercepts (BIV)	Net Market Share
Peapod (All purchases)					
Ajax	1.1	4.61	0.43	-4.38 (2.10)	2.98
All	6.3	5.43	0.65	-5.48 (5.42)	12.56
Arm & Hammer	2.1	4.60	0.45	-8.46 (6.31)	7.34
Cheer	9.4	6.19	0.60	-3.40 (2.17)	6.62
Era	2.2	5.28	0.33	-4.56 (3.05)	5.90
Store brand	1.7	4.41	0.39	-19.81 (13.42)	5.95
Tide	55.6	6.62	1.16	0.00	46.50
Wisk	16.3	7.07	0.86	-9.04 (6.81)	7.60
Yes	5.3	5.26	0.55	-48.22 (29.19)	4.55
Peapod (Category-based purchases)					
Ajax	1.9	4.60	0.44	-4.26 (0.43)	0.74
All	6.2	5.43	0.63	-8.40 (7.35)	10.35
Arm & Hammer	4.0	4.62	0.46	-6.76 (5.59)	9.22
Cheer	4.3	6.19	0.58	-4.23 (2.80)	6.21
Era	2.9	5.25	0.35	-3.92 (2.74)	7.06
Store brand	1.4	4.43	0.41	-25.65 (17.92)	6.74
Tide	56.5	6.50	1.18	0.00	47.70
Wisk	17.3	7.07	0.86	-5.82 (4.52)	7.90
Yes	5.5	5.25	0.58	-49.21 (29.20)	4.08
IRI (H-E)					
Ajax	2.7	4.60	0.30	-2.21 (0.12)	1.69
All	16.3	5.37	0.24	-1.03 (2.16)	13.49
Arm & Hammer	7.0	4.77	0.23	-1.68 (1.07)	4.44
Cheer	9.7	6.11	0.29	-1.15 (4.12)	23.71
Era	4.9	5.14	0.15	-1.95 (2.97)	11.86
Store brand	5.1	4.44	0.15	-6.11 (6.37)	10.20
Tide	36.3	6.73	0.68	0.00	15.26
Wisk	14.5	7.05	0.37	-1.10 (1.62)	9.77
Yes	3.5	5.10	0.13	-7.19 (7.15)	9.58

Notes: (1) The Average Price data is based on any Preferred Customer discount available in Peapod, whereas in IRI, it is based on prices listed in the supermarket. This could account for the higher variability in prices listed in Peapod for this product category. However, model coefficients in Peapod are based on the actual prices paid by the consumer.

(2) For brand intercepts, or brand intrinsic values, the numbers reported are the means and (standard deviations).

(3) Actual market shares are aggregated over SKU's of the same brand. Some brands have a large number of SKU's, while others have few. Therefore, some brands have low actual market shares, even though they have favorable intrinsic brand values. The number of SKU's for each brand are as follows: All (2), Ajax (2), Arm & Hammer (2), Cheer (3), Era (2), Store brand (1), Tide (8), Wisk (4), and Yes (2).

Table 5: Summary of Model and Coefficients for Soft "Light" Margarine Spread

Variable	Peapod All purchases	IRI (H-E)
# of individuals	55	50
# of choices	336	298
# of alternatives	4	4
# of brands	4	4
Fat (g/serv) – Mean – Std dev.	-1.17 (0.35) 8.19 (0.36)	1.66 (0.91) 2.58 (0.91)
LL (without price and promotion)	-108.0	-132.7
LL (Full model including price and promotion)	-107.5	-132.6

Notes:
(1) Numbers in parentheses are asymptotic standard errors.
(2) Brand intercepts are constrained to be orthogonal to fat.
(3) We did not have sufficient number of choices and individuals (41 households and 148 choices) to estimate the model of Category-based purchases.
(4) Price and promotion variables (Feature and Display in IRI, and promotion in Peapod) are not statistically significant in any of the models. This can be seen from the difference in log likelihood between the full model with price and promotion, and the selected model, which excludes these variables from the analysis.

Table 6: Brand Value Analysis for Soft "Light" Margarine Spread

	Actual Market Share	Fat Level	Average Price	Std. Dev. of Price	Brand Intercepts (BIV)	Net Market Share
Peapod (All purchases)						
Promise	11.9	6.0	1.52	0.18	-5.80 (17.86)	15.70
Fleischmann	22.9	4.5	1.56	0.19	2.21 (15.60)	23.68
Brummel & Brown	25.9	5.0	1.50	0.15	-3.31 (23.40)	26.61
I Can't Believe Its Not Butter!	39.3	6.0	1.47	0.11	6.90 (16.07)	34.01
IRI (H-E)						
Promise	26.2	6.0	1.53	0.11	-0.24 (5.23)	18.69
Fleischmann	7.0	4.5	1.53	0.13	-0.67 (6.47)	23.66
Brummel & Brown	37.9	5.0	1.48	0.04	1.00 (9.70)	42.96
I Can't Believe Its Not Butter!	28.9	6.0	1.45	0.01	-0.10 (4.11)	14.96

See notes under Table 4.

Table 7: Summary of Model and Coefficients for Paper Towel

Variable	Peapod			IRI (H-E) (Bias Corrected)
	Bias Corrected		Uncorrected All Purchases	
	All Purchases	Only category-based purchases		
# of individuals	192	166	192	136
# of choices	2270	927	2270	1575
# of alternatives	20	20	20	22
# of brands	4	4	4	4
Average Income ($ '000)	117.0	111.0	117.0	50.8
Price ($/100sq ft) – Mean	-11.55 (0.69)	-10.90 (1.01)	-8.31 (0.63)	-1.13 (0.30)
– Std. Dev.	6.47 (0.26)	7.28 (0.46)	7.00 (0.38)	0.00 (0.01)
Price*Income($ '0,000) – Mean	0.50 (0.04)	0.21 (0.06)	0.16 (0.05)	0.07 (0.04)
– Std Dev.	0.36 (0.02)	0.02 (0.06)	0.15 (0.02)	0.17 (0.02)
Promotion (0/1) – Mean	0.12 (0.13)	-0.07 (0.18)	-0.04 (0.13)	
– Std Dev.	0.23 (0.12)	0.19 (0.24)	0.52 (0.17)	
Feature (0/1) – Mean				1.02 (0.14)
– Std Dev.				0.01 (0.18)
Display (0/1) – Mean				1.52 (0.12)
– Std. Dev.				0.78 (0.10)
Printed Design (0/1) – Mean	-1.87 (0.15)	0.00 (0.17)	-0.63 (0.12)	0.32 (0.10)
– Std. Dev	4.91 (0.22)	3.89 (0.28)	3.43 (0.17)	1.43 (0.10)
Select-Size (0/1)	-2.03 (0.19)	-1.82 (0.34)	-2.08 (0.19)	1.40 (0.09)
LL	-2469.8	-1404.4	-2515.6	-2972.3
Corr(Price Coeff, Store Choice Error)	0.74 (0.01)	0.41 (0.04)		0.00 (0.10)
Market share gain to price promotion	14.1	17.5	11.4	26.5

Notes: (1) The number of alternatives in IRI is larger because of inclusion of two SKU's that had insignificant market shares in the Peapod data.

(2) Market share gain to price promotion is computed by discounting price by 35¢ per 100sq.feet featuring the product in Peapod (feature and put on display in IRI.

Table 8: Brand Value Analysis for Paper Towel

	Actual Market Share	Average Unit Price (100 sh)	Std. Dev. Of Price	Brand Intercepts (BIV)	Net Market Share
Peapod (All purchases)					
Bounty	50.8	1.60	0.02	0 (0)	40.48
Brawny	7.7	1.55	0.05	-6.27 (6.34)	10.71
Store brand	25.2	0.72	0.04	-6.51 (9.19)	18.44
Viva	16.3	2.26	0.04	-3.31 (9.24)	30.36
Peapod (Category-based purchases)					
Bounty	43.0	1.60	0.02	0 (0)	53.26
Brawny	8.1	1.55	0.06	-3.08 (3.12)	13.89
Store brand	25.7	0.72	0.06	-6.35 (3.11)	2.40
Viva	23.2	2.26	0.05	-4.45 (9.41)	30.44
IRI (H-E)					
Bounty	34.5	1.48	0.08	0 (0)	23.01
Brawny	16.0	1.46	0.12	-0.91 (1.67)	15.53
Store brand	31.9	0.71	0.05	-1.09 (2.97)	22.24
Viva	17.6	2.13	0.08	0.23 (3.19)	39.22

Notes: (1) The number of SKU's for each brand are as follows: Bounty (Peapod 7, IRI 8), Brawny (7) Store brand (Peapod 6, IRI 7), Viva (4).

(2) See also notes under Table 4.

Table 9a. Hypothesized Differences Between Online and Offline Supermarkets

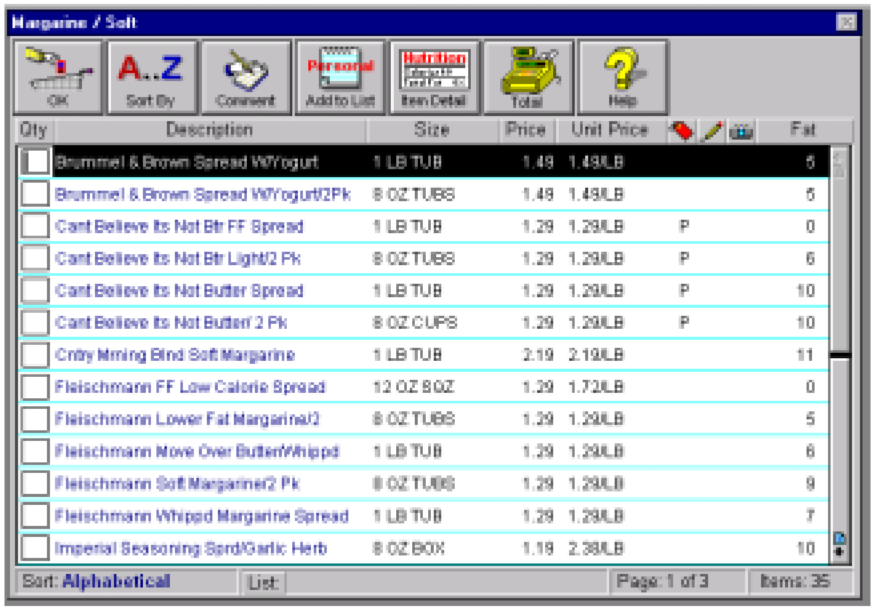
Hypothesis	Liquid Detergent	Soft spread Margarine	Paper Towel
Sensory Attributes (H1a)	Smaller		Smaller
Non-Sensory Attributes (H1b)		Larger	
Brand Name (H2)	Larger	Smaller	Larger
Price (H3)	Smaller	Smaller	Smaller

"Smaller" = impact is smaller online than offline.
"Larger" = impact is larger online than offline

Table 9b: Summary of Results

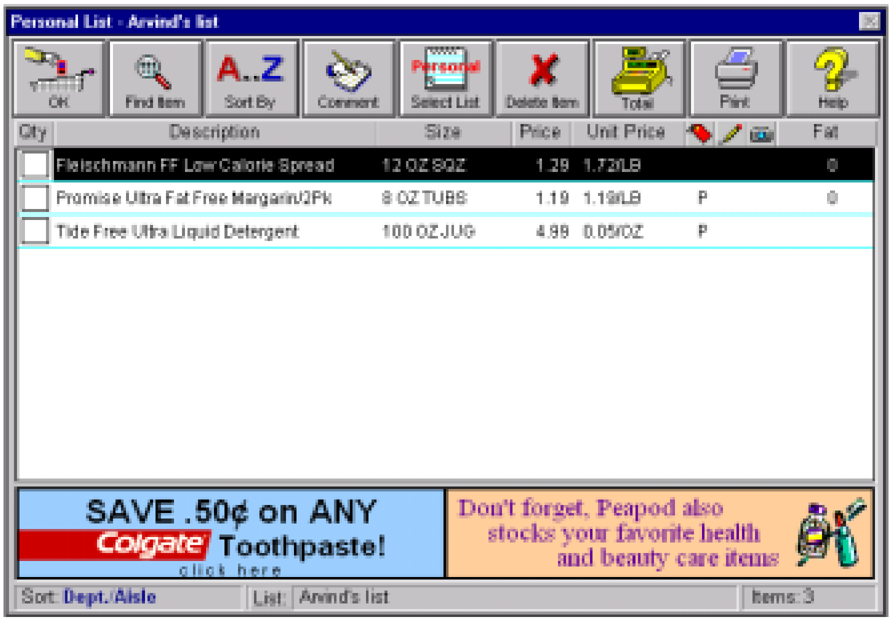
Hypothesis	Liquid Detergent	Soft spread margarine	Paper towel
Sensory Attributes (H1a)	Supported		Supported
Non-sensory Attributes (H1b)		Supported	
Brand name (H2)	Supported	Supported	Supported
Price (H3)	Indirectly Supported	N/A	Indirectly Supported

Figure 1
A Screen Display for Margarine Category in Peapod



This screen shows the default list of search attributes available to consumers in the margarine category. The tag symbol indicates whether the product is on promotion. A “P” in this column indicates that the product is available at a special price to preferred customers who have a store card. A “*” in this column would indicate that the product is on a “Special promotion,” available to all customers. The camera icon indicates whether a product picture is available (no pictures are available in the margarine category at this time). The column labeled Fat provides information on fat content. The **Sort By** button allows consumers to sort the information presented on one criterion at a time. The sort criteria available are: Alphabetical, Calories, Carbohydrates, Cholesterol, Dept/Aisle, Dietary Fiber, Fat (shown by default in all food categories), Kosher, Price, Protein, Size, Sodium, Specials, Sugar, and Unit Price.

Figure 2: An example of a personal list in Peapod



In this example, the member can shop for the items listed in the personal list without having to go to the category aisle. Note, however, that the personal list includes the current price and promotion information