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Usage Experience with Decision Aids and Evolution of Online Purchase Behavior

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Report Summary

Internet retailing has experienced explosive growth for over a decade. As more shoppers begin to make purchases online, it is important to understand how they adapt to this increasingly prominent channel, whether their purchase behavior evolves as they gain more experience with the new shopping environment, and what may drive this evolution. In this study, Savannah Wei Shi and Jie Zhang conduct an empirical investigation on whether and how usage experience with decision aids in an Internet shopping environment may drive the evolution of online purchase behavior, and what roles different types of decision aids may play in the process.

In the context of online grocery stores, they categorize four types of decision aids that are commonly available, namely, (1) those for nutritional needs, (2) those for brand preference, (3) those for economic needs, and (4) personalized shopping lists. The data used in this study are provided by a leading Internet grocery retailer which was among the first to sell groceries online. The dataset was collected during the period when the retailer first launched its web business, which makes it particularly suited to study the evolution of online purchase behavior.

The authors construct a Non-homogeneous Hidden Markov Model (NHMM) of category purchase incidence and purchase quantity, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids. To check the robustness of the findings, they estimate the model on data from two distinct product categories—spaghetti sauce and liquid laundry detergent.

They find that consumers evolve through distinct states of purchase behavior as they become more accustomed to an online store environment. On average, consumers become more loyal to the store and exhibit stronger habitual behavior over time. While their average level of price sensitivity increases first and then decreases, individual consumers show divergent patterns, with some becoming more price-sensitive and others evolving in the opposite direction.

Most importantly, the authors find that consumers' usage experience with online decision aids indeed drives their purchase behavior evolution in the new shopping environment, and the effect of a particular decision aid depends on the specific behavioral state a consumer is in.

Specifically, usage experiences with personal shopping lists and previous order lists increase store loyalty, while those with sorting by brand name and by price decrease store loyalty (when consumers are at an earlier stage of purchase behavior evolution). In terms of the effects on price sensitivity, personal shopping lists and previous order lists have the most prominent effects, and they can significantly reduce price sensitivity in both purchase incidence and quantity decisions.

Findings from this study provide valuable insights for online retailers to improve the design of their store environment, and to modify promotion messages adaptively according to consumers' evolving purchase behavior.

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Introduction

Internet retailing has experienced explosive growth for over a decade. As more shoppers begin to make purchases online, it is important to understand how they adapt to this increasingly prominent retail channel and whether their purchase behavior evolves as they gain more experience with the new shopping environment. Prior research has examined the impact of the Internet environment on purchase decision processes (e.g., Bechwati and Xia 2003; Häubl and Trifts 2000; Hollander and Rassuli 1999; Lee and Geistfeld 1998), and the differences between online and offline purchase behaviors (e.g., Danaher, Wilson, and Davis 2003; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009). What is lacking in the literature is a comprehensive examination of the patterns of purchase behavior evolution in online stores, such as in terms of purchase tendency and price sensitivity, and more importantly, what may drive these behavior changes over time.

It is well documented that the store environment can influence a consumer's decision making process (e.g., Park, Iyer, and Smith 1989; Inman, Winer, and Ferraro 2009). A distinct feature of the Internet shopping environment is the ability to offer a variety of interactive decision aids which can facilitate consumers' shopping processes. For example, many online retailers provide decision aids that allow shoppers to sort alternatives or filter them with certain criteria, to create personalized shopping lists, or to check total basket spending. Studies have shown that this kind of interactive decision aids can influence consumers' information search processes, purchase outcomes, and satisfaction (e.g., Bechwati and Xia 2003; Häubl and Trifts 2000; Hollander and Rassuli 1999; Lee and Geistfeld 1998). Therefore, one can speculate that, as online shoppers accumulate more experience with using various decision aids, their purchase behavior may also change over time as a consequence.

Online purchase behavior has been shown to be systematically different from offline purchase behavior (e.g., Danaher, Wilson, and Davis 2003; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009). The observed behavioral discrepancy can be attributed to two broad sources: differences in intrinsic characteristics between online and offline consumers, and differences in the shopping environments (Zhang and Wedel 2009). Researchers have postulated that interactive decision aids available in online stores can train consumers to shop in certain fashions, which would attribute to purchase behavior differences in the two types of shopping environments (e.g., Alba et al. 1997; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009). We intend to provide an empirical test of this conjecture and shed light on whether decision aids available in online stores indeed lead to purchase behavior changes for the same consumer over time.

Like the above mentioned previous studies that compare online and offline purchase behavior, our empirical investigation is carried out in the context of Internet grocery stores. After initial struggles and some high profile failures, online grocery retailing has shown a resilient comeback and experienced steady growth in recent years. According to a recent report by the Nielsen Company, online grocery retailing has grown at a more than 20% compound annual rate since 2003 and attracts 13 million U.S. Internet users by July 2009 (Swedowsky 2009). Findings from our study will be relevant to a wide range of companies, especially as many powerful brick-and-mortar retailers (e.g., Safeway, Albertson, Wal-Mart) as well as Internet retailers (e.g., Amazon.com) venture into the online grocery retailing business.

The main objective of this study is to conduct an empirical investigation on whether and how usage experience with various decision aids may drive the evolution of online purchase behavior over time, and what roles different types of decision aids may play in the process. Our data are provided by a leading Internet grocery retailer which was among the very first to sell groceries online. The dataset was collected during the period when the retailer first launched its web-based operation, which makes it particularly appealing to study the evolution of online purchase behavior. It includes detailed click-stream navigation information as well as individual household purchase history data in multiple product categories, and thus allows us to identify the patterns of decision aid usage and to link it to household purchase behavior.

We construct a Non-homogeneous Hidden Markov Model (NHMM) of category purchase incidence and purchase quantity, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids. The Hidden Markov Model is well suited for the purposes of this study. Prior research has classified shopping behavior into different states, such as for "hedonic" and "utilitarian" motivations (Babin, Darden, and Griffin 1994; Childers et al. 2001; Hirschman and Holbrook 1982). These studies suggest that online shopping behavior is also likely to be directed by certain latent "behavior states", and the store environment may train consumers and change their behavior states over time. Our model is built to identify these latent states and examine how usage experience with various interactive decision aids may drive transitions between these states.

We intend to address the following managerial questions in this study: 1) Will shoppers exhibit more habitual behavior as they get accustomed to an online store, or are they more likely to engage in on-the-spot decisions as they become more experienced and efficient with using interactive decision aids? 2) How will this affect their tendency to make purchases from an online store and their price sensitivity? 3) What kind of decision aids can mitigate price competition? 4) What kind of decision aids may increase consumers' loyalty to an online store? and 5) How can marketers influence consumers' behavior evolvement by utilizing various decision aids in online stores? Answers to these questions will provide value insights for online retailers to improve the design of their store environments and to modify communication messages adaptively according to consumers' evolving purchase behavior.

The rest of the report is organized as follows. In the next section, we describe the conceptual development and provide a brief review of the relevant literature. We then specify the model formulation, followed by the empirical analyses and results. Finally, we summarize the key findings of the study and discuss their managerial implications.

Conceptual Development and Literature Review

In this section, we present the conceptual development of our study and provide an overview of the relevant literature.

Online decision aids

Online stores can make shopping processes easier and more convenient by offering a variety of interactive decision aids. These decision aids allow consumers to perform a more "thorough and exhaustive search" (Hollander and Rassuli 1999; Lee and Geistfeld 1998). They enable online shoppers to make better purchase decisions and doing so with less effort (Häubl and Trifts 2000). Interactive decision aids are especially popular in online grocery stores. We classify four types of decision aids that are commonly available in these stores.

Decision aids for nutritional needs. Many online grocery stores provide decision aids to facilitate the shopping process for consumers who have special dietary needs (Swedowsky 2009) or are concerned of nutritional information. These decision aids include sorting functions (such as "by calories", "by cholesterol", "by sugar", and "by fat") and precluding functions (such as

“Kosher foods”, “organic food only”) to rank, compare, or filter the available alternatives with certain criteria. For example, www.groceryexpres.com offers 12 functions to fulfill consumers’ special dietary needs. www.freshdirect.com has 16 such functions. Growing health concerns among the public are believed to have contributed to the prevalence of such decision aids.

Decision aids for brand preference. In online stores, consumers with specific brand preference can choose their preferred products by the brand name using functions such as “sorting by brand/name” or “search by (brand name)”. This type of decision aids are ubiquitous in online stores (see www.freshdirect.com, www.coles.com, www.netgrocer.com for examples). Compared to in brick-and-mortar stores, they make the shopping process particularly efficient for consumers who have strong brand preferences by avoiding effortful navigations across physical shelves.

Decision aids for economic needs. Online decision aids such as “sorting by price”, “sorting by promotion”, or “club special first” (see www.freshdirect.com, www.safteway.com, www.peapod.com for examples) make the shopping process easier for price-sensitive consumers. Such decision aids facilitate price comparisons and might induce higher price sensitivity (Alba et al. 1997).

Personalized shopping lists. Some online stores offer consumers the option to create personal shopping lists or automatically save their previous order lists (such as www.peapod.com, www.freshdirect.com, www.safeway.com, and www.walmart.com). They allow consumers who are time-constrained or have relatively consistent shopping baskets to complete the shopping process quickly. Shopping lists can serve as a memory aid (Block and Morwitz 1999). Research has shown that consumers who use shopping lists tend to make fewer unplanned purchases (Inman et al. 2009). We speculate that usage experience with shopping lists may train consumers to engage in habitual decision processes.

Although the specific context of our study is online grocery stores, most of the decision aids classified above, with the exception of those for nutritional needs, apply to other types of retailers and product categories. These interactive decision aids offer online stores a unique advantage over their brick-and-mortar counterparts, by making the purchase decision process less effortful, more efficient, and more suited to individual’s needs and preferences. Therefore, they may also drive purchase behavior changes over time as consumers accumulate usage experience with them.

Evolution of online purchase behavior

In the context of offline stores and unfamiliar new product categories, Heilman, Bowman, and Wright (2000) show that consumers’ purchase behaviors exhibit evolving patterns as their experience with purchasing the category increases. They conjecture two competing forces that drive the purchase behavior evolution: consumers' desire to collect information about alternatives and their aversion to trying risky ones.

Given that the Internet shopping environment is distinctively different from traditional shopping channels with many unique features, shoppers new to the channel are likely to go through learning and adaptation processes, and thus their purchase behavior may also evolve over time. Prior research on channel migration indeed suggests that consumers’ purchase behavior may change over time once they start to make purchases online (e.g., Ansari, Mela, and Neslin 2008). Cheung et al. (2003) classify online shoppers into “intention”, “adoption” (purchase), and “continuation” (repurchase) types based on their purchase intentions. These different stages of purchase intentions may well apply to the same consumer over time and lead to behavioral changes as she learns and adapts to a new store environment.

Usage experience with decision aids and evolution of online purchase behavior

Researchers have postulated several factors that may contribute to the evolution of online shopping behavior over time, most of which are related to experience with the Internet. For example, comfort with the Internet (Mauldin and Arunachalam 2002), perceived ease of usage, and perceived usefulness of online shopping all exert a positive impact on the purchase intention from the Internet channel as a whole (Hoffman and Novak 1996; Chen, Gillenson, and Sherroll 2002; Limayem, Khalifa, and Frini 2000; Pavlou 2003). Consumers' comfort level with the Internet increases through more time spent online or repeated visits (Mauldin and Arunachalam 2002), which implies that their comfort with a particular online store is also likely to increase as they gain more experience with navigating the website and become more familiar with the decision aids available there. Positive experience with a website may in turn induce greater exploratory behavior on the site (Hoffman and Novak 1996; Mathwick and Rigdon 2004). These two processes could reinforce each other and accelerate the learning of decision aid usage. Therefore, as consumers' experience with decision aids accumulates, their propensity to purchase from an online store is likely to increase as well.

In terms of responsiveness to marketing mix variables, the influence of online decision aids is likely to be more nuanced. We focus on price sensitivity in this discussion. Usage experience with online decision aids may affect consumers' price sensitivities at both the store choice stage and the in-store purchase decision stage.

Many online stores allow consumers to create personal shopping lists and/or store other shopping-related information in their personal accounts. These decision aids could create a “lock-in” effect (Smith, Bailey, and Brynjolfsson 2000): a consumer who creates and uses personal shopping lists in one store may face higher switching costs if she decides to shop at other (online or offline) stores. In other words, price is not the only factor to be evaluated when determine where to shop (Bakos 2001). We expect that increased usage of personal shopping lists are likely to enhance consumers’ loyalty to the focal online store, induce habitual purchase behavior, and soften their price sensitivity when it comes to choose the shopping venue. This “lock-in” effect may also apply to other types of decision aids, such as those for nutritional needs.

The Information Integration Theory (Anderson 1971, 1981) provides some guidance in predicting the impact of decision aid usage experience on price sensitivity at the in-store purchase decision stage. According to the theory, certain attributes, such as brand or price, can surrogate information on other attributes if the latter has limited availability; yet when information on other attributes becomes available, weights of existing attributes will be reduced (Anderson 1971, 1981; Bettman, Capon, and Lutz 1975). In brick-and-mortar stores, consumers are more likely to focus on price-related information because it is easily available and highly salient with frequent feature and display advertisements (Degeratu, Rangaswamy, and Wu 2000). In contrast, interactive decisions aids available in online stores allow consumers to more efficiently access and utilize information on other product attributes. They now can find the product that meets their needs based on important attributes other than price at a lower search costs (Alba et al. 1997). This suggests that, at least for some consumers, the weight of price information is likely to reduce while the importance of other attribute information is likely to increase (Degeratu, Rangaswamy, and Wu 2000; Smith, Bailey, and Brynjolfsson 2000), and thus price sensitivity may decrease over time as a consequence for these consumers. On the other hand, online decision aids intended for economic needs make it easier for shoppers to use price related information more efficiently. Therefore, it is also possible that, at least for some consumers, experience with decision aids for economic needs will train them to be more price sensitive (Alba et al. 1997). We leave it as an empirical question regarding the evolving patterns of price sensitivity in online stores over time. More importantly, we intend to find out what types of decision aids may reduce price sensitivity and what types may have the opposite effects.

Model Formulation

This study investigates whether and how the usage experience with various online decision aids may affect consumers' purchase behavior evolution over time. We construct a Non-homogeneous Hidden Markov Model (NHMM) of category purchase incidence and purchase quantity, in which parameters are allowed to vary over time across hidden states as driven by usage experience with different decision aids.

The basic premise of our model is that consumers' purchase decisions at any given time is driven by the hidden behavior states they are in, where the hidden states differ in terms of the baseline tendency to purchase from the online store and their price sensitivity. Consumers are allowed to switch between these states as their experience with decision aids accumulates over time. We adopt a Type II Tobit model (e.g., Amemiya 1984) to jointly capture category purchase incidence and purchase quantity decisions, where parameters in the Tobit model evolve according to a Hidden Markov Model (HMM) with the transition probabilities assumed to be driven by the usage experience with various decision aids. Our model belongs to the category of Non-homogeneous Hidden Markov Models, because the transition probabilities are formulated as functions of time-varying covariates (see Hughes and Guttorp 1994).

A type-II Tobit model of category purchase incidence and quantity

Purchase incidence. Let U_{it}^{c} = household i's latent utility of purchasing category c from the online store in week t; I_{it}^{c} = 1 if household i makes a purchase of category c from the online store in week t, 0 otherwise. Without losing generality, we can scale U_{it}^{c} such that:

$$I_{it}^{c} \begin{cases} =1, & \text{if } U_{it}^{c} > 0 \\ =0, & \text{otherwise} \end{cases}. \tag{1}$$

The utility function is specified as:

$$U_{it}^{c} = \beta^{S} X_{t}^{c} + \varepsilon_{it}^{c}, \quad \varepsilon_{it}^{c} \sim N(0, \delta_{c}^{2}), \tag{2}$$

where X_{t}^{c} is a vector of marketing mix variables for category c in week t, and β^{S} is a vector of their coefficients (including the intercept) given that a household is in hidden state s. The intercept can be interpreted as a household's baseline tendency to purchase category c from the online store in a given state. In order to get clearly-defined interpretations of the hidden states, we choose to focus on price for the marketing mix component in our empirical analysis, because price sensitivity is a key aspect of household purchase behavior that we intend to study here. We fix $\delta_{c}^{2} = 1$ for identification purposes.

Purchase quantity. Purchase quantity is observed only when a household makes a purchase of the focal category from the online store. We denote Q_{it}^{c*} as household i's latent purchase quantity of category c in week t (measured in volume units such as ounces), and Q_{it}^{c} as the household's observed purchase quantity of category c in week t. Then,

$$Q_{it}^{c} = \begin{cases} = Q_{it}^{c*}, & \text{if } I_{it}^{c} = 1 \\ = 0, & \text{otherwise} \end{cases}. \tag{3}$$

We specify Q_{it}^{c*} as:

$$Q_{it}^{c*} = \varphi^{S} Z_{t}^{c} + \upsilon_{it}^{c}, \quad \upsilon_{it}^{c} \sim N(0, \sigma_{c}^{2}), \tag{4}$$

where Z_{t}^{c} is a vector of marketing mix variables for category c in week t, and φ^{S} is a vector of their coefficients (including the intercept) given that a household is in hidden state s. Like in the purchase incidence component, we use price as the key marketing mix variable in the empirical analysis in order to get a clean interpretation of the hidden states.

We take into account the interdependence of purchase incidence and quantity decisions by assuming that the error terms in Equations (2) and (4), ε_{it}^{c} and υ_{it}^{c}, follow a bivariate Normal distribution:

$$\begin{pmatrix} \upsilon_{it}^{c} \\ \varepsilon_{it}^{c} \end{pmatrix} \sim N\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{pmatrix} \sigma_{c}^{2} & \rho_{c}\sigma_{c} \\ \rho_{c}\sigma_{c} & 1 \end{pmatrix} \right). \tag{5}$$

The likelihood for household i in week t given hidden state s can be written as (see Amemiya 1984, page 31):

$$l\left(Q_{it}^{c} \mid \beta^{S}, \varphi^{S}\right) = \left(\frac{1}{(1-\rho_{c}/\sigma_{c})^{\frac{1}{2}}} \Phi\left(\beta^{S} X_{t}^{c} + \frac{\rho_{c}\left(Q_{it}^{c} - \varphi^{S} Z_{t}^{c}\right)}{\sigma_{c}} \right) * \ln \frac{1}{\sigma_{c}} \varphi\left(\frac{Q_{it}^{c} - \varphi^{S} Z_{t}^{c}}{\sigma_{c}} \right) \right)^{I_{it}^{C}} \left(\Phi\left(-\beta^{S} X_{t}^{C} \right) \right)^{(1-I_{it}^{C})}, \tag{6}$$

where $\varphi(\cdot)$ is the probability density function and $\Phi(\cdot)$ is the cumulative distribution function of the Standard Normal distribution, respectively.

Hidden states and transition probabilities

Our main research question is whether and how purchase behavior, as measured by the baseline tendency and price sensitivity in purchase incidence and quantity decisions, evolves with the usage experience with various decision aids. To this end, we model the evolution of the hidden-state-specific parameter vectors β^{S} and φ^{S} in the Tobit model according to a Markov transition matrix P_{it}, the elements of which are specified as functions of usage experience with various decision aids. In our model, consumers are allowed to switch back and forth between the hidden states.

We model the probabilities of switching from hidden state S_{t-1} in week t-1 to hidden state S_t in week t for household i in a K-state NHMM using the ordered logit formulation (see Netzer, Lattin, and Srinivasan 2008, page 190):

$$
\begin{aligned}
&P_{it}(S_t = 1 \mid S_{t-1}, D_{it}) = \frac{\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1+\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},\\
&P_{it}(S_t = 2 \mid S_{t-1}, D_{it}) = \frac{\exp(\lambda_{i2,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1+\exp(\lambda_{i2,S_{t-1}} - \gamma_{s_{t-1}} D_{it})} - \frac{\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1+\exp(\lambda_{i1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},\\
&\ldots\ldots \\
&P_{it}(S_t = K \mid S_{t-1}, D_{it}) = 1 - \frac{\exp(\lambda_{iK-1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})}{1+\exp(\lambda_{iK-1,S_{t-1}} - \gamma_{s_{t-1}} D_{it})},
\end{aligned}
\tag{7}
$$

where K is the number of hidden states. Parameters $\lambda_{i1,s_{t-1}}, \lambda_{i2,s_{t-1}}, \ldots, \lambda_{iK-1,s_{t-1}}$ are household i's state-specific cut-off points and their values are set in ascending order for a given $S_{t-1} \in \{1, 2, .., K\}$. D_{it} is a vector of household *i*'s usage experience variables for a set of decision aids, and $\gamma_{s_{t-1}}$ is a vector of their hidden-state-specific coefficients. In the empirical analysis, we categorize and examine six types of decision aids, including one for nutritional needs, one for brand preference, two for economic needs, and two for personalized shopping lists. Details of these decision aids and variable computation are described later.

Note that, in our model, consumer heterogeneity is accounted for by the individual-specific hidden state transition matrix. It captures individual differences in the behavior evolution, and thus accommodates heterogeneity in parameter values in the purchase incidence and quantity model. We estimate the proposed Hidden Markov model following established Bayesian estimation procedures (see Netzer, Lattin, and Srinivasan 2008 for detailed descriptions).

Empirical Analyses

Data description

Our data are provided by a leading Internet grocery retailer which was among the very first to sell groceries online in the United States. The dataset was collected during a 62-week period in 1996-1997 when the retailer first launched its web business. Given that this retailer was a pioneer of the online grocery business, it is very likely that consumers in our data never had prior exposure to other online grocery stores. This feature makes our dataset particularly suited to study the evolution of purchase behavior in a new online shopping environment.

The data include click-stream records of detailed navigation processes, as well as marketing mix information and purchase history of 225 households in selected product categories. We estimate the proposed model using data of two distinct product categories, spaghetti sauce and liquid detergent, in order to test the robustness of the results. These categories are chosen because they differ in terms of hedonicity and purchase frequency, which have been shown to affect consumers' in-store decision making processes (Inman, Winer, and Ferraro 2009). Only those households that made at least two category purchases during the 62-week period are included in the estimation data for a category, which yields 137 households for spaghetti sauce and 159 households for liquid detergent.

Operationalization of key variables

As explained previously, for the purposes of this research, we use price as the key marketing mix variable in the purchase incidence and quantity model for the empirical analysis. We first obtain the weekly actual price (i.e., regular price minus price discount if any) of each stock-keeping units (SKU) in a category, and then convert it to a common unit price (e.g., cents per ounce). The category-level price variable is computed as a weighted average of the weekly unit prices of all SKUs in the category, where the weights are sales volume shares of the SKUs in the entire time period.

Decision aid usage information is extracted from the click-stream data. We identify six interactive decision aids that are commonly available in most online grocery stores. They fall into one of the four broad categories of decision aids described earlier, including one for nutritional needs, one for brand preference, two for economic needs, and two for personalized shopping lists (see Table 1, following References). For each decision aid, we measure a household's usage experience by week t as the cumulative number of usage counts up to the prior week t-1. This measure avoids possible reverse causality, that is, purchase behavior may influence the usage of decision aids on the current shopping occasion. Note that a household can use the same decision aid multiple times during a single shopping session and the cumulative experience variables count for each and every time a given decision aid is used by a household. A main objective of this research is to investigate how usage experience with different decision aids may drive purchase behavior changes over time. To this end, we include the usage experience variables of multiple decision aids in the transition probability functions of the proposed Hidden Markov Model. Since the usage experience with each decision aid increases monotonically with time and thus is highly correlated with each other, a more meaningful measure to include in the model is the relative usage experience for each decision aid, computed as a percentage of a household's total number of usage counts of all decision aids up to week t-1.

We also include the total decision aid usage variable to account for its potential effect on the transition probabilities.

Descriptive statistics of the usage experience variables and the key variables for each product category are presented in Table 2, following References. Note that the usage experience variables are store-level measures[1] and thus do not vary across categories[2]. For each decision aid examined, we report its cumulative usage counts and as a percentage of the total usage counts, for up to week t-1 as well as by the last week in the data (week 62). As the table shows, shopping list is the most frequently used decision aid (30.66 times in 62 weeks on average), far out-numbering the usage of the other types of decision aids, followed by previous order list (5.27 times), sorting by brand name (4.06 times), sorting by nutrition (1.93 times), sorting by price (1.17 times), and sorting by promotion (.38 times). As shown by the standard deviations, the experience measures vary substantially across individuals. Since we need to exclude at least one of the relative usage experience variables from the model to avoid perfect collinearity, we choose to take out sorting by promotion because it had the lowest occurrence among the six decision aids of interest.

Time-Varying patterns of usage experience with decision aids

To inspect how shoppers' usage patterns of the different decision aids may evolve over time, we take the average of each relative usage experience variable in a week across households and plot them over time (see Figure 1, following References). Note that the relative usage experience measures do not necessarily sum up to 100% in all weeks because some households had not tried

[1] We have also computed and tested category-specific usage experience variables in the model, and found that the store-level measures have better explanatory power.
[2] Their summary statistics in the estimation data can vary by categories due to difference in the household samples.

any decision aids in the earlier weeks. We find that the relative usage experience with personal shopping lists and previous order lists increases over time and dominates the other decision aids, while the relative usage experience with sorting by brand name, by nutritional information, by price, and by promotion levels off in the later stage of the observation period. Since the usage of personal shopping lists and previous order lists are indicative of habitual decision processes, while the usage of specific product attributes (such as nutritional information, brand name, price, and promotion status) suggests on-the-spot decision processes, the above time-varying patterns indicate that, on average, consumers tend to adopt more habitual behavior and make fewer on-the-spot purchase decisions as they become more accustomed to the type of online shopping environment as studied here.

Model estimation results

We compare the Bayesian Information Criterion (BIC), Deviance Information Criterion (DIC), and log-marginal densities of models with different numbers of hidden states to determine the best number of states for each category. These comparisons indicate that a three-state model fits the data best for both spaghetti sauce and liquid detergent. Estimation results of the three-state model for the two categories are presented in Tables 3 and 4 following References, respectively.

As shown in Table 3, households' purchase behavior differs substantially across the three hidden states for the spaghetti sauce category. By the construction of the model, the baseline purchase incidence tendencies are in ascending order from hidden state 1 (S1) to hidden state 3

(S3). Our model estimation result shows that the same order of baseline tendency also holds for purchase quantity decisions across the three states, even though the parameters are not constrained to be so. Price has a negative and "significant" effect on the purchase incidence probability in all three states[3], but its effect is the largest in S2 (-.621), followed by S1 (-.144), and is the smallest in S3 (-.005). The same order of price sensitivity also holds for the purchase quantity decision. Thus, S1 represents a low baseline purchase tendency (i.e., store loyalty[4]) and medium price sensitivity state, S2 is characterized by medium baseline purchase tendency and the highest price sensitivity, and S3 exhibits the highest baseline purchase tendency and the lowest price sensitivity.

The three hidden states of the liquid detergent category show very similar patterns, and can be interpreted in the same fashion (see the upper panel of Table 4).

The lower panels of Tables 3 and 4 report parameter estimates of the variables in the transition probability functions between hidden states. For the spaghetti sauce category, when consumers are in S1 (low purchase tendency and medium price sensitivity), more usage experience with sorting by brand name significantly increases the probability of staying in S1 and reduces the probability of switching to the more store-loyal states S2 and S3, while the total decision aid usage significantly increases the probability of switching to a more store-loyal state. When consumers are in S2 (medium purchase tendency and highest price sensitivity), more usage experiences with sorting by brand name and sorting by price discourage the transition to S3 while encourages the transition to S1, while more usage experiences with sorting by nutrition and personal shopping lists have the opposite effects. When consumers are in S3 (highest

[3] For the ease of exposition, hereafter, we report the posterior means in parentheses and use the term "significant" to refer to the cases where the posterior 95% credible interval does not cover zero.
[4] Throughout our discussion, we use the term "store loyalty" to refer to category-specific store loyalty, a concept described by Bell, Ho, and Tang (1998) among others.

purchase tendency and lowest price sensitivity), more usage experiences with personal shopping lists and previous order lists increase the probability of staying in S3 and reduce the chance of switching to a less store-loyal state, while usage experiences with sorting by brand name and by price do not have any significant effects any more. A plausible reason for the negative effect of usage experience with sorting by brand on store loyalty is that it could strengthening consumers' brand preference, which makes them more willing to switch stores if their preferred brands are not available in the focal store.

The effects of the usage experience variables exhibit a similar pattern in the liquid detergent category. When consumers are in the least store-loyal state (S1), more usage experience with sorting by brand name discourages switching to the states with higher levels of store loyalty (S2 and S3). When consumers are in the medium store-loyalty state (S2), usage experiences with sorting by brand name and sorting by price increase the probability of switching to S1 and reduce the probability of switching to the more store-loyal state (S3), while usage experiences with personal shopping lists and previous order lists, as well as the total decision aid usage count, have the opposite effects. Exactly like in the spaghetti sauce category, when consumers are in the most store-loyal state (S3), usage experiences with personal shopping lists and previous order lists and the total decision aid usage count reinforce the probability of staying in this state and decrease the chance of switching to a less store-loyal state, while usage experiences with sorting by brand name and by price no longer have any significant effects.

An interesting contrast with results of the spaghetti sauce category is that, for the liquid detergent category, usage experience with sorting by nutrition does not have any effects on the purchase behavior evolution. This difference between the two categories is expected, and it attests to the ability of our model to detect the distinct effects (or the lack thereof) of usage experience with different decision aids.

The above results indicate that usage experience with decision aids indeed contributes to purchase behavior changes over time, and that the effect of a particular decision aid depends on the specific "behavioral state" a consumer is in. The total usage experience of decision aids can increase consumers' loyalty to an online store, at least in certain stages of the evolution process. Nonetheless, the effect of usage experience varies by different types of decision aids: while more experience with sorting by nutrition, personal shopping lists and pervious order lists can increase store loyalty, experiences with sorting by brand name and by price appear to have the opposite effects.

Evolution of purchase behavior in the online store

Our model estimation results clearly indicate that consumers switch between distinct behavioral states and the transition between these states is influenced by their usage experience with various decision aids. This implies that their purchase behavior may evolve over time in a certain direction when shopping in a new online store environment. To investigate the time varying patterns of their purchase behavior, we need to compute the posterior distribution of the three states for each household in each week, and then explore the relationship between price sensitivity measures and the usage experience variables.

Probabilities of belonging to the hidden states. To better understand the evolution patterns of purchase behavior, we examine the probabilities of belonging to the hidden states over time. We first compute each household's filtering probability of belonging to state s in week t based on posterior analysis, and then plot the average probabilities of belonging to the three states over time across all households in the data (see Figure 2, following References). For the spaghetti sauce category, the average probability of belonging to S1, which has the lowest store loyalty and medium price sensitivity, decreases substantially over time (from 67.9% in week 1 to 16.0% in week 62). In contrast, the average probabilities of belonging to S2 and S3 increase over time (from 19.0% in week 1 to 30.5% in week 62 for S2; from 13.1% in week 1 to 53.5% in week 62 for S3). On average, consumers are more likely to be in S1 than in the other two states in the first half of the observation period (till week 32), while they are more likely to be in S3, the state with the highest store loyalty and lowest price sensitivity, from week 32 and on. A very similar pattern appears in the liquid detergent category: the average probability of belonging to S1 declines while those for S2 and S3 increase over time, and S3 becomes the dominant behavior state slightly after the midpoint of the observation period (week 39), for the average consumer.

Evolution of price sensitivity over time. Since the purchase behavior states identified by our model are not in ascending or descending order in terms of price sensitivity, we cannot infer the direction of price sensitivity changes and the relationship between decision aid usage experience and price sensitivity directly from the model estimation results. Therefore, we first compute a posterior price sensitivity measure for each household in each week, and then analyze the relationship between it and the usage experience variables. This price sensitivity measure is a weighted average across hidden states, weighted by a household's posterior probability of belonging to each state in each week, and integrated over the posterior distribution of the price coefficients[5]. In Figure 3, following References, we plot the means and standard deviations of the price sensitivity measure for spaghetti sauce and liquid detergent, respectively.

For both categories, the average values of price sensitivity in purchase incidence and purchase quantity decisions firstly increase and then decrease over the observed period (see the

[5] The integration is approximated by the average value across the last 1,000 draws from the estimation procedure.

upper panels in Figure 3). In addition, the standard deviations of these measures increase continuously over time, indicating that consumers' price sensitivity diverges over time, with some becoming less price-sensitive while others becoming more price-sensitive, as they become more accustomed to an online store environment (see the lower panels in Figure 3). Prior research shows that a higher degree of heterogeneity in price sensitivity is conducive to more granular price promotion customization (Zhang and Wedel 2009). The patterns of divergence of price sensitivity over time revealed by our analysis suggest that online retailers have a good opportunity to customize their price promotions to cater to individual needs and preferences, as consumers become more used to shopping online.

Effects of decision aid usage experience on price sensitivity. As explained previously, we cannot infer how decision aid usage experience affects consumers' price sensitivity directly from the parameter estimates. To investigate this issue, we conduct regression analyses where the dependent variable is the price sensitivity measure for the purchase incidence or quantity decision, and the explanatory variables are the relative usage experience measures of different decision aids. To be consistent with the main model, we also include "Total Decision Aid Usage" as an explanatory variable in this analysis. We use a random-effect model to allow heterogeneity in price sensitivity across households. The price coefficients are estimated from the models, and thus the dependent variables are measured with uncertainty. Since the posterior distributions of the price coefficients are unknown (and therefore not necessarily Normal), we use the simulated maximum likelihood estimation (SMLE) method to estimate the models, where the draws of the price coefficients are a natural by-product from the MCMC procedures of the main model estimation. We use the last 1,000 draws of each MCMC procedure for the SMLE.

Table 5 presents the results of these regression analyses. For spaghetti sauce, the most prominent effects are those of usage experiences with personal shopping lists and previous order lists which significantly reduce consumers' price sensitivity in purchase incidence decisions, and the former also has a marginally significant effect for purchase quantity decisions. Interestingly, relative usage experience with sorting by brand name marginally increases price sensitivity in purchase incidence decisions, while experience with sorting by price does not appear to have any significant effect on price sensitivity in this category. For liquid detergent, usage experiences with personal shopping lists and previous order lists also have the most prominent effects, significantly reducing price sensitivity in both purchase incidence and quantity decisions. In addition, usage experience with sorting by price significantly increases price sensitivity when it comes to purchase incidence decisions, while sorting by brand name does not appear to have any "significant" effects in this category. While the effect of experience with sorting by price or by brand name may be unique to the product category, results from both categories consistently show that online retailers can mitigate consumers' price sensitivity by making available and encouraging them to use personal shopping lists and previous order lists. As discussed previously, experiences with these two decision aids also enhance consumers' loyalty to the focal online store. Combining results from the above analyses, it is clear that, among the decision aids examined in this study, personal shopping lists and previous order lists are most influential in driving consumers' purchase behavior evolution in the store and are also the most beneficial ones to the online retailer --- they can enhance store loyalty and mitigate price competition. Between these two decision aids, the effects of personal shopping lists are even stronger, which implies that online retailers should pay particular attention to it and make sure that their stores offer the ability for consumers to create and store their personal shopping lists.

Summary and Discussion

In this study, we have conducted an empirical investigation on whether and how the usage experience with various interactive decision aids drives the evolution of purchase behavior in an online store. We estimate the proposed model for two distinct product categories (spaghetti sauce and liquid detergent) to check the robustness of the results. The following is a summary of our key findings:

1) Among the decision aids examined in this study, personal shopping lists and previous order lists are the most frequently used. Consumers exhibit stronger habitual behavior and make less on-the-spot purchase decisions as they become more accustomed to the online store environment studied here.
2) Consumers evolve through distinct states of purchase behavior as they gain more experience with the online store environment. On average, they become more loyal to the focal store. While their average level of price sensitivity first increases and then decreases, individual consumers show divergent patterns, with some becoming more price-sensitive while others evolving in the opposite direction.
3) Consumers' usage experience with online decision aids indeed drives their purchase behavior evolution in the new shopping environment, and the effect of a particular decision aid depends on the specific "behavioral state" a consumer is in. Moreover, the effects differ by the specific decision aids. Specifically, those with personal shopping lists, previous order lists increase store loyalty, while usage experiences with sorting by brand name and by price decrease store loyalty (when consumers are in the earlier stages of purchase behavior

evolution). In terms of effects on price sensitivity, personal shopping lists and previous order lists have the most prominent effects, and they can significantly reduce price sensitivity in both purchase incidence and quantity decisions.

The above findings are supported by results from both product categories. Our analysis also reveals some category-specific effects. In the spaghetti sauce category, for which nutritional information represents relevant product attributes, usage experience with sorting by nutrition can increase consumers' baseline tendency to make purchases from the focal online store and thus enhance their store loyalty. We did not find this effect in the liquid detergent category, which is expected because nutritional information is irrelevant to this category. Based on the contrast of the two product categories, we speculate that the effect of usage experience with sorting by nutrition on store loyalty is likely to apply to other product categories for which nutritional information is relevant. We also find that price sensitivity in purchase incidence decisions can be intensified by usage experience with sorting by brand name for spaghetti sauce, and by usage experience with sorting by price for liquid detergent. Each of these effects may be related to idiosyncratic characteristics of the category, and we are not certain how generalizable they are to a broader range of product categories.

As discussed previously, prior research has found systematic differences in consumers' purchase behavior in online and offline stores. In addition to differences in the intrinsic characteristics between online and offline consumers, it has been postulated that unique features in the online shopping environment may also contribute to the observed behavioral differences (e.g., Alba et al. 1997; Degeratu, Rangaswamy, and Wu 2000; Zhang and Wedel 2009). Results from our study provide empirical support to this conjecture. We find that the same consumer's purchase behavior evolves through distinct hidden states over time in an online store, and that the behavior changes can be attributed to his/her usage experience with interactive decision aids which are unique to the Internet shopping environment. Therefore, the purchase behavior differences between online and offline consumers are not just caused by self-selection, and differences in the store environments indeed play an important role. Our study also points to the specific causes for certain behavioral differences reported previously. For example, in the context of grocery products, Zhang and Wedel (2009) find that online consumers are less sensitive to price promotions and more state-dependent than their offline counterparts. Our analysis indicates that online consumers' usage experiences with personal shopping lists and previous order lists have contributed to this pattern.

Understanding how consumers' purchase behavior evolves over time as their experience with decision aids accumulates can offer valuable insights for online retailers to improve the design of their store environments. Our analyses indicate that, among the decision aids examined in this study, usage experiences with personal shopping lists and previous order lists have the most prominent effects and are also the most beneficial ones to the online retailer. They not only enhance consumers' store loyalty but also can mitigate the pressure of price competition. For online retailers selling frequently-purchased-low-involvement products, such as grocery, it is important to make available these decision aids and proactively remind and encourage consumers to use them. We also find that, between these two decision aids, personal shopping lists have even stronger (and more positive) effects, which implies that online retailers should give special priority to it and make sure that their stores offer the ability for consumers to create and store their personal shopping lists.

The effects of usage experiences with sorting by brand name and by price, two of the most widely available online decision aids, should bring caution to Internet retailers. We find that, when online consumers are in the earlier stages of their purchase behavior evolution (lower store loyalty and higher price sensitivity), more usage experience with sorting by brand name increases their probability of staying in a less state-loyal state and discourages the transition to a more store-loyal state. A plausible reason is that usage experience with decision aids for brand preference can train consumers to be more brand-loyal, and if their preferred brands are unavailable in the focal store, they are more likely to switch stores. For online retailers, especially those with fairly narrow assortment, it is important to keep in mind that if decision aids for brand preference is provided yet consumers' preferred brands are missing, they are likely to lose store loyalty from relatively new customers. This problem should be less of a concern for well-established online retailers that have already built up a stable customer base.

Usage experience with sorting by price also reduces store loyalty, especially when consumers are in a highly price sensitive state. It could also intensify their price sensitivity, as shown by the results from the liquid detergent category. This implies that decision aids aimed at economic needs are a double-edged sword. A low-price online retailer could benefit from higher consumer responsiveness to price by providing and encouraging the usage of this type of decision aids, but usage of these decision aids could lower consumers' loyalty to the store in the long run. In addition, frequent usage of them can negatively affect the long-term business for retailers that adopt a premier pricing strategy and do not compete on promotions. What decision aids to offer and to emphasize should depend on an online retailer's overall positioning and pricing strategies, and weigh in the trade-offs of the retailer's short-term versus long-term needs.

Last but not least, this study offers some suggestions on how to modify promotion messages adaptively according to consumers' evolving purchase behavior in an online store. We find that the effect of usage experience with a particular decision aid depends on the specific "behavioral state" a consumer is in, which indicates the importance of tracking consumers purchase behavior if an online retailer wishes to fully utilize the potential of its online decision aids. Our proposed Non-homogeneous Hidden Markov Model of category purchase incidence and purchase quantity empirically identifies consumers' hidden purchase behavior states. Based on the model estimation results and through posterior analysis, one can categorize the most likely behavior state that a consumer is currently in, which in turn would suggest the type(s) of decision aids that an online retailer should emphasize in its tailored communications to individual consumers. For example, based on results from the spaghetti sauce category, an online retailer should encourage a consumer new to its store to try out various decision aids available in the store except sorting by brand name, should emphasize sorting by nutrition and creating/using personal shopping lists to a consumer who is in the medium-store-loyalty-high-price-sensitivity state, and should continue to emphasize personal shopping lists and remind him/her of the firm-provided previous order lists to a consumer who is already in the high-store-loyalty-low-price-sensitivity state.

We have conducted our empirical analyses in the context of an online grocery store in this study. One important direction for future research is to examine the usage experience of (potentially different) decision aids and purchase behavior evolution in other types of online store environments. In addition, it would be interesting to investigate whether there are carry-over effects of usage experience across product categories, i.e., would the usage experience in one product category affect the evolution of purchase behavior in other categories. The effects of the store-level usage experience variables demonstrated by our study strongly suggest such possibility. Given the proliferation of multi-channel retailing, another worthy direction is to study the impact of usage experience with online decision aids on offline purchase behavior, which would require matching online navigation data and offline purchase history data. All of these topics offer exciting venues for gaining deeper understanding of purchase behavior evolution in the ever-evolving retail environment.

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Table 1 Types of Online Decision Aids Examined

Broad Category	Decision Aid	Definition
For nutritional needs	Sort by Nutrition	Sort by nutritional criteria, including calories, sodium, fat, Kosher, sugar, carbohydrates, fiber, and cholesterol
For brand preference	Sort by Brand Name	Sort by brand name
For economic needs	Sort by Price	Sort by price information, including unit price and item price
	Sort by Promotion	Sort by promotion status
Personalized shopping list	Shopping List	Retrieve and use a personal shopping list
	Previous Order List	Retrieve and use a previous order list

Table 2 Descriptive Statistics

Store-Level Usage Experience with Decision Aids

Variable	Count		As a percentage of total decision aid usage (%)	
	Mean	**SD**	**Mean**	**SD**
Cumulative usage up to week t-1:				
--- Sort by Nutrition	1.06	4.23	3.96	9.85
--- Sort by Brand Name	2.32	6.36	7.99	16.60
--- Sort by Price	.75	2.25	2.91	8.81
--- Sort by Promotion	.25	.73	1.42	5.65
--- Shopping List	16.70	30.3	55.71	37.35
--- Previous Order List	2.71	5.75	12.42	21.73
--- Total decision aid usage	23.79	38.04		
Cumulative usage by week 62:				
--- Sort by Nutrition	1.93	6.30	4.55	9.19
--- Sort by Brand Name	4.06	8.52	10.29	17.74
--- Sort by Price	1.17	3.03	3.43	10.83
--- Sort by Promotion	.38	.91	1.50	5.34
--- Shopping List	30.66	47.18	63.67	31.36
--- Previous Order List	5.27	8.92	16.56	23.67
--- Total decision aid usage	43.47	57.17		

Category Purchase Behavior and Prices

Variable	Mean	SD
Category 1: Spaghetti Sauce (N = 137 households)		
Purchase frequency (times/per year)	5.63	6.15
Purchase quantity (ounces/occasion)	34.62	21.23
Price (cents/oz.)	8.64	.42
Category 2: Liquid Detergent (N = 159 households)		
Purchase frequency (times/per year)	5.53	6.49
Purchase quantity (ounces/occasion)	124.70	69.25
Price (cents/oz.)	6.67	.45

Table 3 Model Estimation Result for Spaghetti Sauce

	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
Variables in the Tobit Model	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Purchase Incidence									
Intercept	**-2.172**	-3.053	-1.288	-1.787	-2.148	4.170	**-1.080**	-1.255	-.847
Paid price	**-.144**	-.149	-.140	**-.621**	-1.202	-.034	**-.005**	-.007	-.003
Purchase Quantity									
Intercept	**.960**	.302	1.618	**2.192**	2.082	2.314	**2.257**	2.190	3.901
Paid price	-.279	-.605	.046	**-.926**	-1.718	-.135	.001	-.019	.021
	Hidden State 1 (S1)			**Hidden State 2 (S2)**			**Hidden State 3 (S3)**		
Variables in the Transition Probability Model	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Cut-off point 1	1.248	-.014	2.509	**2.066**	1.230	2.900	**.939**	.545	1.133
Cut-off point 2	**1.314**	1.182	1.443	2.648	-.875	6.171	**1.939**	.303	3.579
Sort by Brand Name	**-2.578**	-4.024	-1.131	**-1.071**	-1.459	-.683	-.621	-1.536	.293
Sort by Price	-.234	-1.072	.594	**-.420**	-.597	-.243	-.008	-.269	.253
Sort by Nutrition	-.838	-1.846	.171	**.411**	.019	.804	-.587	-2.330	1.161
Shopping List	1.182	-.051	2.414	**1.951**	.930	2.974	**.946**	.351	1.540
Previous Order List	-.458	-1.270	.350	.686	-.019	1.392	**.494**	.229	.758
Total decision aid usage	**1.153**	.647	1.658	2.013	-.008	4.035	.489	-.713	1.691

Note: The bold font indicates that the 95% credible interval does not cover zero.

Table 4 Model Estimation Result for Liquid Detergent

Variables in the Tobit Model	Hidden State 1 (S1)			Hidden State 2 (S2)			Hidden State 3 (S3)		
	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Purchase Incidence									
Intercept	**-.708**	-1.194	-.219	**1.228**	.102	1.027	**1.382**	.633	2.129
Paid price	-.228	-2.340	1.886	**-.496**	.121	-.733	**-.100**	-.116	-.084
Purchase Quantity									
Intercept	**-1.374**	-1.645	-1.103	3.102	-1.164	5.368	**3.922**	3.042	4.799
Paid price	-.858	-2.055	.338	**-1.440**	-1.569	-1.310	**-.120**	-.239	-.001
Variables in the Transition Probability Model	**Hidden State 1 (S1)**			**Hidden State 2 (S2)**			**Hidden State 3 (S3)**		
	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%	Posterior mean	Posterior 2.5%	Posterior 97.5%
Cut-off point 1	**-1.310**	-2.380	-.241	-.235	-.812	.342	**-1.073**	-1.851	-.296
Cut-off point 2	**-.954**	-1.029	-.876	**.701**	.279	1.123	**1.102**	.537	1.667
Sort by Brand Name	**-.380**	-.532	-.229	**-.104**	-.149	-.059	-.053	-1.711	1.604
Sort by Price	-.804	-1.616	.009	**-1.023**	-1.627	-.420	.157	-1.250	1.563
Sort by Nutrition	-.016	-.578	.546	.134	-1.603	1.870	.034	-1.439	1.509
Shopping List	.143	-.116	.399	**1.149**	.743	1.556	**1.927**	.790	3.061
Previous Order List	.765	-1.001	2.533	**.986**	.603	1.368	**.586**	.118	1.054
Total decision aid usage	1.457	-.220	3.158	**1.259**	.247	2.270	**1.277**	.923	1.627

Note: The bold font indicates that the 95% credible interval does not cover zero.

Table 5 Effects of Decision Aid Usage Experience on Price Sensitivity (Simulated MLE)

Spaghetti Sauce

	Purchase Incidence				Purchase Quantity			
	Estimate	**SE**	**t-stat**	***P*-value**	**Estimate**	**SE**	**t-stat**	***P*-value**
Intercept	.132***	.006	21.135	.000	.239***	.008	29.444	.000
Log(intercept_variance)	-1.251	1.255	-.997	.321	-1.353	2.191	-.618	.538
Sort by Brand Name	-.012*	.007	-1.760	.081	-.006	.014	-.401	.689
Sort by Price	-.011	.030	-.371	.711	-.011	.039	-.272	.786
Sort by Nutrition	.037	.101	.367	.714	.023	.032	.709	.480
Shopping List	.024***	.007	3.299	.001	.027*	.014	1.914	.058
Previous Order List	.008**	.004	2.193	.030	-.016	.039	-.399	.691
Total Decision Aid Usage	5.39E-05	6.52E-05	0.827	.410	4.54E-05	8.1E-05	.560	.576

Liquid Detergent

	Purchase Incidence				Purchase Quantity			
	Estimate	**SE**	**t-stat**	***P*-value**	**Estimate**	**SE**	**t-stat**	***P*-value**
Intercept	.200***	.003	63.405	.000	.718***	.057	12.551	.000
Log(intercept_variance)	-1.544***	.403	-3.828	.000	-1.417***	.186	-7.603	.000
Sort by Brand Name	-.002	.008	-.279	.781	-.007	.020	-.376	.708
Sort by Price	-.138**	.065	-2.128	.035	-.042	.034	-1.266	.208
Sort by Nutrition	.015	.018	.841	.401	.003	.004	.938	.350
Shopping List	.060***	.015	3.961	.000	.759***	.034	22.048	.000
Previous Order List	.031***	.012	2.689	.008	.054***	.009	6.210	.000
Total Decision Aid Usage	2.13E-05	2.64E-05	.810	.419	1.28E-05	2.01E-05	.639	.524

*: $p < .1$; **: $p < .05$; ***: $p < .01$

Figure 1

Time-Varying Patterns of Usage Experience with Decision Aids

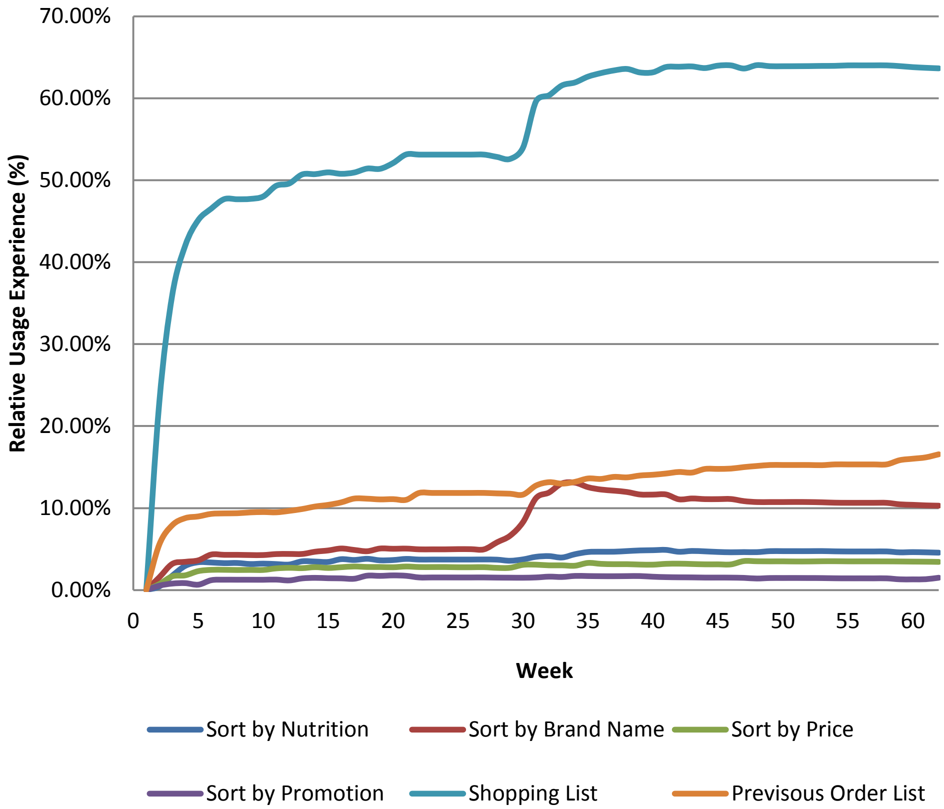
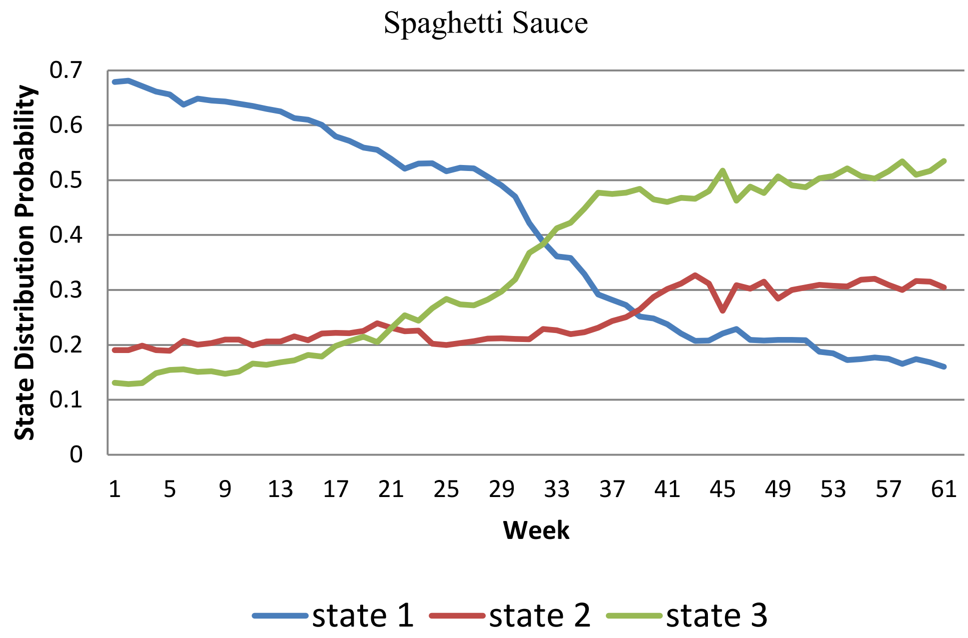


Figure 2 Evolution of Purchase Behavior over Time



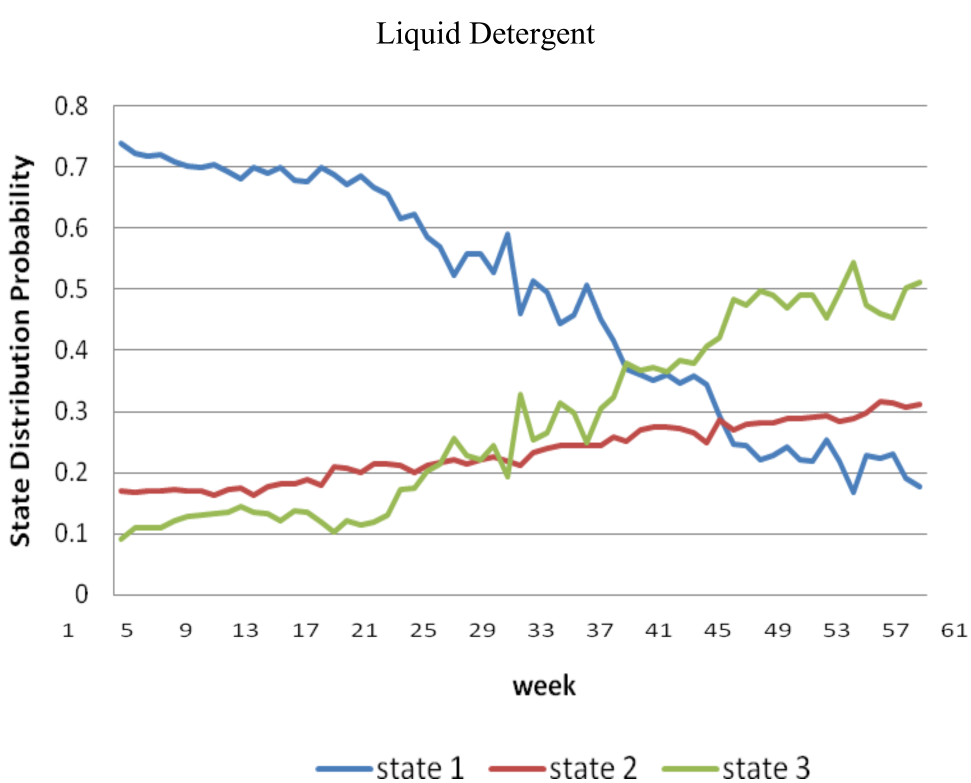


Figure 3 Evolution of Price Sensitivity over Time

Spaghetti Sauce

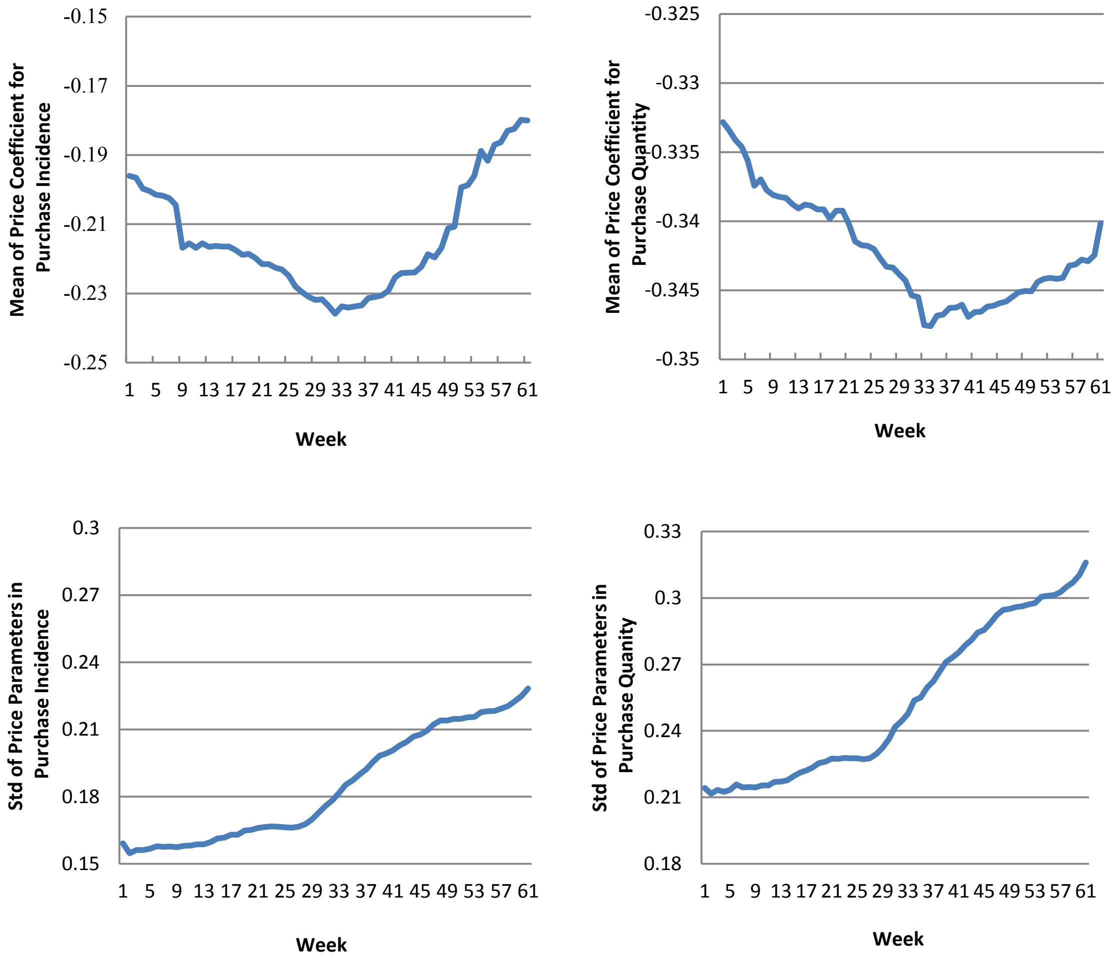


Figure 3 Evolution of Price Sensitivity over Time (continued)

Liquid detergent