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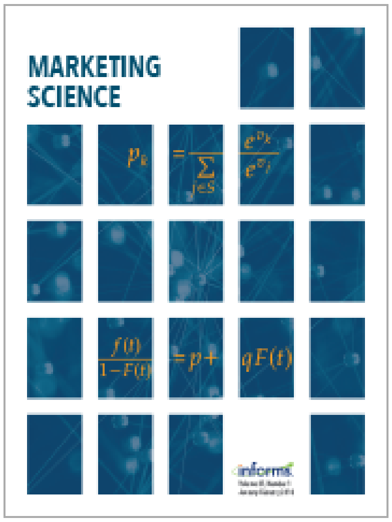

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Karthik Sridhar, Ram Bezawada, Minakshi Trivedi,

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Investigating the Drivers of Consumer Cross-Category Learning for New Products Using Multiple Data Sets

Karthik Sridhar
Dauch College of Business and Economics, Ashland University, Ashland, Ohio 44805,
ksridhar@ashland.edu

Ram Bezawada, Minakshi Trivedi
School of Management, State University of New York at Buffalo, Buffalo, New York 14260
{bezawada@buffalo.edu, mtrivedi@buffalo.edu}

Consumer new product adoption and preference evolution or learning may be influenced by intrinsic or internal factors (e.g., usage experiences, personal characteristics), external influences (e.g., social effects, media), and marketing activities of the firm. Moreover, the preference evolution in a certain category can spill over to other categories; i.e., consumers can exhibit cross-category learning. In this paper, we develop a multicategory framework to analyze the role of the above elements in the formation and evolution of consumer preferences across categories. We analyze these elements by employing multiple data sets, i.e., by combining revealed preference data (from scanner panel), stated data (from surveys measuring consumer lifestyle variables and demographics), and external influences (e.g., media mentions) in a completely heterogeneous framework while considering other facets of the learning process. By jointly estimating the model for organic purchases in six distinct food categories, we also explore the role of category differences. Results show that consumer new product adoption and learning is indeed impacted significantly and to various degrees by the aforementioned factors. We show how, by selectively encouraging purchases under various scenarios, firms can accelerate the learning process, not only for the focal category but also for other categories, thereby realizing considerable incremental profits. These results can be used by both manufacturers and retailers for more efficient allocation of marketing budgets across (new) products.

Key words: consumer new product adoption; multicategory models; sources of information; consumer learning; organic products; food products marketing
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1. Introduction

In today's turbulent marketplace, firms try to continuously introduce new products to gain a competitive edge, thereby enhancing their revenues and profits. Although sales of such products may initially be modest, they steadily evolve into distinct product groups. Examples include Blu-ray DVDs and smartphones for durables, and ethnic (e.g., Mexican entrées) and health (e.g., low carbohydrate/organic) products for packaged goods. For new product adoption to be successful, consumers may need to effectively mitigate the uncertainty that is typically associated with new products. Thus, understanding the factors that enable adoption and evolution of preferences for new products becomes a critical element for efficiently marketing them. Furthermore, comprehending the relative role of the salient factors that enable the above process may prove beneficial for developing superior promotional programs (Urban and Hauser 1993).

Consumer new product adoption and preference evolution occurs in a multifaceted manner. It can be driven by consumer-specific intrinsic factors, external influences, and marketing actions of the firm. To comprehensively discern this behavior, it is helpful to consider certain pertinent issues. For instance, consumers' choice of adopting a particular product depends on their decision to purchase in the category. Thus, new product adoption/learning relate jointly to incidence and new product choice, both of which are salient and managerially relevant depending on firm-specific objectives and marketing actions. Moreover, consumers' preference evolution in a certain category can spill over to other categories; i.e., they can exhibit cross-category learning.

In this paper, we develop a multicategory framework for analyzing the role of internal factors (e.g., consumption experiences), external influences (e.g., peers, media), and marketing mix variables on consumer new product adoption and preference evolution across categories, and we calibrate these factors using a unique data set comprising new product purchases. To accomplish this holistically, we employ multiple data sets by combining data relating to consumer revealed choices, stated preference, and external influences, and we track them from their very first purchase of the new product. We assess the relative role of these different factors on consumer learning for new products in a multicategory context. We show how, by encouraging purchases in the focal category, firms can accelerate the learning process, not only for this category but also other categories. Thus, firms can realize considerable incremental benefits (e.g., revenues) that can be attributed to cross-category spillovers. However, this effect is asymmetric—stimulating purchases in certain categories has a greater influence on the cross-category learning process, and some categories benefit more than others. Moreover, we document the additional benefits that can accrue to firms by considering aspects of cross-category learning for promotional activities in the presence of multiple factors. This can lead to a more efficient allocation of marketing budgets across (new) products. Finally, our framework can be used by managers to develop targeted marketing strategies to facilitate the learning process when consumers are uncertain about the product quality so that they become consistent purchasers.

We conduct our empirical analysis in the context of the organic products industry because it is well suited for our purpose. Recently, because of consumer misgivings regarding food safety, the organic products industry has received a considerable boost (Organic Trade Association 2010). However, there is significant uncertainty regarding the quality of organic products. Given that these products are relatively nascent, consumers constantly assess their efficacy through trial and usage.

2. Literature Review

The first line of research that is relevant to our work concerns studies that investigate the role of consumer characteristics in relation to new product adoption (e.g., Im et al. 2003, Hauser et al. 2006, Gielens and Steenkamp 2007). They find that certain characteristics are strong predictors of new product adoption and acceptance. In a similar vein, the diffusion literature finds that marketing mix variables and consumer characteristics influence the diffusion of new products (e.g., Gatignon and Robertson 1986, Horsky 1990). Chandrasekaran and Tellis (2008) show that information availability is an additional factor aiding new product takeoff. Social networks also play a key role in new product acceptance (Berger et al. 2010). Moreover, the relative impact of the above variables differs across categories, countries, and products. However, these studies do not consider the role of learning and some or all of the specific factors that influence it (e.g., these internal, external, and marketing mix variables) that are key to new product success.

Another research stream related to our study is that of (consumer) Bayesian learning. Since the seminal work of Erdem and Keane (1996), who studied choice behavior using a learning model wherein consumers are uncertain about product attributes, several researchers have found that both marketing mix variables (e.g., prices, promotions) and usage experiences impact the learning process (e.g., Coscelli and Shum 2004, Chintagunta et al. 2009). Recently, there has been a growing interest in cross-category models in marketing (e.g., Manchanda et al. 1999, Niraj et al. 2008). Most studies in this realm investigate responses to marketing mix activities such as prices and promotions (e.g., Ainsle and Rossi 1998). Hansen et al. (2006), using a multicategory model, explore the extent to which consumers exhibit similarities in their purchases for store brands across categories. They find that household-specific factors are more prominent in explaining preferences across product categories than demographics. Similarly, Singh et al. (2005) utilize a multicategory framework for analyzing attribute-based preferences across categories while allowing them to be a function of both observable and unobservable household-specific traits, and they find that consumers have strong preference correlations for certain attributes such as brand names. We contribute by integrating these two lines of enquiry—that is, by considering the role of learning in the context of multicategory models. Moreover, we also augment the above literatures through pertinent extensions such as modeling both incidence (including no purchase) and category choice, using additional factors, employing multiple data sets, and tracking consumers from their very first purchase of the new product to better describe the learning process. Finally, our research also relates to work that aims to combine scanner data with stated data (e.g., Swait and Andrews 2003, Erdem et al. 2005). Although our research context is distinct from the above cases, we also extend this literature by postulating a rich set of variables that influence multicategory choice simultaneously in a dynamic setting. Finally, we consider consumer new product learning across multiple categories for better generalizability. We summarize these issues in Table 1.

3. Conceptual Framework

Consumers' quality perception of new products (e.g., organics) is the most predominant factor influencing their purchases (Zeithaml 1988, Krystallis and Chryssohoidis 2005). Also, consumers may have imperfect information about the true quality of new products owing to skepticism or *risk perception* regarding their quality (Erdem and Keane 1996). But they

Table 1 Literature Review

Literature type	Reference	Nature of research	Characteristics	Marketing mix	Consumer psychographics	External influences	Cross-category learning	Multiple data sets
New product adoption/diffusion	Horsky (1990)	Theoretical	Aggregate sales model of consumer choice in a single category.	✓	×	✓	×	×
	Im et al. (2003)	Empirical/Survey	Adoption behavior model with consumer characteristics.	×	✓	×	×	×
	Gielens and Steenkamp (2007)	Empirical	Quantity model of new products across categories.	✓	×	×	×	✓
	Chandrasekaran and Tellis (2008)	Empirical	Aggregate sales model for product takeoff time.	✓	×	✓	×	×
	Berger et al.(2010)	Empirical/ Experimental	Aggregate sales model for a single category.	✓	×	✓	×	×
Product learning	Erdem and Keane (1996)	Empirical	Consumer product choice and learning model in a single category.	✓	×	×	×	×
	Coscelli and Shum (2004)	Empirical	Consumer product choice and learning model for a new product type.	✓	×	×	×	×
	Chintagunta et al. (2009)	Empirical	Consumer product choice and learning when product receives negative reviews.	✓	×	✓	×	✓
Multicategory models	Ainslie and Rossi (1998)	Empirical	Multicategory model of product choice.	✓	×	×	×	×
	Manchanda et al. (1999)	Empirical	Multicategory purchase incidence model.	✓	×	×	×	×
	Singh et al. (2005)/Hansen et al. (2006)	Empirical	Multicategory model of product choice with common attributes.	✓	×	×	×	×
	Niraj et al. (2008)	Empirical	Cross-category purchase incidence and quantity choice model.	✓	×	×	×	×
Multiple data sets	Swait and Andrews (2003)	Empirical	Product choice model in a single category.	✓	×	×	×	✓
	Erdem et al. (2005)	Empirical/Survey	Product choice model in a single category.	✓	×	×	×	✓
Proposed study		Empirical	Multicategory incidence and product choice model with cross-category learning.	✓	✓	✓	✓	✓

may form initial beliefs about this quality (Coscelli and Shum 2004, Erdem et al. 2005). Quality beliefs may also be formed through consumer *usage awareness*, which may be deemed to be more trustworthy because it is self-generated through actual use (Ching 2010). However, these influences may be category dependent, and those that require extensive processing may benefit more from actual trial, which then lowers the associated risk perception (Zepeda and Li 2007). Apprehensions regarding the *relative quality differential* between new and existing products (Bernard and Bernard 2009) and *media coverage* (Chintagunta et al. 2009) also impact quality perceptions whose relative influence can vary depending on category types. This could be because of increased media coverage for some categories such as produce (Cahill et al. 2010).

In the context of organic products, there is exhaustive evidence that psychographics (compared with demographics) strongly impact buying behavior. Consumers are motivated to buy organics because of health concerns or their *health orientation* (Zanoli and Naspetti 2002). Another prominent determinant is *environmental orientation*—consumers' attitudes concerning environmental issues. In general, positive attitudes toward the environment are positively correlated with organic purchases (Bourn and Prescott 2002). However, the relative importance that consumers attach to these attitudes depends on the nature of the category (Padel and Foster 2005) and is more salient for categories that do not undergo much processing (Aertsens et al. 2011). Consumers' inclination toward organics depends on the degree to which they *trust* the product offerings to be authentic (Grayson and Radan 2004), especially given the entry of large corporations into the organic marketplace. There has been a growing movement in the United States recently to *buy locally* grown products. Studies have shown that consumers who buy local products are more likely to buy organics (Zepeda and Li 2007). Because many consumers associate "buying local" with farm products (Padel and Foster 2005), these effects should be more significant for such categories. Finally, consumers purchase organics because of *taste* considerations (Lusk and Briggeman 2009). In contrast, researchers have found conflicting evidence with respect to demographics on organic purchases (Zepeda and Li 2007, Dimitri and Oberholtzer 2009).

Social influence, a phenomenon wherein an individual's choice behavior is shaped by others (Hui et al. 2009), has been shown to affect new product adoption and learning (Bearden and Etzel 1982, Peres et al. 2010). Researchers have also documented the presence of social effects for new products even in situations where individuals seldom interact with each other (e.g., neighborhoods), provided they have favorable attitudes toward one another (e.g., Thompson and Sinha 2008). New product adoption behavior may also be impacted by signals from the market or media discussions. We label these factors as external influences. Studies utilizing mobilization theory (Walgrave and Manssens 2000) have documented that external influences can effectively change consumer behavior for categories that involve farm animals (Hjelmar 2009). Thus, these factors may be more pronounced for products derived from them (e.g., milk).

The prominent marketing mix variables that affect choice are prices and promotions. Indeed, if the price of the new product is perceived to be appreciably higher than the existing one, consumers will be less likely to buy it (Bolton and Lemon 1999). Likewise, promotions influence new product purchase decisions. A wider assortment of new products increases the availability of certain forms, flavors, and/or package sizes and creates more opportunities for consumers to evaluate them, thereby enhancing purchase probability (Borle et al. 2005).

4. Multicategory Modeling Framework

We conceptualize the multicategory new product buying process as being nested, where the consumer first decides whether to buy in any of the categories or not (incidence) and then decides to buy either the new or the existing product (e.g., Bucklin and Lattin 1991). As a result of purchase and usage experience, consumers learn about the product's quality, and consequently, this learning can spill over to other categories.

4.1. Multicategory Nested Logit Model for New Product Choice

Consumer h at time t is faced with the decision of whether to purchase in any of the K categories, i.e., multicategory incidence, the utility of which is given below (e.g., Silva-Risso and Ionova 2008):

$$U_{ht}^{k} = \theta_{1h}^{k} + \theta_{2h}^{k} Inv_{ht}^{k} + \theta_{3h}^{k} IncVal_{ht}^{k} + \theta_{4}^{k} \bar{C}_{h}^{k} + \varepsilon_{ht}^{k}, \quad \text{where } k = 1, 2, \ldots, K. \quad (1)$$

In the equation above, Inv_{ht}^{k}, $IncVal_{ht}^{k}$, and $\bar{C}_{h}^{k}$ are the inventory, inclusive value, and average daily consumption rate, respectively, for the categories considered; $\boldsymbol{\theta}_{2h} \equiv [\theta_{2h}^{1}, \theta_{2h}^{2}, \ldots, \theta_{2h}^{K}]$, $\boldsymbol{\theta}_{3h} \equiv [\theta_{3h}^{1}, \theta_{3h}^{2}, \ldots, \theta_{3h}^{K}]$, and $\boldsymbol{\theta}_{4} \equiv [\theta_{4}^{1}, \theta_{4}^{2}, \ldots, \theta_{4}^{K}]$ are the corresponding vectors of coefficients associated with them; and $\boldsymbol{\theta}_{1h} \equiv [\theta_{1h}^{1}, \theta_{1h}^{2}, \ldots, \theta_{1h}^{K}]$ are the intercepts. The incidence depends on at-hand inventory levels (Inv_{ht}^{k}) because if they are sufficiently high, consumers may delay incidence (Bucklin and Lattin 1991). Higher mean category consumption rate ($\bar{C}_{h}^{k}$), the speed at which products are consumed (Bucklin et al. 1998), increases consumer incidence in the category. Because we have a nested framework, the incidence is also influenced by the overall attractiveness of products for each category, which is given by their inclusive value (Ben-Akiva and Lerman 1985).

Consumption in a category depends on inventory (Ailawadi et al. 2007), with consumers increasing consumption when inventory is high (Assunção and Meyer 1993) and reducing it when it is low (Folkes et al. 1993). To accommodate this flexible pattern, we have

$$Inv_{ht}^k = Inv_{ht-1}^k + q_{ht-1}^k - C_{ht-1}^k, \tag{2}$$

$$C_{ht-1}^k = Inv_{ht-1}^k \left[\frac{\bar{C}_h^k}{\bar{C}_h^k + (Inv_{ht-1}^k)^{f_k}} \right], \tag{3}$$

where q_{ht}^k denotes the quantity purchased and C_{ht}^k is the daily consumption of the household h for category k at time t, respectively; f_k is the parameter associated with category consumption flexibility (Ailawadi et al. 2007). We use Equations (3) and (2) recursively to arrive at the consumption and inventory levels for each purchase occasion. In Equation (1), ε_{ht}^k is the residual error. The utility when the consumer decides not to purchase in any of the K categories (and thus the $K+1$th option) is set to $U_{ht}^0 = \varepsilon_{ht}^0$. Assuming independent and identically distributed (i.i.d.) Gumbell distribution for the errors, the probability that the consumer makes a purchase in category k is $\text{Prob}_{ht}(k) = e^{\bar{U}_{ht}^k} / (\sum_{k=1}^{K+1} e^{\bar{U}_{ht}^k}) = e^{\bar{U}_{ht}^k} / (1 + \sum_{k=1}^{K} e^{\bar{U}_{ht}^k})$, where $\bar{U}_{ht}^k$ is the deterministic component of U_{ht}^k.

Given category incidence, the consumer is faced with the choice of buying either the new (e.g., organic) product or the existing (e.g., conventional) product in any of the K categories. The utility that consumer h derives from purchasing either the organic product ($p = o$) or its conventional counterpart ($p = c$) at time t in category k is given by

$$V_{pht}^k = \omega_{ph}^k X_{pht}^k + \kappa_p^k PSY_h + \delta_p^k EXT_h + \gamma_{pht}^k + \rho_p^k \sigma_{\gamma_{pht}^k}^2 + \zeta_p^k + \xi_{pht}^k. \tag{4}$$

In the above equation, X_{pht}^k are the marketing mix variables associated with the respective products in category k. Similarly, PSY_h are the consumer personal characteristics (e.g., psychographics) and EXT_h are the external sources influencing consumer product choice. γ_{pht}^k is the (unobserved) quality of the respective products in the kth category, ρ_p^k measures the degree of risk aversion of the consumer toward the purchase of new/existing products in category k, and ζ_p^k is a term that accounts for any correlations resulting from the presence of the same brands across organic and conventional products and is distributed with $N(0, E_p)$. This could result because of the brand extension strategy adopted by firms (e.g., Ragu and Organic Ragu pasta sauce).[1] The idiosyncratic shocks, ξ_{pht}^k, are assumed to be i.i.d. Gumbell. Thus, the probability of purchase of product p in category k given incidence is $\text{Prob}_{ht}(p \mid k) = e^{\bar{V}_{pht}^k} / (\sum_{p \in \{o, c\}} e^{\bar{V}_{pht}^k})$, where $\bar{V}_{pht}^k$ is the deterministic component of V_{pht}^k.

For each category, we constrain the conventional product to be the base case (Hansen et al. 2006), thus identifying the parameters corresponding to marketing mix, ω_{ph}^ks, and consumer characteristics/external factors, κ_p^ks and δ_p^ks (Chen et al. 2008). Similarly, we examine learning for organics vis-à-vis conventionals through the differential organic quality, i.e., $\gamma_{ht}^k \equiv \gamma_{oht}^k - \gamma_{cht}^k$, because consumers are uncertain only about the quality of organics. This is equivalent to assuming that although consumers have incomplete information regarding the quality of the organic product in a certain category, γ_{oht}^k, they are presumed to be knowledgeable about the corresponding conventional product quality, γ_{cht}^k; this is consistent with the prior literature (e.g., Ching 2010, Ferreyra and Kosenok 2011). Finally, assuming that $\zeta^k \equiv \zeta_o^k - \zeta_c^k \sim N(0, E)$ and estimating a category-specific covariance identifies ζ^k. We denote $\boldsymbol{\omega}_{1h}$, $\boldsymbol{\omega}_{2h}$, $\boldsymbol{\kappa}$s (1 to 6), $\boldsymbol{\delta}$s (1 to 3), $\boldsymbol{\rho}$, and $\mathbf{E}$ as the category-stacked vectors for the respective parameters.

4.2. Cross-Category Consumer Learning

We assume that for each category, the mean initial organic quality beliefs ($\bar{\gamma}_{h1}^k$) are influenced by consumers' risk perception ($RiskP$), relative quality apprehension (RQA), usage awareness ($UsgA$), and incipient media exposure (IME) concerning new products. At the beginning of period 1 ($t = 1$), that is, before the consumer purchases the new organic product from any of the K product categories, his or her initial quality beliefs are assumed to be normally distributed and specified as per Equation (5) below. Note that Γ_{h1} is obtained by stacking the category-specific qualities, $[\gamma_{h1}^1, \gamma_{h1}^2, \ldots, \gamma_{h1}^K]$:

$$\Gamma_{h1} \sim N(\bar{\Gamma}_{h1}, \Sigma_{\Gamma 1}), \tag{5}$$

where

$$\bar{\Gamma}_{h1} = \begin{bmatrix} \bar{\gamma}_{h1}^1 \equiv \lambda_0^1 + \lambda_1^1 RiskP_h + \lambda_2^1 RQA_h \\ \quad + \lambda_3^1 UsgA_h + \lambda_4^1 IME_h \\ \bar{\gamma}_{h1}^2 \equiv \lambda_0^2 + \lambda_1^2 RiskP_h + \lambda_2^2 RQA_h \\ \quad + \lambda_3^2 UsgA_h + \lambda_4^2 IME_h \\ \vdots \\ \bar{\gamma}_{h1}^K \equiv \lambda_0^K + \lambda_1^K RiskP_h + \lambda_2^K RQA_h \\ \quad + \lambda_3^K UsgA_h + \lambda_4^K IME_h \end{bmatrix},$$

[1] We thank an anonymous reviewer, the associate editor, and the editor for this suggestion.

$$\Sigma_{\Gamma 1}=\begin{bmatrix} \sigma_{\gamma_1}^{2(1)} & \varphi_{\gamma_1}^{2,1} & 0 & 0 & 0 & 0 \\ \varphi_{\gamma_1}^{2,1} & \sigma_{\gamma_1}^{2(2)} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{\gamma_1}^{2(3)} & \varphi_{\gamma_1}^{3,4} & 0 & 0 \\ 0 & 0 & \varphi_{\gamma_1}^{4,3} & \sigma_{\gamma_1}^{2(4)} & 0 & 0 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 0 & 0 & \sigma_{\gamma_1}^{2(K-1)} & \varphi_{\gamma_1}^{K-1,K} \\ 0 & 0 & 0 & 0 & \varphi_{\gamma_1}^{K,K-1} & \sigma_{\gamma_1}^{2(K)} \end{bmatrix}.$$

As can be seen in Equation (5), there is uncertainty with this initial quality belief vector (Γ_{h1}), which we label as (initial) belief uncertainty. It is captured by the variance ($\Sigma_{\Gamma 1}$) associated with $\bar{\Gamma}_{h1}$ and could emanate from consumer concerns/misgivings and/or a lack of experience of the new product (organics), reliability of information sources, and other unobservables (e.g., sensory variables). Moreover, we impose a block-diagonal structure on $\Sigma_{\Gamma 1}$, implying that consumers have initial information spillovers across similar categories ($\varphi_{\gamma 1}$s), which are independent across, unlike categories. This is to depict the phenomenon that coverage of organics in the media is sometimes specific to like categories (e.g., news reports extolling the virtues of consuming organic produce; see Kluger 2010). We also estimate a benchmark model with only the diagonal elements in $\Sigma_{\Gamma 1}$ (setting $\varphi_{\gamma 1}\text{s}=0$), indicating that consumers possess initial knowledge specific to that particular category. We denote $\boldsymbol{\lambda}$ as the stacked vector of parameters corresponding to the mean of the initial category-specific organic qualities.

Once consumer h purchases the new product from any of the K categories and obtains firsthand experience, he or she is exposed to a variety of signals regarding organic product quality not only in the focal category but also in other $K-1$ categories. Thus, there is cross-category spillover with respect to these signals. Like prior work, we assume that each usage experience provides a noisy but unbiased signal of the true qualities of organics for all categories. From now on, we suppress the subscript h for expositional clarity. Thus, we assume the noisy signals take the following form (Coscelli and Shum 2004):

$$\Phi_t=\Gamma_t+\mathrm{H},\quad \text{where } \mathrm{H}\sim \mathrm{N}(0,\Psi)$$

$$\equiv \mathrm{N}\left(0,\begin{bmatrix} \psi_\eta^{2(1)} & \psi_\eta^1\psi_\eta^2 & \cdot & \cdot & \psi_\eta^1\psi_\eta^K \\ \psi_\eta^2\psi_\eta^1 & \psi_\eta^{2(2)} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \psi_\eta^K\psi_\eta^1 & \cdot & \cdot & \cdot & \psi_\eta^{2(K)} \end{bmatrix}\right). \quad (6)$$

Consumers attempt to form estimates of Γ_t by observing the noisy signals Φ_t. The cross-category matrix (with full covariance) Ψ, which we label as updation uncertainty, captures the idiosyncratic variability corresponding to these noisy signals. This specification of Ψ allows for cross-category updation and hence learning through spillovers about organic product quality in a certain category through purchase from the same as well as other categories.

Consumers partake in cross-category learning about the true quality of the new product after each usage and/or consumption occasion in any one of the K categories. In other words, there is a period by period updating of the signals, Φ_t, and mean quality beliefs, $\bar{\Gamma}_t$. A consumer's posterior beliefs regarding Φ_t and Γ_t can be derived using the conditional mean and variance for multivariate normal distributions (Johnson and Wichern 2007). To this end, we specify the joint normal distribution of (Γ_t, Φ_t) as follows:

$$\begin{pmatrix}\Gamma_t\\ \Phi_t\end{pmatrix}\sim \mathrm{N}\left[\begin{pmatrix}\bar{\Gamma}_t\\ \bar{\Phi}_t\end{pmatrix},\begin{pmatrix}\Sigma_{\Gamma t} & \Sigma_{\Gamma t}\\ \Sigma'_{\Gamma t} & \Sigma_{\Gamma t}+\Psi\end{pmatrix}\right]. \quad (7)$$

From Equation (7), we can compute the posterior distributions of Γ_t in period t, which will be utilized as prior distribution in period $t+1$ as follows:

$$\bar{\Gamma}_{t+1}=\bar{\Gamma}_t+\Sigma'_{\Gamma t}(\Sigma_{\Gamma t}+\Psi)^{-1}(\Phi_t-\bar{\Phi}_t), \quad (8)$$

$$\Sigma_{\Gamma t+1}=\Sigma_{\Gamma t}-\Sigma'_{\Gamma t}(\Sigma_{\Gamma t}+\Psi)^{-1}\Sigma_{\Gamma t}. \quad (9)$$

We apply the above process recursively for all time periods. It is interesting to note that even though the category mean quality beliefs $\bar{\Gamma}_t$ can increase or decrease, the belief uncertainties tend to decrease for each subsequent period. This is understandable as the consumer's contiguous experience with the focal category helps reduce the uncertainty pertaining to the new (i.e., organic) product for both the focal category and other categories. However, as we will illustrate in §6.4, this decrease in the uncertainty emanating from the usage of the focal category will be larger for this category compared with other categories.

4.3. Model Estimation

For our model, the parameters that need to be estimated are $\Theta\equiv[\boldsymbol{\theta}_{1h},\boldsymbol{\theta}_{2h},\boldsymbol{\theta}_{3h}]$, $\boldsymbol{\theta}_4$ in case of category incidence; $W\equiv[\boldsymbol{\omega}_{1h},\boldsymbol{\omega}_{2h}]$, $K\equiv[\boldsymbol{\kappa}_1,\boldsymbol{\kappa}_2,\boldsymbol{\kappa}_3,\boldsymbol{\kappa}_4,\boldsymbol{\kappa}_5,\boldsymbol{\kappa}_6]$, $D\equiv[\boldsymbol{\delta}_1,\boldsymbol{\delta}_2,\boldsymbol{\delta}_3]$, $\boldsymbol{\rho}$, $\mathbf{E}$ for product choice; and $\Lambda\equiv[\boldsymbol{\lambda}_0,\boldsymbol{\lambda}_1,\boldsymbol{\lambda}_2,\boldsymbol{\lambda}_3,\boldsymbol{\lambda}_4]$, $\Sigma_{\Gamma 1}$, Ψ corresponding to the learning component. We incorporate individual-level parameters whenever possible, thus having a fully heterogeneous framework for the components of incidence, product choice, and learning, which are estimated simultaneously. However, the signals and the associated means and variances that are used by the consumer to form posteriors are not observed by the researcher. Therefore, the estimation involves a multivariate integral over the signals

Φ_t and heterogeneous parameters Θ and W. We use a simulated maximum likelihood estimation (SMLE) technique (Train 2003, Mehta 2007) to estimate the model parameters. The likelihood function is

$$L = \int_{\Theta}\int_{W}\int_{\Phi}\Bigg[\prod_{h}\prod_{t}\Bigg(\prod_{k=1}^{K}\Bigg(\mathrm{Prob}_{ht}(k)(\mathrm{Prob}_{ht}(o\mid k))^{Z_{oht}^{k}} \cdot (1-\mathrm{Prob}_{ht}(o\mid k))^{1-Z_{oht}^{k}}\Bigg)^{Y_{ht}^{k}}\Bigg) \cdot \Bigg(1-\sum_{k=1}^{K}\mathrm{Prob}_{ht}(k)\Bigg)^{1-\sum_{k=1}^{K}Y_{ht}^{k}} \Bigg|\, \Theta, W, \Phi\Bigg]\, dF(\Theta)\, dF(W)\, dF(\Phi), \qquad (10)$$

where Y_{ht}^{k} and Z_{oht}^{k} are indicators that are set to 1 if the consumer purchases or buys the organic product in the category k, respectively, and 0 otherwise. We resort to Halton draws to simulate the above integral over the parameter space in order to keep the simulation error low (Train 2003). We run the SMLE for 30 draws for each of the individual-level parameters of the model.

5. Data Description

As discussed earlier, we employ multiple data sets for our analysis by combining/merging three different data sets relating to consumers' revealed choices (i.e., scanner panel data), stated preference (from surveys), and external factors (e.g., influence of media). Because consumer learning is influenced by all the above elements, it provides a more integrated description of the phenomenon while enriching the understanding of their differential impacts.

The revealed data comprise consumer scanner panel transactions at a large retail chain based in the northeastern United States. In this data set, we are able to track consumers from their very first purchase (i.e., trial) of an organic product in all of the analyzed categories and all their subsequent ones (repeat purchases). We thus capture their complete purchase histories. We estimate our model using organic purchases in six distinct categories comprising milk, yogurt, ready-to-eat (RTE) cereal, oatmeal, crackers, and frozen pizza.[2] These categories differ in their characteristics, which provide interesting contrasts for consumer choice and learning. For instance, milk and yogurt are often the "gateway" categories for organic purchases and are viewed as "pure/produce" and "healthy" categories that do not undergo a lot of processing (Demeritt 2004), and organic variants of these categories are produced from farm animals that are treated more "humanely" (e.g., no hormones/antibiotics). Cereal and oatmeal require more processing compared with the pure/produce categories, although it may still be minimal, and crackers and frozen pizza require considerable processing. We label the former as "minimally processed" and the latter as "highly processed," respectively. In general, both these categories warrant the use of additives and preservatives. All categories have a significant presence of established organic stock-keeping units (SKUs), which facilitates the exploration of consumer learning because of reasonable purchase frequencies.

The stated data consist of a survey sent to the *same* random set of consumers pertaining to their lifestyles/psychographics, demographics, grocery shopping behavior, and perceptions regarding organic and conventional products. We are able to match the consumers who fill out the survey with their purchase transactions by assigning unique IDs. The survey, which used a five-point Likert scale for the questionnaire design, was sent to 5,000 consumers.[3] These consumers were randomly selected from a representative pool. The mail-administered survey was sent to consumers in early September 2006. The consumers mailed their responses using the self-addressed, postage-paid envelope attached to the survey. To improve the response rates, consumers submitting completed surveys were given the incentive to take part in a drawing yielding attractive prizes. The surveys were collected over a six-week period after the mailing date. A consumer support (toll-free) number was made available during this period to address any queries. The surveys received were checked for completeness and irregularities. The entire process yielded 674 acceptable respondents (used for estimation) for a response rate of 13.48%.[4]

We obtained information on media mentions (used as part of external influence) by identifying the relevant published news sources on a weekly basis utilizing the LexisNexis database. For each week of the data period (corresponding to that of the scanner data), we scanned through the LexisNexis database using a set of keywords relating to organic products (e.g., Chintagunta et al. 2009).[5] We restricted the

[2] We consider plain milk and plain yogurt (32 oz) for our analysis. We exclude soy, lactose-free, and flavored varieties in our analysis for both these categories.

[3] The survey was pretested using undergraduate students—who participated in lieu of course credit—at a large U.S. midwestern university to ascertain the accuracy, quality, and competency of the survey questions.

[4] Our raw response rate was higher. However, for this analysis we included only households who answered all questions, including the ones pertaining to demographics.

[5] The keywords used for searching in the LexisNexis database are organic foods, natural foods, organic farming, organic attitudes, environmental orientation, and localized farming.

articles to the northeastern United States and tabulated for each week the total as well as the number of positive and negative articles.[6]

5.1. Scanner Panel Variables and Descriptive

We used transaction data from May 2006 to March 2011 to track our consumer purchases. We included consumers who purchase at least once in each of the six categories under consideration. This is required for us to identify and estimate the learning parameters of the model. We used the 26-week period prior to a consumer's first purchase of organics for initializing category-specific variables. For organics, we considered SKUs that carried the U.S. Department of Agriculture (USDA) seal, and for conventionals, we selected all major SKUs constituting 96% of sales.

The inventory and consumption variables (measured in ounces or fluid ounces) that are used for category incidence are calculated as per Equations (2) and (3). To operationalize the price variable, we first calculated the per-unit price for each universal product code (UPC) and share weighed it by the UPC market share using constant weights (Pauwels and Srinivasan 2004). We used the net price, i.e., price net of all promotional discounts in X^k_{1pht} (Equation (4)). This variable thus captures the net impact (prices and promotions) on product choice.[7] The other marketing mix variable, X^k_{2pht}, is assortment, which reflects the effect of increased availability/variety on organic product choice at retail outlets (Enis 2010). We used a proportion, i.e., the number of organic to the total number of SKUs in the category, for our analysis.

We constructed the psychographic variables, *healthy purchase patterns* and *buy local*, from the scanner data. These variables are calculated at the consumer level as a moving average of consumer purchases of healthy products and local brands by tracking their baskets.[8] Because the consumer baskets are quite large, we restricted ourselves to the seven categories of ice cream, cookies, butter, margarine, tortilla chips, maple syrup, and jams. These categories are selected because (a) they are mostly perceived as "indulgent" and hence consumers purchasing healthy products in them may be striving for a healthier lifestyle, and (b) they have a reasonable number of local brands. We identified healthy SKUs using keywords such as "low salt," "less sugar," or "low fat" using the SKU description (Balasubramaniam and Cole 2002). A SKU is considered local if it is produced and distributed within a 100-mile radius from the consumers' location (Smith and MacKinnon 2007). We thus ended up with manufacturers predominantly based in the northeastern United States.

The external factor *geographic peer influence* is constructed using the location information of households as well as their purchase history of organics obtained from the scanner data. For this purpose, we employed the methods expounded in the spatial econometrics literature (e.g., Bronnenberg and Mela 2004). We first calculated the distance between the households based on the latitude/longitude of their residences. The inverse exponential of this distance between households is used in the formulation of a $N \times N$ row normalized weight matrix, W, where N represents the total number of households. We constructed another $N \times 1$ matrix, z_{ht-1}, indicating whether the household has purchased the organic product in time period $t-1$ (1 if the household purchased an organic product, 0 otherwise). The influence of geographic peers on household h at time t is based on how close other households in the geographic vicinity (neighbors) are to household h and whether they have adopted the organic product in the previous period:

$$IGP_{ht} = Wz_{ht-1}. \tag{11}$$

The data descriptive for the scanner panel purchases and variables are given in Table 2. As can be seen, even though the number of organic purchases are high for the categories of cereal and oatmeal (6,758 and 5,670, respectively), the proportion of organic purchases (ratio of organic purchases to total purchases in the category) is highest for the "produce" categories of milk and yogurt (43.90% and 31.72%, respectively). Households purchasing in the organic category tend to purchase products in the pure/produce categories as opposed to the moderately and highly processed categories. The proportion of organic purchase across all the six categories is 25.86%.

From Table 2, we find that organic products are consistently more expensive, although this premium varies by the category. The assortment of organic SKUs (as measured by proportion) is higher in the case of pure/produce and moderately processed categories. On average, consumers buy a fair amount of products labeled healthy (24%), and about a third of all purchases are of local products. The inventory and consumption levels are the highest for milk (26.58 oz/day and 13.89 oz/day, respectively) and lowest for yogurt (2.01 oz/day and 1.01 oz/day, respectively). The mean influence of geographic peers is 0.95.

[6] Two graduate student assistants were employed for this purpose. They further studied each of the articles and classified them as positive, negative, or neutral. The intercoder reliability was quite high with the students agreeing about 85% of the time. When there was a discrepancy, it was resolved by one of the authors. In general, most of the articles were positive in nature. The results did not substantially change when total articles were used instead.

[7] We also estimated an alternative model with the variables *regular prices* and % *promotional discount*. The results were very similar. We retain this specification in the interest of parsimony.

[8] For this purpose, we use 26 weeks prior to the week of category incidence as the moving window.

Table 2 Purchase Data Descriptive

	Milk	Yogurt	Crackers	Frozen pizza	Cereal	Oatmeal
Category-specific descriptive						
Number of organic purchases	23,167	4,344	2,013	5,484	6,758	5,670
Number of purchase occasions	52,766	13,696	12,840	32,138	37,130	34,861
Proportion of organic purchase (%)	43.90	31.72	15.67	17.06	18.20	16.26
Organic price ($/oz)	0.06	0.12	0.23	0.25	0.27	0.20
Conventional price ($/oz)	0.02	0.08	0.21	0.23	0.21	0.17
Proportion of organic SKUs	0.22	0.20	0.08	0.20	0.41	0.32
Inventory (oz/day)	26.58	2.01	2.98	3.98	5.21	3.18
Consumption (oz/day)	13.89	1.01	1.12	2.01	1.79	1.52

Sample-specific descriptive	Overall
Number of households	674
Number of shopping trips	195,713
Health purchase pattern (%)	24
Local brand purchase pattern (%)	33
Influence of geographic peers	0.95

5.2. Survey and External Factors Data Descriptive

We conducted a factor analysis for the responses to the survey questions using the varimax orthogonal rotation procedure and scree plots. Based on this, we were able to identify seven distinct factors of consumer psychographics that influence organic purchases (see Table 3). The identified factors and their associated survey questions and other details are listed in Table 4.

We also collected other information from the survey. We included a few statements pertaining to influence that friends and media have on the consumer's decision to purchase organic products, thereby affecting the learning process. The *influence of friends* variable captures word-of-mouth effects and is measured by respondents' ratings to the following statements: "My friends' opinions influence my organic purchase decisions" and "I purchase healthy products, because my friends are into healthy diet."[9] The *media influence* variable is constructed in the following manner using two sources of information. We first used consumers' ratings on the survey statements "Media ads/publicity has encouraged me to try new products" and "I gather information about products through news articles/talk shows, etc." These statements indicate the degree to which a respective customer trusts media sources and is influenced by them. We then multiplied the ratings on the media statements for each consumer with the difference between positive and negative articles (obtained from the LexisNexis data set) to calculate the media influence variable. Thus, this variable varies both temporally and across consumers. A similar operationalization was used for the incipient media exposure variable affecting initial quality beliefs (Equation (8)). Here, we used the average of the difference between positive and negative mentions over the initialization period to abate any multicollinearity issues. We used a five-point Likert scale to measure the attitudes on all the statements mentioned above and further standardized them after averaging so that the (consumer-specific) values are comparable to the factor scores for psychographics.

In Table 3, we present factor scores for the respective psychographics. Generally speaking, consumers have high usage awareness (0.28) for organic products and consider the consumption of conventional products to be risky (0.22). The higher usage awareness provides face validity to the survey because it is congruous with the high proportion of organic purchases observed across all the categories in the scanner data. Consumers are skeptical about the relative quality of conventional products (0.18), and this is comparable to their health orientation factor scores (0.19). Although taste is an important driver of organic purchases (0.11), it is not as salient as environmental

Table 3 Survey Data Descriptive

Mean factor scores	
Risk perception	0.22
Relative quality apprehension	0.18
Usage awareness	0.28
Health orientation	0.19
Environmental orientation	0.15
Trust (of large corporations)	0.07
Taste importance	0.11
Mean rating[a]	
Influence of friends	2.21
Influence of media	2.85
Mean weekly number of positive–negative media articles	11.28

[a]We use the mean standardized scores of the actual ratings in the analysis to ensure that the values are comparable to the factor scores.

[9] Even though we have accounted for the influence of geographic peers in consumer choice, we envision that the influence of friends who are different from geographic peers can also have an impact. Nonetheless, we estimated models accounting for the individual and interaction effect of these two variables and find that the proposed model offers the best fit.

Table 4 Factor Variables and Questions

Variable	Questions
Risk perception (Cronbach's alpha: 0.77)	The purchase of conventional products is risky because their quality is inferior to organic products. People who do not buy organic products are not concerned about their health. People who do not buy organic products are cheap.
Relative quality apprehension (Cronbach's alpha: 0.85)	There is a great difference in overall quality between organic products and conventional products. There is a great difference in reliability of ingredients between organic products and conventional products. There is a great difference in the nutritional value of the ingredients between organic products and conventional products. Organic products are of excellent quality overall.
Usage awareness (Cronbach's alpha: 0.86)	I have much usage experience with organic products. I frequently purchase products labeled as organic. I am very familiar with the organic products available in the market.
Health orientation (Cronbach's alpha: 0.80)	The claims of healthy labeling made by manufacturers influence my purchase decision. There is a great difference in the nutritional value of the ingredients between healthy products and other products. Whenever I buy a new food product, I check its nutritional information. I often buy products from health-food stores.
Environmental orientation (Cronbach's alpha: 0.84)	Generally, I consider myself to be an environmentally conscious consumer. I frequently purchase products labeled as "green." I associate myself with and take part in activities related to the environment (e.g., Arbor Day Foundation). I usually buy products that help sustain the environment or are eco-friendly. I recycle products (e.g., glass, newspaper) regularly. The ethical treatment of farm animals is very important to me.
Trust (*of large corporations*) (Cronbach's alpha: 0.77)	I feel large corporations are honest about the brands they market.[a] I feel that large corporations are trustworthy with respect to the brands they market.[a] I feel that large corporations are dependable with respect to the brands they market.[a]
Taste importance (Cronbach's alpha: 0.80)	I purchase organic products because they taste better. Conventional products are tasty because they contain additives/preservatives/hormones, etc.[a]

[a]Denotes reverse coding for the responses.

orientation (0.15). Consumers' trust of large corporations (0.07) has the lowest factor score among all the psychographic variables impacting organic product choice. We also present in Table 3 mean ratings for external influence variables. Consumers are influenced by their friends and media articles with respect to their organic purchases.

6. Results and Discussion

6.1. Model Fit and Validation

We compared the performance and the fit of the proposed model with six benchmark models (Table 5). The first benchmark model is a nested logit model without learning (null model). This comparison helps in understanding the performance of the dynamic models vis-à-vis static models. The second and third benchmark models that incorporate dynamics are the Kalman filter and risk-reduction models, respectively. In case of the Kalman filter model (Akçura et al. 2004), although updation of quality beliefs happens with purchase occasions, they evolve devoid of any signals (there is no Φ_t). Thus, this model does not capture the essence of learning by addressing the error in consumer quality beliefs originating because of noisy signals. In the risk-reduction model (Byzalov and Shachar 2004), the overall utility gets updated as a part of risk reduction rather than the learning/updation of quality beliefs. Consumer experiences with the product do not carry forward as priors for future purchases, and thus aspects of consumer learning through usage are not fully accounted for. The other three benchmark models are the nested versions of the proposed model. Benchmark model 4 does not include the influence of internal and external factors. To illustrate the importance of cross-category learning, we estimate as benchmark 5 a model that is devoid of it. Finally, we estimate as benchmark 6 a model with only the diagonal elements for initial belief uncertainty (Equation (5)). For all models we provide both the in-sample fit, as given by the log likelihood, Akaike information criterion (AIC), and Bayesian information criterion (BIC), and the out-of-sample fit measured through hit rates.[10] There is considerable improvement in fit between the proposed and the benchmark models.

[10] For the out-of-sample analysis, we selected households who start their purchase of organics from April to June 2011, and we tried to predict the choice of organic product given incidence in the category. The ratio of the number of correct predictions of consumer choice to the total number of choice occasions gives us the hit ratio.

Table 5 Model Comparison and Goodness of Fit

	Benchmark model 1	Benchmark model 2	Benchmark model 3	Benchmark model 4	Benchmark model 5	Benchmark model 6	Full proposed model
Characteristics	No dynamics	Kalman filter	Risk reduction	Proposed model without internal or external factors	Proposed model without cross-category updation	Proposed model without initial cross beliefs across categories	
Learning equation	No learning and hence $\Gamma_h \sim \mathrm{N}(\bar{\Gamma}, \Sigma_\Gamma)$	$\Gamma_{ht} = \Gamma_{ht-1} + \mathrm{H}_{ht}$ (No signal)	$\Phi_{ht} = \Gamma_{ht} + \omega_h X^k_{pht} + \mathrm{H}_{ht}$	$\Phi_{ht} = \Gamma_{ht} + \mathrm{H}_{ht}$	$\Phi_{ht} = \Gamma_{ht} + \mathrm{H}_{ht}$ $\mathrm{H}_{ht} \sim \mathrm{N}(0, \mathrm{diag}(\Psi))$	$\Phi_{ht} = \Gamma_{ht} + \mathrm{H}_{ht}$ $\Gamma_1 \sim \mathrm{N}(\bar{\Gamma}_1, \mathrm{diag}(\Sigma_\Gamma))$	$\Phi_{ht} = \Gamma_{ht} + \mathrm{H}_{ht}$
Parameters	153	192	174	114	177	189	192
Log likelihood	−44,778	−39,673	−40,017	−43,178	−38,116	−37,678	−35,887
AIC	89,862	79,730	80,382	86,584	76,586	75,734	72,158
BIC	91,420	81,685	82,154	87,745	78,389	77,659	74,113
Model validation (hit ratio)	0.65	0.71	0.75	0.70	0.76	0.78	0.83

We checked for sensitivity of the results to the sample selection. We first estimated the proposed learning model with the current sample of households but without utilizing the survey data. Thus, we did not include information on personal characteristics and some elements of external influences. We then estimated the same model on two distinct samples comprising 700 households—those who were never surveyed and those who were surveyed but never responded. We find that the results are very similar in all the above cases.

High correlation between the independent variables used in the analysis, especially the similar psychographics from the survey and the scanner data, may pose problems for the model estimates. On examining the bivariate correlations, we find that they are below the benchmark levels (e.g., 0.80) reported to cause serious problems (Van den Poel and Larivière 2004). The correlation is the highest for the pairs of health orientation and healthy purchase patterns (0.69), followed by 0.53 for geographic peers and friends, and the rest are below 0.35. We also compute the variance inflation factors (VIFs) for each independent variable (Menard 2001) and find that it is below the recommended threshold of 10 (Kutner et al. 2004).[11] We further examine the stability of the parameters by sequentially deleting variables from the model beginning with the ones with the most correlation (Mitra and Golder 2002). We find that multicollinearity is not a serious concern for the model results. We also explore the possibility of the same variable affecting other components by moving some of the variables from the choice to the learning component, and vice versa, and reestimating the model. We find that the proposed model offers a better fit versus the alternative specifications, and the overall results are similar.

[11] The highest VIF is 5.87 for healthy purchase patterns followed by 3.21 for influence of friends. The rest are below 2.35.

6.2. Results for Multicategory Incidence

All the parameter estimates pertaining to category incidence have the expected sign and are significant for all categories (Table 6, top panel). Moreover, a majority of the standard deviations corresponding to the parameters are also significant, indicating considerable heterogeneity in category incidence. As expected, we find that category incidence decreases (increases) with increased inventory (average consumption) for all categories. The parameter corresponding to inclusive value is positive and significant for all categories. The estimated values of f are negative for all categories, indicating that they exhibit a more flexible consumption pattern; i.e., consumption continually increases with inventory (Ailawadi et al. 2007).

6.3. Multicategory Product Choice

We find that all parameter estimates related to product choice have the correct signs (Table 6, middle panel). Price and assortment impact the choice of organics negatively and positively, respectively, confirming previous findings (e.g., Krystallis and Chryssohoidis 2005). We find that psychographics are important determinants of consumer choice of organic products, although their differential impact varies by category. Specifically, health orientation has significant positive influence on organic purchases in most of the pure/produce and moderately processed categories (1.87, 1.45, and 1.27 for yogurt, cereal, and oatmeal, respectively). It is not so for highly processed categories, plausibly because of the dominance of other lifestyle variables. Environmental orientation significantly impacts organic product choice and is strongest for the produce categories of milk (1.26) and yogurt (1.10). Because organic variants of produce products may involve processes that treat animals more humanely, an environmentally oriented consumer concerned with the ethical treatment of animals may be more inclined to buy them.

Table 6 Multicategory Model Estimates

Variable	Milk	Yogurt	Crackers	Frozen pizza	Cereal	Oatmeal
			Multicategory incidence estimates			
Inventory (θ_2)	-0.65^{***}	-0.95^{***}	-0.76^{***}	-0.89^{*}	-0.87^{**}	-0.98^{***}
	(0.085)	(0.076)	(0.221)	(0.458)	(0.419)	(0.054)
($\sigma_{\theta 2}$)	0.09	0.24^{***}	0.18^{*}	0.32^{*}	0.25^{***}	0.19^{*}
	(0.660)	(0.006)	(0.097)	(0.178)	(0.027)	(0.098)
Inclusive value (θ_3)	0.58^{***}	0.60^{***}	0.48^{***}	0.59^{**}	0.62^{***}	0.51^{***}
	(0.074)	(0.023)	(0.003)	(0.237)	(0.116)	(0.020)
($\sigma_{\theta 3}$)	0.08^{***}	0.46^{**}	1.11^{***}	0.33^{*}	0.97^{***}	0.77^{**}
	(0.006)	(0.219)	(0.033)	(0.191)	(0.042)	(0.324)
Avg. consumption rate (θ_4)	0.30^{**}	0.36^{***}	0.49^{***}	0.45^{***}	0.43^{**}	0.52^{**}
	(0.153)	(0.047)	(0.122)	(0.022)	(0.210)	(0.216)
Consumption flexibility (f)	-0.78^{***}	-0.66^{***}	-0.59^{***}	-0.51^{***}	-0.69^{***}	-0.61^{**}
	(0.056)	(0.004)	(0.005)	(0.100)	(0.012)	(0.230)
			Multicategory choice estimates			
Price (ω_1)	-2.76^{*}	-2.56^{*}	-2.01^{***}	-2.88^{*}	-3.76^{***}	-3.12^{***}
	(1.439)	(1.331)	(0.012)	(1.582)	(1.110)	(0.021)
($\sigma_{\omega 1}$)	0.99	1.42	1.18^{**}	1.62^{*}	0.29^{*}	0.34^{*}
	(0.997)	(2.119)	(0.564)	(0.882)	(0.173)	(0.103)
Assortment (ω_2)	2.83^{***}	2.81^{***}	1.66^{**}	2.01^{***}	1.15^{**}	1.35^{**}
	(0.004)	(0.456)	(0.736)	(0.045)	(0.516)	(0.678)
($\sigma_{\omega 2}$)	0.91	1.03	1.43^{*}	1.01^{*}	0.64	1.78
	(1.646)	(0.972)	(0.828)	(0.605)	(0.755)	(1.439)
Health orientation (κ_1)	1.14	1.87^{*}	0.01	0.11	1.45^{**}	1.27^{***}
	(1.328)	(0.956)	(0.127)	(0.386)	(0.656)	(0.124)
Environmental orientation (κ_2)	1.26^{***}	1.10^{***}	0.31^{***}	0.25^{**}	0.92	1.12^{**}
	(0.075)	(0.045)	(0.029)	(0.106)	(0.981)	(1.473)
Trust (*of large corporations*) (κ_3)	1.67^{*}	1.45^{**}	1.31^{***}	0.75^{**}	0.85^{**}	0.88^{***}
	(0.867)	(0.733)	(0.056)	(0.353)	(0.403)	(0.195)
Taste consideration (κ_4)	1.27	-1.62	-0.19	-0.27^{*}	1.15	-0.11
	(0.955)	(1.677)	(0.639)	(0.138)	(0.832)	(0.684)
Healthy purchase patterns (κ_5)	0.88^{***}	1.46^{*}	1.12^{***}	1.45^{***}	1.00^{***}	1.17^{*}
	(0.085)	(0.842)	(0.038)	(0.003)	(0.059)	(0.684)
Local brand purchase patterns (κ_6)	0.95^{**}	1.01^{***}	0.92^{**}	0.01	0.81^{***}	0.87^{*}
	(0.455)	(0.079)	(0.446)	(0.377)	(0.113)	(0.518)
Influence of geographic peers (δ_1)	0.19^{*}	0.15	-0.05	0.17^{*}	-0.22^{*}	0.48^{**}
	(0.114)	(0.154)	(0.129)	(0.102)	(0.125)	(0.219)
Influence of friends (δ_2)	1.71^{**}	0.86^{***}	0.41^{**}	0.43^{***}	1.19^{**}	1.29^{***}
	(0.812)	(0.033)	(0.203)	(0.117)	(0.593)	(0.193)
Influence of media (δ_3)	1.15^{***}	1.13^{**}	1.10^{**}	0.93^{**}	0.65^{*}	0.75^{**}
	(0.406)	(0.478)	(0.479)	(0.448)	(0.341)	(0.321)
Risk aversion (ρ)	-1.52^{***}	-1.85^{***}	-2.32^{***}	-2.15^{***}	-0.92^{***}	-1.22^{***}
	(0.006)	(0.433)	(0.087)	(0.033)	(0.147)	(0.244)
Brand correlations (σ_E)	0.03	0.34^{*}	0.26^{**}	0.48^{***}	0.12^{*}	0.19^{*}
	(0.021)	(0.204)	(0.106)	(0.011)	(0.071)	(0.112)
			Multicategory learning estimates			
Risk perception (λ_1)	1.14^{***}	1.62	1.38^{***}	1.52^{***}	1.93^{**}	1.98^{***}
	(0.388)	(1.733)	(0.346)	(0.113)	(0.893)	(0.274)
Relative quality apprehension (λ_2)	1.15^{***}	1.29^{**}	1.81^{***}	0.39^{**}	0.31^{***}	1.12^{***}
	(0.222)	(0.649)	(0.004)	(0.189)	(0.034)	(0.294)
Usage awareness (λ_3)	0.43^{***}	0.98^{***}	1.32^{***}	1.65^{***}	0.79^{**}	0.87^{***}
	(0.006)	(0.022)	(0.475)	(0.002)	(0.322)	(0.081)
Incipient media exposure (λ_4)	0.78^{***}	1.02^{***}	0.92	0.45	0.47^{**}	0.17^{*}
	(0.007)	(0.003)	(0.924)	(0.649)	(0.209)	(0.095)

Note. Standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We find that the trust variable positively influences organic product choice for all categories. In other words, if consumers trust organic product offerings as being authentic, i.e., trust small independent manufacturers more (distrust large corporate manufacturers/brands), they are more likely to buy organic products. In contrast to some prior studies, we find that taste does not impact the purchase of organics except in case of frozen pizza category, where the effect is in fact negative (−0.27). Taste in such categories is enhanced by the use of artificial additives/preservatives, and hence, organic products might not taste as good (Eiser et al. 2002).

The psychographics of healthy purchase patterns and buying local (calculated from scanner data) also positively impact organic purchase. In case of the former, this effect is strong across all categories, particularly for highly processed categories (1.45/1.12 for frozen pizza/crackers). This is plausible because these categories are less virtuous, and consumers who are buying organics in them are making a conscious effort to stay healthy. Consumers who are more prone to buying local products are more likely to purchase organics and are strongest for produce categories of milk (0.95) and yogurt (1.01). In contrast, we find that demographics (age, income, employment status, and household size) do not have a significant effect on the choice of organics.

The external factor, influence of geographic peers, has a varied impact on organic purchase. Whereas it is positive for most categories, it is negative in the case of cereal. Friends positively (and significantly) impact consumer organic purchase across all categories—the relative magnitude of which is higher than geographic peers. The effects are stronger for pure and minimally processed categories. Interestingly, this indicates that consumers rely more on friends than neighbors with respect to product trial and usage, thus reflecting the degree of credibility that they place on these information sources. The influence of media is the strongest for the produce categories (1.15 and 1.13 for milk and yogurt, respectively). A likely explanation is that media articles regularly mention that it may be most beneficial for consumers to "go organic" in such categories (Kluger 2010). Nonetheless, they have a significant impact on the adoption of other categories (e.g., processed foods) as well. We find that the impact of external factors on consumer new product adoption is comparable to that of intrinsic and marketing mix variables.

The risk-aversion parameter is significantly negative across all categories, indicating that consumers tend to be risk averse when it comes to the purchase of organics. The estimate for the brand correlation parameter is higher for highly and moderately processed categories. This is because conventional brands have been foraying into processed organic categories through (brand) extensions at a greater rate (e.g., Quaker organic instant oatmeal) than in produce, which still remains the mainstay of smaller/independent brands.

6.4. Results for Cross-Category Learning

We find that consumer's cross-category initial mean quality beliefs are positively influenced by risk perception, relative quality apprehension, and usage awareness across categories (Table 6, bottom panel). Thus, if consumers perceive the conventional products to be more risky, their initial quality beliefs across organic products will be higher. This effect is stronger in the case of highly and minimally processed categories, which could be because of the presence of proportionately more artificial additives/preservatives in conventional products (Mogelonsky 2008). Similarly, the greater the relative quality apprehension across the different organic and conventional products, the higher the consumers' initial quality beliefs regarding organics, an effect that is most prominent for highly processed (e.g., crackers) and pure/produce (e.g., yogurt) categories. Thus, consumers may be more skeptical of the merits of conventional products in these categories that impact their initial quality beliefs and subsequently cross-category learning for organics (Krystallis and Chryssohoidis 2005). We find that the greater the consumers' usage awareness, the stronger their initial quality belief for organics. This effect is more pronounced for fully processed and pure/produce categories. This may be because increased awareness may not be of much help in differentiating between the relative qualities of organics and conventionals in the minimally processed categories (Kalra and Li 2008). Incipient media exposure has a positive effect on initial quality beliefs and is the strongest for pure/produce, likely owing to the greater coverage these categories receive in the media. In summary, we find that the determinants of initial quality beliefs have a differential impact on organic quality perceptions in a cross-category context. For pure/produce, relative quality apprehension is the more salient variable affecting initial beliefs, whereas risk perception is more significant for minimally processed categories. For highly processed categories, usage awareness is the most important factor.

On examining the (initial) belief uncertainty matrix (Table 7, top panel), we find that the own-category values (diagonal elements) are larger for highly processed categories, plausibly because the incremental benefit of consuming organics in this case may be (initially) perceived to be negligible.[12] Additionally,

[12] We are able to conclude this because we also estimate a benchmark model with only the diagonal elements for the initial belief uncertainty matrix and this pattern of results persists (see Table 5). Details are available from the authors on request.

Table 7 Model Estimates—Learning Uncertainties

	Milk	Yogurt	Crackers	Frozen pizza	Cereal	Oatmeal
			Belief uncertainty (Σ_Γ)			
Milk						
Initial	3.92*** (0.077)					
Final	0.136					
Yogurt						
Initial	2.22** (1.021)	3.11*** (0.082)				
Final	0.030	0.141				
Crackers						
Initial	0	0	7.15*** (2.773)			
Final	0.027	0.017	0.048			
Frozen pizza						
Initial	0	0	0.21* (0.118)	6.61** (3.291)		
Final	0.038	0.018	−0.001	0.050		
Cereal						
Initial	0	0	0	0	1.82*** (0.082)	
Final	0.021	0.008	0.004	0.014	0.022	
Oatmeal						
Initial	0	0	0	0	0.77*	2.14*** (0.299)
Final	0.034	0.005	0.004	0.015	0.003	0.053
			Cross-category updation uncertainty (Ψ)			
Milk	6.45*** (0.201)					
Yogurt	1.23*** (0.444)	6.78*** (0.401)				
Crackers	1.28* (0.749)	0.77* (0.412)	2.17*** (0.120)			
Frozen pizza	1.78** (1.383)	0.84*** (0.315)	0.01 (0.051)	2.30*** (0.100)		
Cereal	1.01*** (0.465)	0.35* (0.210)	0.19** (0.082)	0.68*** (0.254)	1.02*** (0.096)	
Oatmeal	1.64*** (0.550)	0.21** (0.111)	0.19 (0.337)	0.71*** (0.265)	0.12* (0.067)	2.49*** (0.221)

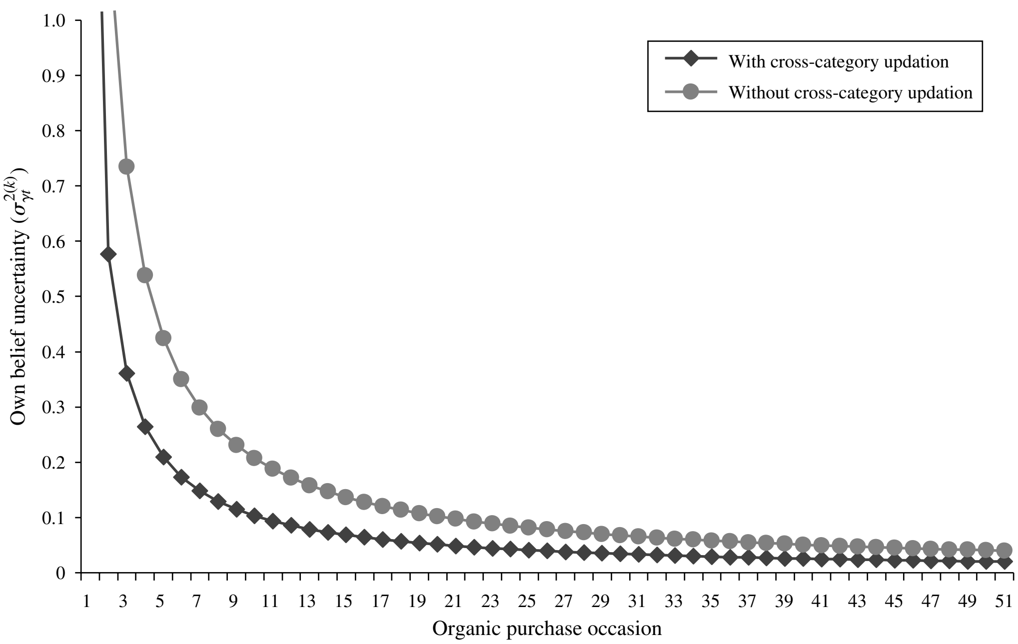
Note. Standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

consumers may be exposed to conflicting reports about the overall benefits of consuming processed organic foods (Bittman 2009). All the values of the matrix are significant, indicating that consumers are uncertain about their initial organic quality beliefs before trial and usage. With respect to the cross-category aspects, surprisingly, the covariance terms are lowest and highest for highly processed and pure/produce categories, respectively. Thus, in contrast to pure/produce, consumers' initial skepticism for highly processed categories does not seem to carry over to other like categories. We conjecture that this is because of the inherent similarity in the risk associated with produce across categories. Moreover, certain elements of production/sourcing are more likely to be common for pure/produce. For example, one product may serve as raw material for another (such as milk and cheese). On the other hand, each processed category may contain a diverse set of ingredients with fewer commonalities.

In case of the updation matrix (Table 7, bottom panel), the own- and cross-category uncertainty values are significant for a majority of cases, indicating that consumers do engage in learning and quality updation across categories. Thus, organic purchases help reduce quality uncertainty not only for the focal but also for other categories—albeit the quantum differs considerably. Regarding the own-category updation uncertainty (diagonal values), they are highest in the pure/produce (6.45 and 6.78 for milk and yogurt) followed by minimally and heavily processed categories. Also, the cross effects of pure/produce (e.g., milk) on other categories are higher, i.e., the off-diagonal elements. However, note that the overall effects will also depend on the values of other elements of matrix.

To analyze this further, we compute the final belief uncertainty matrix ($\Sigma_{\Gamma T}$) as per Equation (9). This is first computed for each consumer using his or her total purchases, which are then averaged out (Table 7, top panel). Although there is considerable reduction in own uncertainty for all categories, it is the greatest for highly processed ones. This indicates that usage experience is more crucial for these categories (Bourn and Prescott 2002). Additionally, we find that there are considerable spillover effects with respect to uncertainty reduction across categories. Focusing on like categories (the block-diagonal elements), the cross-category uncertainty reduction once again is higher for highly and moderately processed categories (almost close to zero). Moreover, an examination of the overall effects reveals that purchases in the these categories lead to the most reduction in quality uncertainty across all the other categories, a pattern

Figure 1 **Own-Category Belief Uncertainty ($\sigma_{\gamma t}^{2(k)}$) vs. Organic Purchase Occasion: Cereal**



that persists even after excluding the like category effects. This could be because purchase/usage experience in these categories could inspire greater confidence in the organic attribute, which then spills over to other categories. These cross-category effects are asymmetric—purchases in processed categories (e.g., frozen pizza) reduce uncertainty in other categories more as opposed to produce (e.g., milk).

6.4.1. An Illustration of Cross-Category Learning and Updation. To further illustrate cross-category learning and updation, we plot the changes in belief uncertainty ($\sigma_{\gamma t}^{2(k)}$) and mean quality beliefs ($\bar{\gamma}_t$) versus the number of organic purchases across a representative category of cereal with and without cross-category learning (Figures 1 and 2, respectively). As can be seen from Figure 2, the decline in belief uncertainty is steeper in the presence of cross-category effects. Thus, uncertainty stabilizes faster and to a lower magnitude as a result of cross-category learning. Examining Figure 2, we find that the mean quality stabilizes to the true mean in fewer purchase occasions in the cross-category case. Additionally, the mean quality approaches a higher mean level with lower intensity in fluctuations.

6.4.2. Cross-Category Learning and Resource Allocation. Using the estimated parameters, we simulate the market shares for the multicategory learning

Figure 2 **Mean Quality Beliefs ($\bar{\gamma}_t^k$) vs. Organic Purchase Occasion: Cereal**

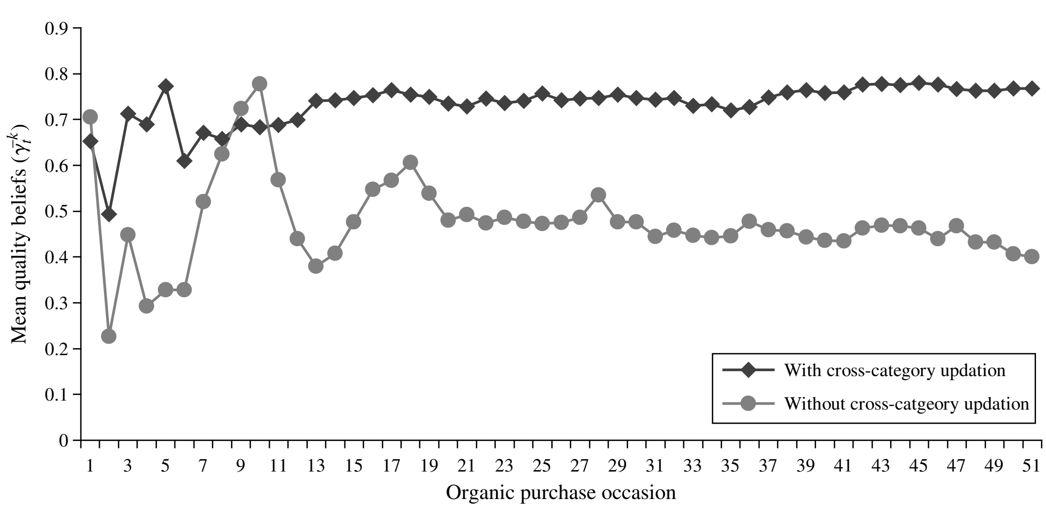


Table 8 Cross-Category Updation vs. No Cross-Category Updation

	Organic market shares (%)		Organic sales ($)		Organic profits ($)	
	No cross-category updation	With cross-category updation	No cross-category updation	With cross-category updation	No cross-category updation	With cross-category updation
Milk	5.13	7.22	29,734	35,367	16,668	17,227
Yogurt	2.64	3.36	5,065	6,631	2,536	2,602
Crackers	0.27	0.36	2,090	2,787	252	267
Frozen pizza	1.36	1.92	5,240	7,085	932	961
Cereal	3.57	4.25	8,940	10,525	1,975	2,011
Oatmeal	2.85	4.05	6,439	8,665	1,465	1,494

model versus the alternative assumption of no cross-category learning (Table 8). We find that there is considerable improvement in market shares and, consequently, revenues and profits for organic products. The share improvement is largest for pure/produce and minimally processed categories. Note that the shares also account for the no-purchase option. Therefore, if managers do not take into account cross-category learning, they may misestimate the category specific impact of promotional responses leading to nonoptimal allocation of marketing resources across categories.

7. Managerial Implications and Insights

7.1. Effective Use of Consumer Characteristics and External Influences

Consumer characteristics strongly influence the purchase decision and cross-category learning for new products.[13] Psychographics influence the initial quality beliefs, which impacts both trial and repeat purchases across categories; thus, managers should invest in programs that enhance consumer initial beliefs by mitigating quality uncertainty for effective cross marketing of new products (we subsequently illustrate how this can be carried out through targeted promotions). These include increasing product awareness, education about product ingredients, and safety. The resulting benefits can both be direct (through the focal category) and indirect (spillover effects on other categories). For new products, external influences are very valuable, attesting to the salience of "buzz" marketing. Firms can build word-of-mouth effects through community events or selective sampling to specific consumers to build social contagion, which could be especially valuable in such contexts because it can amplify across categories (cf. Charles 2008).

[13] For instance, because health and environmental orientation are key drivers of organic purchases, especially for categories that involve farm animals, managers should use thematic/event-based programs or cause-related activities in their campaigns to effectively market such products (e.g., Earth Day and Arbor Day events).

Table 9 Price Elasticity

	Organic own-price elasticity	Within-nest cross-price elasticity	Between-nest cross-price elasticity
Milk	−3.98	0.90	0.10
Yogurt	−3.12	0.84	0.12
Crackers	−2.12	0.38	0.11
Frozen pizza	−3.43	0.42	0.13
Cereal	−3.35	0.55	0.16
Oatmeal	−2.65	0.65	0.12

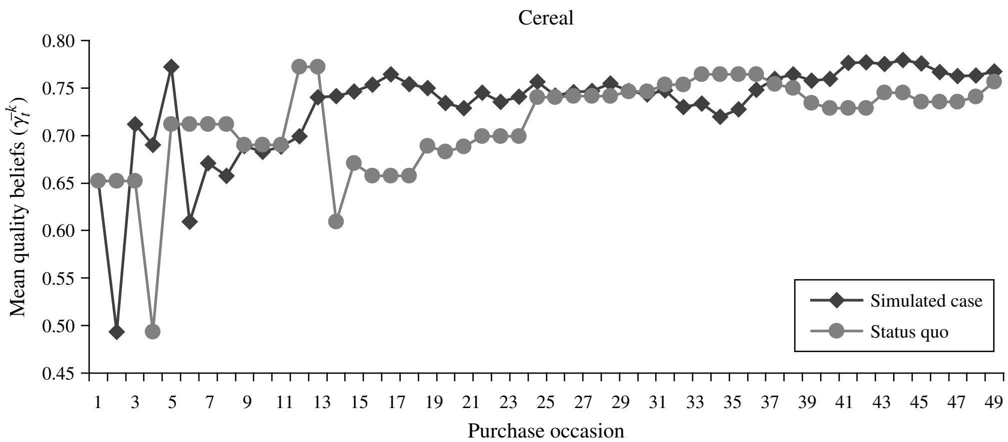
7.2. Effective Promotional Strategies

To understand how promotion policy may vary for categories, we calculate the overall price elasticity, taking into account the across-category spillovers, the results and calculations of which are reported in Table 9 and the appendix. These elasticities are highest and lowest for the produce and processed categories, respectively. Additionally, we calculate within-nest and between-nest cross-price elasticities (Ching et al. 2009). The former captures the effect that price changes have on the respective products within the same category, and the latter signifies the impact they have across categories. We find that in the case of produce, price changes of organics impact the sales of their conventional counterparts more (higher within-nest elasticities). In contrast, the across-category price elasticities seem to be similar, indicating comparable effects.

Our analysis can be used by managers to develop strategies to facilitate cross-category learning where consumers are uncertain about the product quality, through targeted marketing activities, so that they become consistent purchasers across categories, thus enabling better category management decisions. We provide an illustration of this using our model estimated coefficients. We randomly select 300 consumers and reduce their net price (i.e., their actual price) for the organic product by 20% for their first three purchase occasions (van Heerde et al. 2000).[14]

[14] We thank an anonymous reviewer for this suggestion. In some cases, the manufacturers/retailers may have other objectives, such as retaining organic premiums that can be accomplished by having other magnitudes of price discounts. Such an analysis is straightforward.

Figure 3 An Illustration of Targeted Promotional Strategies



Notes. This figure plots the mean quality beliefs versus purchase occasion for the two scenarios—the simulated case with select consumers being targeted for a 20% price cut for their first three purchase occasions and the status quo sans such a price cut. The price cut enables better cross-category product evaluations.

This is equivalent to giving a 20% targeted price discount for them and can be achieved by presenting these consumers with a coupon for their first three purchase occasions. This price cut provides consumers with an additional incentive to repeat purchase the organic product sooner (i.e., expediting organic purchases) in the focal category, which thereby creates spillovers on other categories. Thus, by advancing consumers' repeat purchases, managers can enable better cross-category product evaluations and accelerated learning, because consumers can assess the quality of organics and update their mean quality beliefs (Γ_t) and belief uncertainties ($\Sigma_{\Gamma t}$) with fewer usage occasions not only for the focal category but also other categories.[15] To elucidate this, we plot $\bar{\gamma}_t^k$ versus purchase occasions in Figure 3 for the cereal category for the simulated case above and compare it to the status quo, i.e., sans accelerated learning. The plots show that $\bar{\gamma}_t^k$ gets stabilized faster for the simulated case. Additionally, some of the conventional purchases across all consumers have been replaced by organic purchases, thus aiding the learning process.

It is interesting to note that promotions in one category can influence quality beliefs and uncertainties in other categories. Because the above promotion induced accelerated learning results in an overall increase of purchases for organic products (as consumers substitute organics for conventionals) across all the six categories, the overall category profits also increase because organics have higher margins. Our data set contains information pertaining to the wholesale prices for both organic and conventional products; thus, we can calculate the incremental profits that accrue because of the above promotion policy.[16] In Table 10 (Scenario I), we present the results from such a cross-category analysis, which are computed for the new/simulated consumer purchase histories using the model parameters along with the relevant margin information. The incremental profits are calculated on a per-unit basis averaged across consumer-purchase occasions. As expected, profits increase the most in the focal categories. However, there is considerable increase in profits in other categories, which can be attributed to the spillovers accelerating the cross-category learning process. This effect is strongest for produce. We also calculate the incremental increase in focal category profits induced as a result of cross-category learning compared to a model without such effects and find that it is the most for produce. Note that this increase is because purchases in other categories also influence the learning process of the focal category. Thus, reflecting the asymmetry for cross-category learning discussed earlier, produce benefits more than highly or moderately processed categories because of positive spillovers.

Managers may also be interested in understanding the means by which they can induce consumers

[15] We simulate the purchases of organic and conventional products using the model estimates. For the organic quality beliefs and updation draws, we resort to Monte Carlo techniques, wherein we draw one million multivariate sets of six values (one for each category) from an $N(0, 1)$ distribution for each consumer for each purchase of organic, and we average them for arriving at the new organic quality mean and uncertainty. We plug this new mean into the closed-form probability equations to determine the purchase for organic or conventional products.

[16] Even though we take into account the cost of promotion to the retailer because of the price promotions, we do not consider costs associated with the printing, mailing, or handling of coupons. Generally speaking, some of these costs may be reimbursed by the manufacturers. We thus do not consider the proportion of promotional spending covered by the manufacturers for the retailers.

Table 10 Simulation Results for Targeted Promotions

		Scenario I						Scenario II	Scenario III	
		Incremental profit per unit per customer (¢/oz)							Incremental profit per unit per customer (¢/oz)	
Price cut category	Incremental margin (%)	Milk	Yogurt	Crackers	Frozen pizza	Cereal	Oatmeal	Organic conversion (%)	Healthy product promotion	Local brand product promotion
Milk	93	45 (43)	10	9	19	15	12	35	3.12	1.86
Yogurt	57	5	33 (32)	4	3	2	1	32	1.44	1.23
Crackers	10	9	7	12 (11)	1	3	4	19	0.31	0.33
Frozen pizza	13	13	8	1	22 (21)	5	2	17	0.57	0.24
Cereal	29	12	1	2	4	11 (10)	1	25	0.25	0.21
Oatmeal	15	9	1	3	6	3	18 (17)	22	0.35	0.10

Notes. The table shows the incremental profits that can be obtained as a result of targeted promotions in organic and other related product categories. The standard unit considered for each of the organic categories is 64 oz for milk, 32 oz for yogurt, 8 oz for crackers, 13 oz for frozen pizza, 13 oz for cereal, and 17 oz for oatmeal. The second column is the incremental margin of organics vis-à-vis conventionals and is calculated as (margin for organic category − margin for conventional category) $*$ 100/(margin for conventional category). The next set of columns under Scenario I indicates the extra profit on a per-customer basis and is averaged across consumers and units after the total profits are obtained. The values in parentheses indicate the profits that are obtained by running the simulation without (benchmark model 6) cross-category effects. The column under Scenario II has the percentage of consumers converting to organics (obtained from simulations). The columns under Scenario III depict the incremental profit as a result of promotions in related product categories.

to consistently purchase new products. To explore this, we select consumers from a different sample who have never purchased organics in any of the six categories. We subject these consumers to the same (simulated) promotion policy and, using the average model parameters, estimate how many consistently purchase organic products across the six categories (Table 10, Scenario II).[17] We find that this conversion rate is considerable and is highest for produce categories. We run another set of simulations (Table 10, Scenario III) to track incremental store profits per year through promotions in healthy and local products. Here, instead of price cuts, we assume that retail promotions lead to increases (order of 30%) in healthy and local brand purchases. We track the shifts in purchases across categories (choice of conventional in null model is replaced by choice for organic in the simulation model) because of the increased healthy and local brand purchases and calculate incremental store profits. Although the incremental profits for this case are not as high as they were previously, they are still substantial. The profits are highest for pure/produce and lowest for heavily processed categories.

8. Conclusions, Limitations, and Future Research

In this paper, we develop a multicategory framework to analyze the role of internal factors, external influences, and marketing variables on new product adoption and learning for new products. We calibrate our cross-category learning model using a unique data set consisting of new product purchases (including the first purchase) and by employing multiple data sets.

We summarize our results as follows. We find that with regard to the relative importance of specific variables in influencing organic choice and learning, environmental orientation is more prominent than health orientation. Similarly, friends are more influential than geographic peers/neighbors. Contrary to previous research, we find that taste considerations are not a significant determinant. Although media mentions affect choice and learning for all categories, this impact is the strongest for produce. We find significant evidence of consumer cross-category learning. In contrast to produce, consumers are initially more uncertain about the quality of processed categories, although this does not spill over to similarly processed categories. On a related note, this reduction in uncertainty through usage is greatest for them. We find that although purchases in all categories reduce quality uncertainty across other categories (i.e., through positive spillovers), these cross-category effects are asymmetric, with purchases in processed categories leading to the greatest reduction in quality uncertainty.

In this study, we do not consider consumer brand choice behavior with respect to new (organic) products but rather focus on category choice. Although this may be appropriate, because strong brand preference for such products may not yet have been firmly established, future research can more closely examine this issue. We do not model the supply-side issues affecting the distribution or availability (e.g., assortment) of organics that could impact consumer choice and learning. More recent literature (e.g., Dimitri and Oberholtzer 2009, Cui 2008) suggests that organic farmers have struggled at times to

[17] We assume here that the consumer base is not increasing in the category under consideration because of the promotion policy.

provide sufficient supply to keep up with the rapid growth in demand, and smaller firms have struggled to obtain USDA certification although they were produced in accordance with the guidelines. At the same time, the organic supply chain is becoming more competitive and efficient (Tondel and Woods 2006). Future research can examine such issues. Additionally, similar to other research in this area (e.g., Chintagunta et al. 2009), we do not consider forward-looking behavior, because our focus is on unraveling the role of consumer/category characteristics on new product choice. Consumers can cross shop at multiple retailers for organic products, which affects the learning process. Moreover, this process may also be impacted by the retailers' organic focus. Although we take care to minimize the impact of this process on our model results, this issue deserves more attention. Also, consumers may purchase multiple items from multiple categories in the same shopping trip as a result of which the purchase incidence decisions across categories may be correlated. Such an analysis that focuses on multivariate purchases may also be fruitful for future research. Another avenue can be to further explore the influence of geographic peers to include more consumers, categories, and regions. Finally, because we consider only food categories, future research can focus on other categories (e.g., durables) to obtain further intuitions vis-à-vis consumer characteristics and learning.

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Appendix. Calculation of Price Elasticities

The nested logit formulation presents us with three elasticity calculations. The own-price elasticity captures the effect of price changes on the choice probabilities of the same product. It is computed as $\omega_{1h}^{k} x_{1ot}^{k}(1-\mathrm{Prob}(o \mid k)) + \theta_{3h}^{k} \omega_{1h}^{k} x_{1ot}^{k} \mathrm{Prob}(o \mid k)(1-\mathrm{Prob}(k))$, where ω_{1h}^{k} is the estimated price parameter for product choice in category k, θ_{3h}^{k} is the category attraction parameter for inclusive value of category k, and x_{ot}^{k} is the price of the product in category k at time t. The within-nest cross elasticity is the effect that product price changes have on choice probabilities on other products within the same nest. It is calculated as $\omega_{1h}^{k} x_{1ot}^{k}(-\mathrm{Prob}(o \mid k)) + \theta_{3h}^{k} \omega_{1h}^{k} x_{1ot}^{k} \mathrm{Prob}(o \mid k)(1-\mathrm{Prob}(k))$. The between-nest cross elasticity is the impact that product price changes in one category have on choice probabilities of products in other categories and is given by $-\theta_{3h}^{k} \omega_{1h}^{k} x_{1ot}^{k} \mathrm{Prob}(o \mid k) \mathrm{Prob}(k)$. We use one million Halton draws for each consumer and average them out for the elasticity calculations.

Because the elasticity calculations have to account for the dynamic aspect of the model, we first compute both the conditional product choice probability and the unconditional category incidence probability and calculate the price elasticity at every purchase occasion for each consumer for a given price change. We then average the above elasticities across all consumer and purchase occasions. We use a price cut of 20% for the purpose. Alternatively, we calculate the elasticity for each purchase occasion for each consumer based on his or her draw of parameter estimates. We average the elasticities across all consumers and purchase occasions. We repeat the procedure for one million draws of the parameter estimates. The results obtained are very similar.

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