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The authors empirically study consumer choice behavior in the wake of a product-harm crisis, which creates consumer uncertainty about product quality. They develop a model that explicitly incorporates the impact of such uncertainty on consumer behavior, assuming that consumers are uncertain about the mean product quality level and learn about product quality through the signals contained in use experience and the product-harm crisis and also that consumers are uncertain about the precision of the signals in conveying product quality and update their perception of this precision over time. They estimate this model using a scanner panel data set that includes consumer purchase history before, during, and after a product-harm crisis that affected Kraft Foods Australia's peanut butter division in June 1996. The proposed model fits the data better than the standard consumer learning model, which assumes consumers are uncertain about product quality level but the precision of information in conveying product quality is known. This study also provides insights into consumers' behavioral choice responses to a product-harm crisis. Finally, the authors conduct counterfactual experiments based on the estimation results and provide insights to managers on crisis management.

Keywords: brand choice, perceived risk, product crisis, uncertainty

Consumer Learning in a Turbulent Market Environment: Modeling Consumer Choice Dynamics After a Product-Harm Crisis

At some point, most brand managers must confront a product-harm crisis. A badly managed marketing crisis can easily destroy the affected brand's equity, which might have been nurtured over many years. In recent years, stalwarts such as Sony, Pfizer, Bausch & Lomb, and Intel have had their reputations tarnished because of poorly managed product-harm crises. Several indicators signal a rise in the incidence of such crises (Dawar and Pillutla 2000). For example, Table 1 shows a steady increase in the number of voluntary product recalls the U.S. Consumer Product Safety Commis-sion has initiated since 2000. Product defects can have severe negative effects on the affected brand's market share, image, and long-term sales. A product-harm crisis can also have an impact on affected brands differently such that some brands may come out stronger after the crisis and the sales of others may drop dramatically and never rebound to their precrisis levels. It may also affect the competing brands differently such that the sales of some competing brands increase during and after the crisis, whereas the sales of others remain stable or even drop, depending on the marketing strategies the respective manufacturers adopt and the consistency of product quality level they deliver over time (Roehm and Tybout 2006).

The purpose of this article is to empirically study consumer choice behavior in the wake of a product-harm crisis using scanner data. Consumers are usually imperfectly informed and thus uncertain about product attribute levels such as quality. A product-harm crisis might increase consumers' uncertainty about product quality in the marketplace. However, firms know more about the products they sell than the consumers. To cope with consumer uncertainty,

Table 1

VOLUNTARY RECALLS OF HAZARDOUS PRODUCTS IN THE
UNITED STATES

Year	Number of Recalls	Product Units (in Millions)
2006	471	124
2005	397	67
2004	354	216
2003	279	40
2002	393	50
2001	341	90
2000	288	90

Source: U.S. Consumer Product Safety Commission (2005).

firms can use a range of signals to convey quality, including instruments such as price, warranties, advertising, and brand names (e.g., Byzalov and Shachar 2004; Wernerfelt 1988). Consumers then use such signals to update their product quality beliefs (e.g., Erdem and Keane 1996).

In this study, we develop a structural model of consumer brand choice that explicitly incorporates the impact of uncertainty on consumer behavior. Previous marketing research has used models of consumer learning under uncertainty widely (e.g., Erdem 1998; Erdem and Keane 1996; Erdem, Zhao, and Valenzuela 2004; Mehta, Rajiv, and Srivinisan 2004). In these models, the researchers have assumed that product-related information sources (e.g., advertising, consumption experience) give consumers noisy signals about product quality. Consumers use these signals to update their expectations of product quality using Bayes' rule. The existing learning models in marketing assume that consumers are uncertain about the mean quality level of a brand, but the precision of the signals carried in the information sources (e.g., use experience, advertising) that convey product quality is a constant and known to consumers. Therefore, consumers only update their perceptions of the mean quality level after the new information arrives (e.g., Erdem and Keane 1996). An implication of this assumption is that the more new information a consumer receives about a particular brand, the lower is his or her perceived variance associated with the mean quality level of a brand (i.e., the consumer's perceived risk associated with the brand) (for further details, see Erdem and Keane 1996). In general, this is true when the new information a consumer receives about a brand is congruent with his or her prior knowledge of the brand. However, when this new information is inconsistent with the consumer's prior beliefs, it could raise rather than reduce the consumer's perceived variance associated with the mean quality level of the brand. Thus, we cannot apply the standard learning model in marketing to the context of this study—namely, consumer brand choice in a product-harm crisis setting.

When there is a product-harm crisis, the new information a consumer receives about the product is largely incongruent with his or her previous expectations. As a consequence, the consumer's decision process is likely to be affected. To capture the unique feature of consumer decision making in the context of product-harm crises, we propose an approach that substantially differs from the traditional learning model in marketing. We assume that consumers are uncertain about the mean quality level of a brand and the precision of

information contained in use experience and the product-harm crisis in conveying product quality. Consumers will update both their beliefs of the mean quality level and the precision of the information contained in use experience when new information arrives. Furthermore, in our model we assume that consumers discount their confidences in beliefs about product quality and the precision of information over time to allow for the possibility that the more recently formed beliefs may have a greater role in consumers' evaluations of product qualities.[1] To study the impact of a product-harm crisis on consumers' sensitivities to price, quality, and risk, we allow these model parameters to be different before, during, and after the product-harm crisis. More specifically, we create two dummy variables representing the periods during and after the product-harm crisis. Then, we write consumers' sensitivities as functions of these two dummy variables to capture the possible changes of these sensitivities before, during, and after the product-harm crisis. We calibrate the model on a unique data set that includes consumer purchase behavior spanning the periods before, during, and after a product-harm crisis that occurred in the peanut butter category in Australia in 1996.[2] Our results show that our model fits the data substantially better than the standard learning model, which assumes that consumers know the precision of information and only update their perceived mean quality level. Our model also outperforms a model specification that allows consumers to update both the perceived mean quality level and the information precision but without discounting their beliefs over time.

The contributions of this study to the marketing literature are threefold. First, methodologically, it enriches the existing marketing literature on consumer learning under uncertainty by providing a new model that allows consumers to update their perceptions of both the mean product quality level and the precision of the signals carried in the information sources in conveying product quality. Our proposed model offers a better approach for capturing consumers' decision-making process when there are turbulent changes in the marketplace (e.g., a product-harm crisis, a product reformulation). Second, our study provides substantive insights into consumers' behavioral choice responses to a product-harm crisis. Moreover, we conduct counterfactual experiments based on the estimation results and provide insights to managers on crisis management.

We organize the rest of the article as follows: In the next section, we summarize prior research on product-harm crises.

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[1]Note that we do not allow for forward-looking consumers, because the only way to allow for information discounting or forgetting is to allow for myopic consumers.

[2]The pre–post crisis analysis in this study also relates to the rich literature on the modeling of changing market environments (for a critical review of early research in this area, see Wildt and Winer 1983). Marketing econometrics studies have typically modeled changing market environments through varying coefficient structures. The coefficient variation can be either stochastic or nonstochastic (Hanssens, Parsons, and Schultz 1990, pp. 57–58). Another dimension is whether the structural change occurs at a known or an unknown point. Our model presumes that the structural break coincides with the product recall. Because the particular crisis event that we studied was widely publicized, this is a reasonable assumption. However, as one reviewer observed, for some incidents, it may be more appropriate to model the timing of the structural break stochastically as an unknown.

Then, we propose a consumer brand choice model under uncertainty. Following this, we give a brief overview of the data set we used and present our empirical results. We conclude with a discussion of the practical implications of our findings and directions for further research.

NEGATIVE BRAND PUBLICITY AND PRODUCT-HARM CRISES

Our research extends prior work on product-harm crises and the related literature on brand scandals and negative brand publicity. "Product-harm crises" can be defined as well-publicized events in which products are found to be defective or dangerous (Siomkos and Kurzbard 1994). Despite the potentially crippling effects of such crises, research in marketing in this area has been remarkably sparse to date. Most of the research insights into product-harm crises in the marketing literature come from lab experiments that examined the impact of hypothetical brand crises. These studies have mainly focused on two research questions in the context of a brand crisis: (1) Who will consumers blame? and (2) How does the negative brand publicity engendered by such events affect consumers' brand attitudes and/or purchase intentions? With regard to the first question, researchers have examined the moderating role of variables such as company reputation, corporate social responsibility (Klein and Dawar 2004), and the availability of counterfactual alternatives (Creyer and Gürhan 1997). Studies that shed light on the impact of negative brand publicity on consumers' brand attitudes include Ahluwalia, Burnkrant, and Unnava (2000), Dawar and Pillutla (2000), and Roehm and Tybout (2006). Although these studies offer valuable insights, their external validity is hampered by the usual shortcomings of experimental research (e.g., Shimp, Hyatt, and Snyder 1991). Our study complements the existing behavioral research by building a model of consumers as Bayesian decision makers who update their quality beliefs (Dawar and Pillutla 2000). We then calibrate the model using scanner data.

Longitudinal research on product-harm crises is scarce in marketing. Van Heerde, Helsen, and Dekimpe (2007) use a time-varying error correction model to assess the short- and long-term effects of a brand crisis on baseline sales and the marketing-mix effectiveness. Cleeren, Dekimpe, and Helsen (2008) study how consumer characteristics (brand loyalty, category usage) and advertising influence consumers' first-purchase decisions of the affected brands after their reintroduction. The current study involves the same crisis as in the aforementioned two articles; however, our model differs by focusing on consumer choice behavior and modeling the dynamics as a consumer learning process.

THE MODEL

In this section, we develop a choice model that envisions consumers as Bayesian decision makers in the wake of a product-harm crisis. We also discuss the main assumptions underlying the proposed formulation.

Utility Specification

Consider a market in which there is a set of consumers $I = \{i | i = 1, 2, ..., I\}$. Let $J = \{j | j = 1, 2, ..., J\}$ be the set of brands in the market. Consumers' purchases are observed over the period $T = \{t | t = 1, 2, ..., T\}$, where T is the time span of the period. Let the indicator variable D_{ijt} represent the choice of brand j made by consumer i at time t. The variable D_{ijt} is 1 if a choice j is chosen at time t by consumer i and 0 if otherwise.

We assume that consumers are imperfectly informed and thus uncertain about each brand's quality level. Furthermore, we assume that U_{ijt}, the utility of consumer i from purchasing brand j at time t, depends on product quality, advertising, and price (e.g., Erdem, Keane, and Sun 2008):

$$(1) \qquad U_{ijt} = \lambda_{it}p_{ijt} + \theta_{it}AD_{jt} + \omega_{it}X_{ijt} + \overline{\omega}_t\gamma_{it}X_{ijt}^2 + e_{ijt},$$

where p_{ijt} is the price consumer i faces for brand j at time t, X_{ijt} is the experienced quality of product j at time t for consumer i, and AD_{jt} is the advertising stock variable for brand j at time t, defined as the exponentially smoothed weighted average of past advertising expenses.[3] The parameters λ_{it} and θ_{it} capture the price and advertising sensitivity, respectively, for consumer i; parameter ω_{it} is the weight attached to the experienced quality.[4] We assume that these coefficients are time specific and heterogeneous across consumers. The parameter $\overline{\omega}_t$ represents the mean utility weight of the square of experienced quality levels. Parameter γ_{it} is the time-specific and heterogeneous risk coefficient. If $\overline{\omega}_t > 0$, then $\overline{\gamma}_{it} < 0$ suggests risk aversion at time t, and $\overline{\gamma}_t < 0$ implies risk-taking behavior at time t. To capture consumer unobserved heterogeneity, we assume that λ_{it}, θ_{it}, ω_{it}, and γ_{it} follow normal distributions. Finally, we assume a normal distribution for the random component $e_{ijt} \sim N(0, \Omega_j)$.

Note that in the preceding utility specification, we allow λ, ω, γ, and θ to vary over time to capture the possible change of the consumer's sensitivities before, during, and after the crisis. Because the product-harm crisis is a major incident in the category, we believe that it is imperative to allow consumer response coefficients to be time varying. Structural changes in the marketplace triggered by dramatic events such as product recall are commonly modeled through varying coefficient structures (Hanssens, Parsons, and Schultz 1990, pp. 57–61). More specifically, we define these parameters as follows:

$$(2) \qquad \lambda_{it} = h_{\lambda i} + \Delta_{1\lambda i}DM_{1t} + \Delta_{2\lambda i}DM_{2t},$$

$$(3) \qquad \theta_{it} = h_{\theta i} + \Delta_{1\theta i}DM_{1t} + \Delta_{2\theta i}DM_{2t},$$

$$(4) \qquad \omega_{it} = h_{\omega i} + \Delta_{1\omega i}DM_{1t} + \Delta_{2\omega i}DM_{2t}, \text{ and}$$

$$(5) \qquad \gamma_{it} = h_{\gamma i} + \Delta_{1\gamma i}DM_{1t} + \Delta_{2\gamma i}DM_{2t},$$

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[3]Note that in the current model specification, we do not allow consumers to learn product quality through advertising signals, because we do not have consumer media exposure data. Instead, we put the exponentially smoothed weighted average of past advertising spending in the main utility function as a control variable, as in Erdem and Sun (2002). Specifically, we define the advertising stock variable AD_{jt} as the exponentially smoothed weighted average of past advertising expenses, such that $AD_{jt} = DA_i AD_{j, t-1} + (1 - DA_i)ADEXP_{jt}$, where DA_i is the decay parameter of the advertising stock and $ADEXP_{jt}$ is the advertising expenses for brand j at time t. In a reduced-form way, this captures the demand-shifting effects of advertising. Note that we reparameterize DA_i using a logit transformation because the decay parameter should be between 0 and 1.

[4]Note that according to the utility function we specify in Equation 1, consumers' sensitivity to experienced quality ($\partial U_{ijt}/\partial X_{ijt}$) is equal to $\overline{\omega} + 2\overline{\omega}_t\gamma_{it}X_{ijt}$, which depends on $\overline{\omega}_{it}$ and γ_{it}, the risk coefficient, and X_{ijt}, the experienced quality.

where DM_{1t} is a dummy variable that equals 1 during the product-harm crisis period and 0 otherwise and DM_{2t} is a dummy variable that equals 1 in the period after the product-harm crisis and 0 otherwise. We assume that the price sensitivity $\tilde{\lambda}_i = (h_{\lambda i}, \Delta_{1\lambda i}, \Delta_{2\lambda i})^T$, advertising sensitivity $\tilde{\theta}_i = (h_{\theta i}, \Delta_{1\theta i}, \Delta_{2\theta i})^T$, experienced quality coefficient $\tilde{\omega}_i = (h_{\omega i}, \Delta_{1\omega i}, \Delta_{2\omega i})^T$ and risk coefficient $\tilde{\gamma}_i = (h_{\gamma i}, \Delta_{1\gamma i}, \Delta_{2\gamma i})^T$ are normally distributed with the following mean vector and covariance matrix:

$$
(6) \quad \begin{bmatrix} \tilde{\lambda}_i \\ \tilde{\theta}_I \\ \tilde{\omega}_i \\ \tilde{\gamma}_i \end{bmatrix} \sim N \left\{ \begin{bmatrix} \bar{\lambda} \\ \bar{\theta} \\ \bar{\omega} \\ \bar{\gamma} \end{bmatrix}, \begin{bmatrix} \Sigma_\lambda & & & \\ & \Sigma_\theta & & \\ & & \Sigma_\omega & \\ & & & \Sigma_\gamma \end{bmatrix} \right\},
$$

where $\bar{\lambda}=(\bar{h}_\lambda, \bar{\Delta}_{1\lambda}, \bar{\Delta}_{2\lambda})^T$, $\bar{\theta}=(\bar{h}_\theta, \bar{\Delta}_{1\theta}, \bar{\Delta}_{2\theta})^T$, $\bar{\omega}=(\bar{h}_\omega, \bar{\Delta}_{1\omega}, \bar{\Delta}_{2\omega})^T$, $\bar{\gamma}=(\bar{h}_\gamma, \bar{\Delta}_{1\gamma}, \bar{\Delta}_{2\gamma})^T$, and $\Sigma = \text{Diag}\{\Sigma_\lambda, \Sigma_\theta, \Sigma_\omega, \Sigma_\gamma\}$ make up the variance–covariance matrix.

Consumers are uncertain about product quality. They form expectations about product quality and thus about the utility they will derive by consuming a particular brand. Therefore, the expected utility of consuming brand j at time t for consumer i, given the consumer's information at time t, is

$$
(7) \quad E_{ti}[U_{ijt}] = \lambda_{it}p_{ijt} + \theta_{it}AD_{jt} + \omega_{it}E_{it}[X_{ijt}] + \bar{\omega}_t\gamma_{it}E_{it}[X_{ijt}^2] + e_{ijt}.
$$

Note that each week t constitutes a purchase occasion at which a consumer might decide to buy one of the focal brands in our analysis. However, he or she might also purchase an "other" brand or decide not to purchase the product at all. To allow for the latter two scenarios, we specify the utility of making no purchase or "other" brand purchase as follows:

$$
(8) \quad E(U_{iNPt}) = \phi_{iNP} + DM_{1t}\phi_{iNP1} + DM_{2t}\phi_{iNP2} + (\psi_{iNP}
$$
$$
+ \psi_{iNP1}DM_{1t} + \psi_{iNP2}DM_{2t})t + e_{iNPt}, \text{ and}
$$

$$
(9) \quad E(U_{iOt}) = \phi_{iO} + DM_{1t}\phi_{iO1} + DM_{2t}\phi_{iO2} + (\psi_{iO} + \psi_{iO1}DM_{1t}
$$
$$
+ \psi_{iO2}DM_{2t})t + e_{iOt},
$$

which are functions of the during- and postcrisis dummy variables and a time trend.

We further assume that $\tilde{\phi}_{iNP} = (\phi_{iNP}, \phi_{iNP1}, \phi_{iNP2})^T$, $\tilde{\psi}_{iNP} = (\psi_{iNP}, \psi_{iNP1}, \psi_{iNP2})^T$, $\tilde{\phi}_{iO} = (\phi_{iO}, \phi_{iO1}, \phi_{iO2})^T$, and $\tilde{\psi}_{iO} = (\psi_{iO}, \psi_{iO1}, \psi_{iO2})^T$ are normally distributed with the following mean vector and covariance matrix:

$$
(10) \quad \begin{bmatrix} \tilde{\phi}_{iNP} \\ \tilde{\psi}_{iNP} \\ \tilde{\phi}_{iO} \\ \tilde{\psi}_{iO} \end{bmatrix} \sim N \left\{ \begin{bmatrix} \bar{\phi}_{NP} \\ \bar{\psi}_{NP} \\ \bar{\phi}_O \\ \bar{\psi}_O \end{bmatrix}, \begin{bmatrix} \Sigma_{\phi NP} & & & \\ & \Sigma_{\psi NP} & & \\ & & \Sigma_{\phi O} & \\ & & & \Sigma_{\psi O} \end{bmatrix} \right\}
$$

To reduce the number of parameters, we estimate a block diagonal variance–covariance matrix (24 parameters) instead of estimating a full variance–covariance matrix (78 parameters).

Consumer Learning About Product Quality

In this article, we focus on the information role of product use experience and product-harm crisis on consumer quality perceptions. We assume that consumers are uncertain about the mean quality level of a brand in addition to the precision of signals contained in use experience and the product-harm crisis in conveying product quality. Consumers will shape their perceptions of both the mean quality level and the precision of the information according to signals they receive from their own usage experience. Furthermore, we examine the signaling role of a product-harm crisis. As Dawar (1998, p. 114) pointedly observes, "A crisis situation provides consumers with a critical test of the firm's commitment to the brand that is not otherwise available through routine transactions."

First, we specify consumers' learning of the mean quality level and the precision of information after exposure to use experience. We assume that each experience provides a noisy but unbiased signal of the true quality. More specifically,

$$
(11) \quad X_{ijt} = Q_j + x_{ijt}, \text{ and } x_{ijt} \sim N(0, \sigma_{xj}^2),
$$

where Q_j is the true mean quality level for brand j and x_{ijt} is an i.i.d. error term. We allow the true quality Q_j to be different before and after the product-harm crisis for the affected brands. In particular, let $Q_j = Q_{bj}$ before the crisis, and let $Q_j = Q_{aj}$ after the crisis. Equation 11 indicates that usage experience provides imperfect information about the true product quality (Q_j) of that brand; σ_{xj}^2 is the experience variability that captures the noisiness of information contained in use experience with the brand.

We assume that at time t, a consumer has prior opinions about the mean quality and the precision of the signal from the use experience, which jointly follow the normal inverted-gamma distribution:

$$
(12) \quad Q_j \big| \sigma_{xj}^2 \sim N(\mu_{ijt}, \sigma_{xj}^2 / \tau_{ijt}), \quad 1/\sigma_{xj}^2 \sim \Gamma(\alpha_{ijt}, \beta_{ijt}),
$$

where μ_{ijt}, τ_{ijt}, α_{ijt}, and β_{ijt} are parameters of the prior joint distribution.

After using product j, consumer i begins to update his or her prior opinions on the basis of use experience X_{ijt} with the product (DeGroot 1991, p. 169):

$$
(13) \quad \mu_{ijt}^* = \mu_{ijt} + \frac{D_{ijt}}{\tau_{ijt} + 1}(X_{ijt} - \mu_{ijt}),
$$

$$
(14) \quad \tau_{ijt}^* = \tau_{ijt} + D_{ijt},
$$

$$
(15) \quad \alpha_{ijt}^* = \alpha_{ijt} + \frac{D_{ijt}}{2}, \text{ and}
$$

$$
(16) \quad \beta_{ijt}^* = \beta_{ijt} + \frac{D_{ijt}\tau_{ijt}(X_{ijt} - \mu_{ijt})^2}{2(\tau_{ijt} + 1)},
$$

where μ_{ijt}, τ_{ijt}, α_{ijt}, and β_{ijt} are the parameters of the prior distribution before using the brand and μ_{ijt}^*, τ_{ijt}^*, α_{ijt}^*, and β_{ijt}^* are the parameters of posterior joint distribution after using the brand. We use a preestimation sample in which we assume that consumers have the same quality evaluations for all the brands at the beginning of their purchase histories. We calibrate the model for the preestimation sample and calculate the posterior mean and variance of quality

evaluations for all the brands and each consumer at the end of his or her 20th purchase occasion. Then, we take the posterior mean and variance of quality evaluations as the initial prior mean evaluations for every consumer i in the estimation sample (e.g., Mehta, Rajiv, and Srinivasan 2004).

We assume that consumers also derive information about the product's quality from product-harm crises. We define the quality level signaled by the product-harm crisis information as C. Consumer i perceives the product-harm crisis as a noisy but unbiased signal about product quality, and he or she believes that $C \sim N(Q_j, \sigma^2_{cij})$, where σ^2_{cij} captures the noise of the information contained in the product-harm crisis signal for consumer i. For the sake of simplicity, we let $\sigma^2_{cij} = K_{cij}\sigma^2_{xj}$, where σ^2_{xj} is the experience variability. We could interpret Kc_{ij} as consumer i's perceived precision level of the information contained in the product-harm crisis relative to that contained in the usage experience in conveying product quality. If Kc_{ij} is less (greater) than 1, it suggests that consumer i perceives the precision of information contained in the product-harm crisis as higher (lower) than that in the usage experience. Because not everyone pays equal attention to the crisis information, we allow the relative information weight to be consumer specific. Because the relative information weight should be larger than zero, we reparameterize this parameter as follows:

$$(17) \qquad Kc_{ij} = \exp(\tilde{K}c_{ij}) \text{ with } \tilde{K}c_{ij} \sim N(\overline{K}_{cj}, \sigma^2_{Kcj}).$$

Following a similar logic as for the case of usage experience, we can write the parameters for the posterior distributions associated with the crisis signal as follows:

$$(18) \qquad \mu^*_{ijt} = \mu_{ijt} + \frac{Dc_{jt}}{Kc_{ij}\tau_{ijt} + 1}(C - \mu_{ijt}),$$

$$(19) \qquad \tau^*_{ijt} = \tau_{ijt} + \frac{Dc_{jt}}{Kc_{ij}},$$

$$(20) \qquad \alpha^*_{ijt} = \alpha_{ijt} + \frac{Dc_{jt}}{2}, \text{ and}$$

$$(21) \qquad \beta^*_{ijt} = \beta_{ijt} + \frac{Dc_{jt}\tau_{ijt}(C - \mu_{ijt})^2}{2(Kc_{ij}\tau_{ijt} + 1)},$$

where Dc_{jt} is a dummy variable equal to 1 when consumer i receives a crisis signal of brand j at time t and 0 otherwise.

We define consumer perception errors at time t as $v_{ij}(t)$, with $v_{ij}(t) = \mu_{ijt} - Q_j$. Then, the perception error variance at time t based on Equation 12 is given by the following:

$$(22) \; Var[v_{ij}(t)] = Var[E(\mu_{ijt} - Q_j | \sigma^2_{xj})] + [E(Var(\mu_{ijt} - Q_j | \sigma^2_{xj})]$$

$$= 0 + E(\frac{\sigma^2_{xj}}{\tau_{ijt}}) = \frac{\beta_{ijt}}{\tau_{ijt}(\alpha_{ijt} - 1)}.$$

This measure essentially reflects the variance of consumer quality beliefs and can be viewed as a representation of consumers' perceived risk. Consumer research shows the central role of consumers' risk perceptions in their evaluations, choices, and behaviors (e.g., Campbell and Goodstein 2001; Dowling and Staelin 1994). After receiving signals from use experience (X_{ijt}) and the product-harm crisis (C), the posterior perception error variance becomes the following:

$$(23) \qquad Var[v^*_{ij}(t)] = \frac{\beta^*_{ijt}}{\tau^*_{ijt}(\alpha^*_{ijt} - 1)}.$$

Note that the denominator of the perception error variance will increase with the arrival of new information because τ^*_{ijt} and α^*_{ijt} increase when the consumer is exposed to new information. However, note that the numerator in Equation 23 for the perception error variance (β^*_{ijt}) also increases when new information arrives. Therefore, the perception error variance could become larger or smaller when new information arrives depending on the rate of increase for the denominator and numerator in Equation 23. For example, if the new information is very inconsistent with the prior quality perception μ_{ijt}, β^*_{ijt} will increase dramatically, resulting in an increase of the perception error variance. The standard learning model in marketing assumes that the precision of information is constant over time and is known to consumers, leading to the perception error variance always decreasing when new information arrives. Our model relaxes this assumption. This is a key difference between our proposed learning model and the standard learning model in marketing.

Finally, to allow for the possibility that the more recently formed perceptions might receive more weight in evaluating product qualities, we assume that the consumer's confidence in his or her belief about the quality can diminish over time. The discounting of consumer confidence in quality beliefs could be due to consumers forgetting over time. Forgetting occurs when consumers imperfectly recall their prior brand quality evaluations when making their purchase decision. Memories of prior evaluations typically weaken, which makes them more difficult to retrieve (Anderson 1999). Mehta, Rajiv, and Srinivasan (2004) propose a learning model to study the impact of forgetting on consumer's brand choice decisions in packaged goods. They capture the forgetting process by positing that consumers recall their prior brand evaluations with noise when making a purchase decision in the category. The variance of the random noise is a measure of the amount of forgetting that takes place between purchase occasions t – 1 and t. In our approach, we keep the mean level of the quality perception and the perceived precision of information constant and allow the variances to increase over time. This suggests that the consumer's perceived noisiness of the information sources may increase over time as a result of forgetting. In light of the properties of the gamma and normal distributions, we lay out the consumer's discounting process as follows:

$$(24) \qquad \mu_{ij,t+1} = \mu^*_{ijt},$$

$$(25) \qquad \tau_{ij,t+1} = \delta_i\tau^*_{ijt},$$

$$(26) \qquad \alpha_{ij,t+1} = \delta_i\alpha^*_{ijt}, \text{ and}$$

$$(27) \qquad \beta_{ij,t+1} = \frac{\delta_i\alpha^*_{ijt} - 1}{\alpha^*_{ijt} - 1}\beta^*_{ijt},$$

where δ_i is a parameter that takes a value between 0 and 1.[5]

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[5]For ease of estimation, we reparameterize δ_i as follows: $\delta_i = \exp(\tilde{\delta}_i)/[1 + \exp(\tilde{\delta}_i)]$ and $\tilde{\delta}_i \sim N(\overline{\delta}, \sigma^2_\delta)$.

Let $E_{it}(\cdot)$ and $Var_{it}(\cdot)$ denote the conditional expectation and variance operator given consumer i's information at time t. According to the properties of the gamma and normal distributions, we can write the perceived mean and variance for both Q_j and σ_{xj}^2 as follows:

$$(28) \qquad E_{i,t+1}(Q_j) = \mu_{ij,t+1} = \mu_{ijt}^* = E_{it}^*(Q_j),$$

$$(29) \qquad Var_{i,t+1}(Q_j) = \frac{E_{i,t+1}(\sigma_{xj}^2)}{\tau_{ij,t+1}} = \frac{\beta_{ij,t+1}}{\tau_{ij,t+1}(\alpha_{ij,t+1} - 1)}$$

$$= \frac{1}{\delta_i}\frac{\beta_{ij,t+1}^*}{\tau_{ij,t+1}^*(\alpha_{ij,t+1}^* - 1)} = \frac{1}{\delta_i}Var_{it}^*(Q_j),$$

$$(30) \qquad E_{i,t+1}(\sigma_{xj}^2) = \frac{\beta_{ij,t+1}}{(\alpha_{ij,t+1} - 1)} = \frac{\beta_{ij,t+1}^*}{(\alpha_{ij,t+1}^* - 1)} = E_{it}^*(\sigma_{xj}^2), \text{ and}$$

$$(31) \qquad Var_{i,t+1}(\sigma_{xj}^2) = \frac{\beta_{ij,t+1}^2}{(\alpha_{ij,t+1} - 1)^2(\alpha_{ij,t+1} - 2)}$$

$$= \frac{1}{\delta_i}\frac{\beta_{ij,t+1}^{*2}}{(\alpha_{ij,t+1}^* - 1)^2(\alpha_{ij,t+1}^* - 2/\delta_i)}.$$

Equations 28–31 suggest that, ceteris paribus, the means of quality perception and perceived noisiness of information at time t + 1 are the same as their values at time t, whereas their variances at time t + 1 are inflated compared with their values at time t. Note that when α_{ijt}^* is large and δ_i is close to 1, we have the following:

$$(32) \qquad \frac{1}{(\alpha_{ijt}^* - 2/\delta_i)} \approx \frac{1}{(\alpha_{ijt}^* - 2)},$$

which leads to

$$(33) \qquad Var_{i,t+1}(\sigma_{xj}^2) \approx \frac{1}{\delta_i}Var_{it}^*(\sigma_{xj}^2).$$

Therefore, parameter $1/\delta_i$ captures the discounting of consumer i's confidence in his or her belief of the true mean quality level and is an approximate measure of the discounting of consumer i's confidence on belief of the noisiness of information received over time.

On the basis of previous discussion, we can rewrite consumer's expected utility Equation 7 as follows:

$$(34) \qquad E_{ti}[U_{ijt}] = \lambda_{it}p_{ijt} + \theta_{it} AD_{jt} + \omega_{it}\mu_{ijt}$$

$$+ \bar{\omega}_t\gamma_{it}(\mu_{ijt}^2 + \frac{\tau_{ijt} + 1}{\tau_{ijt}} \times \frac{\beta_{ijt}}{\alpha_{ijt} - 1}) + e_{ijt}.$$

Model Estimation

We estimate the model parameters using a hierarchical Bayesian approach. We executed 100,000 iterations of the Markov chain. We discarded the first 70,000 draws as the initial "burn-in" and kept the last 30,000 for inference. We checked convergence by beginning the chain from multiple points and noting common convergence and by inspecting time-series plots (for further discussion of the estimation, identification, and validation of our model, see the Web Appendix at http://www.marketingpower.com/jmrapril11).

DATA DESCRIPTION

To investigate the model, we focus on a product-harm crisis that hit Kraft Foods Australia's peanut butter division. In June 1996, Kraft was warned about a potential link between an outbreak of salmonella poisoning and its peanut butter products. As a result, Kraft peanut butter products were taken from supermarket shelves across Australia. Seventy percent of the peanut butter market had been affected by the recall, including Kraft's two major brands in the category: Kraft, the leading brand, and Eta, a local brand that Kraft had acquired in 1992. The contamination only affected Kraft's Eta brand. However, the company also recalled core Kraft brand peanut butter products as a precautionary measure. In less than two weeks, Kraft's share of the peanut butter market sank from 67% to 0% (*Business Review Weekly* 1996). Sanitarium, Kraft's key competitor, was not subject to the recall.

ACNielsen Australia provided the data set we use for our model estimation . It includes weekly purchase activities of 262 households in the Sydney and Melbourne metropolitan areas. We selected the sample using the following criteria: (1) The household had at least one purchase in the category before the product-harm crisis, and (2) the household had at least five purchases in the category during the 121-week sample period. In our sample, 14 of the 262 households purchased in the category before crisis but stopped buying after the crisis.

Our empirical analysis focuses on four brands that account for more than 90% of the market share. Our data set spans more than a year (60 weeks) before the beginning of the crisis (April 1995–June 1996), the 21 weeks during the crisis (July 1996–November 1996), and 40 weeks after the crisis. We used the first 20 weeks in the precrisis period to estimate the initial prior mean evaluations for every consumer in the calibration sample. The calibration sample includes 40 weeks in the precrisis period, 21 weeks during the crisis, and 40 weeks after the crisis. Our data set also includes the weekly price and advertising spending for all major media outlets, such as newspapers, magazines, television, radio, and outdoor advertising (see Figure 1), for each of the selected brands. Tables 2–5 show summary statistics. Kraft has the highest average price, followed by Sanitarium, Eta, and the store brand in the periods before, during, and after crisis. Not surprisingly, the market share of Sanitarium soars following the product recall. Sanitarium's share drops after the crisis but is still larger than its precrisis share. It is noteworthy that the sales for the store brand decline during and after Kraft's product-harm crisis. Our empirical analysis in the next section sheds some light on this seemingly counterintuitive phenomenon.

EMPIRICAL RESULTS

Model Comparison

To evaluate our model, we compare it against two benchmark models. The first is similar to ours but does not allow for any discounting of information over time (Model 1). The second is the standard consumer learning model in marketing (e.g., Erdem and Keane 1996), which assumes that consumers know about the precision of information and only update their beliefs about the mean quality level (Model 2). Table 6 reports the model fit statistics. The comparison

of the marginal likelihood shows that our proposed model outperforms Model 1 and Model 2. The superiority of our model over the standard consumer learning model (Model 2) suggests the importance of allowing consumers to update their perceptions of both the mean quality level and the precision of information when new information arrives after a product-harm crisis. The better fit of our model than of Model 1 indicates the need to capture information discounting over time. Because the fit statistics favor the proposed model, we focus our discussion in the next section on the full model specification.

Parameter Estimates

Tables 7–12 present the estimation results of the proposed model. Table 7 presents the price, advertising, experienced quality, and risk coefficients before, during, and after the product-harm crisis. Before the product-harm crisis, the price coefficient is significantly negative, and the advertising coefficient is significantly positive. The precrisis coefficient of experienced quality is significantly positive. The risk coefficient is significantly negative. This result, combined with the positive coefficient of the experienced quality, suggests that consumers are risk averse: The increased perceived quality variance (perceived risk) decreases consumers' expected utility and lowers the brand choice probability.

During the product-harm crisis, the price coefficient rises by .353 (–.377 before vs. –.024 during the crisis), suggesting that consumers become less price sensitive during the crisis period. A possible explanation is that during the product-harm crisis, product quality became the most prominent attribute and consumers put more weight on quality and less weight on price when deciding which brand to purchase. This result is also consistent with previous literature on prices as a cue for product quality (e.g., Gerstner 1985). During the product-harm crisis, a risk-averse consumer is more likely to choose a high-price brand to ensure good quality. The advertising coefficient decreases by .353 during the crisis (.811 before vs. .458 during the crisis). This could be due to the decrease of consumers' confidence in advertising in revealing product quality after the outbreak of the product-harm crisis. The risk coefficient decreases by .242 during the product-harm crisis (–.066 before vs. –.308 during the crisis), implying that consumers became more risk averse during the crisis. The weight attached to the experienced quality decreases by .880 during the crisis

(3.072 before vs. 2.191 during crisis). However, this result does not necessarily mean that consumers' sensitivity to quality decreases during the product crisis. Consumers' sensitivity to product quality is a function of three factors: the

Figure 1
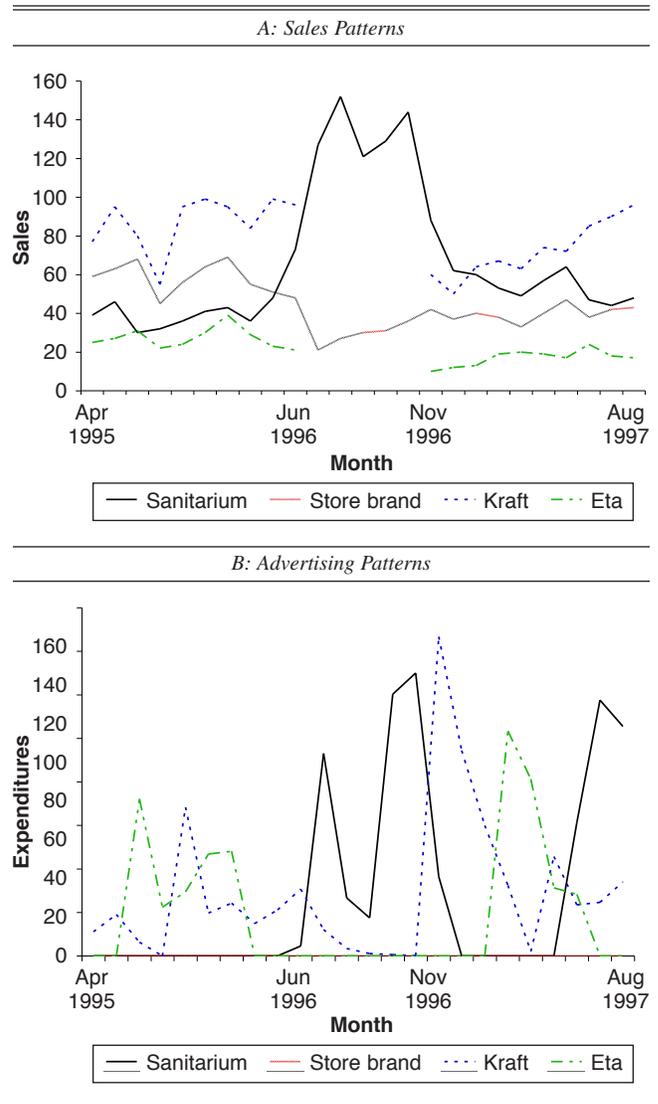SALES AND ADVERTISING PATTERNS

A: Sales Patterns

B: Advertising Patterns

Table 2
OVERALL MARKET SHARES AND AVERAGE PRICES

Brand	Sanitarium	Store Brand	Kraft	Eta	No Purchase	Others
Market share (%)	3.77	2.56	3.64	1.00	87.91	1.11
Price	6.749	4.405	7.456	6.342	N.A.	N.A.

Notes: N.A. = not applicable.

Table 3
MARKET SHARES AT DIFFERENT PERIODS

Brand	Sanitarium (%)	Store Brand (%)	Kraft (%)	Eta (%)	No Purchase (%)	Others (%)
Before crisis	2.40	3.27	5.12	1.53	87.07	.61
During crisis	7.64	2.65	.00	.00	88.78	1.92
After crisis	3.11	2.43	4.07	.99	88.30	1.19

Table 4
SUMMARY OF PRICES AT DIFFERENT PERIODS

Brand	Sanitarium	Store Brand	Kraft	Eta
Before Crisis				
M	6.63	4.23	7.89	6.38
SD	.52	.72	.83	.46
During Crisis				
M	6.79	4.55	N.A.	N.A.
SD	.44	.50	N.A.	N.A.
After Crisis				
M	.74	4.65	7.87	6.33
SD	.43	.40	.86	.53

Notes: N.A. = not applicable.

Table 5
SUMMARY OF ADVERTISING EXPENDITURE AT DIFFERENT PERIODS

Brand	Sanitarium	Store Brand	Kraft	Eta
Before Crisis				
M	.01	N.A.	.54	.55
SD	.10	N.A.	.50	.39
During Crisis				
M	1.93	N.A.	.09	.00
SD	1.85	N.A.	.27	.00
After Crisis				
M	.75	N.A.	1.36	.61
SD	1.80	N.A.	2.14	.36

Notes: N.A. = not applicable.

Table 6
FIT STATISTICS

	Marginal Likelihood
Proposed model	–13,356.52
Model without information discount	–13,572.04
Standard learning model	–14,224.99

experienced quality coefficient, experienced quality, and the risk coefficient ($\omega_{it} + 2\overline{\omega}_t\gamma_{it}X_{ijt}$). We calculated consumers' quality sensitivities before and during the product-harm crisis to determine whether there was any shift over time. Figure 2 illustrates the result. Figure 2, coupled with our finding that consumers are more risk averse during the crisis, suggests that when the perceived product quality level of a brand is relatively high, consumers' during-crisis sensitivities to the brand's quality are lower than their before-crisis sensitivities. In contrast, when the perceived quality level of a brand is relatively low, consumers' during-crisis sensitivities to the brand's quality are higher than their before-crisis sensitivities.

Our results also suggest that the postcrisis price sensitivity decreases significantly compared with its precrisis level but that the magnitude of decrease is smaller than that observed during the crisis (a magnitude of .353 during crisis vs. .005 postcrisis). After the product-harm crisis, consumers tend to be more risk averse than they were before the crisis (–.170 postcrisis vs. –.066 precrisis), but they are less risk

Figure 2
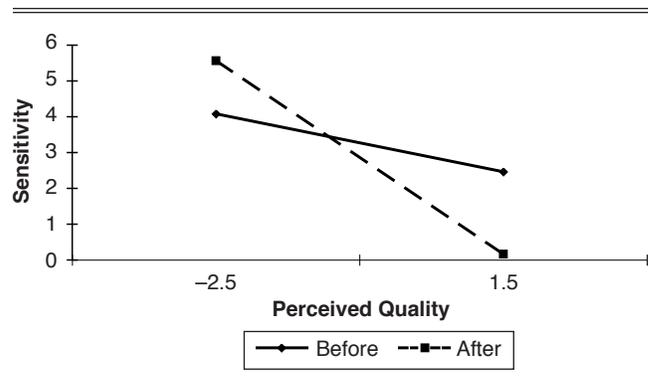#### CHANGE OF QUALITY SENSITIVITIES BEFORE AND DURING THE CRISIS

Table 7
COEFFICIENTS FOR PRICE, UTILITY WEIGHT, AND RISK (MEAN)

	Price Coefficient (λ)	Advertising Coefficient (θ)	Utility Weight (ω)	Risk Averse (γ)
Before crisis	–.3770 (.0104)	.8105 (.1168)	3.0715 (.1558)	–.0661 (.0133)
Difference during crisis Δ_1	.3527 (.0036)	–.3525 (.0268)	–.8804 (.1427)	–.2418 (.0266)
Difference after crisis Δ_2	.0050 (.0005)	–.6547 (.0368)	.5956 (.1977)	–.1043 (.0008)

Table 8
MEAN QUALITY LEVELS AND SIGNAL VARIABILITIES

	Sanitarium	Store Brand	Kraft	Eta
Mean quality level before crisis (Q_{bj})	.0000 FIXED	–.3041 (.053)	.2040 (.046)	–.2564 (.047)
Mean quality level after crisis (Q_{aj})	.0000 FIXED	–.0946 (.074)	.2288 (.071)	–.1967 (.147)
Experience variability (σ_j^2)	1.1862 (.094)	1.6233 (.131)	.7725 (.085)	1.2940 (.119)

averse than they were during the crisis (–.308 during the crisis vs. –.170 postcrisis). In other words, the product-harm crisis seems to have raised consumer risk aversion. We also note that this effect is stronger during the crisis than after the crisis. The results also suggest that consumer's sensitivity to advertising decreases by .655, compared with the precrisis level (.811 vs. .156).[6] We also find that consumers'

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[6]We also calculated the own and cross elasticities of price and advertising and found that the changes in them are mostly directionally the same as those Van Heerde, Helsen, and Dekimpe (2007) report.

Table 9
CRISIS-RELATED COEFFICIENTS

	C	$\tilde{K}_C$ for Kraft	$\tilde{K}_C$ for Eta
Mean	–1.7220	2.0106[a]	1.7705
	(.191)	(.364)	(.370)
Variance		.1099	.0756
		(.023)	(.013)

[a]Because $K_C = \exp(\tilde{K}_C)$, we calculated the means of the relative information weights to be 7.468 for Kraft and 5.874 for Eta, with standard errors of 2.718 and 2.173, respectively.

Table 10
INFORMATION DISCOUNT AND ADVERTISING SMOOTHING COEFFICIENT

	Information Discount $(\tilde{\delta})$	Advertising Smoothing $(\tilde{DA})$
Mean	5.3727[a]	2.1053[b]
	(.0317)	(.0324)
Variance	.0005	.0007
	(.0004)	(.0008)

[a]Because $\delta = \exp(\tilde{\delta})/[1 + \exp(\tilde{\delta})]$, we calculated the information discount coefficient to be .9953 with a standard error of .0002.
[b]Because $DA = \exp(\tilde{DA})/[1 + \exp(\tilde{DA})]$, we calculated the mean of advertising smoothing coefficient to be .8914 with a standard error of .0031.

Table 11
NO PURCHASE AND OTHER PURCHASE-RELATED COEFFICIENTS (MEAN)

	Before Crisis	Difference During Crisis	Difference After Crisis
No Purchase			
Intercept	2.0648	.2729	.2097
	(.081)	(.017)	(.068)
Time trend	–.0267	.0286	.0114
	(.001)	(.000)	(.000)
Other Purchase			
Intercept	–3.6068	3.1681	1.3747
	(.247)	(.216)	(.293)
Time trend	–.0054	.0048	–.0003
	(.001)	(.002)	(.000)

weight attached to the experienced quality increases significantly after the crisis (3.667 postcrisis vs. 3.072 precrisis). This is consistent with the intuition that after going through a major product-harm crisis, consumers may rely more on their own past usage experience than the messages delivered in advertising when making brand choices.

Table 8 presents the estimated product quality level for each brand. As noted previously, for identification reasons, we set the pre- and postcrisis quality levels of Sanitarium at 0. Before the crisis, the leading brand Kraft seems to have the highest level of quality, followed by Sanitarium, then Eta, and, finally, the store brand. The postcrisis quality for Kraft is still the highest, followed by Sanitarium, the store brand, and Eta. The results also suggest that the quality level of all three brands relative to Sanitarium increases after the crisis. This indicates that the two affected brands (Kraft and Eta) and the store brand (a low-quality brand) might have focused on improving product quality because product quality apparently became the most prominent product attribute after the crisis. For example, Kraft put new quality-checking systems in place at its own operations as well as its supplier's (*Sydney Morning Herald* 1996).

Our model also allows us to calculate consumers' perception of the mean quality level for each brand over time. Figure 3, Panel A, shows that before the crisis, consumers perceived the mean quality level of Kraft brand to be the highest, followed by Sanitarium, Eta, and then the store brand. In week 41, when the peanut butter crisis hit Kraft, the perceived mean quality levels for Kraft and Eta dropped significantly. Next, we break down consumers into heavy and light users of the affected brands to examine whether the change of perceived mean quality level due to product crisis would be different across different consumers types.[7] Previous studies have found that heavy users of the category/brand react differently to the negative information of the product (e.g., Ahluwalia 2002). Figure 3, Panel B, presents the results for Kraft. It suggests that for both heavy and light Kraft users, the perceived mean quality level decreases in the wake of the crisis. However, the decline is bigger for light than heavy users.[8] This is consistent with some of the previous findings in the literature that when consumers are familiar with a brand, the negativity publicity effect is attenuated (e.g., Cleeren, Dekimpe, and Helsen 2008).

The experience variabilities (σ^2_{xj}) for all the brands are statistically significant. This implies that usage experience provides noisy information (Table 8). More specifically, the experience variability for Kraft brand (.773) is the smallest, followed by Sanitarium (1.186), Eta (1.294), and the store brand (1.623). Apparently, the use experiences of Kraft and
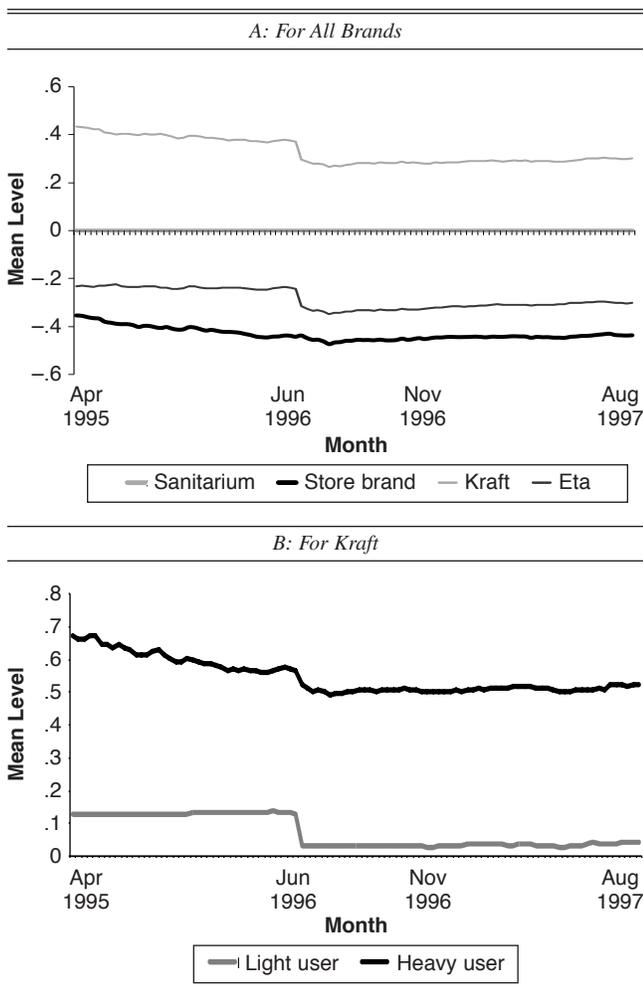
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[7]For each brand, we first ranked consumers according to their purchase frequency. Then, we defined the top 20% of them as the heavy users and the bottom 20% as the light users of the brand.
[8]Because of space limitations, we do not present the results for Eta. These are available on request from the authors.

Table 12
VARIANCE OF THE ERROR TERMS IN THE UTILITY FUNCTION

Brand	Sanitarium	Store Brand	Kraft	Eta	Other Purchase	No Purchase
σ^2_{ej}	1.6607	1.3806	1.1605	.8547	.7936	1.0000
	(.168)	(.171)	(.312)	(.060)	(.167)	(1.000)

Figure 3
PERCEIVED MEAN QUALITY LEVELS

A: For All Brands

Sanitarium — Store brand — Kraft — Eta

*B: For Kraft*

Light user — Heavy user

Sanitarium provide relatively more precise information about their qualities than the use experiences of the store brand and Eta. In other words, Kraft and Sanitarium, the leading national brands, provide relatively more consistent quality levels (real or perceived) over time than the store brand and Eta. This finding, together with the finding that consumers tend to become more risk averse during the crisis, can partially explain why a product-harm crisis affects various brands differently. When there is uncertainty associated with product quality, product quality level delivered consistently over time decreases consumers' perceived risk (variance of quality beliefs) and thus increases risk-averse consumers' choice probability of the brand. The more risk-averse consumers are, the stronger is this effect. Examining the recalled brands, we note that Kraft, the brand with the lowest estimated experience variability, was far more successful in regaining its precrisis market share after the crisis than Eta, the brand with a relatively high estimated experience variability. The competing brands also fared differently. The market share of Sanitarium, the brand with a lower estimated experience variability, increased during and after the crisis, whereas the market share of the store brand, the brand with a high estimated experience variability,

dropped during and after the crisis (compared with its respective precrisis market shares).

We also computed consumers' perceived variance of the mean quality level of each brand over time (see Figure 4). Figure 4, Panel A suggests that there was a sharp decrease in the perceived variability of the mean quality level of Eta during the contamination crisis. However, there was no major change for the perceived variance of Sanitarium, Kraft, and the store brand. This result contradicts the intuition that an inconsistent quality signal would increase consumer's perceived variance of the mean quality level. Figure 4, Panel B, offers an explanation for the counterintuitive aggregate results in Figure 4, Panel A. Figure 4, Panel B, shows that heavy and light users of Kraft exhibit different responses to the brand crisis. As we expected, the light users have a higher perceived variance of quality before the crisis than the heavy users. It is noteworthy that during the crisis, the perceived variance of quality increases for the heavy-user segment and decreases for the light-user segment, leading to no significant change of the overall perceived variance of quality for Kraft during the crisis. Our finding that consumers react differently to the product crisis information is essentially consistent with what the existing learning literature and our model suggest. That is, the perceived variance of the mean product quality decreases if the newly arrived signal is congruent with the existing quality perception and increases otherwise. For example, a heavy user of Kraft, the most frequently purchased brand before crisis, is more likely to have a smaller perceived variance of the mean quality of the brand than a light user. However, the occurrence of the crisis is largely incongruent with the con-

Figure 4
PERCEIVED VARIANCES OF THE MEAN QUALITY LEVEL

A: For All Brands

Sanitarium — Store brand — Kraft — Eta

B: For Kraft

Light user — Heavy user
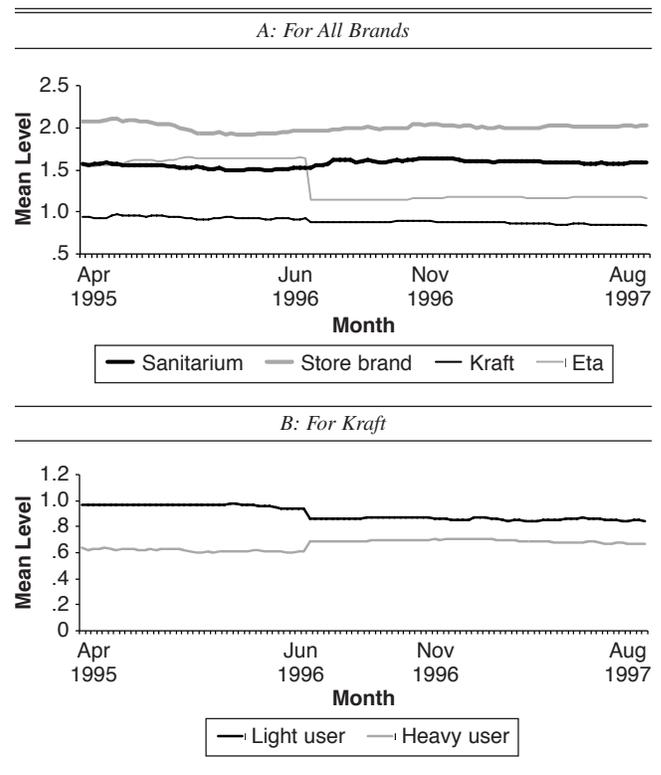
sumer's previous perception of the brand and thus increases the perceived variance of the quality of the brand. In contrast, the occurrence of the product crisis could be perceived as a confirmation of a light user's prior belief about the brand; therefore, the crisis could trigger a decrease in his or her perceived variance of the mean quality.

Table 9 presents the estimates of the crisis-related parameters. The crisis information parameter estimate (C) is significantly negative (–1.722), reflecting a negative signal of quality evoked by the product-harm crisis. The parameter estimates of Kc (i.e., the indicators of consumers' confidence in the information contained in crisis in conveying product quality relative to that of the usage experience) are greater than 1 for both Kraft and Eta and significant (Table 9), with the magnitude of Kc for Kraft being greater than that for Eta. This suggests that consumers trust the signals from use experience more than the signals from the product-harm crisis in conveying product quality. This result is consistent with the findings from previous studies that show that use experience provides more dominant and precise information about product quality than other signal sources (Erdem and Keane 1996; Erdem, Keane, and Sun 2008). Our results also suggest that consumers associate the signal from the product-harm crisis for Eta with less noise than that for the leading brand, Kraft. This could be because Eta was at the center of the crisis.

Table 10 presents the estimate of the information discount variable. We estimated the mean level of the discount coefficient (δ) to be .995. This confirms that consumers' beliefs about product quality are discounted over time.

Counterfactual Predictions and Managerial Implications

When a product-harm crisis occurs, marketing managers would be interested in learning how the crisis affects consumers' preferences for the product and how to cope with it. In this subsection, we report the findings of counterfactual experiments that we conducted to examine how product-harm crises influence consumers' intrinsic preferences for different brands according to our model estimation results. We also provide insights for managers into crisis management strategies.

When exogenous variables (e.g., price, advertising) are set to 0, the remaining part of the consumer-expected utility can be viewed as the consumer's intrinsic preference toward a brand. In our model specification, a consumer's intrinsic preference can be decomposed into two parts. The first part is the brand-specific consumer evaluation $[E_{it}(X_{ijt})]$ of product quality and the uncertainty $[Var_{it}(X_{ijt})]$ about the quality. The second part is the category-specific consumer sensitivities to quality (ω_{it}) and risk (r_{it}), which we assume to be different before, during, and after the product crisis. Our model estimation results confirm that a product-harm crisis can affect consumers' intrinsic preferences toward a brand through both factors.

In the counterfactual experiment described next, we examine how the product-harm crisis affects consumer intrinsic preferences differently toward various brands by simulating brand purchase frequencies under two distinct scenarios. In the first scenario, we assume that consumer sensitivities to price and risk do not change with the occurrence of the product-harm crisis. In the second scenario, we assume that consumers' evaluation of quality and their

uncertainty about the qualities of the affected brands do not change despite the product-harm crisis. We simulated purchase frequencies for each brand under the two scenarios and compared them with the baseline purchase frequencies simulated using the estimated parameters from the proposed model. We focus on the four brands studied here: Sanitarium, the store brand, Kraft, and Eta. Note that Kraft and Sanitarium are brands with high true mean quality and low product variability and that Eta and the store brand are brands with low true mean quality and high product variability.

In the first scenario, the difference between the simulated and baseline purchase frequencies for each affected brand captures the magnitude of the impact of the product crisis on consumers' sensitivities to quality and risk. In the second scenario, the difference between the simulated and baseline purchase frequencies for each affected brand captures the magnitude of the impact of the product crisis information on consumers' evaluations and uncertainties on product quality. Furthermore, because consumers' sensitivities to quality and risk are category specific, the difference between the simulated and baseline purchase frequencies for each of the unaffected brands under the two scenarios captures, at least partially, the spillover effects of the product-harm crisis on the nonrecalled brands.

Figure 5 shows the differences between the simulated and baseline purchase frequencies for each of the four brands under the two scenarios. The results suggest that the product-harm crisis had an impact on the affected brands (Kraft and Eta) in different ways and, likewise, the rival unaffected brands (Sanitarium and the store brand). For both recalled brands, the product-harm crisis lowered consumers' intrinsic preferences for the brands. However, note that for the high-quality brand (Kraft), the crisis hurt consumers' intrinsic preferences mainly through a decrease in their product quality evaluation and an increase in their product quality uncertainty. However, for the low-quality brand (Eta), the crisis affected intrinsic preferences of the brand mainly through an increase of consumers' sensitivities to risk and quality after the crisis. Our experiments also show that the product-harm crisis affected consumers' intrinsic preferences for the unaffected brands because of a change in their sensitivities toward risk and quality after the crisis. In particular, we find that the change of consumers' sensitivities to risk

Figure 5

RELATIVE MARKET SHARE CHANGES UNDER DIFFERENT SCENARIOS
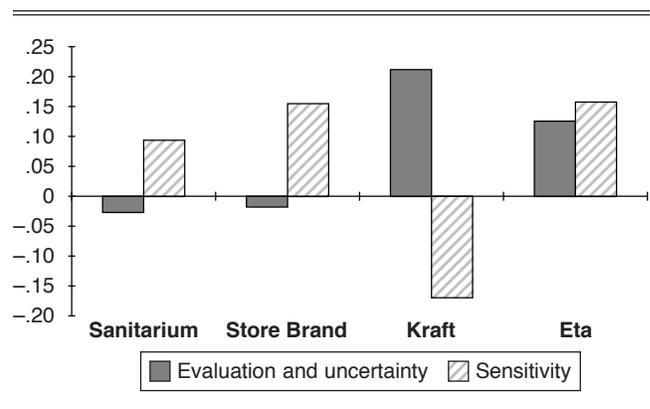
and quality as a spillover effect of the crisis lowered the intrinsic preferences for the store brand more than that for the Sanitarium national brand. Figure 5 also shows that the increase of consumers' product quality uncertainty due to the product-harm crisis had a positive impact on consumers' intrinsic preferences for the nonrecalled brands, suggesting that a product-harm crisis may benefit the competing brands in the category. Roehm and Tybout (2006) also report spillover effects of a brand crisis on competing brands.

What insights can we provide manufacturers on crisis management in light of the findings from these counterfactual experiments? For a strong high-quality brand that is affected by the product crisis (in our case, Kraft), the key objective after the reintroduction should be to stimulate short-term sales through marketing tactics such as price promotions and coupons. Having exposure to the brand will help boost consumer confidence, reduce the uncertainties on product quality, and eventually benefit future sales and profits. In contrast, for a marginal brand with a low-quality reputation, the primary goal should be to increase product quality because our results show that the decrease of consumers' intrinsic preference for the low-quality affected brand is mainly caused by an increase of their sensitivities to risk as a result of the product crisis.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

In this study, we present a new structural modeling approach to investigate the impact of critical events such as a product-harm crisis on consumers' brand choices. Our model is an extension of the consumer learning models that have been used in marketing. With the standard consumer learning model, consumers' perceived variance about the quality of a brand decreases with new incoming information from sources such as advertising. However, when a dramatic event such as a product-harm crisis happens, consumers' uncertainty about the affected brand in the category may increase rather than decline. The standard consumer learning model does not capture such phenomena. Our model relaxes this constraint and allows for situations in which consumers update their beliefs about the product's quality according to information that is incongruent with their prior beliefs. We apply our model to a product-harm crisis that erupted in the peanut butter category in Australia in 1996.

We find that our model substantially outperforms the standard consumer learning model. Our study also provides substantive insights into how a product-harm crisis affects consumers' choice behavioral responses. Finally, we conduct counterfactual experiments based on the estimation results of the proposed model and provide insights to managers on crisis management. Our results have direct managerial implications. The differences observed for the two recalled brands underscore the critical role of brand equity as a buffer against the negative publicity that a product recall generates: Brands with a strong reputation weather a crisis more effectively than their weaker counterparts. Rival brands can also benefit through a positive spillover from the crisis (Roehm and Tybout 2006). Indeed, Sanitarium raised its advertising spending during the recall period and emphasized that it roasted its own peanuts (in contrast to Kraft) in its advertisements. However, our results showed that such potential spillover effects can prove to be short-lived and

vary a great deal across brands. Our findings also suggest that a proactive approach can help a firm manage the crisis effectively.[9] After the crisis hit Kraft Foods Australia, the firm recalled every peanut butter brand it made from the shelves (including those that were not contaminated), communicated openly with its various stakeholders (i.e., consumers, media, and retailers), and installed new quality-monitoring systems in its plants and those of its peanut supplier (*Business Review Weekly* 1996). Finally, our results also suggest that coping mechanisms should differ for strong and weak brands. Strong brands must focus on marketing tools that raise short-term sales to increase consumer exposure, thus restoring trust in the reintroduced brand. Low-reputation brands should concentrate their resources on increasing their quality profile among consumers.

Our model can be applied to other situations in which a dramatic event might affect consumers' quality perceptions and their uncertainty about the precision of their information sources in conveying product quality. Examples include the relocation of a company's manufacturing facilities to another country, a company entering Chapter 11, and another company's takeover of a brand division (e.g., Jaguar/Land Rover by Tata, an Indian company).

Finally, our empirical application has several caveats. Because we study only one case of a product-harm crisis, external validity for other categories and/or settings is questionable. Because recent highly publicized crises have involved consumer durables (e.g., the 2010 Toyota recall), applying the model to non–frequently purchased good product types, such as durables and industrial goods, is a reasonable extension. A major issue is that data collection systems such as scanner data are uncommon for durables (Bayus and Mehta 1995) or services, though this situation is fortunately changing. For example, the German market research company GfK runs a consumer panel of 108,000 households across Europe that provides purchase information on nonpackaged goods such as furniture and consumer electronics (http://www.gfk-living.com/methoden/index.en.html). Furthermore, we focus only on the demand side of the market without modeling firms' strategic decisions in reacting to the crisis. Further research that jointly models the demand and supply side of the market is needed to address the potential endogeneity problem. Another area for further research is a cross-cultural study that contrasts consumers' responsiveness to a global brand or category crisis. Subject to data availability, our model might also be extended to study the spillover effects of a product-harm crisis for the umbrella brand in other categories.

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[9]Although this finding sounds intuitive, Chen, Ganesan, and Liu (2009) find that a proactive recall strategy could actually have a negative impact on the firm's market value.

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