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The Impact of a Product-Harm Crisis on Marketing Effectiveness

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Product-harm crises are among a firm's worst nightmares. A firm may experience (i) a loss in baseline sales, (ii) a reduced own effectiveness for its marketing instruments, (iii) an increased cross sensitivity to rival firms' marketing-mix activities, and (iv) a decreased cross impact of its marketing-mix instruments on the sales of competing, unaffected brands. We find that this quadruple jeopardy materialized in a case study of an Australian product-harm crisis faced by Kraft peanut butter. We arrive at this conclusion by using a time-varying error-correction model that quantifies the consequences of this crisis on base sales, and on own- and cross-brand short- and long-term effectiveness. The proposed modeling approach allows managers to make more informed decisions on how to regain the brands' pre-crisis performance levels.

Key words: brand management; product recalls; brand equity; marketing and public policy; error-correction models; time-varying parameters; time-series models; missing-data problems; Gibbs sampling methods
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1. Introduction

Most market-oriented firms allocate huge resources to build their brands. A brand's equity, however, can be very fragile. Among its biggest threats are product-harm crises, which can be defined as well-publicized events wherein products are found to be defective or even dangerous (Dawar and Pillutla 2000).[1] Product-harm crises can distort long-standing favorable quality perceptions, tarnish a company's reputation, cause major revenue and market-share losses, lead to costly product recalls, and devastate a carefully nurtured brand equity. Usually, the crisis relates to a particular brand. In 2000, Bridgestone/Firestone recalled 6.5 million tires after news broke that more than 100 people had died in accidents involving defective tires (*Advertising Age* 2000). In 1999, Coca-Cola was forced to withdraw 30 million cans and bottles in northern Europe following a scare in Belgium (*Guardian* 1999). Other notorious cases include Intel's flawed Pentium chip, Johnson & Johnson's cyanide-laced Tylenol, and the benzene contamination of Perrier. Occasionally, the crisis involves an entire product category such as poultry (bird flu), silicon breast implants, and beef (mad-cow disease).

Because of the increasing complexity of products and closer scrutiny by manufacturers and policy makers as well as higher demands by consumers, product-harm crises are expected to occur ever more frequently (Dawar and Pillutla 2000), while heightened media attention will also make them more visible to the general public (Ahluwalia et al. 2000). As Kahn pointedly put it, "The good news about brands is that people know who you are. The bad news is that if something goes wrong, everyone knows" (*Knowledge@Wharton* 2005). However, in spite of the devastating impact of product-harm crises, little systematic research exists to assess its marketing consequences. Academic studies in the area have either experimentally investigated consumer reactions to hypothetical product crises (Ahluwalia et al. 2000, Dawar and Pillutla 2000) or used aggregate, event study-based financial measures (Davidson and Worrell 1992, Marcus et al. 1987). Very limited attention has been devoted to adequately quantify the impact of actual product crises on relevant marketing metrics such as sales or market share. This quantification might not only be relevant to the affected brands'

[1] Sometimes the crisis can be triggered by malicious rumors generated by consumers or competitors.

management but also to policymakers or judges who must assess how much a company needs to be compensated for a product-harm crisis brought on by a third party (for a discussion of the use of marketing models in the public-policy domain, see Hanssens et al. 2005).

In this paper, we argue that the implications of a brand-specific product-harm crisis often go beyond the "obvious" short-run sales or market-share loss for a variety of reasons. First, the brand's own marketing-mix effectiveness might be reduced. For instance, because customers' trust might have been breached, advertising might now give less "bang for the buck" than before the crisis. Moreover, the brand might now have less potential to attract potential switchers or has become more sensitive to competitive activities. The latter phenomenon is especially relevant because competitors might try to exploit the marketing opportunities that arise because of the brand's misfortune by reducing their own price or increasing their advertising expenditures. Michelin North America, for instance, hiked its advertising budget to run a print campaign touting tire safety and quality in the wake of Bridgestone/Firestone's tire recall (*Advertising Age* 2000). Because of this changed own and cross-effectiveness, relying on the before-crisis estimates can seriously underestimate the extent of corrective action needed. Insights into postcrisis marketing effectiveness are crucial to managers who want to make informed decisions on how to restore brand performance to its precrisis level.

To investigate whether the implications of a product-harm crisis reach beyond the obvious losses in sales, we present in this paper a case study of a devastating product-harm crisis that affected Kraft Food Australia in the summer of 1996. More than 100 cases of salmonella poisoning potentially linked to Kraft-made peanut butter made management recall its two key brands for multiple weeks. Using weekly advertising and store scanning data for a precrisis period of more than a year and a postcrisis period of more than three years, we calibrate a time-varying error-correction model that quantifies the consequences of this crisis on both brands' base sales and on own- and cross-brand short- and long-term effectiveness, allowing management to make more informed decisions on how to regain the brands' precrisis performance levels.

The rest of the paper is structured as follows. First, we discuss the literature on product-crisis effects. Next, we present our model, discuss the data and results, and conclude with managerial implications and suggestions for further research.

2. Product-Crisis Effects

Even though product-crisis incidents are increasingly prevalent, fairly little systematic research has been conducted on the topic (Klein and Dawar 2004). Existing research can be broadly classified into three streams. The first stream consists of descriptive, often case-based studies suggesting which strategies work or do not work in the marketplace. Checklists are typically provided detailing the appropriate managerial actions to avoid product crises and how to respond when they occur (e.g., Mitroff 2004, Mitroff and Kilmann 1984, Rupp and Taylor 2002, Smith et al. 1996, Weinberger et al. 1993). These studies, while offering sound advice, provide little direction for understanding the underlying mechanisms through which product crises harm the company or brand (Ahluwalia et al. 2000), nor do they quantify the extent of the damage incurred (or averted).

Such an understanding of the underlying mechanisms is explicitly sought in a second research stream where lab experiments are used to assess the impact of hypothetical crises and moderating variables on brand evaluations, such as consumer expectations (Dawar and Pillutla 2000), commitment to the brand (Ahluwalia et al. 2000), brand loyalty (Stockmeyer 1996), the perceived locus of the problem (Griffin et al. 1991), and prior corporate social responsibility (Klein and Dawar 2004). Lab experiments have also been used to determine whether gender differences matter in blame attributions with a product-harm crisis (Laufer and Gillespie 2004). While these studies are well grounded in various psychological theories, their use of experimentally manipulated hypothetical product crises is likely to limit the external validity of the insights. Moreover, these studies typically do not attempt to quantify the financial implications of the crises.

The third stream of research focuses on gauging the effects of actual product-harm crises on a variety of performance measures including security prices (e.g., Chu et al. 2005, Govindaraj et al. 2004, Davidson and Worrell 1992, Marcus et al. 1987) and category consumption (e.g., Burton and Young 1996, Marsh et al. 2004). However, both aforementioned performance metrics are aggregate indicators and may not be as informative as more disaggregate analyses. Primary-demand measures, for example, do not account for the fact that not all incumbents can be affected to the same extent by a crisis. Indeed, the locus of the problem may be internal to some but external to others (Klein and Dawar 2004), while they may also have reacted differently to the crisis (Griffin et al. 1991). Stock-price reactions, while firm specific, do not identify the underlying mechanisms through which the resulting value loss emerged: Is it entirely due to a loss in baseline sales, or do investors also penalize the company for a potential loss in marketing-mix effectiveness because of the crisis? Do they fear that the brand has lost so much equity that it will become more vulnerable to future competitive actions? Moreover, if the company has umbrella branded its products, what part of the combined stock-market reaction can be attributed to, respectively, the product affected directly by the crisis and negative spillovers to other products sold under the same label (Sullivan 1990)?

Our paper contributes to the third research stream in that we explicitly quantify the performance implications of the crisis. However, unlike previous studies in this tradition, we present a much more disaggregate picture of the postcrisis situation in that (i) we explicitly distinguish between the different incumbent firms, recognizing that some players may actually benefit from the misfortune of their competitor(s), (ii) we allow for differential performance implications for different brands owned by the same company, and most importantly (iii) we identify various ways through which the brand may be affected, both in the short and in the long run: a loss in baseline sales, a reduced own marketing-mix effectiveness, an increased cross-sensitivity to competitive actions, and a reduced cross-brand impact for the own actions.

2.1. Baseline Sales

The most obvious effect of a product-harm crisis is the immediate loss in own-brand sales or market share. For example, sales at Wendy's restaurants in the San Francisco Bay area dropped 30% after a woman claimed to have found a finger in her chili (*Financial Times* 2005). Similarly, following a food-poisoning scandal in June 2000, sales of Snow Brand milk in Japan dropped 88% compared to a year earlier, while the brand's market share tumbled from 40% to less than 10% (Finkelstein 2005). To revive the brand's sales (and, in some cases, the entire category), managers might feel inclined to reduce the product's price or to substantially increase its advertising support. For example, after years of disastrous quality problems and product recalls, General Motors ran a major "road to redemption" campaign claiming that the company was "building the best cars and trucks in our history" (*New York Times* 2004). Advertising and promotional efforts could be increased to create awareness about the comeback and regain trust from risk-averse consumers (Byzalov and Shachar 2004).

2.2. Own Effects

Perhaps less obvious is that the crisis might have affected the effectiveness of marketing instruments. The crisis could have damaged the brand's equity (Dawar and Pillutla 2000), the firm's credibility (MacKinsey and Lutz 1989), and thereby the customer-brand relationship (Aaker et al. 2004). These consequences might negatively affect the effectiveness of subsequent advertising investments (Aaker 1991, Goldberg and Hartwick 1990). Similarly, when customers are exposed to negative information about the product, its perceived differentiation might be reduced (Ahluwalia et al. 2000), which could in turn increase the magnitude of its price elasticity (Boulding et al. 1994). Moreover, one should take into account that marketing-mix effects can reach well into the future (Dekimpe and Hanssens 1999, Jedidi et al. 1999), making it important to consider the long-run effects of the crisis as well. Product-harm crises can imperil long-standing favorable impressions and have performance implications that linger into the future. Indeed, negative information is known to be more informative and persistent than positive information (Skowronski and Carlston 1989), and customer trust is more easily lost than restored (Holmes and Rempel 1989). To that extent, we will quantify the impact of the crisis not just in terms of baseline share or sales losses, but also in terms of its implications on various instruments' short- and long-run effectiveness.

2.3. Cross Sensitivity

A product-harm crisis might not only affect a brand's own marketing-mix effectiveness but also various cross-effects: cross-sensitivity (the cross-effect of other brands on the focal brand) and cross-impact (the effect of a focal brand's marketing instrument on another brand). An affected brand's cross-sensitivity could increase as a result of the product-harm crisis. The higher a brand's equity, the smaller its cross-sensitivity to advertising attacks by competing brands (Aaker 1991, Steenkamp et al. 2005). Because of its potential impact on the brand's equity, the product crisis could result in an increased cross-advertising sensitivity. In addition, the brand's relative position in the category might have been negatively affected (Leclerc et al. 2005) because consumers might now classify it in a lower-quality tier. This may lead to stronger sales losses due to cross-brand price cuts (Blattberg and Wisniewski 1989). An increased cross-sensitivity is especially relevant as some rivals may see the product-harm crisis as a unique opportunity to increase their own share. The aforementioned Belgian Coca-Cola crisis was widely seen as giving its number one competitor, Virgin Cola, a unique "chance to reach the Belgian customer" (*Business Week* 1999), allowing it to double its market share over the course of one summer. Likewise, Goodyear and Michelin undertook a multipronged effort to bolster their own business following the well-publicized recall of Firestone tires (*Advertising Age* 2000). Moreover, as the product category is likely to be under close public scrutiny during the crisis, increased advertising efforts by one's competitors might well result in higher awareness than under normal circumstances (Dawar 1998).

2.4. Cross-Impact

An affected brand's cross-impact may decrease as a result of the product-harm crisis. The crisis could cause a decrease in a brand's perceived quality, leading to a reduced ability to attract switchers (Bronnenberg and Wathieu 1996). As a result, the brand's advertising becomes less impactful on other brands. In case postcrisis advertising for the affected brand has mostly an informational role about the reestablished safety to consume products in the category (Dawar and Pillutla 2000), postcrisis cross-advertising effects may even turn out to be positive. Indeed, consumers who stopped buying the product category, and then re-enter it, may first consider buying nonaffected brands in order to limit the perceived risk involved (Byzalov and Shachar 2004). Similary, because the crisis might impact brand differentiation adversely, fewer consumers might be inclined to switch to the affected brand when it decreases its price (Bell et al. 1999), which offers further evidence of its reduced cross-impact.

2.5. Same-Company Brands

Finally, in many product categories, firms own multiple brands. Therefore, a full understanding of the ramifications of a product-harm crisis implies that we should also consider the impact of the crisis on other brands of the same company within the category. In particular, if brand B is owned by the same company as the affected brand A, the negative impact of the crisis might spill over to brand B. Following allegations of a sudden-acceleration defect with the Audi 5000, for example, demand for the Audi 4000 and Quattro dropped as well (Sullivan 1990). Both brands might now be perceived as belonging to a lower quality tier in the postcrisis period, making them more vulnerable to competing brands. However, it is unclear a priori how their relative position to each other will be affected. That is, the overall (i.e., across all competing brands) decrease in cross-impact of one affected brand can be compensated by the increase in cross-sensitivity of the other affected brand. Whether the net change in the impact of one brand on the other is zero, positive, or negative is an empirical issue to which we return in the results section.

3. Model

3.1. The Base Error-Correction Model

To assess the impact of a product-harm crisis on each of the aforementioned own and cross-effects, we propose a new time-varying error-correction model that separately estimates short- and long-run elasticities. These elasticities vary according to transfer functions which account for crisis-induced structural breaks. The model is estimated using a Bayesian updating procedure, thereby allowing for missing observations. Our point of departure is the following vector error-correction model:

$$\Delta \ln S_t = \beta_0 + \sum_{k=1}^{K} A_k^{sr} \Delta X_{kt} + \Pi\left(\ln S_{t-1} - \sum_{k=1}^{K} A_k^{lr} X_{k,t-1}\right) + \nu_t, \quad \nu_t \sim N(0, V) \quad (1)$$

where

$\Delta =$ first difference operator: $\Delta X_t = X_t - X_{t-1}$,
$S_t =$ vector $(B \times 1)$ with sales (in kilo) of brands $b = 1, \ldots, B$ in week t,
$X_{kt} =$ vector $(B \times 1)$ with marketing-mix variable k $(k = 1, \ldots, K)$ of brands $b = 1, \ldots, B$ in week t,
$\beta_0 =$ vector $(B \times 1)$ with intercepts of brands $b = 1, \ldots, B$,
$A_k^{sr} =$ matrix $(B \times B)$ with short-run effects of marketing-mix variable k,
$A_k^{lr} =$ matrix $(B \times B)$ with long-run effects of marketing-mix variable k,
$\Pi =$ diagonal matrix $(B \times B)$ with adjustment effects,
$\nu_t =$ vector $(B \times 1)$ of error terms of brands $b = 1, \ldots, B$ in week t,
$V =$ variance-covariance matrix $(B \times B)$ of the error term ν_t.

The diagonal elements of A_k^{sr} and A_k^{lr} give the own effects of the kth marketing-mix variable of each brand, while the off-diagonal elements (which need not be symmetric) capture the corresponding cross-effects. If the X_{kt} are specified in ln space (e.g., ln prices), these effects can be interpreted as elasticities since the dependent variable is in natural logs as well. Alternatively, if the X_{kt} are untransformed, the elements of A_k^{sr} and A_k^{lr} are quasi elasticities.[2] The elements of A_k^{sr} are the instantaneous or short-run (quasi) elasticities, while the parameters in A_k^{lr} give the marginal effect of a permanent change in X_t on the long-run level of ln sales. As such, the A_k^{lr} parameters describe the long-run equilibrium relationship between the levels of marketing support and sales. Such equilibrium may exist between cointegrated, nonstationary variables (Dekimpe and Hanssens 1999, Franses et al. 1999) or between a set of stationary variables (Bass and Pilon 1980).[3] In the latter case, A_k^{lr} can be shown to also equal the cumulative effect on

[2] We do not take the ln of weekly advertising expenditures because these expenditures are zero in a number of weeks. Hence, the parameters for advertising are quasi elasticities which we transform into elasticities through multiplication with the median of nonzero advertising levels (see Gupta 1991 for a similar practice). We also tested a benchmark model with ln(advertising + 1) as predictor variable, but this model's predictive performance was inferior to the model with untransformed advertising variables (ln Bayes factor = 6.2).

[3] We assess which case applies in our specific setting through various unit-root and/or cointegration tests in §5.1.

current and future ln(sales) of a temporary change in X_t. In both instances, the Π parameters reflect the speed of adjustment toward the underlying long-run equilibrium. We refer to Fok et al. (2006) for a formal proof of these various properties, and to Franses (1994) or Paap and Franses (2000) among others for previous applications. An attractive feature of the error-correction specification is that it disentangles the short- and long-run effects of the marketing mix into two distinct sets of parameters. As such, it differs from recent impulse response-based operationalizations (see, e.g., Nijs et al. 2001, Pauwels et al. 2002) which use complex, nonlinear functions of the model parameters to quantify marketing-mix effectiveness over different planning horizons and typically result in quite large standard errors (Fok et al. 2006).

3.2. The Time-Varying Error-Correction Model

To assess the impact of the product-harm crisis, we allow for time-varying parameters in Equation (1) and obtain:

$$\Delta \ln S_t = \beta_{0t} + \sum_{k=1}^{K} A_{kt}^{sr} \Delta X_{kt} + \Pi_t \left(\ln S_{t-1} - \sum_{k=1}^{K} A_{kt}^{lr} X_{k,t-1} \right) + \nu_t, \quad \nu_t \sim N(0, V). \quad (2a)$$

After multiplying through, we can rewrite Equation (2a) as:

$$\Delta \ln S_t = \beta_{0t} + \sum_{k=1}^{K} A_{kt}^{sr} \Delta X_{kt} + \Pi_t \ln S_{t-1} + \sum_{k=1}^{K} A_{kt}^{lr*} X_{k,t-1} + \nu_t, \quad \nu_t \sim N(0, V), \quad (2b)$$

where $A_{kt}^{lr*} = -\Pi_t A_{kt}^{lr}$.

To model longitudinal parameter evolution, we use a transfer function for the typical scalar element ϕ_t of β_{0t}, A_{kt}^{sr}, or A_{kt}^{lr*}, specified as:

$$\phi_t = \lambda_\phi \phi_{t-1} + Z_t \psi_\phi + \omega_{\phi t}, \quad (3)$$

where $Z_t = (1, AfterCrisis_t) =$ (intercept, step dummy After Crisis), $\psi_\phi = (\psi_{0\phi}, \psi_{\phi AC})'$ and $\omega_{\phi t}$ is a normally distributed error term ($\omega_{\phi t} \sim N(0, W_\phi)$), which is independent from other ω's and independent from ν_t in Equation (2b) and $\lambda_\phi \geq 0$. We use a transfer function for two reasons. First, the autoregressive term in Equation (3) reflects that consumers may need some adjustment period before the new equilibrium response parameters are reached, as they may initially engage in attempts to refute or ignore negative information concerning well-trusted brands (Aaker et al. 2004, Ahluwalia 2000), while also communications aimed at deleting associations with the crisis and creating new brand images may take time to be processed (*Knowledge@Wharton* 2005). A flexible model is needed to accommodate such behavior. A similar gradual adjustment behavior is allowed for in the innovational-outlier model often used in the economic literature to describe how the time path of economic variables changes following a structural break (see Perron 1994 for a review). Second, consistent with prior work by, among others, Gatignon and Hanssens (1987) and Van Heerde et al. (2004), we believe that parameter processes are unlikely to be fully captured by a deterministic model but also need random-parameter errors (see also Gatignon 1993 for a review on this issue), captured by $\omega_{\phi t}$ in Equation (3).

Equation (3) shows how, prior to the crisis, the parameter fluctuates around a fixed mean $\psi_{0\phi}/(1-\lambda_\phi)$ (if $\lambda_\phi < 1$) with random disturbances ($\omega_{\phi t}$) and a gradual adjustment to shocks and deterministic changes captured by λ_ϕ. A structural break is allowed for at the end of the crisis, which causes the parameter to settle at a new level of $(\psi_{0\phi} + \psi_{\phi AC})/(1 - \lambda_\phi)$.[4] In the empirical application, we allow the crisis to impact any marketing-mix parameter that involves the affected brands, both in the equations of the affected brands themselves and in their impact on other brands.[5] In the results section, we report these pre- and postcrisis steady-state values for intercepts and short-run effects. Because the long-run effects A_{kt}^{lr} equal $-\Pi_t^{-1} A_{kt}^{lr*}$, their steady-state values are obtained as $[\psi_{0\phi}/(1-\lambda_\phi)]/[-\pi_0/(1-\lambda_\pi)]$ (before) and $[(\psi_{0\phi} + \psi_{\phi AC})/(1-\lambda_\phi)]/[-\pi_0/(1-\lambda_\pi)]$ (after).

For identification purposes, we exclude the *After-Crisis* effect from the transfer function of the adjustment parameters Π_t. Hence, its typical scalar element π_t evolves as in

$$\pi_t = \lambda_\pi \pi_{t-1} + \pi_0 + \omega_{\pi t}. \quad (4)$$

A simpler alternative to our approach is to estimate a model with piecewise constant parameters, i.e., with different pre- and postcrisis parameters. This model is nested in our model, as it can be obtained by setting all adjustment parameters (λ) and parameter errors (ω) equal to zero in Equations (3) and (4). We estimated the piecewise-constant model as well but found convincing predictive evidence in favor of our model (see Footnote 8).

[4] As such, in line with previous research (see, e.g., Deleersnyder et al. 2002, Perron 1994), we model the crisis as an intervention in the deterministic part of the transfer function.

[5] We may extend the vector Z_t with a step dummy that is one *during* the crisis to capture the impact of the crisis on parameters from brands that remained available during the crisis. In the empirical application, we allow for such an impact on the intercept of the unaffected brand Sanitarium. We also tested whether we should allow for effects of the crisis (during and post) on *own-brand* effectiveness parameters of Sanitarium, but the predictive ln Bayes factor of 21.7 is clearly in favor of the more parsimonious model without these effects (see West and Harrison 1999, p. 328).

3.3. Estimation

For model estimation purposes, we transform Model (2b)–(4) into a transfer function dynamic linear model (West and Harrison 1999, p. 284) by defining $y_t = \Delta \ln S_t$,

$$F_t' = (I_B, (I_B \otimes \Delta X_{1t}', I_B \otimes \Delta X_{2t}', \ldots, I_B \otimes \Delta X_{Kt}'), I_B \otimes \ln(S_{t-1}'), (I_B \otimes X_{1t-1}', I_B \otimes X_{2t-1}', \ldots, I_B \otimes X_{Kt-1}'))$$

with I_B a $B \times B$ identity matrix, and $\theta_t = (\beta_{0t}, \{\text{vec}(A_{kt}^{sr})\}_{k=1}^K, \text{vec}(\Pi_t), \{\text{vec}(A_{kt}^{lr*})\}_{k=1}^K)$:

$$y_t = F_t'\theta_t + \nu_t, \quad \nu_t \sim N(0, V), \tag{5}$$

$$\theta_t = G\theta_{t-1} + Z_t\psi + \omega_t, \quad \omega_t \sim N(0, W), \tag{6}$$

where $Z_t = (I_{n_\theta} \otimes (1, \mathit{AfterCrisis}_t))$, $G = \text{diag}(\lambda_1, \ldots, \lambda_{n_\theta})$, and n_θ is the number of elements in θ_t. Equations (5) and (6) are estimated by Bayesian techniques as outlined in the online appendix.

A product crisis in which a product is removed from the shelves for an extended period of time leads to a prolonged sequence of zero sales. In the salmonella case we study in this paper, 2 major brands were absent for 21 consecutive weeks. As a result, there are no data to estimate the affected brands' response models during their absence. In addition, the crisis leads to missing values in some of the affected brands' marketing instruments (such as price), which also appear on the right-hand side of the response models for the unaffected brands. Classical approaches such as least-squares or maximum-likelihood estimation remove all observations with missing values (Lemieux and McAlister 2005), which leads to a potentially substantial loss of observations and statistical precision (Kamakura and Wedel 2000). Moreover, such listwise deletion precludes the estimation of response parameters during the crisis, even for unaffected brands, which limits the usefulness of conventional VAR models (see, e.g., Krider et al. 2005 or Nijs et al. 2001 for recent applications) when the product crisis causes a prolonged product recall. Alternatively, data-imputation methods could lead to severe biases in regression estimates (e.g., Cooper et al. 1991). In contrast, Bayesian estimation of a dynamic linear model as specified in Equations (5) and (6) enables the estimation of the unaffected brands' models even in the presence of missing values at the right-hand side. Estimation is achieved by sequentially running through the data from time $t = 1$ until $t = T$, the final observation, where the prior parameter distribution at time t equals the posterior from time $t - 1$. When there is data on both the y-(dependent) and X-(independent) variable, the posterior of the corresponding response parameter is obtained by combining the prior and the data. In case there is a missing y or X variable, the posterior stays at its most recently updated value (i.e., the posterior value from just before the missing observation). More details are provided in the online appendix.

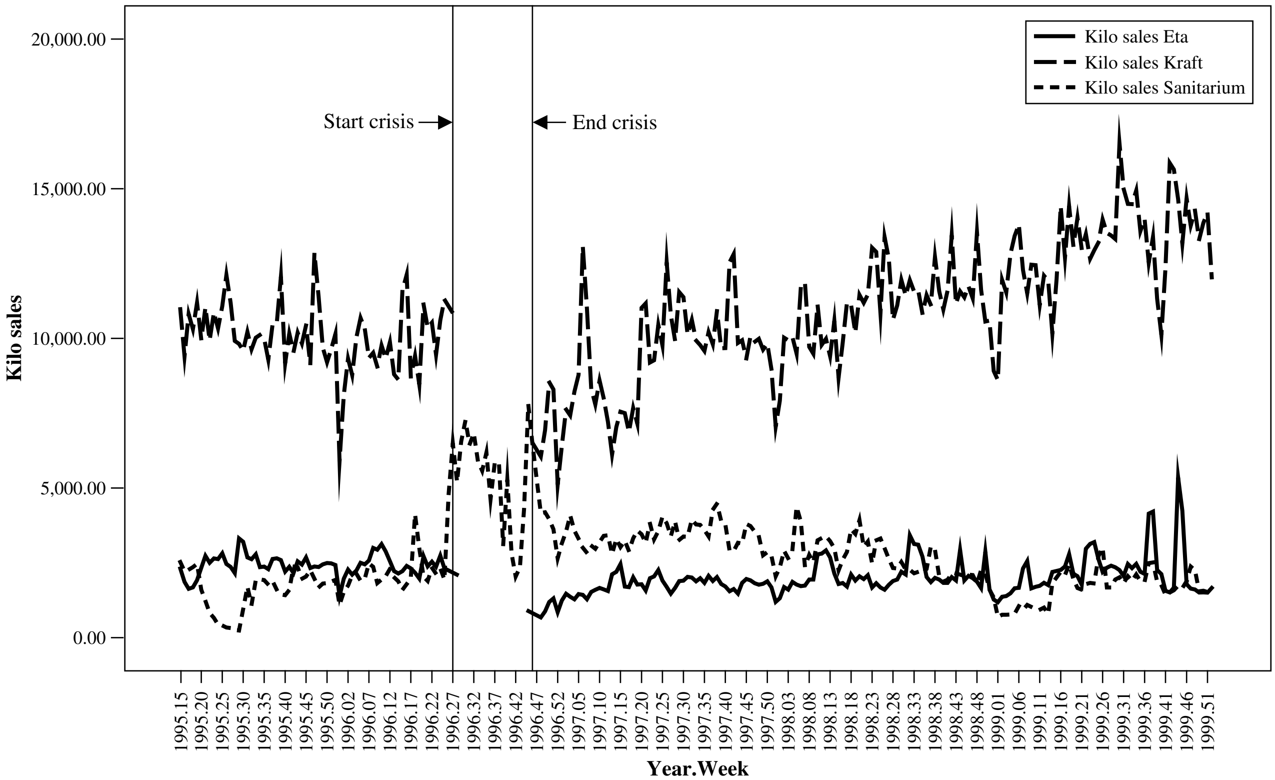
4. Data

In this paper, we study a severe example of a product crisis: the salmonella poisoning of Kraft peanut butter in Australia in 1996. We already referred to this crisis in the introduction. On the evening of Thursday, June 20, the managing director of Kraft Australia received a call from the local health authorities. A potential link had been identified between peanut butter made by Kraft and salmonella poisoning. As a consequence, Kraft Australia faced the worst crisis in its 70-year history (*Business Review Weekly* 1996). On Tuesday, June 25, Kraft was told by suppliers that contaminated peanuts had made their way into Eta peanut butter (*Sydney Morning Herald* 1996a). As a result, Kraft decided to widen the recall to all sizes and forms of Eta and Kraft peanut butter, its top brand in the category. The Kraft brand was included as a purely precautionary measure: Kraft used different raw materials and product specifications for the core brand (ABC Radio National 1996). Seventy percent of Australia's peanut butter market had been affected by the recall (*Sydney Morning Herald* 1996a). By June 30, all Kraft-made peanut butter was removed from stores nationwide. This crisis was severe from several points of views (*Business Review Weekly* 1996). Over 100 cases of salmonella poisoning were reported, and more than 100,000 angry and confused customers contacted the company over a 5-day period. The media and health authorities attacked Kraft for responding slowly to the crisis. A law firm launched a class action suit against Kraft on behalf of 540 people. The distribution of all Kraft peanut butter brands was completely down for more than four months (June 30–November 17, 1996). After upgrading the monitoring and testing procedures at Kraft's Melbourne plant and its peanut supplier, all Kraft brands were reintroduced in fall 1996. Kraft spent up to AU$3 million on national advertising to relaunch its peanut butter brands (*Sydney Morning Herald* 1996b).[6] In this study, we investigate to what extent the crisis led to the various effects discussed in §2.

We also investigate how the competition fared during the crisis. In that respect, it is relevant to note that the source of the contamination was Kraft's external peanut supplier, the Peanut Butter Company of Australia. After the Kraft products were recalled, its primary peanut butter competitor Sanitarium ran newspaper and radio ads to tell consumers that its

[6] AU$1 = US$ ± 0.78 in 1996.

Figure 1 Sales Patterns



peanut butter was not contaminated. In July 1996, it launched a major television commercial campaign promoting the fact it had always been roasting its own peanuts.

To study the effects of this product-harm crisis on the three major brands (Kraft, Eta, and Sanitarium), we use retail-scanner data from AC Nielsen Australia. The data set covers weekly volume sales and retail prices for Woolworth, the leading retailer in New South Wales. Our data set also includes advertising spending across all key media in the state for all brands in the category. The data set spans more than a year before the start of the crisis (April 1995–June 1996), the five months of the crisis (July 1996–November 1996), and more than three years after the crisis (December 1996–December 1999). The marketing instruments in model (2b) are operationalized as $(X_{1t}, X_{2t}) = (Ad_t, \ln P_t)$, where Ad_t is a vector with the brands' advertising expenditures in week t and $\ln P_t$ is a vector with the ln of the brands' prices in week t (in AU$ per kilo).

In Figure 1, we show the sales patterns of the three brands, illustrating the impact of the crisis. Kraft and Eta sales were down to 0 during the crisis, as these brands were not distributed during this 21-week period. In the first 4 weeks after the crisis, average Eta sales were down by 59% relative to the final 4 weeks before the crisis, whereas Kraft's volume tumbled by 29%. In the longer run, both Eta and Kraft seem to recover from the crisis (Figure 1). During the crisis, Sanitarium sales tripled (see Table 1), whereas its sales seem to return to precrisis levels after the crisis (Figure 1). Table 1 also shows that Sanitarium spent 36 times more on weekly advertising during the crisis than before. Kraft responded by increasing weekly advertising expenditures after the crisis as well, while it cut down Eta advertising by a small amount. Brand prices were not changed very much after the crisis.

5. Results

5.1. Overall Results

Prior to model estimation, we tested whether all variables are stationary. For the Sanitarium brand, which was available during the entire time span but whose performance and/or marketing-support variables could be altered around the start and end of the product crisis, we applied the test procedure of Lumsdaine and Papell (1997), which allows for two structural breaks in the deterministic part (intercept and trend) of each series. For the Eta and Kraft brands, no price data were available during the crisis, while the sales and advertising series were zero for all observations during the crisis. For the Eta and Kraft series, we therefore excluded the observations during the crisis and applied the structural-break

Table 1 Descriptive Statistics: Weekly Means and Standard Deviations

Variable	Brand	Overall ($n=247$ for Sanitarium and $n=226$ for Eta and Kraft)	Before crisis ($n=64$)	During crisis ($n=21$)	After crisis ($n=162$)
Sales (kilo)	Eta	2,097 (602)	2,427 (348)	.	1,967 (632)
	Kraft	10,742 (2,141)	10,052 (1,088)	.	11,015 (2,383)
	Sanitarium	2,627 (1,304)	1,780 (684)	5,319 (1,611)	2,612 (927)
Advertising (AU$)	Eta	3,023 (10,158)	3,357 (9,371)	.	2,891 (10,477)
	Kraft	10,551 (20,246)	7,006 (11,289)	.	11,952 (22,716)
	Sanitarium	3,627 (12,616)	607 (2,766)	21,925 (22,510)	2,448 (11,339)
Price (AU$)	Eta	6.3 (0.3)	6.0 (0.1)	.	6.4 (0.3)
	Kraft	7.7 (0.2)	7.5 (0.2)	.	7.7 (0.2)
	Sanitarium	7.0 (0.4)	6.6 (0.4)	6.8 (0.4)	7.2 (0.3)

unit-root test of Perron (1989)[7] in which we allow for one structural break in the deterministic part of the data-generating process at the transition between pre- and postcrisis observations. In all instances, the unit-root null hypothesis was rejected at the 5% level. The long-run parameters obtained from our error-correction specification can therefore be interpreted both as permanent effects of permanent changes and as the cumulative effects of temporary changes, as discussed in §3.1. Because no unit roots were found, no subsequent cointegration tests were called for.

Next, we apply Model (2b)–(4) to the data set, and report adjustment parameters in Table 2 and regression parameter summaries in Table 3 (Eta) and Table 4 (Kraft).[8] Table 2 shows that the parameter adjustment to the new equilibrium is fairly rapid on average; the 90% duration interval (Leone 1995) equals 2.7 weeks. The adjustment is even faster for the affected brands Eta (1.8 weeks) and Kraft (1.5 weeks), consistent with the theory that negative information that can not be refuted has a strong impact on attitudes (Ahluwalia 2000). The parameters of the unaffected brand Sanitarium adjust somewhat slower (on average 4.6 weeks), underlining the importance of allowing for gradual parameter adjustment.

The parameters in Tables 3 and 4 are the steady-state values described in §3. The parameter estimates tend to have the expected signs. Consistent with the advertising literature (Vakratsas and Ambler 1999), own advertising elasticities[9] are between 0 and 0.34 (short and long run, before and after crisis). The average[10] short-run advertising elasticity (0.05) is smaller than the average long-term elasticity (0.24), which is consistent with positive carry-over effects of current advertising on future sales (Leone 1995). Cross-advertising effects are positive or zero, indicating positive primary-demand effects of advertising (Lancaster 1984, Schultz and Wittink 1976).

The average short-run own price elasticity is −2.75, which is close to the average price elasticity (−2.62) reported in the literature (Bijmolt et al. 2005). Similar to Fok et al. (2006), we find that the average long-term own price elasticity (−0.58) is closer to 0 than the average short-run own price elasticity (−2.75). This finding is consistent with the notion that short-term price-promotion bumps are partially offset by post-promotion dips (Van Heerde et al. 2000). All significant short-run cross-price elasticities are in the $[0, 2]$ range, which is the case for 85% of the reported cross-price elasticities in the literature (Sethuraman et al. 1999).

5.2. Parameter Changes

We find that the number of significant response-effect changes is higher for advertising (11) than for price (4). To judge to what extent these changes are in the expected direction, we use the same classification of own effects, cross-sensitivity, cross-impact, and same-company brands as in §2.

5.2.1. Baseline and Own Effects of Eta. Consistent with our expectations, we find that the product-harm crisis has a significant impact on both the intercept and advertising effects of Eta (Table 3). We illustrate the temporal pattern of these three parameters in Panels a, b, and c of Figure 2. Eta exhibits a significantly positive intercept before the crisis (2.78), which becomes nonsignificant after the crisis (0.99).

[7] See Deleersnyder et al. (2002) for a recent marketing application.

[8] As we alluded to in §3.2, we compared the Model (2b)–(4) to a model with piecewise constant parameters. The predictive ln Bayes factor (35.1) is strongly in favor of Model (2b)–(4) (see West and Harrison 1999, p. 328).

[9] While the parameter estimates obtained from Equations (5)–(6) are quasi-advertising elasticities, we report in Tables 3 and 4 the associated advertising elasticities to facilitate their interpretation (see Footnote 2).

[10] The averages reported in this subsection are across four cases: pre- and postcrisis Eta and pre- and postcrisis Kraft.

Table 2 Results for Adjustment Parameters

	λ		90% Duration interval (weeks)	
Brand	Mean	Standard deviation	Mean	Standard deviation
Eta	0.24	0.15	1.8	1.2
Kraft	0.21	0.10	1.5	0.5
Sanitarium	0.38	0.27	4.6	6.4
Overall	0.28	0.20	2.7	4.1

Note. A detailed table with all individual adjustment parameters is available from the first author upon request.

While both the short- and long-run advertising elasticities are significantly positive before the crisis (0.09 and 0.32, respectively), they reduce to nonsignificant and smaller magnitudes after the crisis (0.01 and 0.06, respectively). The changes are significant despite the wide credibility intervals in Figures 2b and 2c. In contrast, the short- and long-run price elasticities do not change significantly due to the crisis.

5.2.2. Cross-Sensitivity of Eta. As we expected, the crisis also decreases the benefits that Eta derives from advertising by its larger sister brand Kraft. The long-term elasticity collapses significantly from 0.24 (significant) to 0.03 (insignificant). The crisis also significantly decreases Eta's short-term (primary-demand) benefit from advertising by Sanitarium, from a significant 0.14 to an insignificant 0.02. Whereas the long-run effect of Sanitarium price on Eta sales is insignificant before the crisis (−1.05), this effect turns significant after the crisis (2.21). This significant increase in cross-sensitivity is again as we expected. However, there are no significant changes in Eta's cross-sensitivity to Kraft price. This finding suggests that even though both Eta and Kraft suffered from the crisis, their relative strength might have stayed rather constant.

5.2.3. Cross-Impact of Eta. We also find that the crisis reduces the short-run benefits Kraft derives from advertising by Eta, i.e., from 0.01 to −0.04 (significant decrease). Moreover, Eta's advertising becomes beneficial for Sanitarium in the long run (from an insignificant 0.08 to a significant 0.14). This is also illustrated in Figure 2, Panel d. Thus, Sanitarium benefits from Eta's efforts to recover from the crisis by means of advertising, suggesting that Eta's advertising informs consumers that it is safe again to consume products in the category (Dawar and Pillutla 2000). Nevertheless, some consumers seem to prefer to first try out the nonaffected brand Sanitarium rather than the affected brands Eta or Kraft. Also, Eta's price has

Table 3 Empirical Results for Eta: Steady-State Posterior Distributions

Effect	Independent variable	Period	Before crisis median (2.5th, 97.5th percentiles)	After crisis median (2.5th, 97.5th percentiles)	Significant change
Own effects	Constant		2.78* (1.50, 4.47)	0.99 (−0.12, 1.54)	<u>Decrease</u>
	Advertising	Short run	0.09* (0.03, 0.13)	0.01 (−0.01, 0.04)	<u>Decrease</u>
		Long run	0.32* (0.18, 0.55)	0.06 (−0.02, 0.13)	<u>Decrease</u>
	Price	Short run	−3.65* (−6.72, −1.09)	−3.83* (−4.33, −3.22)	No
		Long run	−0.06 (−4.61, 4.97)	−1.60 (−3.01, 2.75)	No
Cross-sensitivity	Advertising Kraft	Short run	0.04* (0.02, 0.06)	0.01 (−0.01, 0.03)	No
		Long run	0.24* (0.03, 0.46)	0.03 (−0.07, 0.13)	<u>Decrease</u>
	Advertising Sanitarium	Short run	0.14* (0.04, 0.23)	0.02 (−0.06, 0.05)	<u>Decrease</u>
		Long run	0.13 (−0.12, 0.80)	0.09 (−0.22, 0.42)	No
	Price Kraft	Short run	0.97* (0.19, 2.15)	1.54* (0.72, 2.41)	No
		Long run	−0.37 (−4.39, 3.46)	0.48 (−3.43, 3.93)	No
	Price Sanitarium	Short run	0.82* (0.09, 1.49)	1.00* (0.34, 2.14)	No
		Long run	−1.05 (−5.36, 1.27)	2.21* (1.00, 3.72)	Increase
Cross-impact	Advertising impact on Kraft	Short run	0.01 (−0.02, 0.04)	−0.04 (−0.06, 0.01)	Decrease
		Long run	0.11 (−0.25, 0.27)	0.07 (−0.24, 0.29)	No
	Advertising impact on Sanitarium	Short run	0.01 (−0.02, 0.10)	0.02 (−0.03, 0.10)	No
		Long run	0.08 (−0.00, 0.13)	0.14* (0.09, 0.19)	Increase
	Price impact on Kraft	Short run	−0.58 (−1.98, 1.13)	0.38 (−0.45, 1.42)	No
		Long run	4.79 (−5.53, 12.33)	4.24* (1.74, 11.01)	No
	Price impact on Sanitarium	Short run	1.48* (0.13, 3.76)	0.12 (−0.56, 0.98)	<u>Decrease</u>
		Long run	1.96 (−0.77, 4.90)	0.30 (−0.18, 1.33)	No
Adjustment effect	Lagged ln kilo sales Eta		−0.25* (−0.40, −0.14)	−0.25* (−0.40, −0.14)	na**

*Indicates that zero is not included in the 95% posterior density interval. Underlined changes are significant at the 5% level; other changes, the 10% level. A change is labeled significant when the posterior 95% (or 90%) credible interval for the change in a parameter's steady-state value excludes zero. **This parameter is assumed to be unaffected by the crisis (see Equation 4).

Table 4 Empirical Results for Kraft: Steady-State Posterior Distributions

Effect	Independent variable	Period	Before crisis median (2.5th, 97.5th percentiles)	After crisis median (2.5th, 97.5th percentiles)	Significant change
Own	Constant		1.44* (0.77, 2.77)	−0.44 (−1.61, 1.13)	Decrease
	Advertising	Short run	0.045 (−0.01, 0.08)	0.037* (0.01, 0.06)	Decrease
		Long run	0.34* (0.17, 0.90)	0.24* (0.12, 0.82)	Decrease
	Price	Short run	−0.50 (−5.16, 0.95)	−3.00* (−4.24, −2.19)	Decrease
		Long run	−0.93 (−9.63, 3.31)	0.26 (−7.06, 2.98)	No
Cross-sensitivity	Advertising Eta	Short run	0.01 (−0.02, 0.04)	−0.04 (−0.06, 0.01)	Decrease
		Long run	0.11 (−0.25, 0.27)	0.07 (−0.24, 0.29)	No
	Advertising Sanitarium	Short run	−0.07 (−0.11, 0.05)	0.09* (0.01, 0.14)	Increase
		Long run	0.52 (−0.92, 1.33)	0.42 (−0.01, 1.22)	No
	Price Eta	Short run	−0.58 (−1.98, 1.13)	0.38 (−0.45, 1.42)	No
		Long run	4.79 (−5.53, 12.33)	4.24* (1.74, 11.01)	No
	Price Sanitarium	Short run	0.20 (−1.04, 1.63)	0.32 (−0.84, 1.36)	No
		Long run	−2.05 (−10.97, 2.06)	1.74 (−2.73, 6.16)	Increase
Cross-impact	Advertising impact on Eta	Short run	0.04* (0.02, 0.06)	0.01 (−0.01, 0.03)	No
		Long run	0.24* (0.03, 0.46)	0.03 (−0.07, 0.13)	Decrease
	Advertising impact on Sanitarium	Short run	−0.03 (−0.07, 0.01)	0.02* (0.00, 0.03)	Increase
		Long run	−0.12 (−0.24, 0.07)	0.05 (−0.00, 0.12)	Increase
	Price impact on Eta	Short run	0.97* (0.19, 2.15)	1.54* (0.72, 2.41)	No
		Long run	−0.37 (−4.39, 3.46)	0.48 (−3.43, 3.93)	No
	Price impact on Sanitarium	Short run	0.90 (−0.37, 1.75)	0.83 (−0.23, 1.89)	No
		Long run	0.46 (−0.90, 2.34)	0.36 (−0.54, 1.68)	No
Adjustment effect	Lagged ln kilo sales Kraft		−0.24 (−0.49, −0.05)	−0.24 (−0.49, −0.05)	na**

*Indicates that zero is not included in the 95% posterior density interval. Underlined changes are significant at the 5% level; other changes, the 10% level. A change is labeled significant when the posterior 95% (or 90%) credible interval for the change in a parameter's steady-state value excludes zero. **This parameter is assumed to be unaffected by the crisis (see Equation 4).

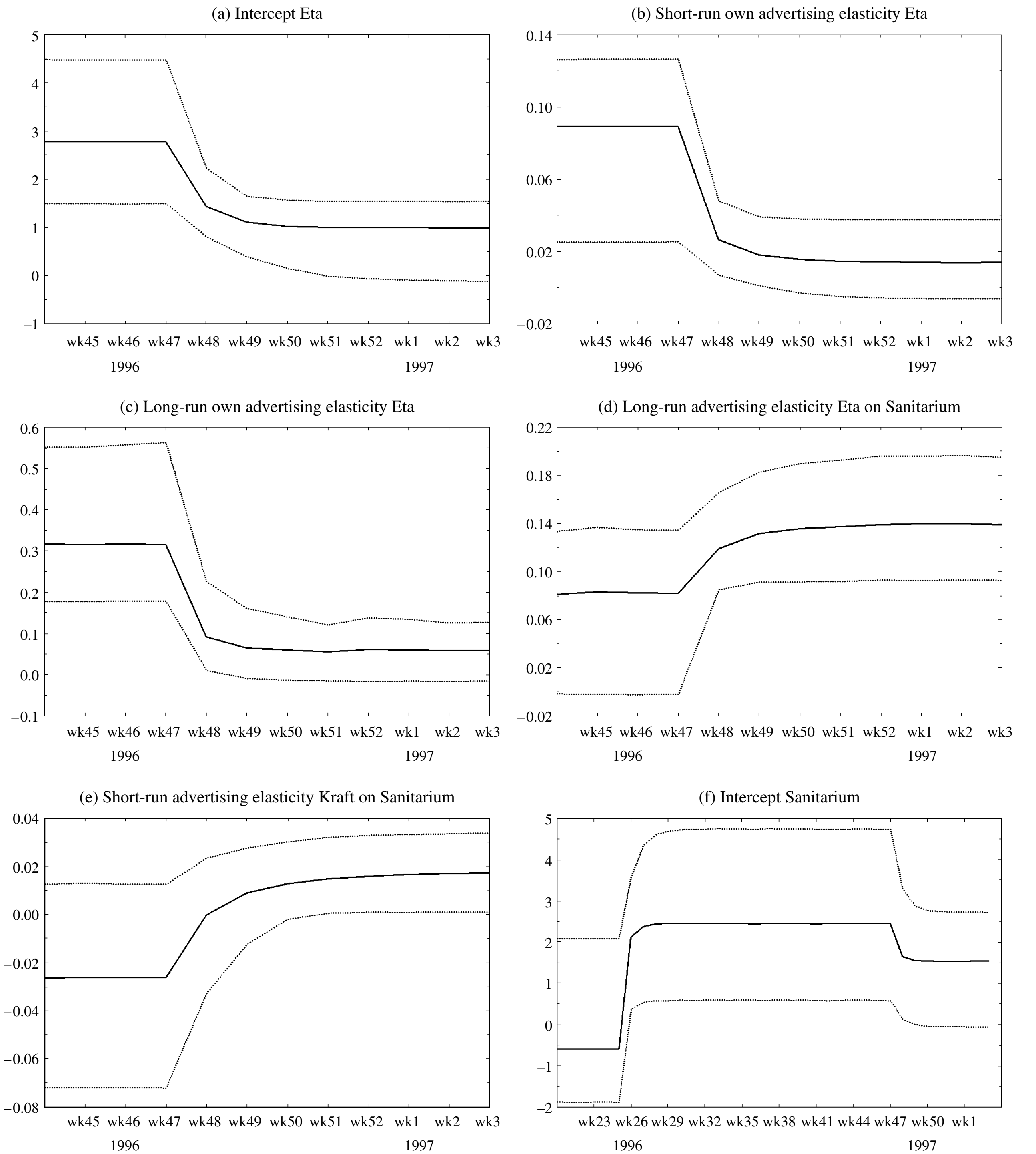
less short-run cross-impact on Sanitarium after the crisis (0.12, insignificant) than before (1.48, significant). This corresponds with the notion that postcrisis Eta becomes a less attractive brand to switch to when it is on discount (Bell et al. 1999). The price impacts of Eta on Kraft do not change appreciably, which is again consistent with constant relative strengths.

5.2.4. Same-Company Brands. Although the Kraft brand was not affected by the salmonella poisoning, as a precaution it was taken from the shelves for the same 21-week period as Eta. Table 4 shows that the crisis had a substantial impact on Kraft as well. Its postcrisis intercept turns from significant (1.44) to insignificant (−0.44). Kraft's own short- and long-run advertising suffer from the expected reduced effectiveness (Aaker 1991, Goldberg and Hartwick 1990). For example, its long-run elasticity estimate reduces significantly from 0.34 (significant) before the crisis to 0.24 (significant) after.

While Kraft's precrisis short-run price elasticity is only −0.50 and insignificant, its postcrisis elasticity is −3.00 and significant. Thus, whereas its insignificant price elasticity indicates that Kraft was strongly differentiated before the crisis (Boulding et al. 1994), it becomes much less so postcrisis. In other words, the Kraft brand can no longer raise its price unpenalized after the crisis.

Finally, advertising of Kraft and Sanitarium have mutually beneficial effects in the postcrisis era. That is, postcrisis advertising by Kraft may play an informational role (Dawar and Pillutla 2000). As a result, it significantly benefits Sanitarium sales more after the crisis (short-run: 0.02 (see Figure 2e); long-run: 0.05) than before (short run: −0.03 (see Figure 2e); long run −0.12). However, counter to our initial prediction, post crisis advertising by Sanitarium helps Kraft more after the crisis (short-run effect = 0.09, significant) than before (−0.07, insignificant). This finding, however, is in line with Dawar's (1998) argumentation that during a crisis, the whole category comes under closer public scrutiny (reflected in decreased peanut butter consumption), making it easier to create higher levels of awareness and returns with one's advertising. Sanitarium's advertising may therefore help to bring the message across that it is safe to again consume peanut butter. Once the crisis is over, some consumers, in response to this message, apparently start to switch back to the precrisis market leader Kraft. This signals that Kraft was able to bounce back and reclaim some of its market share lost to

Figure 2 Illustrations of Time-Varying Parameters



Notes. Bold (dotted) lines represent the median (2.5th and 97.5th percentiles) of the posterior parameter draws from Model (2a). We have transformed advertising quasi elasticities into elasticities using the procedure described in Footnote 2.

Sanitarium. Ahluwalia et al. (2000) found that consumers who have a high level of commitment to a brand are more likely to counterargue negative information. Hence, a strong brand like Kraft's core brand might be better able to weather a product-harm crisis (see also Hoeffler and Keller 2003).

5.2.5. Other Results. While Sanitarium's precrisis intercept is insignificant (−0.60),[11] it becomes significantly positive during the crisis (2.46) but turns

[11] The parameter estimates for Sanitarium are available from the first author upon request.

insignificant again after the crisis (1.53). We illustrate this pattern in Figure 2, Panel f. These findings match well with Sanitarium's sales graph in Figure 1. As indicated before (see Footnote 5), we do not allow the own-effectiveness parameters of Sanitarium to differ in the pre-, during, and postcrisis intervals. Its own-price elasticities in the short run (−2.52, significant) and long run (−2.01, insignificant) are comparable to the results from, respectively, Bijmolt et al. (2005) and Fok et al. (2006). It is further interesting to note (see also §5.3) that Sanitarium's own-brand advertising elasticities in the short run (0.08, significant) and in the long run (0.18, significant) are weak relative to the precrisis elasticities of Eta (Table 3) and Kraft (Table 4).

5.3. Managerial Implications

5.3.1. Revenue Loss Due to Crisis. An important question for both firms and policy makers is how much revenue is lost due to a product-harm crisis. This requires a comparison of actual revenues (in which the product-harm crisis took place) with hypothetical revenues in case the product-harm crisis had not taken place. To that extent, we obtained predictions of prices, advertising levels, and volume sales. The former two were obtained based on the models we used for the unit-root tests (see §5.1) in which we now restrict the crisis-induced changes in baseline and trend to zero. As for the latter, median model parameters from the precrisis era (since these are unaffected by the crisis) were used to derive dynamic forecasts of ln(sales) using Equation (2b), which were subsequently transferred into level forecasts using the procedure described in Hanssens et al. (2001, p. 395). Finally, hypothetical revenues were obtained by multiplying volume sales and price predictions for each week and aggregating them across weeks. Remember that the crisis took place in the second half of 1996 (July 1996–November 1996). We estimate that Eta revenues have been reduced by 90% (minus AU$262,000) in the second half of 1996, and Kraft revenues by 84% (minus AU$1,435,000). Eta's revenue loss is 7% in the first half of 1997, while Kraft's loss is 6%. The changes are getting close to 0 in the second half of 1997: Eta +2%, Kraft −2%. Our estimate for the total revenue loss for these two Kraft company brands in the period July 1996–December 1997 incurred at the Woolworth chain is AU$1,860,000.

5.3.2. Recovering the Loss. Another important managerial question is how much marketing investment an affected brand should make to recover losses in baseline sales, based on the updated postcrisis parameters.[12] Answering this question requires that we can actually use the postcrisis parameters for policy implications, i.e., the model is not subject to the Lucas critique (Bronnenberg et al. 2005, Franses 2005, Van Heerde et al. 2005). To test whether the Lucas critique applies, we test for superexogeneity (Engle et al. 1983) after the product crisis, closely following Ahumada (1992). First, we test whether there are policy changes in a marketing instrument. Specifically, we use moving-window Chow breakpoint tests (at $\alpha = 0.05$) for a first-order autoregressive model for the instrument. Second, we test whether the corresponding response parameter of interest stays constant for those observations in which there may have been a policy change (i.e., where the Chow test's p values are smaller than α). Specifically, we test whether step dummies for such observations in an autoregressive model for the posterior median parameter series are significant. Superexogeneity is established when the test of the instrument says there have been policy changes whereas the corresponding response parameter did not change significantly.[13] Applying the tests for each of the implications derived below yields the conclusion that superexogeneity is established and hence the Lucas critique does not apply.

To derive the managerial implications, we take the perspective of an affected brand's manager who finds out that his brand experienced a major sales loss in the first four weeks after the crisis. In the Australian salmonella case, average Eta sales were down by 59% relative to the final four weeks before the crisis, corresponding to an ln sales loss of 0.93 (see Table 5). Eta's postcrisis long-run quasi elasticity of advertising is 2.50 (see Table 5), indicating that a permanent weekly advertising increase of AU$1 million leads to a 2.50 ln sales increase in the long run.[14] Hence, to reestablish its precrisis (ln) sales level, Eta's brand manager should have spent a whopping $(0.93/2.50) * 10^6 =$ AU$373,578 on permanent weekly advertising, even ignoring the finding that 2.50 is an insignificant estimate. The incorrect required spending level based on the precrisis long-run advertising quasi elasticity (13.36) is much lower, $(0.93/13.36) * 10^6 =$ AU$69,782 (see Table 5). Interestingly, Eta's manager may have realized that spending advertising dollars on postcrisis Eta would be a waste of money. Accordingly, in reality he did not spend a dime on advertising during the four weeks after the crisis (see Table 5).

Relative to the final 4 weeks before the crisis, Kraft lost 29% sales in the first 4 weeks after the

[12] Because we lack margin data, we cannot assess what brands should do to reach precrisis profit levels (rather than sales levels).

[13] We refer to Ericsson (1992) and Ericsson et al. (1998) for an in-depth discussion on the concept of superexogeneity, and to various chapters in Ericsson and Irons (1994) for other applications of this testing sequence.

[14] This section reports quasi elasticities (instead of elasticities) to facilitate the calculation of absolute advertising levels.

Table 5 Required Weekly Advertising Spending to Recover from Product-Harm Crisis

	Eta	Kraft
Average sales (kg) in final 4 weeks before crisis	2,491	10,471
Average sales (kg) in first 4 weeks after crisis	1,013	7,453
Difference	−1,478 (−59%)	−3,018 (−29%)
Average ln sales in final 4 weeks before crisis	7.82	9.25
Average ln sales in first 4 weeks after crisis	6.89	8.91
Difference	−0.93	−0.35
Postcrisis long-term advertising quasi elasticity	2.50	10.71
Implied (correct) advertising level (AU$) to recover difference	373,578	32,444
Precrisis long-term advertising quasi elasticity	13.36	15.61
Implied (incorrect) advertising level (AU$) to recover difference	69,782	22,268
Actual advertising spending (AU$) in first 4 weeks after crisis	0	44,177

crisis. Right after the crisis, Kraft actually spent on average AU$44,177 on weekly advertising, which compares favorably to the permanent weekly advertising spending of AU$32,444 required to equalize post- to precrisis long-run sales levels (see Table 5). If Kraft management had believed that the precrisis quasi elasticity (15.61) still applied after the crisis, the implied (but incorrect) required weekly advertising spending would have been AU$22,268. In order to validate the robustness of these findings, we performed similar calculations for Eta and Kraft based on eight- (rather than four-) week pre- and postcrisis periods, which did not lead to substantively different conclusions.

Although in the precrisis period the long-run advertising quasi-elasticity estimates for Eta (13.36) and Kraft (15.61) were quite similar, after the crisis Kraft Australia decided to invest heavily in advertising for the Kraft brand rather than for Eta. Our model corroborates the appropriateness of this decision, given that in the postcrisis period, the long-run advertising quasi-elasticity estimate for Kraft (10.71) is more than 4 times larger than the insignificant estimate for Eta (2.50). This focus on the Kraft brand seems to have paid off, given its relatively quick postcrisis recovery in sales (see Figure 1).

Sanitarium responded quite opportunistically by spending 36 times more on weekly advertising during the crisis (AU$21,925) than before (AU$607; see Table 1). However, its long-run advertising quasi elasticity (4.56) is much lower than for postcrisis Kraft (10.71). Hence, Sanitarium has been trying to benefit from the crisis by investing a lot of money in a relatively weak marketing instrument. Moreover, the high advertising spending levels were not sustainable in the postcrisis period (down to AU$2,448). Additional investments in advertising would not have been very beneficial anyway, given its relatively low effectiveness.

It also seems that Sanitarium missed the opportunity to use its increased price cross-impact to hurt Eta and Kraft. Sanitarium's long-run price impact on both brands increases significantly after the crisis (see Tables 3 and 4). However, Sanitarium decided to *increase* its kilo price from on average AU$6.6 before the crisis to AU$7.2 after, an increase of 8%. In case Sanitarium would have decided to permanently *decrease* its price by the same percentage after the crisis, the long-run sales level of Eta would have decreased by 17% (=% price change $*$ long-run cross-price elasticity of Eta to Sanitarium $= -8 * 2.21$). This price decrease would have inflicted a 13% sales loss for Kraft. One of the possible reasons that Sanitarium missed this opportunity is that it may not have realized its brand gained so much cross-impact because of the crisis. The model proposed in this study is uniquely suited to provide such insights.

6. Conclusions

Product-harm crises are among the worst disasters that can happen to firms. The single best strategy is to avoid product-harm crises altogether by implementing very careful business processes with sufficient checks and balances. The second-best strategy is to react in an appropriate fashion when, despite all pre-cautions, a product crisis occurs which endangers the health and well-being of the firm's customers. The management literature provides various qualitative guidelines on how to regain consumer confidence (e.g., Smith et al. 1996). Because marketing investments can be instrumental to convince consumers to again purchase products of the firm, it is important to provide an adequate measurement of the effectiveness of marketing investments especially after the crisis. This paper provides a methodology to assess the impact of such crises in a quantitative way and applies the model to an Australian product-harm crisis for peanut butter.

A key take-away from this paper is that it is not only important to assess the extent to which business is lost as a result of the crisis, but also to find the new postcrisis response parameters to marketing activities. The case study showed that we have to reject the naive idea that firms can recoup from the crisis by advertising investments that remain equally effective as before the crisis. Instead, the required investments are much higher. On top of that, the impacted brands became more vulnerable to competitors whereas their cross-impact on competitors was strongly reduced.

The parameter estimates from this salmonella case in Australia are most likely not directly applicable to other product-harm crises. So how can, say, a manager of bottled water in the United States benefit from this paper in case she is faced with a product-harm crisis? Our recommendation is to keep track of the short- and long-run impact of the marketing mix by updating our time-varying error-correction model on a weekly basis as time progresses in the aftermath of the crisis (the estimation procedure described in the online appendix is in fact designed to do this; see also West and Harrison 1999). In the bad-case scenario of a product crisis for the brand leading to a product recall, one can update the response parameters as of the moment that the brand is on the shelves again. Based on the new (perhaps less favorable) parameters, the manager can take informed decisions to recoup at least part of the sales and revenue loss or decide this is fruitless. As more data become available, one can each time update the various response estimates and dynamically adjust one's recovery strategy.

A limitation of this study is that unlike lab studies on product-harm crises we lack a control group that did not suffer from the crisis. As a result, we only observe the scenario as it played out. While a control group would be desirable from an internal-validity point of view, it is impossible to subject only part of the population to a product crisis (Dekimpe and Hanssens 2007). In addition, it would obviously be unethical to purposely administer potentially hazardous products to randomly chosen subjects. However, to enhance the credibility of our results we have implemented several of the validity tests advocated in Franses (2005). Our paper has shown that the model's predictive validity is better than that of several benchmarks (Footnotes 2, 5, and 8), which corroborates the stability of the parameters for out-of-sample observations. In addition, superexogeneity tests (§5.3) show that the Lucas critique does not apply, which lends support for using the model parameters to derive policy implications. This justification, however, rests on the assumption that superexogeneity tests have sufficient power to detect parameter instability in the response relationship (Van Heerde et al. 2005), which has recently been questioned by Lindé (2001). Recent research by Rudebusch (2005) refutes this concern, stating that "it is unlikely that the inability to detect structural shifts in the reduced form stems from the low power of the statistical test" (p. 270). Still, as testing for superexogeneity becomes more widely used in the marketing literature to validate the use of econometric models in policy evaluations (see, e.g., Franses 2005, Naik and Raman 2003, Shugan 2005, Van Heerde et al. 2005), more research would be useful to further investigate this power issue.

The marketing literature has identified several double (or higher) jeopardies. For example, Ehrenberg et al. (1990) underscore that a small brand faces a double jeopardy relative to a larger brand: A small brand has far fewer buyers and its buyers tend to buy it less often. Fader and Schmittlein (1993) found evidence of a triple-jeopardy phenomenon: Low-share brands also have a much lower degree of repeat buying. This paper concludes that a product-harm crisis may represent a quadruple jeopardy to firms: (i) loss of baseline sales, (ii) loss of effectiveness of own marketing instruments, (iii) increased cross-sensitivity, and (iv) decreased cross-impact. Even though each of the four jeopardies we identified was present in the salmonella poisoning under investigation, this need not always be the case. More research is needed to assess their relative frequency and magnitude in other product crises and to determine whether the jeopardies are moderated by brand or category characteristics.

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