

## Managing Product-Harm Crises

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## **Abstract**

### **Managing Product-Harm Crises**

Product-harm crises are among a firm's worst nightmares. Since marketing investments may be instrumental to convince consumers to purchase the firm's products again, it is important to provide an adequate measurement of the effectiveness of these investments, especially after the crisis. We provide a methodology through which firms can assess the impact of product crises in a quantitative way. Based on the model estimates, firms can estimate the required level of investment to recoup from the crisis. A key finding of 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 study of an Australian product-harm crisis for peanut butter reveals that a product crisis may represent a quadruple jeopardy for a firm: (i) loss of baseline sales, (ii) a reduced own effectiveness for its marketing instruments, (iii) increased vulnerability, and (iv) decreased clout. We arrive at this conclusion by using a time-varying error-correction model that allows for (i) short- and long-term marketing mix effects, (ii) intercepts and response parameters that change over time as a result of the crisis, and (iii) missing observations, which result from the absence of the impacted brands during the product-recall period. The time-varying error-correction model is applicable to other marketing-research areas in which these three requirements (or any subset thereof) apply.

Key words: Brand Management, Error-Correction Models, Time-Varying Parameters, Time-Series Models, Missing-Data Problems, Gibbs Sampling Methods

## 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).<sup>1</sup> 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 a hundred 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 (The 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, the closer scrutiny by manufacturers and policy makers, as well as the higher demands by consumers, product-harm crises are expected to occur ever more frequently (Dawar and Pillutla 2000), while the heightened media attention will also make them more visible to the general public (Ahluwalia, Burnkrant and Unnava 2000). 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 (e.g. Ahluwalia et al. 2000; Dawar and Pillutla 2000), or have used aggregate, event-study based, financial measures (Davidson III and Worrell 1992; Marcus, Swidler, and Zivney 1987). Very limited attention has been devoted to adequately quantify the impact of product crises on relevant marketing metrics such as sales, market share, and marketing-mix effectiveness. Still, insights into these measures are crucial to managers who want to take appropriate corrective actions to restore brand performance to its pre-crisis level.

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<sup>1</sup> Sometimes the crisis can be triggered by malicious rumors, generated by consumers or competitors.

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 may be reduced. For instance, as customers’ trust may have been breached, advertising may now give less “bang for the buck” than before the crisis. Moreover, the brand may now have less clout to attract potential switchers, and/or may have become more vulnerable to competitive activities. The latter phenomenon may be especially relevant, as competitors may 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/or cross-effectiveness, relying on the before-crisis estimates may seriously underestimate the extent of corrective action needed.

We therefore develop a time-varying error-correction model that allows for crisis-induced changes in both short- and long-run response parameters. In so doing, we integrate two research streams. First, we extend recent literature that accommodates differences in short- and long-run effectiveness (see e.g. Dekimpe and Hanssens 1999; Pauwels, Hanssens, and Siddarth 2002) by allowing for time-varying parameters in the error-correction model proposed by Fok et al. (2005). While such time variation was allowed for in the Bayesian Dynamic Linear Model (DLM) of Van Heerde, Mela and Manchanda (2004), these authors did not yet distinguish short- from long-run marketing-mix effectiveness. The current paper's methodological contribution is that it combines both aforementioned approaches. Moreover, unlike traditional varying-parameter models (see e.g. Foekens, Leeflang and Wittink 1999), the Bayesian updating mechanism we advocate can handle prolonged (systematic) sequences of missing values caused by a complete loss of distribution, a phenomenon often encountered when the product-harm crisis triggers a product recall.

We apply the proposed methodology to 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 pre-crisis period of 1.5 years and a post-crisis period of 3.5 years, we calibrate a model that quantifies the consequences of this crisis on both brands' base sales, own effectiveness, clout and vulnerability, allowing management to make more informed decisions on how to regain the brands' pre-crisis 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 broadly be 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, Thomas, and Quelch 1996; Weinberger, Romeo and Piracha 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, Babin and Attaway 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 crisis.

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, Lin and Prather 2005; Govindaraj, Jaggi and Lin 2004; Davidson III and Worrell 1992; Marcus, Swidler, and Zivney 1987) and category consumption (Burton and Young 1996; Marsh, Schroeder, and Mintert 2004; Pesaran and Samiei 1991; Piggott and Marsh 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 may 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, Babin and Attaway 1991). Stock-price reactions, while being 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 post-crisis 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) 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 vulnerability to competitive actions, and a reduced clout for the own actions.

## *2.1 Own effects*

The most obvious effect (# 1) 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 percent compared to a year earlier, while the brand's market share tumbled from 40 percent to less than 10 percent (Finkelstein 2005). To revive the brand's sales (and in some case the entire category), managers may 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" (The 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).

Perhaps less obvious is that the crisis may have affected the effectiveness of marketing instruments (effect # 2). The crisis could have damaged the brand's equity (Dawar and Pilluta 2000) and the firm's credibility (MacKinsey and Lutz 1989), which may negatively affect the effectiveness of its subsequent advertising investments (Aaker 1991, Goldberg and Hartwick 1990). Similarly, when customers are exposed to negative information about the product, its perceived differentiation may be reduced (Ahluwalia et al. 2000), which could in turn increase the magnitude of its price elasticity (Boulding, Lee and Staelin 1994, Nicholson 1972). Moreover, one should take into account that marketing-mix effects may reach well into the future (Dekimpe and Hanssens 1999), making it important to consider the crisis' long-run effects as well. Product-harm crises may imperil long-standing favorable impressions, and have performance implications that linger well 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 crisis' impact 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.

## ***2.2 Vulnerability***

A product-harm crisis may not only affect a brand's marketing-mix effectiveness, but also various cross-effects. The higher a brand's equity, the smaller its vulnerability to price promotions or advertising attacks by competing brands, while its own actions are expected to have a greater effect on the sales of other brands (Aaker 1991). Because of its potential impact on the brand's equity, the product crisis could result in an increased vulnerability and reduced clout as well.

We first consider the cross-effect of other brands on the affected brand (vulnerability; effect # 3). Because of the product-harm crisis, customers may now classify the affected brand in a lower-quality brand tier, leading to stronger sales losses due to cross-brand price cuts (Blattberg and Wisniewski 1989), while competitors' advertising may now have more pronounced competitive effects (Steenkamp et al. 2005). An increased vulnerability 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 No. 1 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, while Goodyear and Michelin undertook a multipronged effort to increase 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 may well result in higher awareness and returns than under normal circumstances (Dawar 1998).

## ***2.3 Clout***

The impact of a brand's marketing instruments on other brands is commonly defined as clout (e.g., Kamakura and Russell 1989). An affected brand's clout may decrease as a result of the product-harm crisis (effect # 4). The crisis may cause a decrease in a brand's perceived quality, leading to a reduced ability to attract switchers (Bronnenberg and Wathieu 1996). As a result, its advertising becomes



less impactful on other brands. In case post-crisis advertising for the affected brand has mostly an informational role about the re-established safety to consume products in the category (Dawar and Pillutla 2000), post-crisis cross-advertising effects may even turn out to be positive. Indeed, consumers that stopped buying the product category may first consider to again buy non-affected brands in order to limit the perceived risk involved (Byzalov and Shachar 2004). Similarly, since the crisis may impact brand differentiation adversely, fewer consumers may be inclined to switch to the affected brand when it decreases its price (Bell, Chiang, and Padmanabhan 1999), which offers further evidence of its reduced clout.

#### *2.4 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. In particular, if brand B is owned by the same company as the affected brand A, the negative impact of the crisis may 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 (see Sullivan 1990 for an in-depth discussion). Both brands may now be perceived as belonging to a lower quality tier in the postcrisis period, making them more vulnerable to competitive 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 clout of one affected brand can be compensated by the increase in vulnerability of the other affected brand. Whether the net change in the impact of one brand on the other brand 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, a time-varying error-correction model is developed that separately estimates short- and long-run elasticities. These elasticities vary according to a transfer function which accounts for crisis-induced structural breaks. The model is estimated using a Bayesian updating procedure, which allows one to estimate the various parameters of interest, even when several key variables have prolonged sequences of missing observations.

Our point of departure is the following vector error-correction model,

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

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  $b=1, \dots, B$  in week  $t$
- $X_{kt}$  = Vector ( $B \times 1$ ) with marketing mix variable  $k$  ( $k = 1, \dots, K$ ) of brands  $b=1, \dots, B$  in week  $t$
- $\beta_0$  = Vector ( $B \times 1$ ) with intercepts of brands  $b=1, \dots, B$
- $A_k^{sr}$  = 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
- $v_t$  = Vector ( $B \times 1$ ) of error terms of brands  $b=1, \dots, B$  in week  $t$
- $V$  = Variance-Covariance matrix ( $B \times B$ ) of the error term  $v_t$

The diagonal elements of  $A_k^{sr}$  and  $A_k^{lr}$  give the own effects of the  $k$ -th 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 the ln space (e.g., ln prices), these effects can be interpreted as elasticities since the dependent variable is in natural log as well. Alternatively, if the  $X_{kt}$  are

untransformed, the elements of  $A_k^{sr}$  and  $A_k^{lr}$  are quasi-elasticities<sup>2</sup>. 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, non-stationary variables (Dekimpe and Hanssens 1999; Franses, Kloek and Lucas 1999), or between a set of stationary variables (Bass and Pilon 1980). In the latter case,  $A_k^{lr}$  can be shown to also equal the cumulative effect on current and future ln(sales) of a temporary change in  $X_t$ . In both instances, the  $\Pi$  parameters reflect the speed of adjustment towards the underlying long-run equilibrium. We refer to Fok et al. (2005) 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, non-linear 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. 2005).

### ***3.2. The time-varying error-correction model***

To assess the impact of the product-harm crisis, one could estimate model (1) twice, once before the crisis and once after the crisis. Such an approach was adopted in Pauwels and Srinivasan (2004) in the context of private-label introductions. To allow the market to reach a new equilibrium after the product-harm disturbance, one could opt to estimate the second model on data starting some time after the crisis. However, Van Heerde et al. (2004) recently criticized such an approach as it (i) results in an efficiency

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<sup>2</sup> We do not take the ln of weekly advertising expenditures, since these expenditures are zero in a number of weeks. Hence, the parameters for advertising are quasi-elasticities.

loss, and (ii) assumes constant parameters within each subsample, which may be too stringent an assumption in dynamic markets. To that extent, we allow for time-varying parameters in (1), and obtain:

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

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

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

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

We model the typical scalar element  $\phi_t$  of  $\beta_{0t}$ ,  $A_{kt}^{sr}$  or  $A_{kt}^{lr*}$  via a transfer function:

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

where  $Z_t = (1, \text{AfterCrisis}_t) = (\text{intercept}, \text{step dummy After Crisis})$ ,  $\psi_\phi = (\psi_{\phi 0}, \psi_{\phi AC})'$  and  $\omega_{\phi t}$  is a normally-distributed error term ( $\omega_{\phi t} \sim N(0, W_\phi)$ ), which is independent from other  $\omega$ 's and independent from  $v_t$  in (2b). For identification purposes, we exclude the *AfterCrisis* effect from the transfer function of the adjustment parameters  $\Pi_t$ ; hence, its typical scalar element  $\pi_t$  evolves as in:

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

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.<sup>3</sup>

Equation (3) shows how, prior to the crisis, the parameter fluctuated around a fixed mean,

$\psi_{0\phi} / (1 - \lambda_\phi)$ , with random disturbances ( $\omega_{\phi t}$ ) from that mean having a geometrically decaying impact on the value of  $\phi_t$ . A structural break is allowed for at the end of the crisis, which causes the parameter to

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<sup>3</sup> 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. For parsimony reasons, we do not allow for effects of the crisis on *own-brand* effectiveness parameters of Sanitarium.

settle at a new level of  $(\psi_{0\phi} + \psi_{\phi AC})/(1 - \lambda_\phi)$ .<sup>4</sup> In the results section we report these pre- and postcrisis steady-state values for intercepts and short-run effects. Since 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).

### 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  $y_t = \Delta \ln S_t$ ,

$$F_t' = (I_B, (I_B \otimes \Delta X'_{1t}, I_B \otimes \Delta X'_{2t}, \dots, I_B \otimes \Delta X'_{Kt}), I_B \otimes \ln(S'_{t-1}), (I_B \otimes X'_{1t-1}, I_B \otimes X'_{2t-1}, \dots, I_B \otimes X'_{Kt-1}))$$

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

$$(5) \quad y_t = F_t' \theta_t + v_t, \quad v_t \sim N(0, V)$$

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

where  $G = \text{diag}(\lambda_1, \dots, \lambda_{n_\theta})$ ,  $Z_t = (I_{n_\theta} \otimes (1, \text{AfterCrisis}_t))$ , and  $n_\theta$  is the number of elements in  $\theta_t$ .

Equations (5) and (6) are estimated by Bayesian techniques as outlined in the 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 missing values in both the dependent variable (the affected brand's  $\ln$  sales) and the independent variables (various elements of the affected brand's marketing mix, such as its  $\ln$  price). In the salmonella case we study in this paper, two 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. Moreover, also the response models for the unaffected brands cannot be estimated when there is a missing value in any of the independent variables (the relevant cross-effects in those models cannot be assessed). A typical solution in classical approaches such as OLS, VAR models or maximum-likelihood

<sup>4</sup> 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.

estimation is to remove all observations for which there is any missing value on the left- or right-hand side of the equation (see Lemieux and McAlister 2005 for a recent review). However, such list-wise deletion leads to a potentially severe loss of observations and statistical precision (Kamakura and Wedel 2000). Alternatively, data-imputation methods may lead to severe biases in regression estimates (e.g., Cooper, de Leeuw and Sogomonian 1991). In contrast, Bayesian estimation of a DLM as specified in (5) and (6) enables the estimation of the full model even in the presence of missing values, preserving all available observations. Estimation is achieved by sequentially updating the posterior distribution of each parameter running through the data from time  $t=1$  till  $t=T$ , the final observation. Only when there is data on both the  $y$ -(dependent) and  $X$ -(independent) variable, the posterior of the corresponding response parameter is updated. In case there is a missing  $y$  and/or  $X$ -variable, the posterior is set equal to the prior. More details are provided in the appendix.

#### **4. DATA**

In this paper, we study a very 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, Tom Park, managing director of the Kraft Australia, received a call from the 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-line 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 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 had been 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.

More than 100,000 angry and confused customers rang the company over a five-day period. The media and health authorities attacked Kraft for responding slowly to the crisis. A law firm launched a class action against Kraft on behalf of 540 people. The distribution of all Kraft brands was completely down for more than four months (June 30-November 17, 1996). The total cost of the recall and lost sales for Kraft was estimated to be around AU\$ 15 million.<sup>5</sup> After upgrading the monitoring and testing procedures at Kraft's Melbourne plant and its peanut supplier, all Kraft brands were re-introduced in Fall 1996. Kraft spent up to AU\$ 3 million on advertising to relaunch its peanut-butter brands (Sydney Morning Herald 1996b). In this study, we investigate to what extent the crisis led to the various effects discussed in Section 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 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 players, Kraft, Eta, and Sanitarium, we use retail-scanner data from AC Nielsen Australia. The dataset covers weekly volume sales and retail prices for Woolworth, the leading retailer in New South Wales. Our dataset also includes advertising spending across all key media in the state for all brands in the category. The dataset 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).

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<sup>5</sup> 1 AU\$ = ± 0.78 US\$ in 1996.

In Figure 1, we show the sales patterns of the three brands, illustrating the major impact of the crisis. Kraft and Eta sales were down to zero during the crisis, as these brands were not distributed during this 21-week period. Hence, during the crisis their price and advertising series are missing, which implies that the effects on own- and cross-brand sales are not updated in our Bayesian model estimation framework. The benefit of this framework is that it keeps updating those parameters for which the dependent and independent variables are observed during the crisis (e.g., the effect of Sanitarium's price on its sales), something that cannot be achieved by traditional methods such as OLS.

In the first four weeks after the crisis, average Eta sales were down by 59% relative to the final four weeks before the crisis, whereas Kraft lost 29%. In contrast, Sanitarium sales tripled during the crisis (see Table 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.

[Insert Table 1 and Figure 1 about here]

## 5. RESULTS

### *5.1 Overall results*

We apply model (2b)-(4) to the dataset, and report parameter summaries in Table 2 (Eta) and Table 3 (Kraft). The parameters are the steady state values described in section 3. The parameter estimates tend to have the expected signs. Advertising effects are quasi elasticities, and give percent change in sales due to a one million Australian dollar increase in advertising. Own advertising has significant positive or zero effects in all cases (short and long run, before and after crisis). The average short-run advertising quasi-elasticity<sup>6</sup> (2.02) is smaller than the average long-term quasi-elasticity (10.54), which is consistent with positive carry-over effects of current advertising on future sales (Leone 1995). Cross-advertising effects are positive or zero, consistent with positive primary-demand effects of advertising (Lancaster 1984, Schultz and Wittink 1976).

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<sup>6</sup> The averages reported in this subsection are across four cases: pre- and postcrisis Eta and pre- and postcrisis Kraft.



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, Van Heerde, and Pieters 2005). Similar to Fok et al. (2005), we find that the average long-term own price elasticity ( $-.58$ ) is closer to zero 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 postpromotion dips (Van Heerde, Leeflang, and Wittink 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, Srinivasan, and Kim 1999).

[Insert Tables 2 and 3 about here]

## ***5.2 Parameter changes***

We find that the number of significant response effect changes is higher for advertising (nine) than for price (four). To judge to what extent these changes are in the expected direction, we use the same classification of own effects, vulnerability, clout, and same-company brands as in section 2.

### *5.2.1. Own effects Eta*

Consistent with our expectations, we find that the product-harm crisis has a devastating 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 experiences a significantly positive intercept before the crisis (2.78), which becomes insignificant after the crisis (0.99). Both the short- and long-run advertising parameters are significantly positive before the crisis (3.77 and 13.36, respectively), but reduce to insignificant and smaller magnitudes after the crisis (.59 and 2.50, respectively). In contrast, the short- and long-run price elasticities do not change significantly due to the crisis.

[Insert Figure 2 about here]

### *5.2.2. Vulnerability of Eta*

As we expected, the crisis also decreases the benefits that Eta derives from advertising by its larger "sister brand" Kraft. The short-run effect reduces from 1.80 (significant) to 0.34 (insignificant),

and the long-term effect collapses from 11.11 (significant) to 1.59 (insignificant). The crisis also decreases Eta's short-term (primary-demand) benefit from advertising by Sanitarium, from a significant 3.65 to an insignificant 0.46. 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 increase in vulnerability is again as we expected. However, there are no significant changes in Eta's vulnerability to Kraft price. This finding suggests that even though both Eta and Kraft suffered from the crisis, their relative strength may have stayed rather constant.

### 5.2.3. *Clout of Eta*

We also find that the crisis reduces the short-run benefits Kraft derives from advertising by Eta, i.e. from .57 (insignificant) to -1.63 (significant). Moreover, Eta's advertising becomes beneficial for Sanitarium in the long run (jump from an insignificant 3.45 to a significant 5.70). This is also illustrated in Figure 3, 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 non-affected brand Sanitarium rather than the affected brands Eta or Kraft. Also, Eta's price has less short-run clout 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, Chiang, and Padmanabhan 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 by Kraft Australia for the same 21-week period as Eta. Table 3 shows that the crisis had a substantial impact on Kraft as well. Its post-crisis intercept turns from significant (1.44) to insignificant (-0.44). Kraft's own short-term advertising effect shows an interesting phenomenon:

although it becomes (as expected) lower in magnitude (from 2.04 to 1.67), it turns from insignificant into significantly positive (counter to the expectation). Table 3 shows that the postcrisis confidence bound becomes narrower, and excludes zero. A possible reason is that since Kraft spends more on advertising (with a higher standard deviation) postcrisis (Table 1), the effectiveness can be estimated with a higher precision. Kraft's own long-run advertising suffers from the expected reduced effectiveness (Aaker 1991, Goldberg and Hartwick 1990), and its quasi elasticity estimate reduces significantly from 15.61 (significant) before the crisis to 10.71 (significant) after.

While Kraft's pre-crisis short-run price elasticity is only  $-0.50$  and insignificant, its post-crisis elasticity is  $-3.00$  and significant (see also Figure 3, panel e). Thus, whereas its insignificant price elasticity indicates that Kraft was strongly differentiated before the crisis (Boulding, Lee, and Staelin 1994, Nicholson 1972), it becomes much less so postcrisis. In other words, the Kraft brand can no longer raise its price unpenalized in the postcrisis era.

Finally, advertising of Kraft and Sanitarium have mutually beneficial effects in the post-crisis 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: 0.81; long-run: 2.41) than before (short run:  $-1.20$ ; long run  $-5.63$ ). However, counter to our initial prediction, post-crisis advertising by Sanitarium helps Kraft more after the crisis (short-run effect = 2.36, significant) than before ( $-1.67$ , insignificant). This finding, however, is in line with Dawar's (1998) argumentation that because of the crisis, the whole category has come under closer public scrutiny, 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 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 pre-crisis market leader Kraft. This signals that Kraft was able to bounce back and reclaim some of its market share lost to Sanitarium. Ahluwalia et al. (2000) found that consumers who have a high level of commitment to a brand are more likely to counterargue with 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 pre-crisis intercept is insignificant ( $-0.60$ )<sup>7</sup>, it becomes significantly positive during the crisis (2.46), but turns 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 3), 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, Van Heerde, and Pieters (2005) and Fok et al. (2005). It is interesting to note (see also section 5.3) that Sanitarium's own-brand advertising quasi-elasticities in the short run (1.89, significant) and in the long run (4.56, significant) are weak relative to the pre-crisis quasi-elasticities of Eta (Table 2) and Kraft (Table 3).

### 5.3 *Managerial implications*

An important managerial question is how much marketing investment an affected brand should make to recover losses in baseline sales, based on the updated post-crisis parameters. To answer this question, we take the perspective of an affected brand's manager who finds out that his/her 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 a  $\ln$  sales loss of .93 (see Table 4). Eta's post-crisis long-run quasi-elasticity of advertising is 2.50, indicating that a permanent weekly advertising investment of 1 million AU\$ leads to a 2.50  $\ln$  sales increase in the long run. Hence, to re-establish its pre-crisis ( $\ln$ ) sales level, Eta's brand manager should have spent a whopping  $(.93/2.50)*10^6 = \text{AU\$ } 373,578$  on permanent weekly advertising, even ignoring the finding that 2.50 is an insignificant estimate. The incorrect required spending level based on the pre-crisis long-run advertising quasi elasticity (13.36) is much lower,  $(.94/13.36)*10^6 = \text{AU\$ } 69,782$  (see Table 4). Interestingly, Eta's manager may have realized spending advertising dollars on post-crisis Eta

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<sup>7</sup> The parameter estimates for Sanitarium are available from the first author upon request.

would be a waste of money. Accordingly, in reality s/he did not spend a dime on advertising during the four weeks after the crisis (see Table 4).

[Insert Table 4 about here]

Relative to the final four weeks before the crisis, Kraft lost 29% sales in the first four weeks after the 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 4). If Kraft management had believed that the pre-crisis effectiveness (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 pre-crisis 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 four 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 2).

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 clout 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% ( $= \% \text{ price change} * \text{long-run cross-price elasticity of Eta to Sanitarium} = -8 * 2.21$  ). This price decrease would have inflicted a 13% sales loss for Kraft. One of the possible reasons that Sanitarium missed this opportunity is that they may not have realized their brand gained so much clout 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. This paper provides a methodology to assess the impact of such crises in a quantitative way. Specifically, we propose a time-varying parameter error-correction model, cast in a Dynamic Linear Model format and estimated by Bayesian techniques, that separates short- and long-term marketing-mix effects, allows for intercepts and response parameters that change as a result of the crisis, and that copes with missing observations due to the absence of the impacted brand during the product-recall period.

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, Thomas, and Quelch 1996). Since marketing investments may 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.

A key take-away from this paper is therefore 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, post-crisis response parameters to marketing activities. The study of an Australian product-harm crisis for peanut butter showed that we have to reject the naive idea that firms can recoup from the crisis by advertising investments that are

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 clout on competitors was strongly reduced.

The marketing literature has identified several double (or higher) jeopardies. For example, Ehrenberg, Goodhardt, and Barwise (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, while Jones (1990) argues that sales promotions could lead to a multiple jeopardy: less profits on more sales in the short run, and a worrying long-term legacy: no increase in sales, increased competition, and a diluted brand image. 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 vulnerability, and (iv) decreased clout. Even though each of the four jeopardies we identified was present in the peanut-butter case under investigation, this need not always be the case. More research is needed to assess their relative importance in other product crises, and determine whether the jeopardies are moderated by brand or category characteristics.

## Technical Appendix: Model Estimation

The model is estimated by using the *filtering forward, backward sampling* algorithm (Carter and Kohn 1994, Frühwirth-Schnatter 1994). The *forward filtering* equations assume that  $G$ ,  $V$ , and  $W_t$  are known, an assumption we shall relax shortly (West and Harrison 1999, p. 103-104)

1. Posterior at  $t - 1$

$$(7) \quad \theta_{t-1} | D_{t-1} \sim N(m_{t-1}, C_{t-1})$$

2. Prior at  $t$

$$(8) \quad \theta_t | D_{t-1} \sim N(a_t, R_t) \text{ where } a_t = Z_t \psi + G_t m_{t-1} \text{ and } R_t = G_t C_{t-1} G_t' + W$$

3. One-step forecast

$$(9) \quad y_t | D_{t-1} \sim N(f_t, Q_t) \text{ where } f_t = F_t' a_t \text{ and } Q_t = F_t' R_t F_t + V$$

4. Posterior at  $t$

$$(10) \quad \theta_t | D_t \sim N(m_t, C_t),$$

where  $m_t = a_t + A_t(Y_t - f_t)$ ,  $Y_t$  is the realization of  $y_t$ ,  $C_t = R_t - A_t Q_t A_t'$  and  $A_t = R_t F_t Q_t^{-1}$ .

The *backward filtering* part samples the parameters,  $\theta_t$ , as described by West and Harrison (1999, p. 570). We simulate the individual state vectors  $\theta_T, \theta_{T-1}, \dots, \theta_1$  as follows:

$$(11) \quad \text{Sample } \theta_T \text{ from } (\theta_T | D_T) \sim N(m_T, C_T), \text{ then}$$

$$(12) \quad \text{For each } t = T - 1, T - 2, \dots, 1, 0 \text{ sample } \theta_t \text{ from } p(\theta_t | \theta_{t+1}, D_t), \text{ where the conditioning value of}$$

$\theta_{t+1}$  is the value just sampled. The required conditional distributions are:

$$(\theta_t | \theta_{t+1}, D_t) \sim N(g_t, H_t), \text{ where } g_t = m_t + B_t(\theta_{t+1} - a_{t+1}) \text{ and}$$

$$H_t = C_t - B_t R_{t+1} B_t' \text{ with } B_t = C_t G_t' R_{t+1}^{-1}.$$

As noted above, the process assumes that  $\lambda$ ,  $V$ ,  $W$  and  $\psi$  are known. By using Gibbs sampling techniques (Gelman, Carlin, Stern and Rubin 1995), we can sample from each of these distributions:



1)  $W$ . We assume a time-constant diagonal state equation covariance matrix  $W$ . The diagonality assumption is not that restrictive, as it does not imply  $\theta_{jt}$  are independent – because we allow correlations via the equations for the brands. Rather, the assumption of diagonal  $W$  implies only conditional independence and thus  $W$  captures longitudinal rather than cross sectional variance. The prior on diagonal element  $W_{mb}$  (for brand  $b$ , independent variable  $m$ ) is Inverse Gamma ( $\nu_W/2, S_W/2$ ). Then the full conditional distribution for  $W_{mb}$  is Inverse Gamma  $\sim$

$\left( (\nu_W + T)/2, S_W/2 + \sum_{t=1}^T (\theta_{mbt} - G_{mb}\theta_{t-1} - Z_t\psi_{mb})^2/2 \right)$ , where  $G_{mb}$  is the row from  $G$  corresponding to

$\theta_{mbt}$ . We choose a diffuse prior for  $W$ :  $\nu_W = 3$  and  $S_W = \frac{1}{1000}$ .

2)  $V$ . We allow for nonzero covariances between the errors of the brand in sales equations. We specify the prior on the covariance matrix  $V$  is Inverse Wishart ( $\nu_V, S_V$ ). The full conditional

distribution for  $V$  is Inverse Wishart  $\sim \left( \nu_V + T, S_V + \sum_{t=1}^T (y_t - F_t'\theta_t)(y_t - F_t'\theta_t)' \right)$ . We use a diffuse prior

for  $V$ , with  $\nu_V = B + 2 = 5$  and  $S_V = \frac{1}{1000} * I_B$ .

3)  $\lambda$ . We use the same prior specification for each element of  $\lambda$ . Specifically, for brand  $b$ , independent variable  $m$  we assume a truncated normal prior:  $\lambda_{mb} \sim TN(\mu_\lambda, \Sigma_\lambda) I_{\lambda_{mb} > 0}$ . The likelihood

may be derived as follows. Note that, by rearranging (6) and stacking the observations for parameter

$\theta_{mbt}$  across time in  $\theta'_{mbT} = (\theta_{mb2}, \dots, \theta_{mbT})$  and in  $\theta'_{mbT-1} = (\theta_{mb1}, \dots, \theta_{mbT-1})$ , we obtain

$y_{\lambda mbT} \equiv \theta_{mbT} - Z'_{mbT}\psi_{mb} = \lambda_{mb}\theta_{mbT-1} + \omega_{mbT}$ , where  $\omega_{mbt} \sim N(0, W_{mb})$ ,  $\lambda_{mb}$  is a scalar and  $W_{mb}$  is the

diagonal element from  $W$  corresponding to  $\theta_{mb}$ . Then this yields the standard form for a regression with

the likelihood  $\lambda_{mb} \sim N\left(\left[\theta'_{mbT-1}\theta_{mbT-1}\right]^{-1}(\theta'_{mbT-1}y_{\lambda mbT}), \left[\theta'_{mbT-1}\theta_{mbT-1}\right]^{-1}W_{mb}\right) \equiv N(l_{\lambda_{mb}}, S_{\lambda_{mb}})$ . Given that the

prior and likelihood are normal, the full conditional posterior distribution is given by

$\lambda_{mb} \sim TN((\Sigma_{\lambda}^{-1} + S_{\lambda_{mb}}^{-1})^{-1}(\Sigma_{\lambda}^{-1}\mu_{\lambda} + S_{\lambda_{mb}}^{-1}I_{\lambda_{mb}}), (\Sigma_{\lambda}^{-1} + S_{\lambda_{mb}}^{-1})^{-1})I_{\lambda_{mb}>0}$ , i.e., we draw  $\lambda_{mb}$  from a normal distribution truncated at zero. For  $\lambda$  we use a diffuse prior:  $\mu_{\lambda} = 0.50$  and  $\Sigma_{\lambda} = 100$ .

4)  $\psi$ . For brand  $b$ , independent variable  $m$  we assume a normal prior:  $\psi_{mb} \sim N(\mu, \Sigma_{\psi})$ . We construct the likelihood as follows. Rearranging equation (6) yields

$y_{\psi_{mb}T} \equiv \theta_{mbT} - \lambda_{mbT-1} = Z_{mbT}\psi_{mb} + \omega_{mbT}$  where  $\omega_{mbT} \sim N(0, W_{mb})$ . This is a standard regression equation. Thus the likelihood for  $\psi_{mb} \sim N((Z'_{mbT}Z_{mbT})^{-1}Z'_{mbT}y_{\psi_{mb}T}, (Z'_{mbT}Z_{mbT})^{-1}W_{mb}) \equiv N(d_{\psi_{mb}}, S_{\psi_{mb}})$ .

When combined with the normal prior, the full conditional posterior distribution is given as

$\psi_{mb} \sim N((\Sigma_{\psi_{mb}}^{-1} + S_{\psi_{mb}}^{-1})^{-1}(\Sigma_{\psi_{mb}}^{-1}\mu_{mb} + S_{\psi_{mb}}^{-1}d_{\psi_{mb}}), (\Sigma_{\psi_{mb}}^{-1} + S_{\psi_{mb}}^{-1})^{-1})$ . We use diffuse priors:  $\mu = 0$ ,  $\Sigma_{\psi} = 100$ .

### *Inferences*

The model is estimated by sequentially running through the forward-filtering, backward sampling equations (7)-(12). Next we draw the parameters specified at 1)-4) above, and that completes one Gibbs draw. We generate 400,000 draws in total of which we use the first 200,000 draws for burn-in purposes; based on visual checks the chain converges already after approximately 10,000 draws. We use every 100<sup>th</sup> of the final 200,000 draws for inferences, since thinning the series of draws reduces autocorrelation (Gelman et al. 1995). Hence, the effective sample size is 2,000.

### *Missing values*

The DLM copes naturally with missing data. A missing brand in week  $t$  causes missing values in the dependent variables (vector  $y$ ) and in the independent variable (matrix  $F$ ). The corresponding rows are omitted from  $y$  and  $F$ , as are the corresponding rows and columns in matrix  $V$  (see also Van Heerde, Mela, and Manchanda 2004). The parameters associated with the missing brand are not updated in week  $t$ , which is achieved by equaling the posterior distribution to its prior. Specifically, for such parameters we use in equation (10)  $m_t = a_t$  and  $C_t = R_t$  (West and Harrison 1999, p. 351).

## References

- Aaker, David A. (1991), *Managing Brand Equity: Capitalizing on the Value of a Brand Name*, New York: Free Press.
- ABC Radio National (1996), "Recalls, Reputation, and Public Relations," *The Business Report*, July 12.
- Advertising Age (2000), Firestone Woes Create Opportunity, September 18.
- Ahluwalia, Rohini, Robert E. Burnkrant, and H. Rao Unnava (2000), "Consumer Response to Negative Publicity: The Moderating Role of Commitment," *Journal of Marketing Research*, 37 (May), 203-214.
- Bass, Frank M. and Thomas L. Pilon (1980), "A Stochastic Brand Choice Framework for Econometric Modeling of Time Series Market Share Behavior," *Journal of Marketing Research*, 17 (4), 486-497.
- Bell, David R., Jeongweng Chiang, and V. Padmanabhan (1999), "The Decomposition of Promotional Response: An Empirical Generalization," *Marketing Science*, 18 (4), 504-526.
- Bijmolt, Tammo H.A., Harald J. van Heerde, and Rik Pieters (2005), "New Empirical Generalizations on the Determinants of Price Elasticity," *Journal of Marketing Research*, 42 (May), p. 141-156.
- Byzalov, Dmitri and Ron Shachar (2004), "The Risk Reduction Role of Advertising," *Quantitative Marketing and Economics*, 2, 283-320.
- Blattberg, Robert C. and Kenneth J. Wisniewski (1989), "Price-Induced Patterns of Competition," *Marketing Science*, 8 (4), 291-309.
- Boulding, William, Eunkyoo Lee, and Richard Staelin (1994), "Mastering the Mix: Do Advertising, Promotion, and Sales Force Activities Lead to Differentiation?," *Journal of Marketing Research*, 31 (May), 159-172.
- Bronnenberg, Bart J. and Luc Wathieu (1996), "Asymmetric Promotion Effects and Brand Positioning," *Marketing Science*, 15 (4), 379-394.
- Burton, Michael and Trevor Young (1996), "The impact of BSE on the Demand for Beef and Other Meats in Great Britain," *Applied Economics*, 28 (6), 687-694
- Business Review Weekly (1996), "Peanut Butter King Loses a Kingdom," September 1.
- Business Week (1999), "Have a Coke and a Smile—Please. After the Debacle in Europe, It's Pushing Hard to Rebound," August 23.
- Carter, C.K. and R Kohn (1994), "On Gibbs Sampling for State Space Models," *Biometrika*, 81 (3), 541-53.
- Chu, Ting-Heng, Che-Chun Lin, and Larry J. Prather (2005), "An Extension of Security Price Reactions Around Product Recall Announcements," *Quarterly Journal of Business and Economics*, 44 (3/4), 33-48.
- Cooper, Lee G., Jan de Leeuw, and Arum G. Sogomonian (1991), "An Imputation Method for Dealing with Missing Data in Regression," *Applied Stochastic Models and Data Analysis*, 7 (3), 213-235.
- Davidson, Wallace N. III and Dan L. Worrell (1992), "The Effect of Product Recall Announcements on Shareholder Wealth," *Strategic Management Journal*, 13 (6), 467-473.
- Dawar, Niraj (1998), "Product-Harm Crises and the Signaling Ability of Brands," *International Studies of Management and Organisation*, 28 (3), 109-119.
- Dawar, Niraj and Mdan M. Pillutla (2000), "Impact of Product-Harm Crises on Brand Equity: The Moderating Role of Consumer Expectations," *Journal of Marketing Research*, 37 (May), 215-226.
- Dekimpe, Marnik and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397-412.
- Deleersnyder, Barbara, Inge Geyskens, Katrijn Gielens and Marnik G. Dekimpe (2002), "How Cannibalistic is the Internet Channel? A Study of the Newspaper Industry in the United Kingdom and The Netherlands," *International Journal of Research in Marketing*, 19 (4), 337-348.
- Ehrenberg, Andrew S.C., Gerald J. Goodhardt, and T. Patrick Barwise (1990), "Double Jeopardy Revisited," *Journal of Marketing*, 54 (July), 82-91.
- Financial Times (2005), "Food Chain 'Thrilled' by Arrest of Woman Who Said She Found a Finger in her Chili," April 23.
- Finkelstein, Sydney (2005), "When Bad Things Happen to Good Companies: Strategy Failure and Flawed Executives," *Journal of Business Strategy*, 26 (2), 19-28.

- Foekens, Eijte W., Peter S.H. Leeftang, and Dick R. Wittink (1999), "Varying Parameter Models to Accommodate Dynamic Promotion Effects," *Journal of Econometrics*, 89 (1-2), 249-268.
- Fok, Dennis, Csilla Horváth, Richard Paap, and Philip Hans Franses (2005), "A Hierarchical Bayes Error Correction Model to Explain Dynamic Effects of Price Changes," *Working paper, Erasmus University*.
- Franses, Philip Hans (1994), "Modeling New Product Sales: An Application of Cointegration Analysis," *International Journal of Research in Marketing*, 11 (5), 491-502.
- Franses, Philip Hans, Teun Kloek and André Lucas (1999), "Outlier Robust Analysis of Long-run Marketing Effects for Weekly Scanning Data," *Journal of Econometrics*, 89 (1-2), 293-315.
- Frühwirth-Schnatter, Sylvia (1994), "Data Augmentation and Dynamic Linear Models," *Journal of Time Series Analysis*, 15 (2), 183-202.
- Gelman, Andrew, John B. Carlin, Hal S. Stern, and Donald B. Rubin (1995), *Bayesian Data Analysis*, New York: Chapman and Hall.
- Goldberg, Marvin E. and Jon Hartwick (1990), "The Effects of Advertising Reputation and Extremity of Advertising Claim on Advertising Effectiveness," *Journal of Consumer Research*, 17 (September), 172-179.
- Govindaraj, Suresh, Bikki Jaggi, and Beixin Lin (2004), "Market Overreaction to Product Recall Revisited – The Case of Firestone Tires and the Ford Explorer," *Review of Quantitative Finance and Accounting*, 23, 31-54.
- Griffin, Mitch., Barry J. Babin, and Jill S. Attaway (1991), "An Empirical Investigation of the Impact of Negative Publicity on Consumer Attitudes and Intentions," *Advances in Consumer Research*, 18, 334-341.
- Hoeffler, Steve and Kevin L. Keller (2003), "The Marketing Advantages of Strong Brands," *Brand Management*, 10 (6), 421-445.
- Holmes, John G. and John K. Rempel (1989), *Trust in Close Relationships in: Review of Personality and Social psychology*, Vol. 10, Thousand Oaks, CA: Sage Publications.
- Jones, John Philip (1990), "The Double Jeopardy of Sales Promotions," *Harvard Business Review*, 68 (5), 145-152.
- Kamakura, Wagner A. and Gary J. Russell (1989), "A Probabilistic Choice Model for Market Segmentation and Elasticity Structure," *Journal of Marketing Research*, 26 (November), 379-390.
- Kamakura, Wagner A. and Michel Wedel (2000), "Factor Analysis and Missing Data," *Journal of Marketing Research*, 37 (November), 490-498.
- Klein, Jill and Niraj Dawar (2004), "Corporate Social Responsibility and Consumers' Attributions and Brand Evaluations in a Product-Harm Crisis," *International Journal of Research in Marketing*, 21 (3), 203-217.
- Lancaster, Kent M. (1984), "Brand Advertising Competition and Industry Demand," *Journal of Advertising*, 13 (4), 19-30.
- Laufer, Daniel and Kate Gillespie (2004), "Differences in Consumer Attributions of Blame between Men and Women: The Role of Perceived Vulnerability and Empathic Concern," *Psychology & Marketing*, 21 (2), 141-157.
- Lemieux, James and Leigh McAlister (2005), "Handling Missing Values in Marketing Data: A Comparison of Techniques," *Marketing Science Institute Report 05-002*, 41-60.
- Leone, Robert P. (1995), "Generalizing What is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, 14 (Part 2 of 2), G141-G150.
- MacKinsey, Scott B. and Richard J. Lutz (1989), "An Empirical Examination of the Structural Antecedents of Attitude Toward the Ad in an Advertising Pretesting Context?," *Journal of Marketing* 53 (April), 48-65.
- Marcus, Richard D., Steve Swidler, and Terry L. Zivney (1987), "An Explanation of Why Shareholders' Losses are so Large After Drug Recalls," *Managerial and Decision Economics*, 8 (4), 295-300.
- Marsh, Thomas L., Ted C. Schroeder, and James Mintert (2004), "Impacts of Meat Product Recalls on Consumer Demand in the USA," *Applied Economics*, 36 (9), 897-910.
- Mitroff, Ian I. (2004), *Crisis Leadership: Planning for the Unthinkable*. New York: John Wiley & Sons.

- Mitroff, Ian I. and Ralph H. Kilmann (1984), *Corporate Tragedies: Product Tampering, Sabotage, and other Catastrophes*. New York: Praeger.
- Nicholson, Walter (1972), *Microeconomic Theory: Basic Principles and Extensions*. Hinsdale, IL: The Dryden Press.
- Nijs, Vincent, Marnik G. Dekimpe, Jan Benedict Steenkamp, and Dominique M. Hanssens (2001), "The Category Demand Effects of Price Promotions," *Marketing Science*, 20 (1), 1-22.
- Paap, Richard and Philip Hans Franses (2000), "A Dynamic Multinomial Probit Model for Brand Choice with Different Long-Run and Short-Run Effects of Marketing-Mix Variables," *Journal of Applied Econometrics*, 15 (6), 717-744.
- Pauwels, Koen, Dominique M. Hanssens, and S. Siddarth (2002), "The Long-Term Effects of Price Promotions on Category Incidence, Brand Choice and Purchase Quantity," *Journal of Marketing Research*, 39 (November), 421-439.
- Pauwels, Koen and Shuba Srinivasan (2004), "Who Benefits from Store Brand Entry," *Marketing Science*, 24 (3), 364-390.
- Perron P. (1994), "Trend, Unit Root and Structural Change in Macro-Economic Time Series," in B. Bhaskara Rao (Ed.), *Cointegration for the Applied Economist*. New York: St. Martin's Press, 113-146.
- Pesaran, M. Hashem and Hossein Samiei (1991), "Persistence, Seasonality and Trend in the UK Egg Production," *Applied Economics*, 23 (3), 479-484.
- Piggott, Nicholas E. and Thomas L. Marsh (2004), "Does Food Safety Information Impact U.S. Meat Demand?," *American Journal of Agricultural Economics*, 86 (1), 154-174.
- Rupp, Nicholas G. and Curtis R Taylor (2002), "Who Initiates Recalls and Who Cares: Evidence from the Automobile Industry," *The Journal of Industrial Economics*, 50 (2), 123-149.
- Schultz, Randall L. and Dick R. Wittink (1976), "The Measurement of Industry Advertising Effects," *Journal of Marketing Research*, 13 (February), 71-75.
- Sethuraman, Raj, V. Srinivasan, and Doyle Kim (1999), "Asymmetric and Neighborhood Cross-Price Effects: Some Empirical Generalizations," *Marketing Science*, 18 (1), 23-41.
- Skowronski, John J. and Donal E. Carlston (1989), "Negativity and Extremity Biases in Impression Formation: A Review of Explanations," *Psychological Bulletin*, 105 (1), 131-142.
- Smith, N. Craig, Robert J. Thomas, and John A. Quelch (1996), "A Strategic Approach to Managing Product Recalls," *Harvard Business Review*, 74 (5), 102-112.
- Steenkamp, Jan Benedict E.M., Vincent R. Nijs, Dominique M. Hanssens, and Marnik G. Dekimpe (2005), "Competitive Reactions to Advertising and Promotion Attacks," *Marketing Science*, 24 (1), 35-54.
- Stockmeyer, J. (1996), "Brands in Crisis: Consumer Help for Deserving Victims," *Advances in Consumer Research*, 23 (1), 429-435.
- Sullivan, Mary (1990), "Measuring Image Spillovers in Umbrella-brand Products," *Journal of Business*, 63 (3), 309-329.
- The Guardian (1999), <http://www.guardian.co.uk/food/Story/0,2763,205762,00.html>
- The New York Times (2004), "GM Rides Bumpy Road to Quality Redemption," April 29.
- The Sydney Morning Herald (1996a), "Peanut Butter Recall Widened in Health Scare," June 26.
- The Sydney Morning Herald (1996b), "Kraft Ad Campaign to Cost More than Peanuts", November 26.
- Van Heerde, Harald J., Peter S.H. Leeflang, and Dick R. Wittink (2000), "The Estimation of Pre- and Postpromotion Dips with Store-Level Scanner Data," *Journal of Marketing Research*, 37 (August), 383-395.
- Van Heerde, Harald J., Carl F. Mela, and Puneet Manchanda (2004), "The Dynamic Effect of Innovation on Market Structure," *Journal of Marketing Research*, 41 (May), 166-183.
- Weinberger, Marc G., Jean B. Romeo and Azhar Piracha (1993), "Negative Product Safety News: Coverage, Responses, and Effects," *Business Horizons*, 34 (3), 23-31.
- West, Mike and Jeff Harrison (1999), *Bayesian Forecasting and Dynamic Models*. Second Edition. New York: Springer.

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)

Table 2  
Empirical results for Eta: steady-state posterior distributions

Effect	Independent variable	Period	Before crisis Median (2.5 <sup>th</sup> , 97.5 <sup>th</sup> percentiles)	After crisis Median (2.5 <sup>th</sup> , 97.5 <sup>th</sup> percentiles)	Significant Change <sup>b</sup>
Own effects	Constant		2.78*	0.99	<u>Decrease</u>
			(1.50,4.47)	(-0.12,1.54)	
	Advertising <sup>a</sup>	Short run	3.77*	0.59	<u>Decrease</u>
			(1.07,5.32)	(-0.26,1.59)	
	Price	Short run	13.36*	2.50	<u>Decrease</u>
			(7.50,23.12)	(-0.69,5.43)	
	Long run	-3.65*	-3.83*	No	
		(-6.72,-1.09)	(-4.33,-3.22)		
		Long run	-0.06	-1.60	No
			(-4.61,4.97)	(-3.01,2.75)	
Vulnerability	Advertising Kraft	Short run	1.80*	0.34	<u>Decrease</u>
			(0.80,2.51)	(-0.32,1.25)	
		Long run	11.11*	1.59	<u>Decrease</u>
			(1.40,20.86)	(-3.34,6.03)	
	Advertising Sanitarium	Short run	3.65*	0.46	<u>Decrease</u>
			(1.06,5.78)	(-1.52,1.28)	
		Long run	3.32	2.30	No
			(-3.13,20.17)	(-5.62,10.70)	
	Price Kraft	Short run	0.97*	1.54*	No
			(0.19,2.15)	(0.72,2.41)	
		Long run	-0.37	0.48	No
			(-4.39,3.46)	(-3.43,3.93)	
Price Sanitarium	Short run	0.82*	1.00*	No	
		(0.09,1.49)	(0.34,2.14)		
	Long run	-1.05	2.21*	<u>Increase</u>	
		(-5.36,1.27)	(1.00,3.72)		
Clout	Advertising impact on Kraft	Short run	0.57	-1.63	Decrease
			(-0.65,1.78)	(-2.39,0.24)	
		Long run	4.44	2.98	No
			(-10.63,11.59)	(-10.17,12.09)	
	Advertising impact on Sanitarium	Short run	0.52	0.82	No
			(-0.82,4.23)	(-1.08,4.37)	
		Long run	3.45	5.70*	<u>Increase</u>
			(-0.08,5.68)	(3.77,8.01)	
	Price impact on Kraft	Short run	-0.58	0.38	No
			(-1.98,1.13)	(-0.45,1.42)	
	Long run	4.79	4.24*	<u>Increase<sup>c</sup></u>	
		(-5.53,12.33)	(1.74,11.01)		
Price impact on Sanitarium	Short run	1.48*	0.12	<u>Decrease</u>	
		(0.13,3.76)	(-0.56,0.98)		
	Long run	1.96	0.30	No	
		(-0.77,4.90)	(-0.18,1.33)		
Adjustment effect	Lagged ln kilo sales Eta		-0.25*	-0.25*	na <sup>d</sup>
			(-0.40,-0.14)	(-0.40,-0.14)	

A \* indicates that zero is not included in the 95% posterior density interval.

a. Advertising expenditures are measured in millions of AU\$.

b. Underlined changes are significant at the 5%-level, other changes at the 10% level.

c. Although the magnitude decreases, the estimate becomes positively significant.

d. This parameter is assumed to be unaffected by the crisis (see equation (4)).

Table 3  
Empirical results for Kraft: steady-state posterior distributions

Effect	Independent variable	Period	Before crisis Median (2.5 <sup>th</sup> , 97.5 <sup>th</sup> percentiles)	After crisis Median (2.5 <sup>th</sup> , 97.5 <sup>th</sup> percentiles)	Significant Change <sup>b</sup>	
Own	Constant		1.44* (0.77,2.77)	-0.44 (-1.61,1.13)	<u>Decrease</u>	
	Advertising <sup>a</sup>	Short run	2.04 (-0.43,3.86)	1.67* (0.51,2.84)	<u>Increase<sup>c</sup></u>	
		Long run	15.61* (7.65,161.63)	10.71* (5.24,37.48)	Decrease	
	Price	Short run	-0.50 (-5.16,0.95)	-3.00* (-4.24,-2.19)	<u>Decrease</u>	
		Long run	-0.93 (-9.63,3.31)	0.26 (-7.06,2.98)	No	
	Vulnerability	Advertising Eta	Short run	0.57 (-0.65,1.78)	-1.63 (-2.39,0.24)	Decrease
Long run			4.44 (-10.63,11.59)	2.98 (-10.17,12.09)	No	
Advertising Sanitarium		Short run	-1.67 (-2.88,1.26)	2.36* (0.27,3.62)	<u>Increase</u>	
		Long run	13.09 (-23.36,33.62)	10.54 (-0.30,30.74)	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)	<u>Increase<sup>c</sup></u>	
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	
Clout		Advertising impact on Eta	Short run	1.80* (0.80,2.51)	0.34 (-0.32,1.25)	<u>Decrease</u>
			Long run	11.11* (1.40,20.86)	1.59 (-3.34,6.03)	<u>Decrease</u>
		Advertising impact on Sanitarium	Short run	-1.20 (-3.27,0.58)	0.81* (0.06,1.57)	<u>Increase</u>
			Long run	-5.63 (-10.74,2.96)	2.41 (-0.14,5.52)	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 <sup>d</sup>	

A \* indicates that zero is not included in the 95% posterior density interval.

a. Advertising expenditures are measured in millions of AU\$.

b. Underlined changes are significant at the 5%-level, other changes at the 10% level.

c. Although the magnitude decreases, the estimate becomes positively significant.

d. This parameter is assumed to be unaffected by the crisis (see equation (4)).



Table 4  
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

Figure 1  
Sales patterns

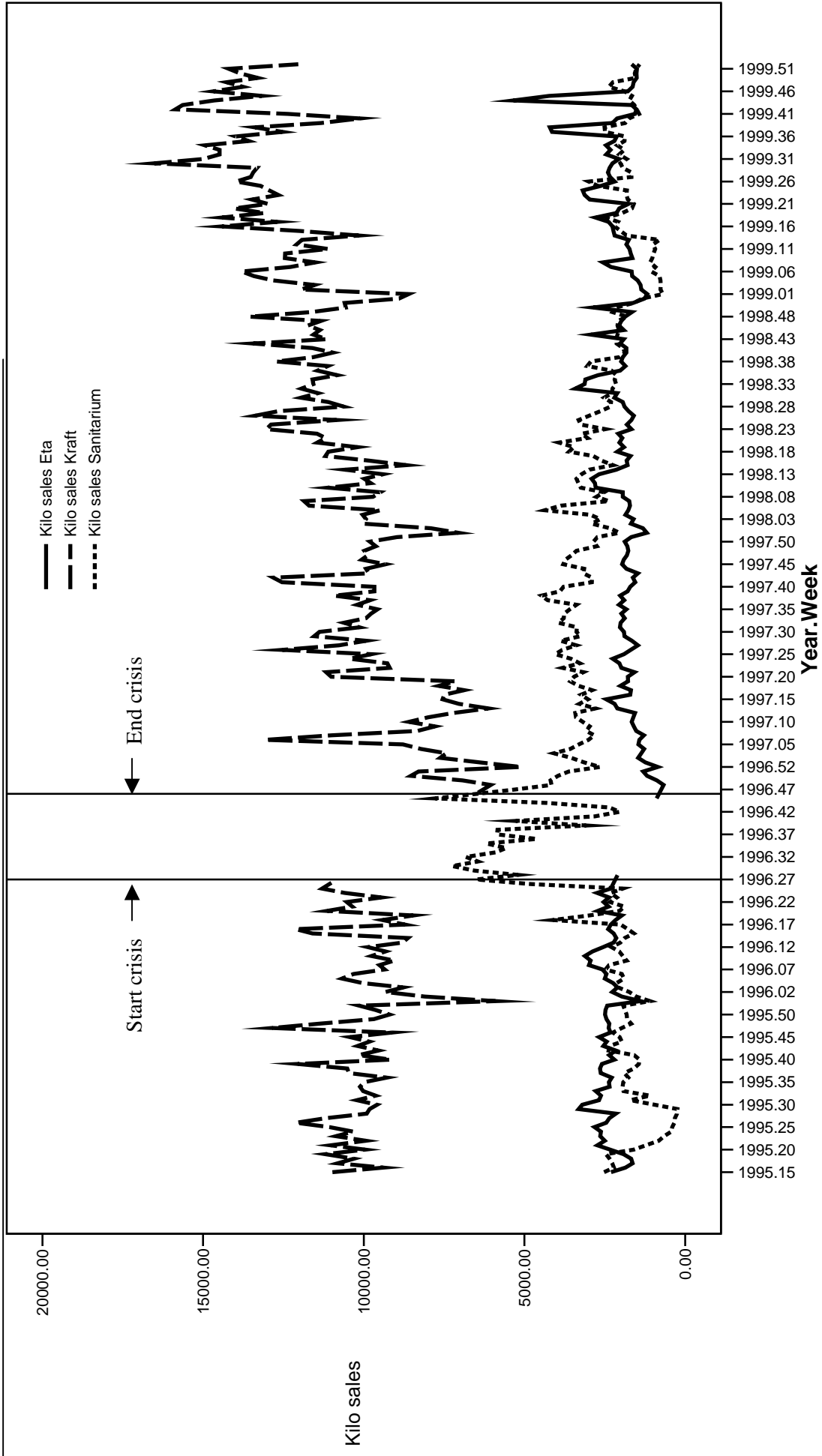


Figure 2  
Illustrations of time-varying parameters

